

Article

A Generative AI-Based Framework for Business Process Orchestration in Industrial Enterprises

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Abstract

This study develops an integrated generative artificial intelligence (GAI) framework for improving business process performance in industrial enterprises. The framework treats GAI not as the isolated use of generative tools, but as a governable information systems capability embedded in recurring workflows, enterprise architectures, documented knowledge, and human decision roles. It integrates four functional subframeworks—manufacturing, marketing and sales, accounting and finance, and human resource management—with a shared orchestration and governance layer. This layer coordinates process architecture, approved data and knowledge sources, reusable GAI capabilities, human-in-the-loop validation, traceability, escalation, and performance measurement. A proof-of-concept maturity-readiness validation is conducted in an electronics company using maturity-readiness logic inspired by the Smart Industry Readiness Index (SIRI). The assessment shows an increase in the overall readiness score from 41.60 in the pre-GAI baseline to 79.08 in the post-GAI implementation scenario. Accordingly, the score increase is interpreted as expert-assessed maturity-readiness evidence rather than as a measured causal effect on operational performance. This study contributes a process-centric reference architecture designed for technical implementability, traceability, auditability, and human-supervised enterprise-scale GAI adoption.

Keywords: generative artificial intelligence; industrial enterprises; AI-enabled enterprise architecture; business process management; GAI chatbots; GAI agents; human-in-the-loop governance; Smart Industry Readiness Index; maturity assessment; enterprise process orchestration



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1. Introduction

Industrial enterprises increasingly operate through digitally instrumented and data-intensive business processes that translate market demand, technical knowledge, material resources, financial capital, and human competencies into products and services. Manufacturing, marketing and sales, accounting and finance, and human resource management (HRM) remain core functional areas in which process performance directly affects operational efficiency, customer value, financial reliability, and organizational capability. These areas are typically supported by enterprise resource planning (ERP), manufacturing execution systems (MES), customer relationship management (CRM), quality management systems (QMS), accounting platforms, and human resource information systems (HRIS). In Industry 4.0 environments, their integration is further shaped by reference architectures

and readiness models that emphasize lifecycle-spanning information flows, interoperable digital representations across technical and organizational levels, and staged transformation toward smart manufacturing [1,2]. Nevertheless, many operational and managerial decisions still depend on fragmented documentation, manual interpretation, siloed knowledge, and time-consuming cross-functional coordination.

Generative artificial intelligence (GAI), represented by large language models (LLMs) and related generative systems, has rapidly emerged as a general-purpose technology with important implications for intelligent information systems, enterprise software, and AI-enabled decision support. GAI refers to computational techniques capable of generating new and meaningful content, including text, images, audio, code, designs, and structured outputs, from training data [3]. Rather than automating only predefined rules, GAI can summarize, transform, compare, explain, and generate information in forms that are directly usable in business processes. Empirical evidence further indicates that GAI can improve workplace productivity and service performance when it is used to augment, rather than replace, human expertise [4].

For industrial enterprises, however, the value of GAI depends less on the model alone than on how it is embedded into enterprise information architectures, data flows, process logic, user roles, and governance mechanisms. This paper therefore uses GAI as an umbrella term, while distinguishing between GAI chatbots and GAI agents. GAI chatbots mainly provide conversational assistance, explanation, summarization, and draft generation. GAI agents extend these capabilities by combining language models with retrieval, memory, planning, tool use, and bounded workflow execution [5]. This distinction is important because industrial applications range from low-risk documentary support to higher-impact actions that require escalation, validation, and managerial approval.

Across functional areas, GAI can support process documentation, production planning, quality-related knowledge work, customer communication, employee service workflows, analytical reporting, and exception handling [3,6,7]. This study distinguishes conversational GAI chatbots, which support explanation, summarization, and drafting, from bounded GAI agents, which combine retrieval, memory, planning, and tool use within predefined workflows. In both cases, generated outputs should be treated as decision-support artifacts and subjected to human review when they may affect product quality, customer commitments, financial reporting, workforce decisions, compliance, or cybersecurity.

Despite the growing number of pilots and use cases, enterprise adoption remains fragmented. Current implementations often target isolated activities such as document drafting, chatbot-based service interactions, maintenance assistance, or internal knowledge retrieval. Such initiatives may create local efficiencies, but they provide limited guidance on how GAI chatbots, GAI agents, enterprise systems, validation roles, and process-performance measurement can be combined into a coherent enterprise-level operating model. This gap is especially relevant for industrial organizations, where digital tools must interact with established control structures, audit requirements, and cross-functional process dependencies.

The need for an integrated perspective is consistent with digital transformation and business process management (BPM) research. Digital transformation creates value when technologies are embedded into process architecture, managerial routines, and organizational strategy rather than introduced as disconnected tools [8]. BPM, in turn, views organizations as systems of interrelated processes that can be modeled, executed, monitored, controlled, and improved [9]. Recent work further indicates that LLMs can support process modeling and refinement, while still requiring systematic evaluation and error handling [10]. In this sense, GAI should be conceptualized not as an isolated application, but as a process-oriented enterprise capability.

The research problem addressed in this manuscript is therefore organizational and architectural rather than purely technical: how can GAI be organized as a governed enterprise capability for improving business process performance across several functional areas of an industrial enterprise? To address this problem, the paper proposes an integrated GAI-based framework that links enterprise data, process knowledge, GAI-supported workflows, and functional subframeworks through a common orchestration layer. In this study, the orchestration layer denotes the coordination mechanism that connects prompts or agents, enterprise systems, validation roles, and output logging across process stages. The framework is intended for industrial enterprises and is illustrated through an electronics manufacturing case.

Because GAI outputs may influence high-impact industrial decisions, their implementation requires traceability, accountability, risk management, and meaningful human control consistent with established AI governance and human-centered AI guidance [11–14].

The manuscript makes four contributions. First, it conceptualizes GAI as a governable enterprise information-systems capability rather than as isolated chatbot use. Second, it proposes reusable process-cycle structures for the main functional areas of an industrial enterprise. Third, it specifies technical orchestration through controlled enterprise-system access, retrieval-augmented generation (RAG), bounded agents, role-based validation, logging, escalation, and human approval. Fourth, it develops an author-adapted, SIRI-inspired PoC maturity-readiness assessment. The primary novelty lies in integrating these elements within one enterprise reference architecture.

The framework is assessed through an author-adapted, SIRI-inspired maturity-readiness analysis of an electronics company. The assessment evaluates organizational readiness, process integration, governance preparedness, and technological capability rather than measured causal effects on operational performance [15].

The remainder of the paper is organized as follows. Section 2 reviews related work on GAI, enterprise process augmentation, functional applications, agentic systems, and AI governance. Section 3 introduces the proposed integrated framework and its functional subframeworks. Section 4 presents the SIRI-based validation logic and case application. Section 5 discusses the implications of the framework in comparison with existing research. Section 6 concludes the paper and outlines limitations and future research directions.

2. Related Work

This section reviews the main research streams that inform the proposed GAI-based framework for industrial enterprises. First, it discusses GAI as a process-augmentation technology within business process management and enterprise information systems. Second, it summarizes recent GAI applications in the four functional areas addressed in this study. Third, it distinguishes GAI chatbots from GAI agents and discusses governance, traceability, auditability, and human-in-the-loop control. Finally, it clarifies the research gap related to enterprise-level integration, process-cycle logic, and maturity-oriented validation.

2.1. GAI and Enterprise Process Augmentation

GAI has become an important research topic in business and information systems because it can generate, summarize, transform, compare, and explain both structured and unstructured information. Feuerriegel et al. conceptualize GAI as a socio-technical system rather than only a technical model, emphasizing its effects on work practices, information flows, and organizational decision support [3]. This interpretation is directly relevant to industrial enterprises, where business value is created through coordinated processes, enterprise systems, data flows, and human decision roles.

In the context of business process management (BPM), GAI can be interpreted as a process-augmentation technology. BPM views organizations as systems of interrelated processes that can be modeled, executed, monitored, controlled, and improved. Recent studies show that large language models (LLMs) can support process modeling and refinement by transforming textual descriptions into process models, assisting non-experts, and enabling iterative improvement [10]. However, these outputs still require validation, error handling, and governance.

This process-centric view is consistent with digital transformation research, which argues that business value emerges when digital technologies are embedded into process architecture, managerial routines, and organizational strategy rather than introduced as disconnected tools [8]. For industrial enterprises, this means that GAI should be connected not only to individual user tasks, but also to enterprise information architectures, process cycles, data structures, validation roles, and control points. The unresolved issue is how such process augmentation can be organized across several enterprise functions rather than within a single application or department.

2.2. GAI in Manufacturing Operations

Manufacturing is a central GAI domain because Industry 4.0 environments already combine ERP, MES, IoT, analytics, and quality-management systems. Recent research identifies applications in design, process planning, production documentation, quality control, predictive maintenance, supply-chain optimization, and operator support [6,16].

These applications combine technical evidence and operational knowledge, but safety-, quality-, and compliance-sensitive outputs require human validation. Existing studies mainly address individual use cases and provide limited guidance on integrating them into a production–batch–operation cycle linked with other enterprise functions.

2.3. GAI in Marketing and Sales

Marketing and sales use GAI for content, customer communication, segmentation, CRM analysis, campaign design, and proposal preparation. Prior research links these applications with customer interaction, innovation, administrative efficiency, and B2B sales performance [17,18].

Adoption nevertheless depends on organizational readiness and controls over brand consistency, product claims, pricing, privacy, and commercial commitments. The unresolved issue is how these activities can be embedded in a governed campaign–segment–interaction cycle and connected with production, finance, and HRM.

2.4. GAI in Human Resource Management

GAI applications in HRM include workforce planning, recruitment, onboarding, training, performance support, and employee services [7]. Evidence indicates that automation can improve recruitment efficiency and decision preparation when embedded in structured organizational processes [19].

Because HR outputs may affect individual rights and career opportunities, GAI should remain assistive in hiring, promotion, compensation, monitoring, and disciplinary contexts. The principal integration challenge is to combine workforce-cycle support with fairness, privacy, traceability, and accountable human decisions.

2.5. GAI in Accounting and Finance

Accounting and finance provide document-intensive and rule-sensitive settings for GAI-supported classification, policy interpretation, variance commentary, reporting, forecasting assistance, internal-control checking, and audit-evidence preparation [20].

These uses can improve explanation and documentation, but postings, payments, tax submissions, audit conclusions, and compliance decisions require professional judgment and formal approval. The remaining challenge is to connect GAI support with evidence completeness, transaction validity, internal controls, audit trails, and escalation.

