

AI-Enabled Business Process Management: An Integrated Capability Framework for Process Mining, Intelligent Automation and Business Process Performance

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Abstract:

Purpose: This study develops and empirically evaluates an integrated AI-enabled business process management (BPM) capability framework that explains how BPM capability, IT integration, process mining, AI capability and intelligent automation combine to improve business process performance. It responds to a gap between technology-specific studies and the organizational capability perspective needed to understand how these technologies work together.

Design/methodology/approach: A quantitative cross-sectional organizational survey was conducted in Libya. From 578 questionnaires received, 78 were removed using predefined data-quality criteria, yielding 500 valid responses from managers and professionals across banking and financial services, oil and gas, telecommunications, government, manufacturing, logistics and other sectors. The model was estimated with PLS-SEM in SmartPLS 4 using 10,000 BCa bootstrap subsamples.

Findings: All five antecedent capabilities significantly predict AI-enabled BPM capability. AI capability is the strongest antecedent ($\beta = 0.283$), followed by process mining ($\beta = 0.224$), intelligent automation ($\beta = 0.195$), BPM capability ($\beta = 0.187$) and IT integration ($\beta = 0.165$). AI-enabled BPM strongly predicts business process performance ($\beta = 0.551$, $p < 0.001$). The mediation analysis shows indirect-only mediation for BPM, process mining and intelligent automation, and complementary partial mediation for IT integration and AI capability. Measurement quality, discriminant validity, collinearity and predictive assessment are satisfactory.

Originality: The study conceptualizes AI-enabled BPM as a distinct integrative organizational capability rather than as isolated AI adoption, process mining or

automation. It provides empirical evidence from an underrepresented emerging-market setting and shows that process performance gains depend on orchestrating technological and managerial capabilities through an AI-enabled BPM mechanism.

Keywords: AI-enabled BPM; business process management; process mining; artificial intelligence capability; intelligent automation; business process performance; dynamic capabilities; Libya

Article classification: Research paper

إدارة عمليات الأعمال المدعومة بالذكاء الاصطناعي: إطار متكامل للقدرات في تنقيب العمليات والأتمتة الذكية وتحسين أداء عمليات الأعمال

الملخص

الغرض: تهدف هذه الدراسة إلى تطوير إطار متكامل لقدرات إدارة عمليات الأعمال المدعومة بالذكاء الاصطناعي (*AI-enabled BPM*) وتقييمه، بما يفسر كيفية تكامل قدرات إدارة عمليات الأعمال (*BPM*)، وتكامل تقنية المعلومات، وتنقيب العمليات (*Process Mining*)، وقدرات الذكاء الاصطناعي، والأتمتة الذكية، من أجل تحسين أداء عمليات الأعمال. وتتناول الدراسة فجوة بحثية قائمة بين الدراسات التي تركز على تقنيات محددة بصورة منفصلة، وبين منظور القدرات التنظيمية اللازم لفهم كيفية عمل هذه التقنيات معًا بصورة متكاملة.

التصميم/المنهجية/المدخل: اعتمدت الدراسة منهجًا كميًا مقطعيًا قائمًا على استبيان تنظيمي أُجري في ليبيا. ومن أصل 578 استبانة تم استلامها، استُبعدت 78 استبانة استنادًا إلى معايير محددة مسبقًا لجودة البيانات، ليصبح العدد النهائي 500 استبانة صالحة للتحليل من مديرين ومختصين يعملون في قطاعات المصارف والخدمات المالية، والنفط والغاز، والاتصالات، والقطاع الحكومي، والتصنيع، والخدمات اللوجستية، وقطاعات أخرى. وتم تقدير النموذج باستخدام نمذجة المعادلات الهيكلية بطريقة المربعات الصغرى الجزئية (*PLS-SEM*) من خلال برنامج *SmartPLS 4*، بالاعتماد على 10,000 عينة إعادة معاينة *Bootstrap* مصححة للتحيز ومسرّعة (*BCa*).

