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Accelerating Business Innovation: A Low-Code Framework for Rapid Deployment of AI Systems to Enhance Operational Efficiency*

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Abstract

The ability to quickly and cost-effectively deploy solutions based on Artificial Intelligence (AI) is a key factor in determining competitive advantage in the modern market. However, traditional AI system development cycles represent a bottleneck for innovation, being a lengthy process that requires highly specialized skills. In response to this challenge, this paper presents a universal business framework that enables the rapid prototyping and deployment of intelligent Decision Support Systems (DSS) using low-code platforms. The paper presents a model of such a generic process template, prepared in the Plus Workflow Editor tool using BPMN notation. The framework's architecture separates the business logic, which analysts can independently model in a graphical environment, from the complex data analysis, which is delegated via API to external AI models. The article demonstrates how the same process template, once prepared, can be adapted within hours to entirely different business problems—from financial planning to operational risk assessment. The key conclusion is the demonstration that a low-code approach drastically reduces implementation time (time-to-market), lowers costs, and democratizes access to advanced technologies, allowing business departments to autonomously implement innovations and enhance operational efficiency.

Keywords: Low-code, Business Process Management (BPM), BPMN, Artificial Intelligence (AI), operational efficiency, time-to-market, digital transformation, Decision Support Systems (DSS)

Introduction

In the modern market, the ability to quickly and cost-effectively deploy solutions based on Artificial Intelligence (AI) has become a critical factor for maintaining a competitive advantage. However, organizations face significant barriers to adopting AI-powered solutions. Traditional development cycles are often slow, resource-intensive, and require deep technical expertise, creating a bottleneck that hinders innovation (Goes, 2014). This creates a clear need for a new type of solution that can democratize access to AI, reduce implementation time, and lower costs.

The academic and practitioner literature has extensively covered the benefits of low-code development platforms (LCDPs) for accelerating application delivery (Rymer, 2019) and the challenges of integrating AI into business operations (Davenport and Ronanki, 2018). However, a significant research gap exists in the synthesis of these domains. While many studies discuss bespoke integrations of AI services, there is a scarcity of formal, reusable frameworks that leverage low-code platforms to orchestrate AI services as part of a managed and

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auditable business process. Existing approaches often treat the AI component as an opaque, black-box function to be called, rather than an integral, transparent step within a governable workflow (Wanner et al., 2020).

In a previous paper (Szczepankiewicz, 2024), we demonstrated the practical feasibility of building a dedicated intelligent decision support system. While that case study confirmed the effectiveness of the approach, it also raised a question: can the same principles be applied to create a flexible, reconfigurable framework for entirely different business areas?

This paper answers that question affirmatively. Building on the foundations of our previous research we address the identified research gap by presenting a flexible framework for orchestrating API-based AI services. The aim of this work is to present not just another tool, but rather a repeatable and scalable method that enables the rapid deployment of diverse AI-based solutions. To achieve this, we employed the Design Science Research (DSR) methodology to guide the creation of our primary research artifact—the framework itself. This paper is structured as follows: Section 2 outlines our methodological approach in detail, Section 3 presents the design of the framework artifact, Section 4 provides a demonstration through illustrative case studies, and Section 5 presents our conclusions.

Methodological Approach

Design Science Research Paradigm

To ground this study in a formal and recognized academic methodology, we have adopted the Design Science Research (DSR) paradigm. DSR is a problem-solving approach widely accepted in the Information Systems (IS) discipline, focused on the creation and evaluation of innovative IT artifacts intended to solve identified organizational problems (Hevner et al., 2004). Unlike behavioral science, which seeks to find truth and explain reality, DSR is fundamentally a creative endeavor that aims to build new and purposeful artifacts to extend human and organisational capabilities (March and Smith, 1995).

In the context of this study, the primary artifact is the generic, low code framework for AI integration. This artifact is not merely a technical implementation but a conceptual model, instantiated through the BPMN process map and the detailed data architecture we have presented. It represents a prescriptive, novel solution to the persistent business challenge of deploying AI-powered systems in an agile, cost-effective, and governable manner. The creation of such an artifact is recognized as a legitimate form of research contribution, provided it is novel, useful, and has been rigorously developed and evaluated (Gregor and Hevner, 2013).