2.6. Agentic GAI Systems, Governance, and Auditability

Recent enterprise GAI development is moving beyond simple chatbot use toward agentic systems. GAI chatbots are primarily conversational interfaces that provide explanation, summarization, draft generation, and interactive assistance. GAI agents extend this capability by combining language models with memory, retrieval, planning, tool use, and iterative execution in order to perform multi-step tasks under defined objectives and constraints [5]. The generative-agents literature further shows that agentic behavior depends on architectural components such as memory, reflection, planning, and interaction with an environment [21]. Other work on reasoning-and-acting patterns and reflective agents also shows that LLM-based systems can be extended from text generation toward action selection, tool use, and iterative self-improvement [22,23]. Multi-agent research additionally indicates that several LLM-based agents may coordinate, communicate, and divide tasks in complex environments, which further increases the need for governance and monitoring [24].

Human-centered AI research emphasizes that AI systems should be designed for transparency, reliability, accountability, and meaningful human control [13,14]. These principles are especially important when GAI outputs may influence production release, customer commitments, financial reporting, audit evidence, recruitment, training, or employee-related decisions. At the organizational level, the NIST AI Risk Management Framework (RMF) structures trustworthy AI implementation around governance, mapping, measurement, and management functions [11]. The International Organization for Standardization/International Electrotechnical Commission (ISO/IEC) 42001:2023 complements this view by specifying requirements for establishing, implementing, maintaining, and continually improving an artificial intelligence management system [12].

For the proposed framework, governance means that GAI-supported outputs must be linked to input data, source documents, prompts, model versions, tool calls, reviewers, approvals, and subsequent process decisions. Traceability means that the organization can identify where an output came from and how it was used. Auditability means that the organization can reconstruct how a recommendation, document, workflow action, or decision-support artifact was generated, reviewed, accepted, modified, rejected, or escalated. These principles are essential because the proposed framework connects GAI tools with enterprise systems, process-cycle logic, validation roles, and management decisions.

Table 1 distinguishes the proposed framework from related approaches, including BPM, enterprise architecture, AI governance, Industry 4.0 maturity models, function-specific GAI studies, and LLM-agent architectures.

This comparison shows that the novelty of the proposed framework does not lie in inventing BPM, AI governance, maturity assessment, or LLM agents separately. Its contribution lies in combining these elements into a process-cycle-based and technically governable reference architecture for GAI-supported industrial enterprise workflows.

Table 1. Comparison of the proposed framework with related approaches to enterprise GAI integration.

Approach	Main Focus	Limitation for Enterprise GAI Integration	Position of the Proposed Framework
BPM and LLM-supported process modeling [9,10]	Process modeling and improvement	Does not specify GAI retrieval, prompt control, agent orchestration, or auditability	Uses BPM logic but embeds GAI chatbots/agents, validation roles, and traceability into functional process cycles
Enterprise architecture and digital transformation [2,8]	Alignment of processes, data, applications, and technology	Does not define GAI-specific workflows	Connects ERP/MES/CRM/QMS/accounting/HRIS with retrieval-augmented generation (RAG), prompts, logs, and human review
AI governance/NIST AI RMF/ISO/IEC 42001 [11–14]	Trustworthiness, risk management, accountability	Provides general principles but not process-cycle implementation	Operationalizes governance through validation roles, approval gates, logging, and escalation
Industry 4.0 and SIRI maturity models [1,15]	Digital readiness assessment	Not designed specifically for GAI, RAG, LLM agents, or prompt governance	Adapts maturity logic to assess GAI-supported process readiness
Function-specific GAI studies [6,7,16–20]	GAI use cases in separate domains	Often isolated within one department or task type	Integrates four functional areas into one cross-functional operating model
LLM-agent architectures [5,21–24]	Planning, memory, tool use, and multi-step execution	Often not mapped to enterprise roles, controls, and process accountability	Restricts agents to bounded workflows with access control, logging, and human approval

2.7. Research Gap

Prior research demonstrates the relevance of GAI to manufacturing, marketing and sales, accounting and finance, and HRM, but most studies remain limited to individual functions or task categories. Consequently, they provide insufficient guidance on coordinating GAI chatbots and agents, enterprise systems, approved knowledge sources, validation roles, logging, escalation, and performance monitoring across departments.

BPM, enterprise architecture, AI governance, and maturity models provide important but partial foundations. They do not jointly specify how governed GAI capabilities can be embedded within function-specific process cycles and connected through an enterprise orchestration layer. A further gap concerns maturity-oriented validation of such integration. The proposed framework addresses both gaps through a cross-functional reference architecture and an author-adapted, SIRI-inspired maturity-readiness assessment.

3. Proposed GAI-Based Frameworks for Industrial Enterprises by Functional Areas and Their Orchestration

The proposed GAI-based framework is grounded in the view that GAI should not be introduced into industrial enterprises as a collection of isolated tools, but as a governed, process-oriented, and architecture-level enterprise capability. In this manuscript, GAI is conceptualized as a reusable capability that connects business processes, enterprise data, documented knowledge, human roles, validation routines, and performance feedback. This view is consistent with research showing that the organizational value of GAI emerges when generative models are linked with decision routines, business processes, domain knowledge, and role-specific responsibilities rather than used only as free-standing assistants for ad hoc prompting [3,25,26]. It is also aligned with responsible-AI and GAI

governance research, which emphasizes lifecycle-based control, organizational accountability, risk management, and responsible engineering of information systems [27–29].

The framework consists of two connected levels. The first level is the integrated enterprise orchestration and governance framework. It defines the common architecture through which GAI capabilities are coordinated across the main functional areas of an industrial enterprise. The second level comprises four functional subframeworks, one for each main area. These subframeworks translate the general orchestration logic into process-cycle structures specific to manufacturing, marketing and sales, accounting and finance, and HRM.

The primary methodological novelty lies in connecting four function-specific process cycles through one technical orchestration and governance layer. This layer applies consistent rules for authorized retrieval, bounded agent execution, role-based validation, traceability, escalation, and maturity monitoring while preserving the ownership and approval requirements of each functional area. The individual components are grounded in previous research; their process-cycle and architecture-level integration constitutes the proposed contribution.

3.1. Integrated Enterprise GAI Orchestration and Governance Framework

The integrated framework positions GAI as a cross-functional enterprise capability that supports, connects, and governs the main functional areas of an industrial enterprise. Its central element is the enterprise GAI orchestration and governance layer. This layer consists of five interrelated components: enterprise process architecture, data and documented knowledge, the GAI capability layer, governance and human oversight, and performance measurement and continuous improvement.

The first component, enterprise process architecture, defines the end-to-end process structure and cross-functional alignment. It ensures that GAI is embedded in recurring enterprise processes rather than used only as an isolated conversational tool. The second component, data and documented knowledge, represents enterprise data, standard operating procedures (SOPs), policies, records, lessons learned, and external knowledge sources. These sources form the knowledge base from which GAI chatbots and agents retrieve, summarize, interpret, and generate process-relevant outputs. The third component, the GAI capability layer, includes large language models (LLMs), retrieval tools, automation services, analytical modules, and agentic capabilities. This layer enables content generation, task decomposition, decision support, verification and validation, analytics and insights, and process improvement support [3,25,26].

The fourth component, governance and human oversight, defines the boundaries of responsible GAI use. It includes policies, access rules, validation roles, escalation paths, audit trails, and human-in-the-loop decision points. The fifth component, performance measurement and continuous improvement, connects GAI-supported processes with key performance indicators (KPIs), analytics, benchmarking, feedback loops, and lessons learned. Thus, the integrated framework links process execution with organizational learning and maturity improvement. This logic is aligned with responsible-AI governance frameworks, which stress the importance of structural controls, procedural mechanisms, human oversight, traceability, and continuous risk management across the AI lifecycle [27–29].

Figure 1 presents the integrated enterprise GAI orchestration and governance framework. It connects the four functional subframeworks through a common enterprise process architecture, shared data and documented knowledge, reusable GAI capabilities, human-in-the-loop governance, and performance measurement and continuous-improvement mechanisms.

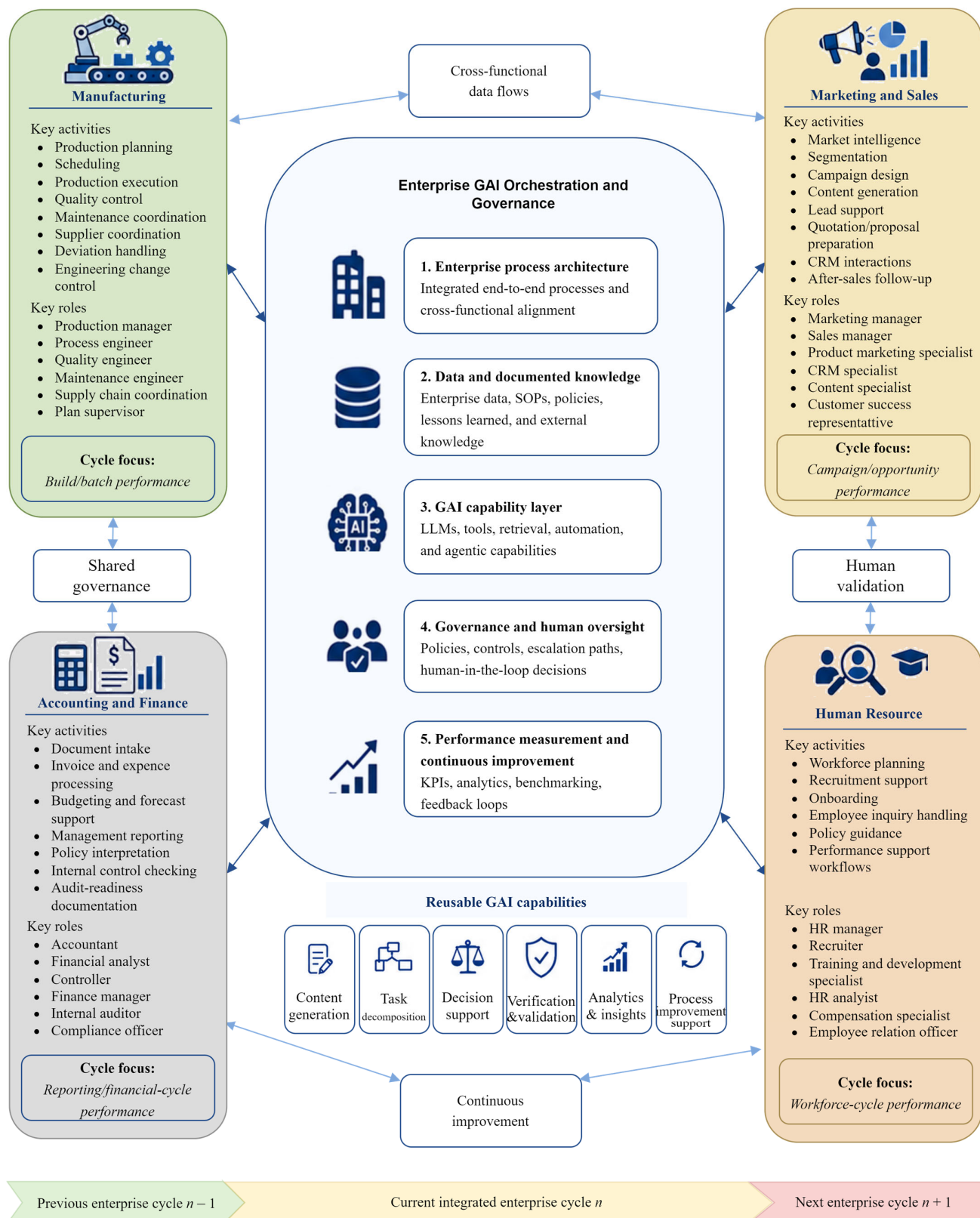


Figure 1. Integrated GAI orchestration and governance framework for industrial enterprises.