النتائج: أظهرت النتائج أن جميع القدرات الخمس السابقة في النموذج تسهم بصورة دالة إحصائياً في التنبؤ بقدرة إدارة عمليات الأعمال المدعومة بالذكاء الاصطناعي. وقد جاءت قدرة الذكاء الاصطناعي بوصفها أقوى العوامل تأثيراً ($\beta = 0.283$)، تلتها قدرة تنقيب العمليات ($\beta = 0.224$)، ثم الأتمتة الذكية ($\beta = 0.195$)، وقدرة إدارة عمليات الأعمال ($\beta = 0.187$)، وأخيراً تكامل تقنية المعلومات ($\beta = 0.165$). كما أظهرت النتائج أن إدارة عمليات الأعمال المدعومة بالذكاء الاصطناعي ترتبط بقوة بأداء عمليات الأعمال ($\beta = 0.551, p < 0.001$). وأظهر تحليل الوساطة وجود وساطة غير مباشرة فقط (*Indirect-only mediation*) بالنسبة إلى قدرة إدارة عمليات الأعمال، وتنقيب العمليات، والأتمتة الذكية، في حين ظهرت وساطة جزئية تكاملية (*Complementary partial mediation*) بالنسبة إلى تكامل تقنية المعلومات وقدرة الذكاء الاصطناعي. كما أظهرت الاختبارات أن جودة القياس، والصدق التمييزي، ومستويات التعدد الخطي، والتقييم التنبؤي جاءت جميعها ضمن مستويات مرضية.

الأصالة: تقدم الدراسة مفهوم إدارة عمليات الأعمال المدعومة بالذكاء الاصطناعي بوصفه قدرة تنظيمية تكاملية متميزة، بدلاً من النظر إلى تبني الذكاء الاصطناعي، أو تنقيب العمليات، أو الأتمتة باعتبارها ممارسات منفصلة. كما تسهم الدراسة في توسيع المعرفة المتعلقة بإدارة عمليات الأعمال المدعومة بالذكاء الاصطناعي من خلال تناولها في سياق سوق ناشئة لم تحظَ بتمثيل كافٍ في الأدبيات السابقة، وتوضح أن التحسينات في أداء العمليات تعتمد على تنسيق وتكامل القدرات التكنولوجية والإدارية من خلال آلية متكاملة لإدارة عمليات الأعمال المدعومة بالذكاء الاصطناعي. **الكلمات المفتاحية:** إدارة عمليات الأعمال المدعومة بالذكاء الاصطناعي؛ إدارة عمليات الأعمال؛ تنقيب العمليات؛ قدرة الذكاء الاصطناعي؛ الأتمتة الذكية؛ أداء عمليات الأعمال؛ القدرات الديناميكية؛ ليبيا.

تصنيف المقالة: ورقة بحثية



1. Introduction

Business process management (BPM) has evolved from a discipline focused primarily on process modeling, redesign and workflow execution into a broader organizational capability for continuously managing process performance. Contemporary BPM increasingly operates in environments where process data, machine learning, artificial intelligence (AI), process mining and robotic or intelligent automation are available alongside traditional process-management practices. This development creates substantial opportunities for organizations, but it also creates a coordination problem: technologies that can enhance processes are frequently introduced as separate projects, owned by different functions and governed by different objectives. The practical challenge is therefore no longer simply whether an organization possesses AI or automation tools, but whether it can integrate them with process-management routines in a way that produces sustained process improvement.

This distinction matters because the emerging literature shows strong but fragmented evidence. BPM capability research emphasizes governance, process ownership, methods, culture and performance management (vom Brocke et al., 2014; Van Looy, 2020; Badakhshan et al., 2023). Process-mining research demonstrates how event data can reveal actual execution patterns, bottlenecks, deviations and improvement opportunities (vom Brocke et al., 2021; Martin et al., 2021; Zerbino et al., 2021). AI capability research, in turn, emphasizes the complementary roles of data, infrastructure, skills and managerial coordination in realizing organizational value from AI (Mikalef and Gupta, 2021). Intelligent-automation research links RPA and AI to workflow execution, task automation and increasingly adaptive decision support (Syed et al., 2020; Ng et al., 2021; El-Gharib and Amyot, 2023). Recent work also highlights a drift toward more AI-intensive BPM and shows that AI can create value through BPM-related mechanisms rather than through technology adoption alone (Rosemann et al., 2024; Zebec and Indihar Štemberger, 2024).