Our Research Process

To structure our research and guide the development of the artifact, we followed the six-step Design Science Research Process model proposed by Peffers et al. (2007). This widely recognized model provides a nominal sequence for conducting DSR projects, ensuring both rigor and relevance. Our application of this process began with Problem Identification and Motivation, where we identified the significant barriers organizations face in adopting AI-powered solutions, such as slow, resource-intensive development cycles that hinder innovation (Goes, 2014). This established the need for a solution to democratize AI access and reduce implementation costs. Next, we proceeded to Define Objectives for a Solution, setting qualitative goals for our artifact, including a significant reduction in time-to-market and the embedding of governance mechanisms. The core of our research effort was the Design and Development phase, which involved the iterative creation of the framework artifact, including its BPMN process model and data architecture.

To prove the artifact's viability, the Demonstration step will involve applying the framework to two distinct business case scenarios within this paper. Subsequently, the Evaluation phase will assess how well the artifact meets its objectives, based on an analytical argument and the results of the demonstration. Finally, the Communication of this research is realized through this paper, intended for publication and presentation at the 46th IBIMA Conference, to share our findings with both academic and practitioner audiences.

Methodological Rigor

The evaluation of the research artifact is a crucial activity within the DSR paradigm, designed to rigorously assess its utility, quality, and efficacy (Hevner et al., 2004). For this study, we have planned a multi-faceted evaluation strategy. The primary method will be an illustrative case study, a well-established method for examining phenomena in their real-world context (Yin, 2018). We will instantiate the framework by implementing two distinct business scenarios, providing tangible proof of the framework's operational capabilities and flexibility. The outcomes will then form the basis for an analytical argumentation, comparing our approach against traditional development cycles. To complement the case study, we plan a subsequent phase of expert evaluation, soliciting qualitative feedback on the framework's usability, innovativeness, and potential business value from experienced practitioners (Venable et al., 2012).

The novelty of our work lies at the intersection of low-code development, AI integration, and Business Process Management (BPM). While literature has covered these areas in isolation (e.g., Rymer, 2019; Davenport and Ronanki, 2018), a research gap exists in formal, reusable frameworks that leverage low-code platforms to orchestrate AI services as part of a managed and auditable business process. Our artifact addresses this gap by proposing a modular process architecture that embeds principles of responsible AI (e.g., human-in-the-loop) directly into the business process. Furthermore, our structured data model for managing AI interactions within a BPMN context is a novel contribution that enhances the maintainability, reusability, and scalability of AI-driven solutions, reframing AI analysis as a transparent and auditable business activity (van der Aalst, 2011).

It is essential to acknowledge the boundaries of this research. First, the artifact was instantiated on a specific low-code platform (Plus Workflow Editor), and while its principles are intended to be platform-agnostic, performance may vary across different environments (Langer et al., 2021). Second, our evaluation is primarily qualitative, based on an illustrative case study. It demonstrates feasibility but does not offer the statistical generalizability of a large-scale quantitative study (Yin, 2018). Finally, the framework was demonstrated using Large Language Models (LLMs), and its applicability with other AI paradigms has not been investigated. These limitations define the boundaries of our claims and provide a foundation for future research.

The AI Integration Framework: Artifact Design and Architecture

This section details the design of our primary research artifact: a generic, low-code framework for AI integration. The artifact consists of two core components: a conceptual process model visualized in BPMN, which defines the workflow and architecture, and a structured data model, which defines the process variables (attributes) that enable its dynamic and flexible operation.

The Process Model

To provide a clear, visual representation of the framework's architecture, we developed a detailed process map using Business Process Model and Notation (BPMN) 2.0. The model, designed in the Plus Workflow Editor environment, is presented in Figure 1. It illustrates the complete flow of information and control between the three key actors involved in the process: the **Initiator** (the end-user), the **System** (automating the analysis and data handling), and the **Expert** (responsible for the human-in-the-loop verification). This visual model serves as the primary blueprint for the low-code implementation of our framework.