The four surrounding functional blocks represent the operational domains in which GAI capabilities are applied. Manufacturing focuses on build and batch performance; marketing and sales focuses on campaign and opportunity performance; accounting and finance focuses on reporting and financial-cycle performance; and HRM focuses on workforce-

cycle performance. These domains are connected through cross-functional data flows, shared governance mechanisms, human validation, reusable GAI capabilities, and continuous improvement.

The integrated framework also has a temporal logic. Previous enterprise cycles provide historical data, performance results, lessons learned, and documented corrective actions. The current enterprise cycle applies GAI-supported orchestration and governance across functional areas. The next cycle incorporates updated knowledge, improved workflows, refined recommendations, and enhanced performance indicators. In this way, the framework connects GAI adoption with continuous organizational learning and cross-functional process improvement.

3.2. Technical Implementation Architecture and Operating Logic

The proposed orchestration layer can be implemented as a layered enterprise information-systems architecture rather than as a stand-alone chatbot interface. ERP, MES, CRM, QMS, accounting, and HRIS platforms remain the systems of record. The GAI layer does not directly overwrite transactional data. Instead, it operates as a controlled cognitive and workflow-support layer that retrieves approved data, generates decision-support outputs, prepares structured drafts, detects missing evidence, and routes outputs to authorized human reviewers.

The technical architecture consists of six layers. The first layer is the enterprise systems layer, which includes ERP, MES, CRM, QMS, accounting, HRIS, production-control systems, document repositories, and selected Internet of Things (IoT) or shop-floor data sources. The second layer is the integration layer, which connects these systems through application programming interfaces (APIs), database views, middleware, or secure file exchange. This layer applies role-based access control, authentication, authorization, and data-minimization rules.

The third layer is the knowledge and retrieval layer, which implements RAG using approved enterprise knowledge sources such as SOPs, work instructions, quality manuals, product documentation, customer communication templates, accounting policies, HR policies, training materials, audit checklists, and selected external regulatory or technical references. Each knowledge object is stored with metadata, including document owner, version, date, access level, functional area, and validity status.

The fourth layer is the GAI capability layer. It includes LLM-based chatbots for conversational assistance and bounded GAI agents for multi-step workflow support. Chatbots are used for explanation, summarization, drafting, and question answering. Agents are used only for predefined workflows, such as preparing a corrective and preventive action (CAPA) dossier, checking document completeness, generating variance-analysis drafts, summarizing CRM interactions, or preparing onboarding documentation. The fifth layer is the orchestration and governance layer. It coordinates prompts, retrieval, tool calls, workflow state, escalation rules, output logging, and human review. The sixth layer is the performance and feedback layer, which monitors process KPIs, validation outcomes, user corrections, rejected outputs, escalation cases, and improvement actions.

Agent orchestration follows a bounded sequence: process trigger or user request; role and workflow authorization; approved prompt-template selection; metadata-filtered retrieval from authorized knowledge sources; evidence sufficiency and source-validity checking; bounded agent execution; schema and grounding validation; human review; approval, approval with edits, revision, rejection, request for additional evidence, or escalation; and logging of the request, retrieved sources, generated output, reviewer decision, and final outcome.

Prompt engineering is standardized through reusable templates. Each prompt template includes the functional area, task objective, permitted data sources, required output format, risk level, validation checklist, escalation rule, and responsible reviewer. For example, a manufacturing CAPA-support template requires the agent to retrieve relevant SOPs, deviation records, inspection evidence, and prior corrective actions; summarize the problem; identify possible root-cause categories; mark missing evidence; and prepare a draft CAPA record for quality-manager review. A finance variance-analysis template requires the agent to retrieve approved accounting reports, compare current and previous-period figures, generate possible explanations, and flag unsupported causal interpretations for human review.

Traceability is implemented through structured logs. For each GAI-supported output, the system records the user role, prompt template, model version, retrieved sources, source-document versions, tool calls, intermediate outputs, final output, reviewer, validation decision, edits, approval status, and subsequent process action.

Human-in-the-loop validation influences GAI-supported workflows through a controlled feedback mechanism. Reviewer actions are recorded as approval, approval with edits, rejection, escalation, or request for additional evidence. These outcomes do not automatically retrain the model in an uncontrolled manner. Instead, they are used to update prompt templates, refine retrieval rules, correct or remove unreliable knowledge-base documents, add missing SOPs or policy references, adjust validation checklists, and improve escalation thresholds. In this way, human feedback improves the GAI-enabled workflow through governed prompt, retrieval, knowledge-base, and orchestration updates rather than through unsupervised autonomous learning.

3.3. Technical Control Model and Implementation Artifacts

The orchestration layer can be implemented as a controlled service architecture between enterprise systems and GAI capabilities. ERP, MES, CRM, QMS, accounting, and HRIS systems remain the systems of record, while the GAI layer operates through controlled read-only or draft-write adapters. Read-only adapters retrieve approved records, documents, reports, policies, and process evidence. Draft-write adapters may create draft artifacts, such as CAPA drafts, variance-commentary drafts, proposal drafts, onboarding drafts, or HR service-response drafts, but they do not perform final transactional actions. Final actions such as production release, financial posting, customer commitment, pricing approval, hiring, compensation, disciplinary action, or external reporting remain under authorized human approval.

Each GAI-supported workflow is mediated by five technical controls: identity and role verification, workflow-type authorization, retrieval-scope limitation, tool-call allowlisting, and approval-gate enforcement. For example, a quality engineer may retrieve production deviations, SOPs, and inspection records for CAPA preparation, but may not approve batch release. A finance analyst may retrieve accounting reports and variance data, but may not post journal entries. An HR specialist may retrieve policy documents and onboarding templates, but may not use GAI outputs as final hiring or disciplinary decisions. This role- and task-based restriction prevents the GAI layer from becoming an uncontrolled execution layer.

In RAG-supported workflows, enterprise documents are indexed at chunk level with metadata fields such as document ID, source system, functional area, document owner, version, validity date, approval status, confidentiality class, and permitted user roles. Retrieval combines semantic search with metadata filtering and keyword constraints. Retrieved passages are passed to the GAI model together with a structured prompt that requires source-grounded output, explicit uncertainty marking, and a “missing evidence”

section. If the retrieved evidence is insufficient, outdated, contradictory, or outside the permitted access scope, the workflow is closed and is escalated to a human reviewer.

Prompt templates are governed as version-controlled process artifacts. Each template contains a template ID, functional area, task objective, permitted data sources, required output schema, risk level, forbidden actions, validation checklist, escalation threshold, and mandatory reviewer role. Output logging is implemented as an immutable event record containing the request ID, timestamp, user role, workflow type, prompt-template ID, model version, retrieved sources, source-document versions, tool calls, generated output hash, reviewer decision, approval status, edits, escalation flag, and downstream process action. These elements enable reconstruction of how a GAI-supported output was generated, reviewed, modified, accepted, rejected, or escalated.

Detailed technical implementation artifacts, including prompt-template structures, access-control logic, audit-log fields, workflow examples, governance diagrams, and pseudocode for bounded agent orchestration, are provided in Supplementary Section S2. The generalized RAG approval and audit-logging logic is shown in Figure S2.1, and the corresponding interaction sequence is shown in Figure S2.2.

3.4. Practical Procedure for Applying the Framework

The proposed framework can be reproduced through the following methodological procedure:

1. Identify the focal functional areas and define the process cycle in each area.
2. Map the enterprise systems, data sources, document repositories, and knowledge sources used in each process cycle.
3. Classify process activities according to their suitability for GAI chatbot support, bounded GAI-agent support, or no GAI support.
4. Define risk levels, validation roles, approval gates, escalation rules, and logging requirements.
5. Develop reusable prompt templates and RAG source sets for each approved GAI-supported workflow.
6. Apply the GAI-supported workflow in a bounded proof-of-concept (PoC) scenario.
7. Evaluate maturity under the pre-GAI baseline and post-GAI implementation scenarios using the author-adapted, SIRI-inspired maturity-readiness protocol.
8. Review rejected outputs, human corrections, missing evidence, and escalation cases to improve prompt templates, retrieval sources, validation checklists, and workflow rules.

These steps provide a reproducible procedure for applying the framework. The supporting scoring worksheet, expert ratings, evidence notes, prompt templates, RAG source definitions, access rules, validation checklists, and audit-log fields are reported in the Supplementary Materials.

3.5. Common Design Logic of the Four Functional Subframeworks

All four subframeworks share an external manufacturing-sector context comprising regulatory, professional, contractual, labor, audit, market, and industry requirements. Within this context, each diagram contains a central process cycle, a left-side operational owner, a right-side validation or control role, and a lower inter-cycle learning connection.

The central cycle represents activities, decision gates, corrective actions, and objective assessment, while the side roles separate execution from validation. Each cycle transfers data, unresolved issues, and lessons learned to the next cycle.

GAI chatbots support explanation, summarization, drafting, and comparison, whereas bounded agents support evidence retrieval, completeness checking, dossier preparation,

exception routing, and workflow coordination. High-impact approvals and legally binding, safety-related, financial, or employee-related decisions remain under human responsibility [27–29].

3.6. GAI-Based Manufacturing Framework

The manufacturing framework is organized around a nested production logic with three levels: production cycle, batch, and operation. The central part starts with the production cycle. The enterprise sets production objectives, performs production planning, and completes pre-production preparation activities. The batch then starts, and the framework enters the operation level. The current operation is set up, followed by execution and operational control. The main decision gate evaluates whether the operation result is acceptable.

If the result is acceptable, the process moves to the next operation. If it is not acceptable, operational-level corrective actions are triggered. After all required operations are completed, the batch ends, and the broader production cycle evaluates whether production objectives have been achieved. If the objectives are not achieved, production-cycle corrective actions are initiated and transferred into the following cycle.

This central structure is consistent with industrial production logic, where product-level objectives are achieved through batch-level execution and operation-level control. It is also aligned with recent literature on AI and GAI in manufacturing, where applications increasingly cover design and planning, process optimization, quality management, predictive maintenance, human-centered assistance, and next-generation intelligent manufacturing [6,30–32].

Figure 2 presents the manufacturing subframework. It organizes GAI-supported production activities around a production cycle, batch subcycle, and operation-level control. The production team and operations manager are responsible for execution, while the quality manager and improvement team are responsible for validation, compliance, and continuous improvement.

