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INTELLIGENT PROCESS ANALYSIS BASED ON ARTIFICIAL INTELLIGENCE AND LOW-CODE PLATFORMS

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Abstract: The rapid development of artificial intelligence (AI), machine learning, process mining, and low-code development platforms is transforming the methods used to analyze and optimize organizational processes. Traditional process analysis generally depends on manually constructed process models, expert knowledge, and retrospective examination of operational indicators. By contrast, intelligent process analysis combines event-log data, artificial intelligence algorithms, process mining techniques, predictive analytics, and visual low-code environments to support automated discovery, diagnosis, prediction, and improvement of business processes. This article examines the conceptual and technological foundations of intelligent process analysis based on AI and low-code platforms. The research is based on a structured analysis of scientific literature, systematic reviews, established process-mining research, artificial intelligence governance frameworks, and contemporary studies of low-code development. Particular attention is given to process discovery, conformance checking, predictive process monitoring, machine learning, explainable artificial intelligence, automated machine learning, and human-centered AI. The analysis demonstrates that low-code platforms can reduce the technical barrier to implementing AI-supported process-analysis solutions by providing visual modeling, reusable components, integration mechanisms, and automated workflows. However, low-code environments do not eliminate fundamental requirements concerning data quality, model validation, security, explainability, governance, and human oversight. Recent systematic research also indicates that the benefits of low-code development are context-dependent and that security, complexity, and governance remain important challenges. The article proposes an integrated conceptual architecture in which low-code platforms function as the implementation and orchestration layer, while AI and process-mining technologies provide analytical intelligence. Such an approach can contribute to faster process diagnosis, predictive decision support, continuous monitoring, and evidence-based process improvement.

Keywords: Artificial intelligence, intelligent process analysis, process mining, machine learning, predictive process monitoring, low-code development, no-code platforms, automated machine learning, explainable artificial intelligence, business process management, digital transformation.

Introduction

Digital transformation has fundamentally changed the volume, diversity, and velocity of organizational data. Enterprise resource planning systems, customer relationship management systems, workflow applications, information portals, financial systems, production-management systems, and digital communication platforms continuously generate records describing operational activities. These records create an opportunity to move from assumptions about how processes operate toward evidence-based analysis of how processes actually behave.

Process mining represents an important scientific approach in this transformation. Van der Aalst describes process mining as a discipline positioned between process science and data

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science that uses event data to discover, monitor, and improve real processes [1]. Process discovery can reconstruct process models from event logs, while conformance checking compares observed behavior with prescribed or reference models [2]. These capabilities are particularly important because organizational processes frequently differ from their documented representations.

Artificial intelligence extends this analytical capability by enabling systems to identify patterns, generate predictions, classify cases, estimate risks, and support decisions. The OECD's updated definition describes an AI system as a machine-based system that infers, from received inputs, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments [3, pp. 4–11]. In process analysis, this capability can be applied to questions such as whether an ongoing case is likely to violate a service-level agreement, whether a transaction is likely to be delayed, or which process conditions are associated with undesirable outcomes.

An additional technological development is the emergence of low-code and no-code platforms. These platforms provide visual development environments, reusable components, declarative configuration, integration facilities, and workflow orchestration. Their development has been accompanied by increasing academic attention. Bucaioni, Cicchetti, and Ciccozzi reported that low-code development had become a significant software-engineering approach and noted that the global revenue of low-code development technologies reached USD 13.8 billion in 2021 [7, pp. 1959–1981]. More recent systematic research confirms that low-code development has become an important research area, although evidence regarding quality, complexity, cost, and security remains context-dependent [8].

The combination of AI and low-code platforms therefore creates an important research direction: intelligent process analysis can be transformed from a specialized activity requiring substantial programming expertise into an integrated analytical capability accessible through visual development environments.

The objective of this article is to examine the scientific and technological foundations of intelligent process analysis based on AI and low-code platforms, identify its principal components and benefits, analyze its limitations, and formulate an integrated conceptual approach for implementation.

Methodology

The research employs a qualitative structured literature-analysis methodology. The study does not introduce fabricated experimental observations or artificial statistical datasets. Instead, it synthesizes findings from peer-reviewed scientific publications, academic books, systematic literature reviews, and authoritative institutional publications.