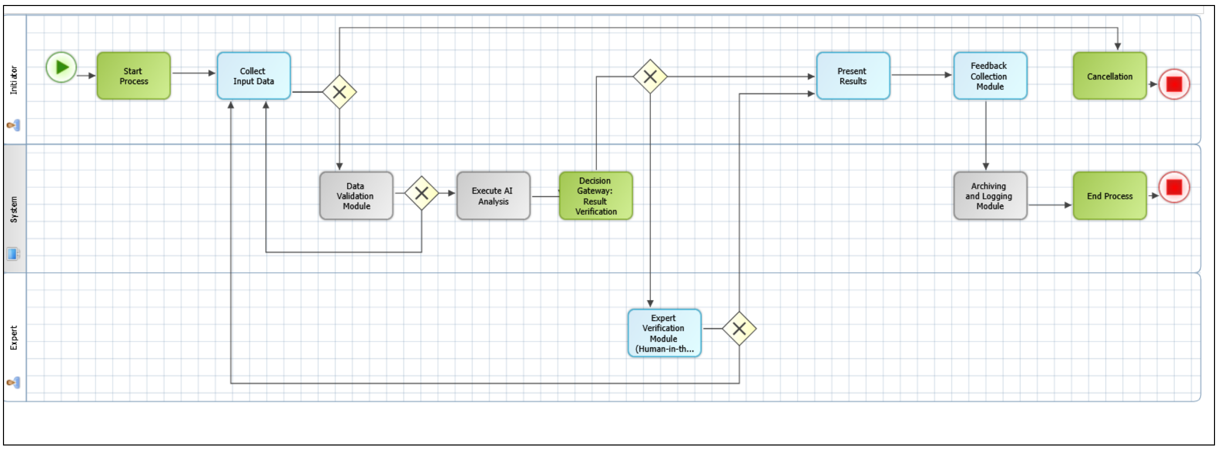

Fig 1: The BPMN Process Model of the AI Integration Framework. Source: own elaboration.

The process model in Figure 1 visually confirms the key architectural principles of our framework. Notably, it highlights the built-in data validation loop, which ensures data quality before engaging the AI model, thereby increasing the process's robustness. Furthermore, the conditional path leading to the Expert Verification Module demonstrates the practical implementation of the human-in-the-loop concept, which is critical for managing risk in high-stakes scenarios. The clear separation of tasks into swimlanes not only enhances readability but also reflects a modular design that facilitates maintenance and future extensions of the framework. This process-centric approach ensures that the integration of AI is not only technologically sound but also transparent and aligned with business governance requirements.

Process Tasks and Modules

The architecture of the process has been designed in a modular fashion to ensure maximum flexibility. Each task represents a distinct logical step, which can be independently configured. The workflow begins with the **Start Process** event, which initiates a new instance. This is followed by the **Collect Input Data** user task, a form-based step where the Initiator selects a Business Scenario and provides the necessary Input Data. The system then takes over with the **Data Validation Module**, an automated service task that checks the data against predefined rules. As shown in Figure 2, the implementation of this module in Plus Workflow Editor involves configuring a sequence of built-in applications to execute this logic without custom code.