GAI can support this operational logic by generating contextualized operator guidance, summarizing deviations, explaining anomalies, drafting corrective-action records, preparing maintenance or production summaries, and supporting knowledge transfer across shifts, batches, and teams. Recent studies on AI and GAI in manufacturing show that such systems can support operator assistance, production knowledge management, quality improvement, and intelligent manufacturing workflows [6,30–32]. However, GAI-generated outputs remain advisory and must be validated before they influence production parameters, batch release, or formal quality records.

The separation between operational execution and validation is conceptually important. The left side drives production execution, while the right side validates process quality, risk control, and improvement evidence. This structure ensures that GAI support remains coupled with engineering controls, inspection logic, and quality-management routines rather than acting autonomously in manufacturing decisions.

3.7. GAI-Based Marketing and Sales Framework

The marketing and sales framework is organized around a campaign cycle containing a target-segment subcycle and recurring interaction-level activities. The central part begins with the campaign cycle start, followed by the setting of campaign objectives, campaign planning, and campaign preparation activities. Once the campaign is configured, the target-segment cycle starts. The current interaction activity is set up, followed by segment campaign execution and interaction control.

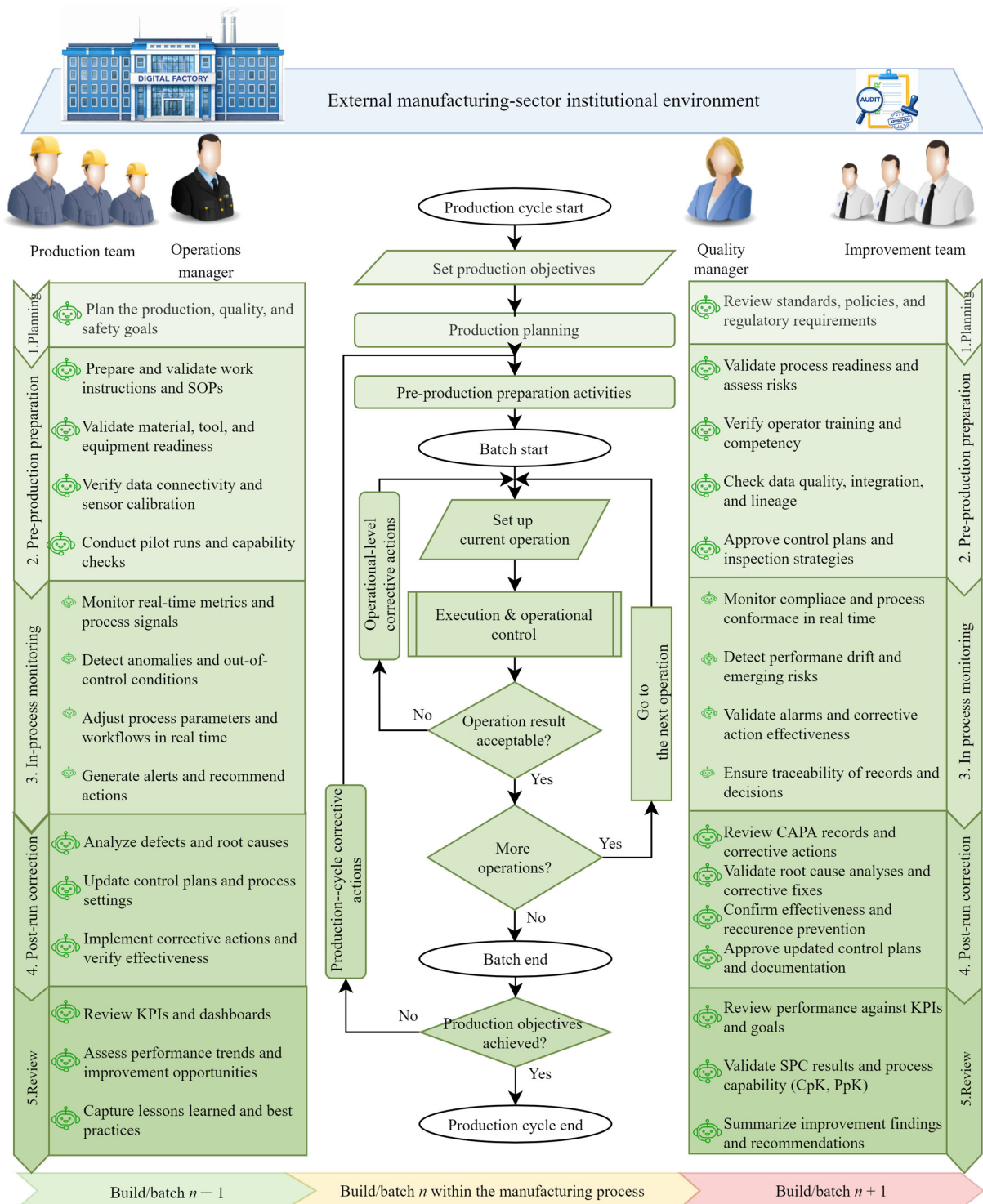


Figure 2. GAI-based manufacturing subframework showing the production cycle, batch subcycle, and operation-level control.

The first decision gate evaluates whether the interaction result is acceptable. If it is acceptable, the process proceeds to the next interaction. If it is not acceptable, interaction-level corrective actions are activated. After the planned interaction activities for the target segment are completed, the target-segment cycle ends. The broader campaign cycle then evaluates whether campaign objectives have been achieved. If they have not, campaign-cycle corrective actions are triggered and used to improve the next cycle.

This structure reflects the logic of commercial processes, where campaign-level objectives are achieved through segment-level targeting and interaction-level execution. It is aligned with current marketing and sales research showing that GAI affects content generation, personalization, CRM use, customer communication, campaign management, sales-support processes, and customer-experience enhancement [33–36].

Figure 3 presents the marketing and sales subframework. It structures GAI-supported commercial activities around a campaign cycle, target-segment subcycle, and interaction-level control. The marketing and sales team and marketing manager drive campaign execution, while the commercial controller and customer insights team validate customer-facing outputs, risks, and performance results.

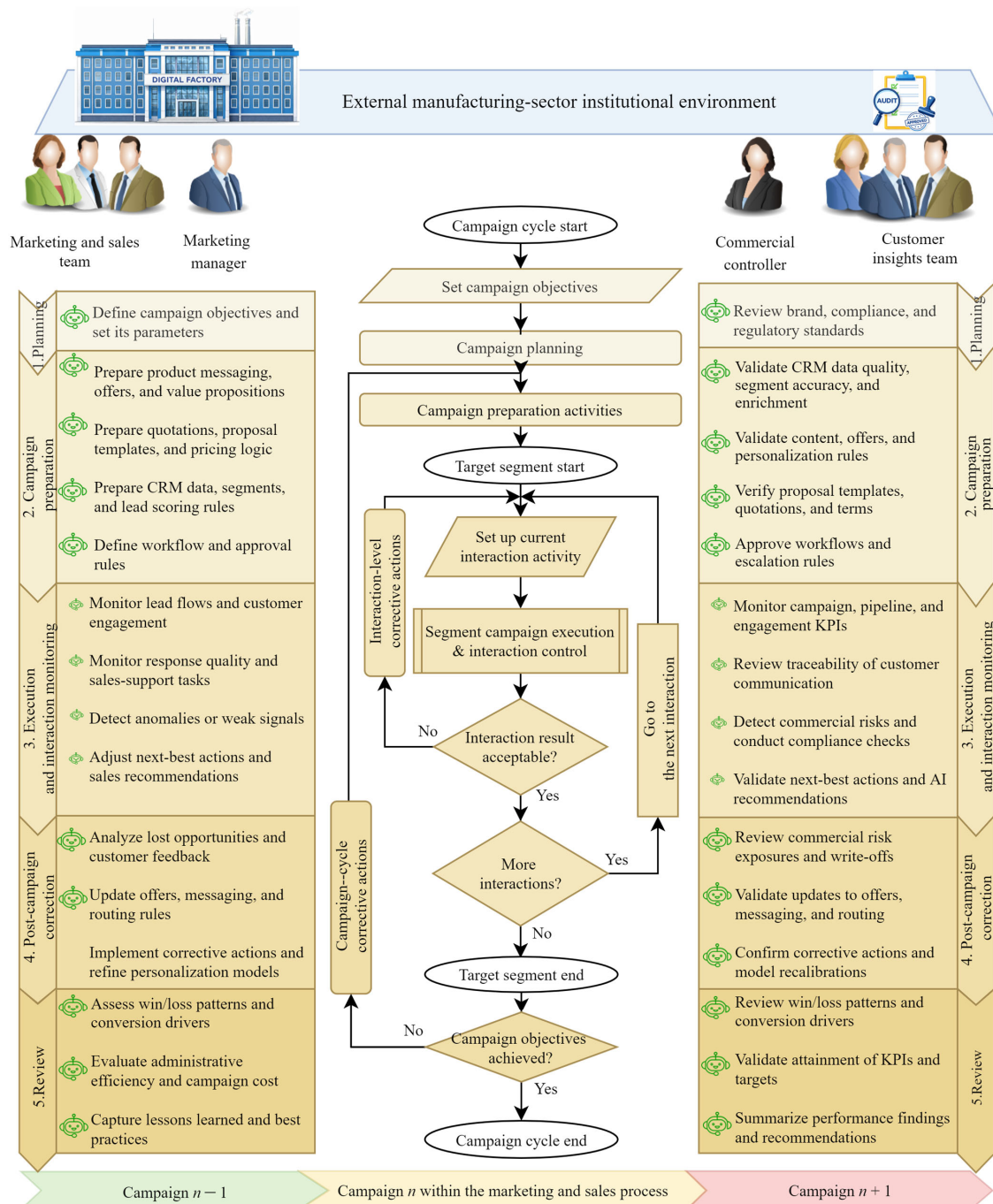


Figure 3. GAI-based marketing and sales framework based on campaign-cycle, target-segment, and interaction-level logic.

GAI can support this commercial logic by drafting campaign content, creating message variants, summarizing CRM interactions, explaining customer-segment behavior, preparing proposal drafts, suggesting follow-up messages, analyzing customer feedback, and supporting customer-specific communication. However, human control must remain over pricing, contractual terms, product claims, discounts, and customer commitments. This distinction is important because recent marketing literature emphasizes both the value of GAI for customer experience and the need to manage trust, personalization, transparency, and strategic marketing risks [33–36].

This right-side structure balances creativity and customer personalization with commercial discipline, legal consistency, and risk control. It ensures that GAI-enabled marketing and sales activities are not only efficient and personalized, but also traceable, compliant, and aligned with business strategy.

3.8. GAI-Based Accounting and Finance Framework

The accounting and finance framework is organized around a financial cycle containing a recurring document and transaction-processing subcycle. The central part begins with the start of the financial cycle, the setting of objectives, planning, and preparation activities. The financial process then begins, and the current document or transaction activity is set up. The core execution stage is that of document and transaction processing and control.