Despite these advances, the streams are often examined independently. This makes it difficult to explain the organizational mechanism that connects underlying capabilities to process-level performance. A firm may, for example, possess sophisticated AI models but lack reliable process data or integration with operational systems. Another



organization may have process-mining technology but lack governance to translate discovered bottlenecks into redesign decisions. A third may automate tasks at scale without coordinating automation with end-to-end process objectives. In each case, the presence of technology is not equivalent to an organizational capability to sense process conditions, interpret opportunities, redesign processes and execute changes.

This study addresses that problem by conceptualizing AI-enabled BPM capability as an integrative organizational capability: the ability to coordinate BPM practices, process data, AI, process mining and intelligent automation to continuously sense, analyze, redesign, execute and optimize business processes. Dynamic Capability Theory provides the main theoretical lens. The theory is appropriate because the proposed capability combines sensing mechanisms (process data, monitoring and mining), seizing mechanisms (AI-supported interpretation and decision support) and transforming mechanisms (redesign, workflow change and intelligent automation) (Teece, 2007). The proposed model therefore treats BPM capability, IT integration, process-mining capability, AI capability and intelligent-automation capability as antecedents of AI-enabled BPM, which in turn predicts business process performance.

The empirical setting is organizations operating in Libya. The reviewed BPM and AI-value literature is dominated by European and other developed-economy settings, whereas evidence from Libya remains limited within the literature base used for this study. The context is theoretically useful because organizations operate at different levels of digital maturity and AI adoption, creating variation in the organizational capabilities needed for integration. The final sample includes 500 managers and professionals across financial services, oil and gas, telecommunications, government, manufacturing and logistics, allowing the framework to be tested across multiple process-intensive sectors rather than within one industry.

The study makes four contributions. First, it provides an integrative conceptualization of AI-enabled BPM that differs from isolated AI adoption, process mining or automation. Second, it extends Dynamic Capability Theory by showing how five organizational antecedents jointly build a process-oriented sensing-seizing-transforming capability. Third, it provides empirical evidence for a mediation mechanism linking underlying

capabilities to process performance. Fourth, it contributes evidence from Libyan organizations, thereby extending the geographic base of empirical BPM and AI-capability research. The remainder of the paper reviews the relevant literature, develops the theoretical model and hypotheses, describes the research method, reports the PLS-SEM results, and discusses theoretical and practical implications.

2. Literature Review

2.1 BPM capability

BPM is a holistic management discipline concerned with the identification, design, execution, monitoring and improvement of organizational processes. Capability-based research emphasizes that sustained BPM performance depends on more than isolated methods or technologies. Good BPM requires strategic alignment, governance, methods, process-aware information systems, people, culture and the ability to continuously manage processes across organizational boundaries (vom Brocke et al., 2014). Measurement work by Van Looy (2020) and Badakhshan et al. (2023) further demonstrates that BPM capability can be operationalized at the organizational level rather than treated merely as a project characteristic.

For this study, BPM capability represents the organization's ability to systematically identify, govern, monitor, redesign and improve important business processes. This capability provides the managerial architecture within which AI and process technologies can be used. It establishes process ownership, objectives, performance indicators and improvement routines. In an AI-enabled environment, these practices remain important because advanced analytics do not themselves determine which process outcomes matter or who is responsible for acting on insights. BPM capability is therefore expected to be a foundational antecedent of the integrative AI-enabled BPM capability.

2.2 IT integration capability

AI-enabled process management depends on the ability to connect applications, data and organizational functions across end-to-end processes. Information-technology capability research has long argued that business value depends not only on IT assets but also on the ability to integrate and deploy them in support of organizational objectives (Bharadwaj, 2000). Digitally enabled integration capabilities can improve coordination and information flows across process boundaries (Rai et al., 2006).

In this study, IT integration capability is defined as the ability to connect information systems, data, applications and IT/business functions so that process-relevant information can move across the organization with limited manual fragmentation. This capability is essential for event-data extraction, AI deployment, workflow orchestration and automation. Without system integration, process mining may be limited by incomplete event logs, AI models may remain disconnected from operational workflows and automation may produce local efficiency while preserving end-to-end fragmentation.