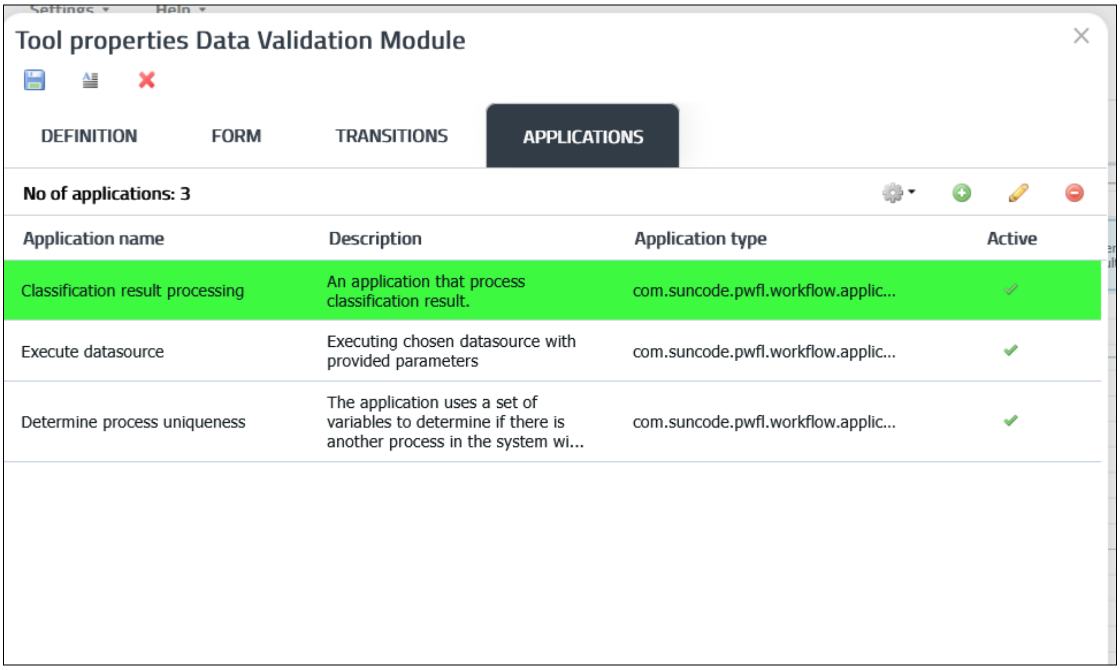

Fig 2: Configuration of applications for the Data Validation Module task in Plus Workflow Editor. Source: own elaboration.

Following successful validation, the **Execute AI Analysis** service task assembles the Full AI Prompt and sends it to the AI model's API. The configuration of this operation, illustrated in Figure 3, demonstrates how complex interactions can be orchestrated visually. The process then reaches the **Decision Gateway**, a system-driven point that evaluates the result, often using the AI Confidence Score, to determine if human oversight is required. If so, the workflow is routed to the **Expert Verification Module (Human-in-the-loop)**, a user task for a designated expert to review the AI's recommendation. The final Analysis Result is then displayed to the Initiator in the **Present Results** task. The process also includes an optional **Feedback Collection Module**, allowing the user to provide a rating and comments. Finally, the **Archiving and Logging Module** service task saves all key data to ensure a complete audit trail before the workflow concludes with the **End Process** event.

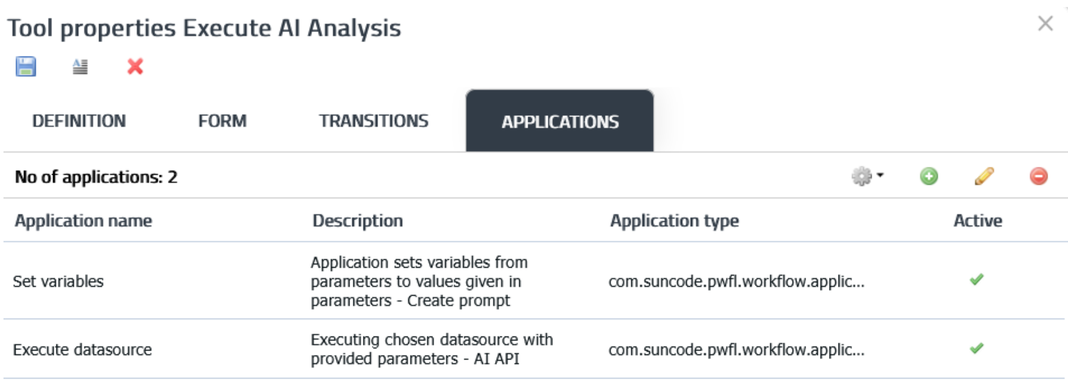

Fig 3: Configuration of applications for the Execute AI Analysis task. Source: own elaboration.