The main decision gate evaluates whether the document or transaction result is acceptable. If the result is acceptable, the process continues to the next document or transaction. If it is not acceptable, document–transaction corrective actions are triggered. Once the document- and transaction-processing subcycle is completed, the financial process ends. The broader financial cycle then evaluates whether financial objectives have been achieved. If not, financial-cycle corrective actions are initiated before the next cycle begins.

This structure reflects the financial-cycle logic of planning, document intake, transaction control, evidence validation, reporting, and review. It is compatible with finance and accounting literature, where GAI is increasingly discussed in relation to decision support, risk management, back-end processing, compliance work, audit preparation, financial reporting, alternative data, and financial-control activities [37–40].

Figure 4 presents the accounting and finance subframework. It organizes GAI-supported financial activities around a financial cycle, financial process subcycle, and document/transaction-processing level. The finance team and finance manager are responsible for execution, while the internal auditor and control and reporting team are responsible for evidence validation, control monitoring, and audit readiness.

GAI can support this finance logic by classifying documents, drafting variance explanations, preparing management-reporting narratives, summarizing audit evidence, supporting reconciliation, comparing transactions with policies, and converting accounting data into understandable managerial commentary. However, GAI outputs must remain decision-support artifacts, not final accounting judgments. This position is consistent with recent finance and auditing research, which emphasizes both the opportunities of AI for efficiency and analytics and the need for explainability, robustness, evidential reliability, and professional judgment [37–40].

This right-side architecture is essential because finance and audit decisions require reproducibility, evidence completeness, internal-control reliability, and formal approval. The framework therefore reserves final approval of postings, financial-reporting judgments, audit interpretations, and external disclosures for authorized human roles.

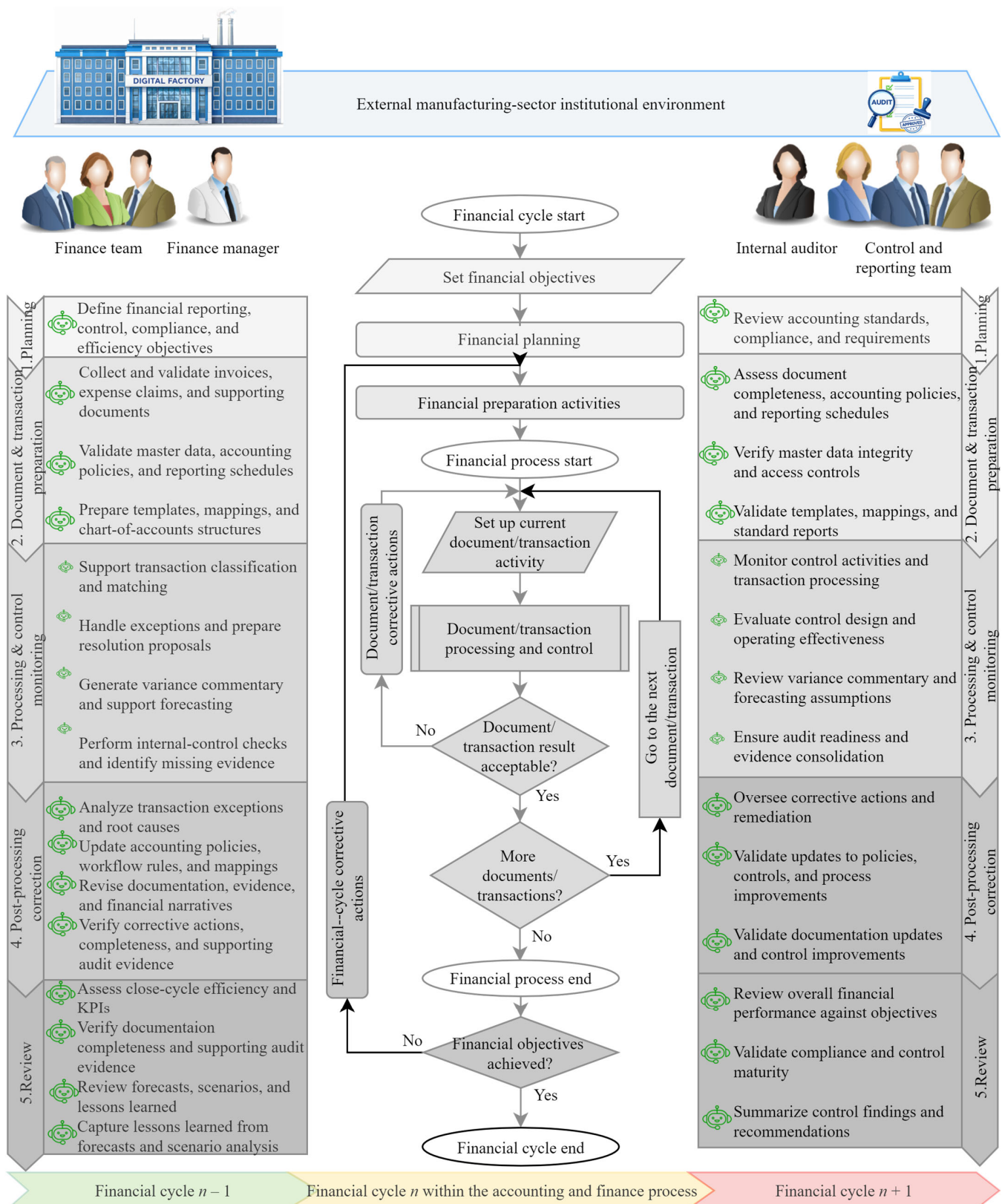


Figure 4. GAI-based accounting and finance framework based on financial-cycle, process-area, and document/transaction-level logic.

3.9. GAI-Based Human Resource Management Framework

The HRM framework is organized around a workforce cycle containing a recurring HR process and employee/case-level activities. The central part begins with the workforce

cycle start, followed by the setting of workforce objectives, HR process planning, and HR process preparation activities. The framework then enters the employee/case stage, where the current HR case is set up and handled through HR service execution and case control.

The key decision gate evaluates whether the case result is acceptable. If it is acceptable, the process continues to the next case activity or closes the case. If it is not acceptable, case-level corrective actions are triggered. Once the employee/case subcycle ends, the broader workforce cycle evaluates whether workforce objectives have been achieved. If not, workforce-cycle corrective actions are initiated and transferred into the next cycle.

This logic reflects the HRM process structure, where workforce-level objectives are achieved through HR process planning and employee/talent case handling. It is aligned with recent AI-HRM literature, which shows that AI and GAI affect HR planning, recruitment, selection, onboarding, training, performance management, employee services, and work redesign, while requiring human-centric implementation and careful treatment of fairness, trust, privacy, and compliance [41–43].

Figure 5 presents the HRM subframework. It structures GAI-supported workforce activities around a workforce cycle, HR-process subcycle, and employee/case-level control. The HR team and HR manager are responsible for operational HR service delivery, while the ethics and compliance officer and HR review team are responsible for fairness, privacy, compliance, and human-in-the-loop validation.

GAI can support this HRM logic by drafting vacancy texts, job descriptions, onboarding instructions, frequently asked question (FAQ) responses, policy explanations, training materials, case summaries, and learning-content variants. It can also help HR staff summarize employee inquiries, identify recurring workforce issues, and prepare structured documentation for review. However, AI-supported HR outputs require particular caution because HR processes concern individual rights, career opportunities, fairness, privacy, and workplace trust [41–43].

This right-side structure directly addresses one of the main conclusions of recent AI-HRM research: HR adoption cannot be evaluated only through efficiency gains. It must also be assessed in terms of fairness, trust, acceptance, well-being, privacy, ethics, and the continuing strategic role of HR in aligning technology with people management, culture, and compliance [41–43].

The four subframeworks instantiate a common enterprise architecture in which function-specific process cycles share controlled retrieval, logging, validation, escalation, and feedback mechanisms. This common layer enables cross-functional coordination while preserving domain-specific ownership, accountability, and approval boundaries.

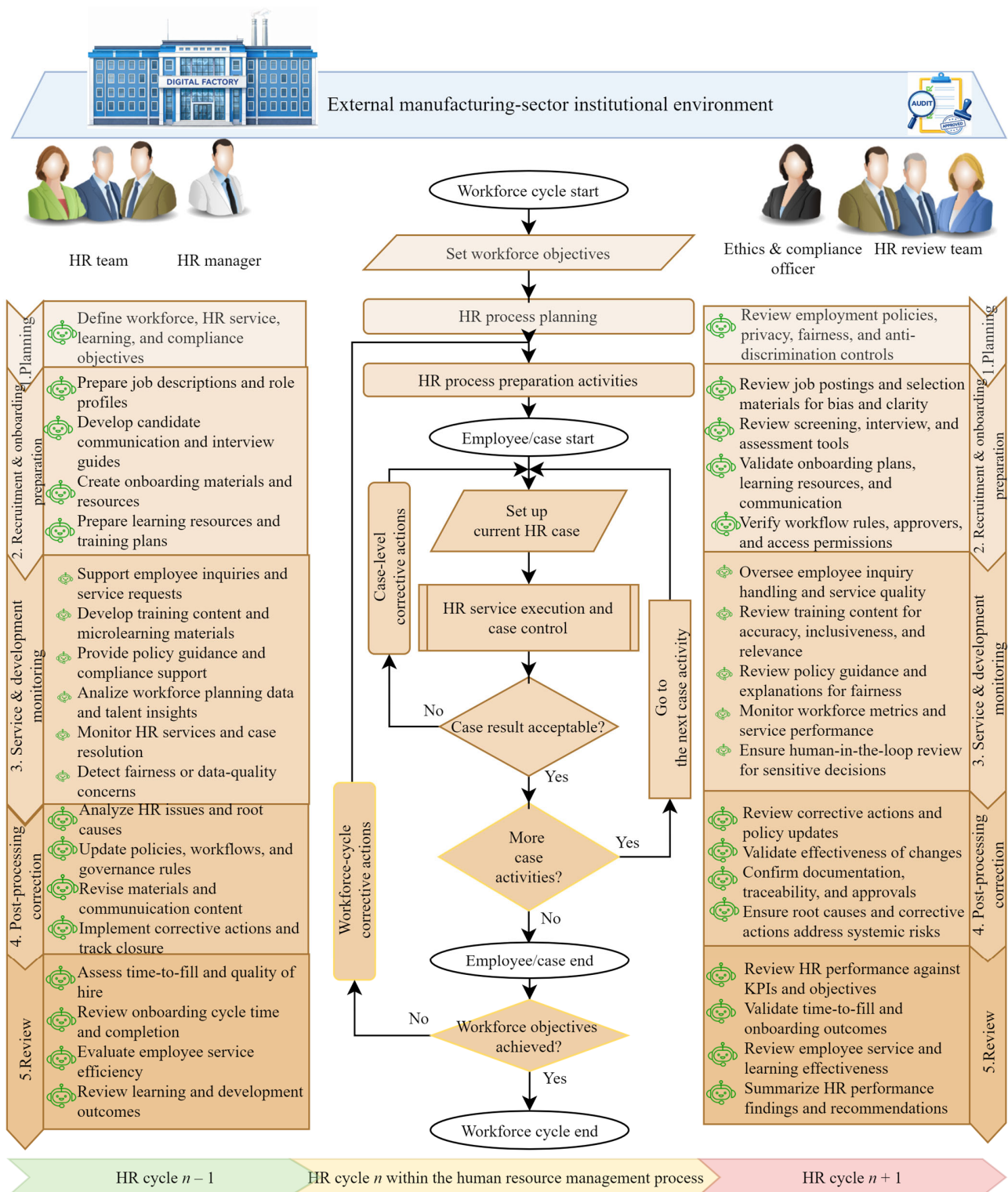


Figure 5. GAI-based HRM framework based on workforce-cycle, HR-process, and employee/case-level logic.