The literature was organized into four analytical groups. The first group concerns process mining and intelligent process analysis. The foundational works of van der Aalst were examined with particular attention to process discovery, conformance checking, operational support, and the relationship between process mining and data science [1,2,4].

The second group concerns AI-based process prediction. Neu, Lahann, and Fettke conducted a systematic literature review of deep-learning methods for process prediction and analyzed approaches for outcome prediction, time prediction, and control-flow prediction [5, pp. 801–827]. This literature provides an important foundation for understanding how machine learning can move process analysis from retrospective description toward predictive monitoring.

The third group concerns low-code development. Research by Bucaioni et al. [7], Käss et al. [9], Velásquez et al. [10], Trieflinger et al. [11], and Ajimati et al. [8] was analyzed to identify

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the principal characteristics, opportunities, adoption patterns, and risks associated with low-code and no-code platforms.

The fourth group concerns responsible and explainable AI. The research incorporated the NIST Artificial Intelligence Risk Management Framework, which emphasizes validity and reliability, safety, security, transparency, explainability, privacy, and fairness [12, pp. 12–18]. The literature on explainable AI was also considered because intelligent process-analysis systems may influence operational decisions and therefore require understandable analytical outputs [6, pp. 82–115].

The analytical procedure consisted of four stages: identification of technological components; comparison of their functions; synthesis of complementary capabilities; and formulation of an integrated conceptual model. The approach is therefore exploratory and analytical rather than experimental.

Results

The analysis demonstrates that intelligent process analysis based on AI and low-code platforms can be conceptualized as a multilayer architecture consisting of data, process intelligence, artificial intelligence, low-code orchestration, and human governance.

Data and event-log layer

The foundation of intelligent process analysis is process data. A process event normally contains information concerning an activity, a case or process instance, and a temporal dimension. Depending on the organizational environment, additional attributes may include organizational unit, employee role, transaction value, geographic location, product category, or process status.

Process mining research emphasizes that event data makes it possible to reconstruct actual process behavior rather than relying exclusively on theoretical models [1, pp. 125–162]. However, data quality is fundamental. Missing timestamps, inconsistent identifiers, duplicated events, incomplete process traces, and incompatible data structures can substantially reduce analytical reliability.

Consequently, AI cannot compensate automatically for fundamentally inadequate process data. An intelligent architecture must therefore incorporate data validation, preprocessing, transformation, and quality monitoring before applying predictive or prescriptive models.

Process discovery and conformance analysis

Process discovery is one of the central functions of process mining. Instead of requiring analysts to manually construct every process model, discovery algorithms can derive representations of observed process behavior from event logs [1, pp. 163–194].

Conformance checking provides a complementary function. It compares observed behavior with an existing process model and identifies deviations [1, pp. 243–274]. In organizational applications, this can support compliance monitoring, identification of unnecessary process steps, and detection of exceptional process paths.

The Process Mining Handbook further identifies process discovery, conformance checking, process enhancement, monitoring, and related analytical techniques as central components of the field [4, pp. 3–34]. Thus, AI-enabled process analysis should not be viewed as a replacement for process mining; rather, AI can extend process mining with prediction, classification, anomaly detection, and recommendation capabilities.

AI-based predictive process analysis

A major advantage of integrating AI with process mining is the possibility of predicting future process behavior.

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Traditional process analysis answers questions such as: “What happened?” or “How does the process normally operate?” Predictive process analysis introduces questions such as: “What is likely to happen next?” and “Which cases are at risk?”

Deep-learning research demonstrates the potential of sequence-based methods for process prediction. Neu et al. reviewed approaches using deep learning for predicting future events, process outcomes, performance indicators, and control-flow behavior [5, pp. 801–827]. Such methods can process sequences of historical events and learn relationships between preceding activities and subsequent outcomes.

For example, in a customer-service process, an AI model may estimate whether a currently active case is likely to exceed a predefined response time. In a financial process, it may identify transactions with a high probability of requiring additional review. In manufacturing, predictive models can analyze sequences of production events to identify conditions associated with delays or quality problems.