This sequence of tasks creates a complete and error-resilient workflow. Key modules, such as the Data Validation Module and the Expert Verification Module, have been intentionally built into the architecture to ensure high data quality and to enable expert oversight at critical points in the process. This structure not only automates the AI analysis but also introduces the necessary control points that are fundamental to building trust and ensuring compliance in a business environment.

Data Architecture: Process Variables

The logic and dynamics of the process model are driven by a structured set of variables, referred to as attributes in low-code platforms like Plus Workflow Editor. These attributes form the informational backbone of the framework, managing the data flow between user tasks, system modules, and integrated AI services. The design of this data architecture, detailed below, is of fundamental importance to the solution's overall flexibility and scalability. Table 1 provides a complete specification of the key attributes, defining their data types and their function at each stage of the process.

Table 1. List of Process Variables (Attributes)

Attribute Name (Variable)	**Data Type**	**Description**	**Tasks where it is used**
Case ID	Text	A unique identifier for the process instance.	*Available throughout the entire process*
Process Initiator	Text	The identifier of the user who started the process.	*Available throughout the entire process*
Business Scenario	Dropdown List	The selected scenario that determines the process logic.	Start Process, Data Validation Module, Execute AI Analysis
Input Data	Text (multiline)	Data collected from the user, most often in TEXT/JSON format.	Collect Input Data, Data Validation Module
Is Data Valid	Boolean	The result of the data validation (true/false).	Data Validation Module (Created)
AI System Context	Text (multiline)	Defines the role and general task for the AI (e.g., "You are an expert...").	Execute AI Analysis (Read)

AI Output Structure	Text (multiline)	Defines the required AI response format (e.g., "Respond in JSON...").	Execute AI Analysis (Read)
Full AI Prompt	Text (multiline)	The final prompt sent to the AI, assembled from Context, Data, and Structure.	Execute AI Analysis (Created)
AI Raw Response	Text (multiline)	The raw response from the AI model's API.	Execute AI Analysis (Created)
AI Confidence Score	Number	A value (e.g., 0-1) returned by the AI, indicating its confidence in the response.	Execute AI Analysis (Created), Decision Gateway (Read)
Expert Decision	Text	The decision made by the expert ("Approved", "Rejected") along with comments.	Expert Verification Module (Created)
Analysis Result	HTML / Text	The final, formatted result to be displayed to the user.	Execute AI Analysis / Expert Verification Module, Present Results
User Rating	Number	A rating (e.g., 1-5) given by the end-user.	Feedback Collection Module (Created)
User Comment	Text	An optional comment from the user.	Feedback Collection Module (Created)
Process Status	Text	The current status of the process.	*Updated at each task*

Source: own elaboration

The modular variable architecture presented is a key feature of our framework. The deliberate separation of prompt components, such as AI System Context and AI Output Structure, makes it possible to configure different Business Scenarios without interfering with the process logic itself. Moreover, attributes like AI Confidence Score, Expert Decision, and User Rating play an instrumental role in governance processes, directly supporting quality monitoring and enabling the implementation of the human-in-the-loop verification. This data model is the central element of our research artifact, ensuring both operational flexibility and full auditability of the decisions made.

Framework in Action: An Illustrative Example

To demonstrate the practical utility and flexibility of the designed artifact, we instantiated the framework to support two distinct, simplified business scenarios. This illustrative case study serves to fulfill the demonstration and evaluation requirements of our Design Science Research methodology. The objective is to show how the same generic process model and data architecture can be rapidly configured to address different organizational problems, thereby proving the framework's core value proposition of accelerating AI deployment.

Case A: Sales Lead Qualification

The first scenario addresses a common business need: the initial qualification of a new sales lead to determine its potential. The goal is to automate the preliminary assessment, allowing sales teams to focus on the most promising opportunities.