4. SIRI-Inspired Validation of the Proposed GAI-Based Framework

This section presents an author-adapted, SIRI-inspired maturity-readiness assessment of the proposed framework.

4.1. Validation Logic and Case-Study Context

The proposed framework is validated through a maturity-oriented case analysis of an electronics company. The company develops, manufactures, markets, sells, and services electronic security and electronics products, including alarm systems, fire detection devices, access-control modules, sensors, smart control panels, IoT-based monitoring devices, and related software-supported solutions. Its operations are organized around the four functional areas addressed in the proposed framework.

The validation does not aim to establish that GAI causes business-performance changes. The case study does not include a randomized control group, a matched non-adopting enterprise, or an experimental comparison of alternative AI-integration approaches. It therefore follows a PoC maturity-validation design that evaluates expert-assessed readiness for integrated, traceable, and human-supervised process management rather than the isolated operational effect of GAI.

The assessment combines expert scoring with available documentary evidence. Where possible, the retrospective baseline and post-GAI scenario assessments were triangulated with enterprise documentation, process records, accounting reports, and published 2023–2024 financial information. These sources support the plausibility of differences in documentation, reporting, control readiness, and cross-functional coordination, but concurrent digital transformation, management optimization, market changes, and organizational learning may also influence the assessed readiness.

For this purpose, the validation applies an author-adapted, SIRI-inspired maturity-readiness logic. The official SIRI framework was developed to assess industrial companies' readiness for smart manufacturing transformation through process, technology, and organization dimensions [15]. The present study does not apply SIRI as an official audit instrument. Instead, it adapts its maturity logic to evaluate GAI-supported readiness across four enterprise functions. The adaptation is necessary because the proposed framework extends beyond manufacturing operations and includes marketing and sales, accounting and finance, and HRM. Therefore, the resulting scores should be interpreted as structured expert-assessed maturity-readiness indicators, not as certified SIRI scores or direct operational performance measures. The adaptation of SIRI is supported by Industry 4.0 maturity research, which treats digital transformation as a staged capability-building process rather than a single technological intervention [44]. Digital transformation research also emphasizes that value emerges when digital technologies are embedded in organizational processes, routines, and decision structures [8].

The case context is relevant to electronics and computer-engineering research because the enterprise operates in an electronic manufacturing environment where physical products, embedded devices, IoT-enabled monitoring, production-control data, enterprise software, and AI-supported decision workflows must be coordinated. The proposed framework therefore addresses not only managerial process redesign, but also the integration of GAI capabilities with the software and data infrastructure that supports electronic product manufacturing, quality assurance, customer support, financial control, and workforce coordination.

4.2. Proof-of-Concept Implementation Scenario

The validation is based on a PoC implementation scenario rather than on a full longitudinal deployment. The scenario assumes that the company implements the four proposed GAI-based functional subframeworks and connects them through a common enterprise GAI orchestration and governance layer. The implementation scope is limited to decision support, documentation, retrieval, summarization, exception preparation, and workflow-support tasks. It does not include autonomous execution of high-impact deci-

sions or direct modification of transactional records in ERP, MES, CRM, QMS, accounting, or HRIS systems.

In manufacturing, GAI supports production planning, work-instruction preparation, SOP drafting, quality-control documentation, deviation analysis, root-cause analysis, CAPA documentation, maintenance summaries, and production KPI reporting.

In marketing and sales, GAI supports market intelligence, customer segmentation, campaign content generation, product messaging, proposal preparation, CRM interaction summaries, lead qualification, customer follow-up, and after-sales communication.

In accounting and finance, GAI supports invoice and expense document summarization, transaction classification, variance commentary, reporting, internal-control checklists, audit-readiness documentation, and financial KPI explanation.

In HRM, GAI supports job-description drafting, recruitment communication, onboarding materials, employee service responses, training content, policy guidance, skills-gap summaries, and performance-support workflows.

The integration of the four subframeworks is achieved through the enterprise orchestration and governance layer. This layer connects data, documents, thresholds, process events, and feedback across functional areas. For example, increased demand identified by marketing and sales may trigger production-capacity analysis, financial forecasting, and HR workforce-capacity assessment. Similarly, a manufacturing quality deviation may trigger customer communication, cost-impact analysis, and operator training. This cross-functional logic is central to the proposed enterprise-level framework.

4.3. Validation Dimensions

The SIRI-inspired maturity-readiness assessment uses three main maturity dimensions: process, technology, and organization. The process dimension evaluates whether workflows are structured, standardized, traceable, repeatable, and connected across functional areas. The technology dimension evaluates whether GAI chatbots, GAI agents, digital tools, enterprise systems, data repositories, and analytics capabilities are embedded into daily workflows. The organization dimension evaluates whether people, responsibilities, governance rules, validation procedures, training, collaboration, and managerial control support sustainable GAI adoption.

For each functional area, five function-specific evaluation dimensions are selected. The scores are differentiated to reflect realistic differences in baseline maturity and post-implementation development. The weighting scheme also differs by dimension, because not all dimensions have the same relevance for each functional area.

Each maturity score is assigned on a 0–5 scale, as shown in Table 2.

Table 2. Maturity scale for the adapted SIRI-based assessment of GAI-supported business processes.

Score	Maturity Level	Quantitative and Operational Judgment Criteria	Industrial Scenario Example
0	No digital support	No structured digital records; less than 10% of relevant process evidence is digitally available; no systematic digital workflow; no GAI support.	Paper-based production deviation records, manually stored HR files, or informal customer feedback without digital traceability.
1	Basic digital records	Basic digital storage exists; approximately 10–30% of relevant process evidence is digitally available; records are mostly static; no workflow integration; no systematic GAI use.	Invoices, SOPs, customer files, or HR documents are stored digitally but searched, interpreted, and summarized manually.
2	Partly digital process	Approximately 30–60% of relevant process evidence is digital; ERP, MES, CRM, accounting, QMS, or HRIS tools are used in selected activities; integration remains limited; no governed GAI workflow.	CRM records exist, but segmentation, campaign analysis, proposal preparation, and customer follow-up are still largely manual.

Table 2. *Cont.*

Score	Maturity Level	Quantitative and Operational Judgment Criteria	Industrial Scenario Example
3	GAI-supported process	Selected GAI-supported tasks are introduced; approximately 60–75% of relevant process evidence is available for retrieval or human review; GAI outputs are manually checked but not yet fully embedded into recurring workflows.	GAI drafts CAPA records, variance explanations, job descriptions, onboarding texts, or customer messages for human review.
4	Integrated GAI workflow	Approximately 75–90% of relevant process evidence is connected to approved repositories or enterprise systems; role-based access, RAG, output logging, validation rules, and human approval are defined; GAI is embedded into recurring workflows.	A GAI agent retrieves SOPs, quality records, and deviation logs, prepares a CAPA dossier, and routes it to the quality manager for approval.
5	Adaptive GAI-driven process	More than 90% of relevant process evidence is digitally integrated; feedback loops update prompts, knowledge bases, workflows, and KPIs; GAI-supported recommendations are continuously improved; human approval remains mandatory for high-impact decisions.	Cross-functional GAI orchestration links demand signals, production capacity, financial forecasts, and HR skill gaps through monitored learning loops.

The percentage thresholds are indicative judgment criteria rather than certified audit thresholds. They support consistent expert scoring by distinguishing basic digitalization, partial digital process support, GAI-assisted tasks, integrated GAI workflows, and adaptive learning-oriented GAI-enabled processes.

4.4. Expert Assessment Protocol, Evidence Base, and Weighting Logic

The assessment was performed by three experts with complementary perspectives. Expert 1 represented process and operations expertise, Expert 2 represented digital transformation and enterprise information systems expertise, and Expert 3 represented governance, control, and compliance expertise. The use of three different expert profiles was intended to reduce single-perspective bias and to reflect the three main maturity dimensions used in the adapted SIRI logic: process, technology, and organization.

The experts first evaluated the maturity dimensions independently using the same 0–5 maturity scale, the same functional-area dimensions, and the same description of the pre- and post-GAI implementation states. This independent scoring step was used as an independence safeguard and to reduce anchoring, dominance, and group-consensus bias. After the independent assessment, the scores were compared. Where differences between expert scores exceeded one maturity level, the item was discussed in a consensus meeting. The discussion was based on available process evidence, enterprise records, documentation practices, system use, governance controls, and the plausibility of the assumed GAI-supported process changes. If full consensus could not be reached, the arithmetic mean of the independent expert scores was retained.

The decimal scores reported in Tables 3–6 are therefore not direct measurements from operational sensors or enterprise KPIs. They represent arithmetic means of the three expert maturity ratings. For example, a value such as 2.1 reflects the averaged expert assessment of a dimension located between “partly digital process” and “GAI-supported process” in the adapted maturity scale. A value such as 4.1 reflects the averaged expert assessment of a dimension slightly above “integrated GAI workflow”, but below a fully adaptive GAI-driven process.

The pre-GAI scores were reconstructed retrospectively from historical process knowledge, enterprise documentation, existing system use, prior reporting and control practices, and, where available, published 2023 accounting information. The post-GAI scores represent expert-assessed maturity under the proposed implementation scenario and were

triangulated, where possible, with 2024 documentation and process evidence. This PoC comparison is weaker than a prospective longitudinal design and is not interpreted as measured operational change.

To reduce reliance on subjective judgment alone, the expert assessment was triangulated with available documentary and process evidence. In accounting and finance, the evaluation used available general-ledger-derived summaries, income/cost reports, financial statements, reporting practices, and audit-readiness evidence where accessible. In manufacturing, the assessment considered production documentation, quality records, deviation handling, work instructions, and corrective-action practices. In marketing and sales, the assessment considered CRM use, customer communication, campaign preparation, quotation and proposal support, and customer-feedback handling. In HRM, the assessment considered recruitment, onboarding, employee-service documentation, training materials, and governance procedures.

The documentary evidence was used as supporting evidence for maturity classification rather than as a source of causal performance measurement. For each assessed dimension, the experts checked whether the available evidence supported the assigned maturity level. Examples included the existence of digital records, completeness of process documentation, use of ERP/MES/CRM/QMS/accounting/HRIS data, availability of approved SOPs or policies, evidence of human validation, traceability of process outputs, and availability of reporting or control records. Where the evidence was incomplete or ambiguous, the score was kept below the next maturity threshold. This conservative rule was used to avoid overstating the maturity-readiness effect of the proposed framework.