Automated machine learning

Another important component is automated machine learning (AutoML). Traditional machine-learning development often requires specialists to select algorithms, preprocess data, engineer features, optimize hyperparameters, and evaluate alternative models. AutoML seeks to automate parts of this workflow.

Hutter, Kotthoff, and Vanschoren describe AutoML methods including hyperparameter optimization, meta-learning, neural architecture search, and automated model selection [13, pp. 3–77]. This is particularly relevant to low-code environments because visual platforms can expose automated model-building functions without requiring users to manually implement every algorithmic step.

Nevertheless, automation does not remove the need for domain expertise. The selection of target variables, interpretation of outcomes, definition of acceptable errors, identification of biased data, and assessment of business consequences remain organizational and scientific responsibilities.

Low-code implementation layer

Low-code platforms provide an implementation environment through which AI and process-analysis capabilities can be integrated into operational workflows. Systematic research identifies graphical interfaces, reusable components, integration with external services, collaborative development, and component reuse among characteristic features of low-code platforms [10, pp. 30–37].

This architecture can be represented conceptually as follows:

Event Data → Data Preparation → Process Mining → AI/ML Model → Prediction or Recommendation → Low-Code Workflow → Human Decision → Feedback

The low-code platform can connect data sources, invoke analytical models, display dashboards, trigger notifications, route cases, and initiate predefined actions.

For example, an AI model can classify a process case as “normal,” “at risk,” or “high risk.” A low-code workflow can then automatically route high-risk cases to an experienced employee while allowing low-risk cases to continue through a standard workflow.

This demonstrates an important distinction: AI provides analytical intelligence, whereas the low-code environment provides orchestration and application logic.

Human-centered and explainable AI

AI-based process decisions can have significant consequences. An opaque model that automatically changes workflows may produce operational risks if its predictions are incorrect or cannot be understood by responsible employees.

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

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

Explainable AI research emphasizes the importance of interpretability for trustworthy deployment of complex AI models [6, pp. 82–115]. Similarly, Shneiderman's human-centered AI approach emphasizes meaningful human control, reliability, safety, and human values [14, pp. 6–16].

Accordingly, intelligent process-analysis systems should provide not only predictions but also appropriate explanations. A process manager should be able to understand why a case has been classified as high risk, which process characteristics contributed to the prediction, and what uncertainty is associated with the model output.

Analysis and Discussion

The synthesis of the reviewed literature indicates that AI and low-code platforms are complementary rather than interchangeable technologies.

The primary contribution of AI is analytical. Machine learning can identify patterns in historical data, estimate probabilities, detect anomalies, classify cases, and predict future events. Process mining contributes process awareness by connecting these predictions to the actual structure and dynamics of organizational processes.

The primary contribution of low-code platforms is operationalization. They provide a mechanism through which analytical results can become part of an operational workflow without requiring every business analyst to implement software manually.

Recent empirical research supports the importance of organizational and technological factors in low-code adoption. Käss, Strahringer, and Westner analyzed 36 cases and identified several archetypes of low-code adoption, including approaches associated with IT-resource shortages, application-development democratization, and organizational synergies [9, pp. 118762–118786]. Their findings demonstrate that low-code adoption is not purely a technical decision; organizational conditions and the relationship between social and technical systems are also important.

The same conclusion is supported by systematic research. Ajimati, Carroll, and Maher reviewed 40 primary studies concerning low-code/no-code adoption and citizen development and identified benefits, challenges, theoretical perspectives, and research gaps [8]. Their findings indicate that successful implementation requires consideration of organizational context rather than assuming that the technology will automatically produce transformation.

A similar conclusion follows from research on the risks of low-code. Trieflinger and colleagues identified both opportunities and risks associated with low-code development, emphasizing the importance of governance when organizations distribute application-development capabilities beyond professional developers [11, pp. 63–73]. Therefore, the democratization of development should be accompanied by standards for security, architecture, data access, testing, documentation, and maintenance.

Data quality as a critical limitation

The first major limitation of AI-enabled process analysis is data quality. An AI system trained on incomplete or systematically biased data may produce unreliable predictions. Process mining itself also depends on accurate event logs.