To configure the framework for this task, the Business Scenario attribute was set to "Sales Lead Qualification." An initiator from the sales team starts the process and, in the Collect Input Data task, provides a short, unstructured text describing the potential client in the Input Data field (e.g., "Company XYZ, a mid-sized logistics firm in the manufacturing sector, is looking to optimize its supply chain."). The AI System Context was pre-configured to instruct the AI to act as an experienced sales analyst and to score the lead on a scale of 1-10. Upon execution, the system performed the analysis and, in the Present Results task, returned a structured Analysis Result such as: "Lead Score: 8/10. Justification: The company operates in a target industry (manufacturing) and has a clearly defined business need (supply chain optimization) that aligns with our core product offering. High potential for a follow-up." This simple configuration provides immediate and direct value by standardizing the initial lead assessment process.

Case B: Initial Operational Risk Assessment

The second scenario demonstrates the framework's capability to handle more critical and nuanced tasks that may require human oversight, such as the initial assessment of an operational risk event reported by an employee.

Here, the initiator selects the "Operational Risk Assessment" Business Scenario and describes the issue in the Input Data field (e.g., "Repeated server downtime on the main production line over the past week is causing minor but consistent delays."). For this scenario, the AI System Context was configured to instruct the AI to act as a risk analyst, assess the potential severity, and provide a recommendation. Crucially, this is a scenario where an automated decision could be insufficient. The AI model processed the information and returned a low AI Confidence Score of 0.65, reflecting the ambiguity of terms like "minor delays."

This low score automatically triggered the Decision Gateway, routing the case to the Expert Verification Module. A designated risk manager received a task to review the AI's preliminary analysis ("Potential Severity: Low. Recommendation: Monitor the situation."). The expert, using their domain knowledge, edited the assessment and added a comment in the Expert Decision field: "Rejected. The risk is higher than assessed. The main production line is a critical asset. Recommendation: Escalate to IT for immediate root cause analysis." This verified Analysis Result was then presented to the process initiator. This case effectively demonstrates the framework's support for the human-in-the-loop pattern, which is essential for building trust and ensuring responsible AI deployment in critical business functions.

Summary of Demonstration

These two brief examples illustrate the core strengths of the proposed framework. They show that the same underlying process model and data architecture can be rapidly adapted to serve entirely different business functions—one focused on speed and standardization, the other on safety and expert oversight. The ability to reconfigure the framework by simply changing the Business Scenario and its associated parameters, without altering the process model itself, confirms the effectiveness and flexibility of the designed artifact.

The ability to reconfigure the framework is demonstrated by the fact that adapting the generic template to the 'Sales Lead Qualification' scenario took a business analyst approximately 2 hours. In contrast, a traditional development approach for a similar tool would be estimated at 3-5 weeks of work involving both developers and analysts. This confirms the effectiveness and flexibility of the designed artifact.

Conclusion

This research confronts the persistent gap between the strategic promise of Artificial Intelligence and the practical difficulties organizations face in its timely and economical implementation. To counter this problem, we designed, developed, and demonstrated a novel, generic framework for the rapid deployment of AI-powered systems using a low-code, process-centric approach. The core contribution is a reusable and configurable artifact whose key strengths—speed, flexibility, and auditability—were confirmed through our illustrative case study.

The implications of this work for practice are significant. Our framework empowers business units to independently prototype and deploy AI solutions, fundamentally shifting the role of IT form a gatekeeper to an enabler of innovation. For managers and analysts, this provides a structured yet agile method to experiment with AI, test hypotheses, and deliver value without being constrained by long development backlogs. This democratized approach can accelerate an organizations digital transformation journey by fostering a culture of data-driven experimentation at the departmental level.

From a research perspective, this work contributes a novel model for embedding AI governance within Business Process Management. By treating step like data validation and human-in-the-loop verification as configurable process modules, our framework offers a process-centric alternative to purely data-centric or algorithmic approaches to trustworthy AI. It provides a tangible artifact that can be used in further studies to explore the socio-technical challenges of human-AI collaboration in organizational workflows.

In conclusion, this work provides a practical and theoretically grounded solution that bridges the gap between BPM and the operational deployment of AI. The proposed framework serves as both a valuable tool for practitioners and as a contribution to the Design Science Research knowledge base. Future research will focus on a quantitative evaluation of the framework's impact across a wider range of platforms and AI models, further exploring its scalability and performance in complex enterprise environments.

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