The weights in Tables 3–6 were determined through structured expert judgment. Each dimension was evaluated according to three criteria: relevance to the specific functional area, expected contribution to GAI-enabled process maturity, and governance, risk, or evidence significance. Dimensions that directly influence process integration, evidence quality, control readiness, cross-functional coordination, or human validation received higher weights. The sum of weights within each functional area equals 1.

To check the rationality of the weighting scheme, the experts reviewed whether the assigned weights reflected the relative importance of each dimension in the corresponding functional area. A simple sensitivity check was also performed by varying the dimension weights within moderate intervals while preserving the total weight of 1. The direction of improvement and the interpretation of the four functional areas remained stable, which supports the robustness of the maturity-assessment conclusions.

Inter-rater agreement was evaluated descriptively by comparing the dispersion of expert scores across maturity dimensions. Given the three-expert PoC design and the limited number of assessed dimensions, these results are interpreted cautiously and are not presented as certified audit reliability.

The expert-scoring worksheet, raw expert ratings, descriptive inter-rater summary, and recalculation check are reported in Supplementary Section S1.

4.5. SIRI-Based Evaluation Formulas

For each functional area FA , the adapted SIRI readiness score $SIRI_{FA}$ is calculated as:

$$SIRI_{FA} = \frac{\sum_{i=1}^n w_i x_i}{5 \cdot \sum_{i=1}^n w_i} \times 100 \quad (1)$$

where x_i is the maturity score of dimension i , w_i is the weight assigned to dimension i , and n is the number of assessed dimensions.

Since the weights within each functional area sum to 1, the formula can be simplified as:

$$SIRI_{FA} = \frac{\sum_{i=1}^n w_i x_i}{5} \times 100 \quad (2)$$

The scenario-based absolute maturity-readiness increase associated with the proposed GAI framework is calculated as:

$$\Delta SIRI_{FA} = SIRI_{FA}^{post} - SIRI_{FA}^{pre} \quad (3)$$

where $SIRI_{FA}^{pre}$ is the pre-implementation readiness score and $SIRI_{FA}^{post}$ is the post-implementation readiness score.

The relative maturity-readiness increase is calculated as:

$$Improvement_{FA} = \frac{SIRI_{FA}^{post} - SIRI_{FA}^{pre}}{SIRI_{FA}^{pre}} \times 100. \quad (4)$$

The overall enterprise readiness score is calculated as the arithmetic mean of the four functional-area readiness scores:

$$SIRI_{Overall} = \frac{SIRI_M + SIRI_{MS} + SIRI_{AF} + SIRI_{HRM}}{4} \quad (5)$$

where $SIRI_M$, $SIRI_{MS}$, $SIRI_{AF}$, and $SIRI_{HRM}$ represent the readiness scores for manufacturing, marketing and sales, accounting and finance, and HRM, respectively.

For the expert-based assessment, the maturity score of each dimension is calculated as the average of the evaluations provided by the experts.

4.6. Manufacturing Subframework Validation

The manufacturing subframework is evaluated through five dimensions: production process integration, quality documentation, shop-floor data use, maintenance support, and human-in-the-loop control (Table 3). In the retrospective pre-GAI baseline, production documentation and shop-floor data are partly digital but knowledge remains fragmented. Under the post-GAI implementation scenario, GAI supports work-instruction preparation, deviation summaries, defect analysis, CAPA drafting, maintenance documentation, KPI reporting, and lessons-learned reuse.

Table 3. Weighted pre- and post-implementation maturity assessment of the GAI-based manufacturing subframework.

Manufacturing Dimension	Weight	Pre-GAI	Post-GAI
Production process integration	0.25	2.1	4.0
Quality documentation	0.20	1.8	4.1
Shop-floor data use	0.20	2.4	3.6
Maintenance support	0.15	1.7	3.3
Human-in-the-loop control	0.20	2.6	4.2

The pre- and post-implementation maturity scores are calculated as arithmetic means of the evaluations provided by three experts: Expert 1, representing process/operations expertise; Expert 2, representing digital transformation and IT expertise; and Expert 3, representing governance, control, and compliance expertise.

According to Equations (2)–(4), the weighted pre-implementation score, weighted post-implementation score, absolute SIRI change, and relative SIRI improvement for the manufacturing subframework are calculated as follows:

$$SIRI_M^{pre} = \frac{0.25(2.1) + 0.20(1.8) + 0.20(2.4) + 0.15(1.7) + 0.20(2.6)}{5} \times 100 = 42.80$$

$$SIRI_M^{post} = \frac{0.25(4.0) + 0.20(4.1) + 0.20(3.6) + 0.15(3.3) + 0.20(4.2)}{5} \times 100 = 77.50$$

$$\Delta SIRI_M = 77.50 - 42.80 = 34.70$$

$$Improvement_M = \frac{34.70}{42.80} \times 100 = 81.07\%.$$

The manufacturing subframework shows a strong scenario-based maturity-readiness increase, particularly in quality documentation and production process integration. Shop-floor data use and maintenance support remain below the highest level because adaptive manufacturing intelligence would require deeper real-time integration with MES, IoT sensors, maintenance systems, and closed-loop control.

4.7. Marketing and Sales Subframework Validation

The marketing and sales subframework is evaluated through CRM data use, campaign preparation, lead and opportunity support, customer feedback analysis, and commercial governance (Table 4). The retrospective baseline includes basic CRM records but largely manual campaign, segmentation, feedback, and follow-up activities. Under the post-GAI scenario, GAI supports messaging, campaign variants, CRM summarization, proposal preparation, lead qualification, customer follow-up, and performance review.

Table 4. Weighted pre- and post-implementation maturity assessment of the GAI-based marketing and sales subframework.

Marketing and Sales Dimension	Weight	Pre-GAI	Post-GAI
CRM data use	0.25	2.3	4.0
Campaign preparation	0.20	1.9	4.2
Lead and opportunity support	0.20	2.2	3.7
Customer feedback analysis	0.20	1.4	4.0
Commercial governance	0.15	2.5	3.6

The weighted pre-implementation score, weighted post-implementation score, absolute SIRI change, and relative SIRI improvement for the marketing and sales subframework are calculated as follows:

$$SIRI_{MS}^{pre} = \frac{0.25(2.3) + 0.20(1.9) + 0.20(2.2) + 0.20(1.4) + 0.15(2.5)}{5} \times 100 = 41.00$$

$$SIRI_{MS}^{post} = \frac{0.25(4.0) + 0.20(4.2) + 0.20(3.7) + 0.20(4.0) + 0.15(3.6)}{5} \times 100 = 78.40$$

$$\Delta SIRI_{MS} = 78.40 - 41.00 = 37.40$$

$$Improvement_{MS} = \frac{37.40}{41.00} \times 100 = 91.22\%.$$

The scenario-based readiness increase is strongest in campaign preparation and customer feedback analysis, which are content- and communication-intensive. Commercial governance develops more moderately because customer-facing messages, prices, contractual terms, and product claims continue to require human review.

4.8. Accounting and Finance Subframework Validation

The accounting and finance subframework is evaluated through document control, transaction processing, reporting support, internal-control readiness, and audit-evidence traceability (Table 5). The retrospective baseline is document-heavy and dependent on manual checking and reporting. Under the post-GAI scenario, GAI supports document summarization, transaction classification, policy interpretation, variance commentary, internal-control checks, missing-evidence detection, and report drafting.

Table 5. Weighted pre- and post-implementation maturity assessment of the GAI-based accounting and finance subframework.

Accounting and Finance Dimension	Weight	Pre-GAI	Post-GAI
Document control	0.25	2.0	4.3
Transaction processing	0.20	2.4	3.8
Reporting support	0.20	2.1	4.2
Internal-control readiness	0.20	2.5	4.0
Audit evidence traceability	0.15	1.6	4.1

The weighted pre-implementation score, weighted post-implementation score, absolute SIRI change, and relative SIRI improvement for the accounting and finance subframework are calculated as follows:

$$SIRI_{AF}^{pre} = \frac{0.25(2.0) + 0.20(2.4) + 0.20(2.1) + 0.20(2.5) + 0.15(1.6)}{5} \times 100 = 42.80$$

$$SIRI_{AF}^{post} = \frac{0.25(4.3) + 0.20(3.8) + 0.20(4.2) + 0.20(4.0) + 0.15(4.1)}{5} \times 100 = 81.80$$

$$\Delta SIRI_{AF} = 81.80 - 42.80 = 39.00$$

$$Improvement_{AF} = \frac{39.00}{42.80} \times 100 = 91.12\%.$$

Accounting and finance shows the highest post-GAI scenario readiness because its document-intensive and rule-sensitive activities suit controlled summarization, classification, checking, explanation, and reporting. Final accounting, payment, tax, audit, and compliance decisions nevertheless require formal human approval and documented accountability.

4.9. HRM Subframework Validation

The HRM subframework is evaluated through recruitment support, onboarding support, employee service, learning and development, and HR governance and fairness (Table 6). The retrospective baseline relies on manual document preparation, repetitive communication, and fragmented learning records. Under the post-GAI scenario, GAI supports job descriptions, candidate communication, onboarding, employee-service responses, training content, skills-gap summaries, fairness checks, and escalation of sensitive cases.

Table 6. Weighted pre- and post-implementation maturity assessment of the GAI-based HRM subframework.

HRM Dimension	Weight	Pre-GAI	Post-GAI
Recruitment support	0.25	2.2	4.1
Onboarding support	0.20	1.9	4.0
Employee service	0.20	1.5	3.5
Learning and development	0.20	2.0	4.1
HR governance and fairness	0.15	2.4	3.9

The weighted pre-implementation score, weighted post-implementation score, absolute SIRI change, and relative SIRI improvement for the HRM subframework are calculated as follows:

$$SIRI_{HRM}^{pre} = \frac{0.25(2.2) + 0.20(1.9) + 0.20(1.5) + 0.20(2.0) + 0.15(2.4)}{5} \times 100 = 39.80$$

$$SIRI_{HRM}^{post} = \frac{0.25(4.1) + 0.20(4.0) + 0.20(3.5) + 0.20(4.1) + 0.15(3.9)}{5} \times 100 = 78.60$$

$$\Delta SIRI_{HRM} = 78.60 - 39.80 = 38.80$$

$$Improvement_{HRM} = \frac{38.80}{39.80} \times 100 = 97.49\%.$$

HRM shows substantial scenario-based maturity-readiness increases in recruitment support, onboarding, learning-content preparation, and employee service. Governance and fairness remain comparatively constrained because employee-related processes require careful human review, privacy control, and ethical oversight.