2.3 Process-mining capability

Process mining uses event data from information systems to reconstruct and analyze actual process execution. Its core functions include process discovery, conformance checking and process enhancement. The field has matured beyond algorithmic development toward organizational questions concerning adoption, governance, skills and value realization (vom Brocke et al., 2021). Martin et al. (2021) show that organizations face both substantial opportunities and nontrivial challenges when applying process mining, while Zerbino et al. (2021) highlight its growing role in management-oriented process analysis.

The construct used here therefore treats process mining as an organizational capability rather than as tool ownership. It captures the ability to obtain event data, understand actual process flows, identify bottlenecks and deviations, monitor performance, use findings in managerial decisions and integrate process-mining insights into broader BPM and analytics activities. This capability directly supports the sensing component of Dynamic Capability Theory by revealing operational problems and improvement opportunities that may remain invisible in designed process models.

2.4 AI capability

AI capability is broader than the adoption of individual AI applications. Mikalef and Gupta (2021) conceptualize AI capability as a firm-level bundle of resources that includes data, technology, skills and organizational mechanisms needed to exploit AI. This resource-bundle perspective is particularly suitable for BPM because AI can contribute to multiple lifecycle activities, including prediction, decision support, anomaly detection, resource allocation and process redesign. Reviews of machine-learning applications in BPM show that AI-based methods are being used across several process-management tasks rather than in one isolated stage (Weinzierl et al., 2024).

Accordingly, AI capability in the present framework captures the organization's ability to provide infrastructure and suitable data, develop or access AI-related skills, integrate AI with existing systems, identify process use cases, coordinate AI initiatives, deploy applications and evaluate their effectiveness. This capability is expected to be especially important for the seizing function because it helps convert process information into recommendations, predictions and decisions about where and how processes should change.

2.5 Intelligent-automation capability

Robotic process automation initially focused on automating repetitive, rule-based user interactions with information systems. Contemporary research increasingly situates RPA within a broader intelligent-automation landscape that combines workflow, AI, decision logic and human intervention (Syed et al., 2020; Ng et al., 2021). Process mining can further support automation by identifying candidates and understanding execution patterns before automation is implemented (El-Gharib and Amyot, 2023).

Intelligent-automation capability is therefore defined as the organizational ability to identify suitable automation opportunities, implement automated workflows, integrate automation with enterprise systems, use AI to enhance automated processes, manage exceptions, monitor performance and scale successful solutions. This capability is primarily associated with the transforming dimension of Dynamic Capability Theory because it enables organizations to operationalize process redesign and embed new decision or execution logic into day-to-day work.

2.6 AI-enabled BPM as an integrative capability

Recent BPM research suggests that the increasing role of AI changes the nature of process management. Rosemann et al. (2024) describe important shifts in BPM as AI changes how processes are discovered, designed and managed. Fettke and Di Francescomarino (2025) similarly identify a growing research agenda at the intersection of BPM and AI. Most importantly for the present study, Zebec and Indihar Štemberger (2024) show that AI business value can be realized through BPM-related mechanisms, providing empirical support for the proposition that process capabilities mediate the path from technology to organizational outcomes.

This study advances the integration argument by defining AI-enabled BPM capability as the organization's ability to combine BPM practices, process data, AI, process mining

and intelligent automation to continuously sense, analyze, redesign, execute and optimize business processes. The construct is intentionally not synonymous with AI capability or automation maturity. AI-enabled BPM exists when these elements are coordinated around process outcomes rather than implemented as disconnected initiatives. This distinction creates a testable organizational mechanism linking antecedent capabilities to business process performance.

2.7 Business process performance

Business process performance concerns the extent to which processes achieve desired outcomes in efficiency, cost, quality, productivity, responsiveness and agility. A structured review by Van Looy and Shafagatova (2016) demonstrates the multidimensional nature of process performance and the wide range of indicators used in the literature. The present study focuses on process-level outcomes rather than broad firm performance because the theoretical mechanism operates through the management and execution of processes.