Therefore, implementation should include a data-quality layer capable of checking completeness, consistency, uniqueness, temporal validity, and case identification. This is especially important when multiple enterprise systems contribute data to a single process.

Model risk and explainability

The second limitation concerns AI model risk. High predictive performance on historical data does not necessarily guarantee reliable behavior in future operational environments. Changes

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

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

in customer behavior, regulations, organizational structures, or business strategies may alter the relationship between process inputs and outcomes.

The NIST AI Risk Management Framework recommends systematic consideration of validity, reliability, safety, security, transparency, explainability, privacy, and fairness [12, pp. 12–18]. These principles are directly applicable to AI-enabled process analysis.

In practice, this means that organizations should establish model monitoring, validation procedures, version control, documentation, human oversight, and mechanisms for reporting AI errors.

Security and governance of low-code environments

Low-code platforms can increase development speed, but increased accessibility can also expand the number of people capable of creating applications and connecting data sources. This creates governance challenges.

A poorly governed low-code environment may produce duplicated applications, inconsistent data flows, excessive permissions, insecure integrations, or dependence on platform-specific components. Recent research indicates that security and cost remain open questions in the broader low-code research agenda [8].

Therefore, intelligent process-analysis environments should incorporate role-based access control, secure API management, data-classification policies, application inventories, testing procedures, and centralized governance.

Toward continuous intelligent process management

The most important conceptual result of this research is that intelligent process analysis should not be limited to static dashboards.

A more advanced architecture operates continuously:

Observe → Discover → Predict → Explain → Recommend → Act → Monitor → Learn

The system observes operational events, discovers process behavior, predicts future outcomes, explains important deviations, recommends possible interventions, executes approved workflow actions, monitors the consequences, and uses new information for future model improvement.

Such a cycle transforms process management from periodic analysis into continuous intelligence.

However, automation should be proportional to risk. Low-risk operational actions may be automated, whereas high-impact decisions should generally remain subject to appropriate human review. This principle is consistent with human-centered AI and responsible AI frameworks [12, pp. 20–32; 14, pp. 6–16].

Scientific and practical implications

From a scientific perspective, the integration of AI, process mining, and low-code development creates an interdisciplinary research field connecting process science, machine learning, software engineering, human-computer interaction, and information systems.

From a practical perspective, the architecture can be applied to customer service, financial operations, supply chains, healthcare administration, manufacturing, education, public administration, and other domains where digital process records are available.

The key condition is not simply the availability of an AI model or low-code platform. Sustainable implementation requires alignment among data, process design, AI models, organizational objectives, human roles, and governance mechanisms.

Conclusion

Artificial intelligence and low-code platforms provide complementary capabilities for the development of intelligent process-analysis systems. Process mining makes it possible to

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reconstruct and evaluate actual organizational processes from event data, while machine learning and deep learning extend this capability toward prediction, anomaly detection, classification, and decision support. Low-code platforms, in turn, provide visual and reusable mechanisms for integrating analytical models into operational applications and workflows.

The literature demonstrates that this combination has substantial potential but should not be interpreted as an automatic solution to organizational inefficiency. The effectiveness of intelligent process analysis depends fundamentally on data quality, appropriate model selection, validation, explainability, security, organizational readiness, and human oversight.

The analysis also indicates that low-code technology can reduce the technical barrier to implementing AI-supported process applications, but it does not eliminate the need for software-engineering principles and governance. Research on low-code adoption demonstrates that outcomes depend on organizational and technological context, while research on responsible AI emphasizes the need to manage reliability, security, transparency, explainability, privacy, and fairness.

The proposed integrated architecture—event data, process mining, AI/ML, low-code orchestration, human decision-making, and continuous feedback—provides a conceptual foundation for intelligent process management. Its principal advantage is the transition from retrospective process reporting toward continuous, predictive, and increasingly adaptive process intelligence.

Future research should focus on empirical evaluation of AI-enabled low-code process systems in specific sectors, standardized evaluation metrics, explainable predictive process monitoring, object-centric process intelligence, automated model governance, and methods for maintaining human control over high-impact automated decisions. Such research can contribute to the development of reliable and scalable intelligent process-analysis systems capable of supporting evidence-based organizational transformation.

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