4.10. Overall Enterprise-Level Maturity-Readiness Comparison

Using Equation (5), the overall maturity-readiness score of the proposed framework is calculated as the average of the four functional-area scores:

$$SIRI_{Overall}^{pre} = \frac{42.80 + 41.00 + 42.8 + 39.80}{4} = 41.60$$

$$SIRI_{Overall}^{post} = \frac{77.50 + 78.40 + 81.80 + 78.60}{4} = 79.08$$

$$\Delta SIRI_{Overall} = 79.08 - 41.60 = 37.48$$

$$Improvement_{Overall} = \frac{37.48}{41.60} \times 100 = 90.10\%.$$

The overall expert-assessed maturity-readiness score increases from 41.60 in the retrospective pre-GAI baseline to 79.08 under the post-GAI implementation scenario. This represents a scenario-based absolute increase of 37.48 points and a relative increase of 90.10%. The functional profiles differ: manufacturing has stronger baseline shop-floor data use, marketing and sales has weaker customer-feedback analysis, accounting and finance has weaker audit-evidence traceability, and HRM has weaker employee-service maturity.

4.11. Cross-Functional Integration and Governance Readiness

The SIRI-inspired assessment also considers whether the company's functional areas could become better connected under the implementation scenario. Cross-functional integration is reflected when demand informs production, finance, and workforce planning; quality deviations trigger customer, cost, and training responses; and all functions use shared GAI-supported documentation and governance rules.

Governance readiness is evaluated through the presence of AI-use policies, approved knowledge sources, role-based access, output logging, validation procedures, escalation paths, traceability, and human approval for high-impact decisions. These controls are aligned with the NIST AI Risk Management Framework, which structures AI risk management around governance, mapping, measurement, and management functions [11]. They are also aligned with ISO/IEC 42001:2023, which frames AI governance as a management-system issue requiring documented processes, monitoring, performance evaluation, and continual improvement [12]. The NIST Generative AI Profile further stresses risks specific to GAI systems, including confabulation, data leakage, cybersecurity, intellectual property, and information-integrity risks [28].

The scenario illustrates how the framework can connect function-specific GAI support through shared integration and governance mechanisms rather than treating each application as an isolated task.

4.12. Interpretation and Limitations of the Validation

The author-adapted, SIRI-inspired assessment indicates that the four proposed GAI-based subframeworks are associated with higher maturity-readiness scores under the adopted expert-scoring protocol. The improvement is observed in three main readiness

dimensions. First, process maturity increases because fragmented manual activities are reorganized into structured, repeatable, and monitored workflows. Second, technology maturity increases because GAI chatbots, bounded agents, enterprise data, and digital tools are embedded into operational and managerial processes. Third, organizational maturity increases because the framework strengthens human-in-the-loop governance, role clarity, cross-functional collaboration, and responsible AI control.

The strongest improvements are observed in accounting and finance and HRM, mainly because these areas contain many document-intensive, communication-intensive, and rule-sensitive activities that can benefit from GAI-supported drafting, summarization, classification, checking, and explanation. Manufacturing and marketing and sales also show substantial improvements through better planning, monitoring, documentation, decision support, and feedback integration.

Nevertheless, the maturity scores are based on an author-adapted, SIRI-inspired assessment rather than an official SIRI audit and should be interpreted as a PoC maturity evaluation, not as externally certified readiness or causal evidence. Future multi-company validation should use prospective operational evidence, larger expert panels, and formal agreement measures, such as ordinal Krippendorff's alpha or an appropriate intraclass correlation coefficient, before aggregating expert ratings.

5. Discussion

Our findings position GAI as a process- and architecture-level enterprise capability rather than a collection of isolated applications. The framework presented here extends prior research by combining function-specific process cycles with shared orchestration, validation, and maturity-readiness logic [3,25,26].

5.1. Comparison with Existing GAI and Enterprise Process Research

Previous studies establish that GAI can support productivity, decision preparation, process modeling, and digitally enabled organizational change [3,4,8,10]. The proposed framework extends this work by embedding GAI within recurring functional cycles, decision gates, validation roles, and cross-functional orchestration. Its unit of contribution is therefore an enterprise information architecture rather than a single productivity tool or isolated use case.

5.2. Comparison with Function-Specific GAI Applications

Prior studies establish function-specific GAI applications in manufacturing [6,16,30–32], marketing and sales [17,18,33–36], accounting and finance [20,37–40], and HRM [7,19,41–43]. Their main contribution is domain-specific task support rather than enterprise-wide coordination.

The proposed framework complements these studies by applying a common process-cycle architecture while preserving functional differences. This cross-functional perspective connects demand with production and workforce planning, quality deviations with customer and cost responses, and financial signals with commercial and investment decisions.

5.3. Chatbots, Agents, and Human-in-the-Loop Governance

The distinction between GAI chatbots and agents has direct governance implications. Chatbots mainly support explanation, summarization, and drafting, whereas agents combine retrieval, planning, tool use, and multi-step execution [5,21–24].

Because bounded agents can retrieve data, call tools, and route process cases, they require stronger access controls, logging, validation, escalation, and human approval. The framework applies these controls according to workflow risk rather than treating all GAI uses identically.

This risk-based human-in-the-loop logic operationalizes principles of transparency, accountability, meaningful human control, and continuous risk management expressed in human-centered AI guidance, the NIST AI Risk Management Framework, ISO/IEC 42001:2023, and the NIST Generative AI Profile [11–14,28].

5.4. Interpretation of the SIRI-Inspired Validation Results

The maturity-readiness profile is more informative as a comparison among functional areas than as evidence of operational performance. Accounting and finance reaches the highest post-scenario readiness because document-intensive, rule-sensitive, and evidence-dependent activities are particularly suitable for controlled retrieval, summarization, checking, and draft generation [20,37–40]. HRM also shows substantial readiness potential, although fairness, privacy, and employee-related consequences require stronger governance constraints [7,19,41–43]. Manufacturing remains more dependent on real-time MES, IoT, maintenance, and shop-floor integration [30–32], whereas marketing and sales must balance rapid content generation with human control over product claims, pricing, and customer commitments [17,18,33–36].

The overall increase from 41.60 to 79.08 therefore represents the experts' assessment of readiness under the defined implementation scenario. It identifies areas of potential organizational and technological readiness but does not measure changes in cycle time, costs, error rates, quality, customer response, or employee workload.

5.5. Theoretical Implications

Theoretically, the framework extends process-augmentation and digital-transformation research by defining a reusable enterprise reference artifact that connects process cycles, knowledge retrieval, implementation controls, human roles, and maturity-readiness criteria.

The framework also operationalizes responsible-AI principles by locating validation, evidence, escalation, and accountability within recurring functional workflows [11–14,27,28].

Finally, its SIRI-inspired evaluation offers a bounded approach for assessing integration capability and governance preparedness when longitudinal performance effects are not yet observable.

5.6. Managerial and Practical Implications

For industrial managers, implementation should begin with process analysis, workflow-risk classification, and the definition of approved knowledge sources, validation roles, logging requirements, escalation paths, and human approval rules before chatbots or agents are introduced.

The cross-functional perspective is particularly important in manufacturing: demand signals should inform production, inventory, workforce, and cash-flow planning, while quality deviations may require customer communication, cost analysis, and operator training.

Practically, implementation should start with low-risk, read-only, and draft-generation workflows before moving to bounded agentic workflows. A recommended implementation sequence is: first, connect approved document repositories and enterprise-system views; second, define role-based access and approved RAG source sets; third, create prompt templates for recurring tasks; fourth, introduce structured logging and reviewer decisions; fifth, pilot one bounded workflow per functional area; and sixth, evaluate rejected outputs, missing evidence, reviewer edits, and escalation cases before wider deployment. This phased approach reduces the risk of overreliance on GAI outputs and supports gradual movement from isolated experimentation toward governed enterprise orchestration.

6. Conclusions

This study proposes an integrated GAI-based reference framework that connects manufacturing, marketing and sales, accounting and finance, and HRM through a common orchestration layer. Its primary contribution is the integration of function-specific process cycles, enterprise systems, approved knowledge retrieval, bounded GAI agents, validation roles, traceability, and maturity monitoring within one process-oriented architecture.

The author-adapted, SIRI-inspired PoC assessment indicates an increase from 41.60 in the retrospective pre-GAI baseline to 79.08 under the post-GAI implementation scenario. This difference represents expert-assessed maturity-readiness under the defined scoring protocol; it is not causal evidence of improvements in cycle time, cost, error rates, quality, customer response, or employee workload.

For managers, the framework offers a structured path from isolated experimentation toward governed enterprise implementation, beginning with low-risk, read-only, and draft-generation workflows. High-impact decisions, including production release, financial reporting, customer commitments, pricing, hiring, compensation, and disciplinary action, remain under authorized human responsibility.

The study is limited by its single-company PoC design, retrospective baseline reconstruction, three-expert assessment, absence of a control group, and lack of measured operational KPIs. The assessment is neither a longitudinal deployment study nor an official SIRI audit.

Future research should test the framework longitudinally across multiple industrial enterprises, report formal inter-rater agreement, compare GAI-supported and alternative workflows, and examine operational and human-centered KPIs, agent autonomy, data integration, cybersecurity, and human oversight. Subject to these limitations, the framework provides a reusable reference architecture for responsible, cross-functional GAI adoption.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/electronics15153392/s1>, Sections S1–S3. Supplementary Section S1 provides the expert-scoring worksheet, raw expert ratings, weighting rationale, consensus protocol, descriptive inter-rater agreement summary, and weighted-score recalculation check. Supplementary Section S2 provides the technical implementation artifacts, including the layered implementation architecture, enterprise-system adapter examples, RAG metadata schema, access-control and tool-allowlist matrix, prompt-template structure, validation checklist, audit-log schema, workflow examples, governance diagrams, implementation KPIs, and pseudocode for bounded agent orchestration. Supplementary Section S3 provides the reproducibility package, including the deployment procedure, configuration table, prompt repository index, benchmark scenarios, evaluation protocol, sample dataset structures, suggested folder structure, and reproducibility checklist.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
API	Application Programming Interface
B2B	Business-to-Business
BPM	Business Process Management
CAPA	Corrective and Preventive Action
CRM	Customer Relationship Management
CV	Curriculum Vitae
ERDF	European Regional Development Fund
ERP	Enterprise Resource Planning
ESG	Environmental, Social, and Governance
FA	Functional Area
FAQ	Frequently Asked Questions
GAI	Generative Artificial Intelligence
HR	Human Resources
HRIS	Human Resource Information System
HRM	Human Resource Management
IoT	Internet of Things
ISO/IEC	International Organization for Standardization / International Electrotechnical Commission
IT	Information Technology
KPI	Key Performance Indicator
LLM	Large Language Model
MES	Manufacturing Execution System
NIST	National Institute of Standards and Technology
PoC	Proof-of-Concept
PRIDST	Programme Research, Innovation and Digitalisation for Smart Transformation
QMS	Quality Management System
RAG	Retrieval-Augmented Generation
RMF	Risk Management Framework
SIRI	Smart Industry Readiness Index
SOP(s)	Standard Operating Procedure(s)
SPC	Statistical Process Control

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