An integrated AI-enabled BPM capability should improve performance by enabling faster problem detection, better decision support, more targeted redesign, reduced manual work and continuous adaptation. This does not imply that technology alone causes performance gains. Rather, the expected benefit arises from the coordination of process-management and digital capabilities.

3. Theoretical Foundation: Dynamic Capability Theory

Dynamic Capability Theory explains how organizations purposefully integrate, build and reconfigure resources in response to changing environments. Teece (2007) organizes dynamic capabilities around three broad activities: sensing opportunities and threats, seizing opportunities through decisions and commitments, and transforming or reconfiguring organizational assets and routines. The theory is especially useful for AI-enabled BPM because process transformation requires more than possession of technological resources; it requires an organizational ability to repeatedly convert information into coordinated process change.

In the proposed framework, process-mining capability, analytics and monitoring contribute strongly to sensing because they reveal how processes actually operate and where problems or opportunities exist. AI capability contributes strongly to seizing by

allowing organizations to evaluate patterns, predict outcomes and support process-related decisions. Intelligent automation and BPM redesign contribute to transforming by changing workflows, reallocating activities and embedding automated execution. BPM capability and IT integration cut across all three dimensions: BPM provides governance and improvement routines, while IT integration provides the connected data and system infrastructure needed for sensing, decision support and execution.

The theoretical proposition is therefore that the five antecedent capabilities do not simply add independent technology effects to performance. Instead, they create value when coordinated through a higher-level integrative mechanism - AI-enabled BPM capability. This mechanism should explain why some organizations realize performance gains from AI, process mining and automation while others obtain only fragmented local benefits.

4. Conceptual Framework and Hypotheses

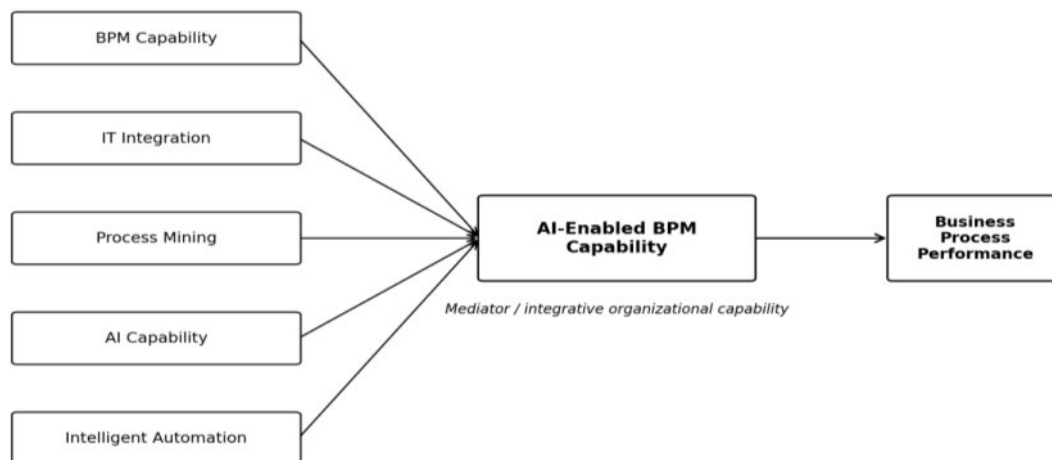


Figure 1. Conceptual framework

BPM capability establishes the governance, ownership, performance-management and improvement routines needed to coordinate AI-related process transformation. Organizations with stronger BPM foundations should therefore be better able to integrate advanced technologies into process-management practice.

H1. BPM capability has a positive effect on AI-enabled BPM capability.

AI-enabled BPM requires connected systems and accessible data across process boundaries. Integration reduces fragmentation and enables process data, AI services and automation to operate within end-to-end workflows.

H2. IT integration capability has a positive effect on AI-enabled BPM capability.

Process mining supplies evidence about actual process execution and therefore strengthens the sensing and monitoring functions required for continuous AI-enabled improvement.

H3. Process-mining capability has a positive effect on AI-enabled BPM capability.

AI capability supplies the data, technical infrastructure, skills and managerial coordination needed to deploy AI-supported process analysis and decision support.

H4. AI capability has a positive effect on AI-enabled BPM capability.

Intelligent automation provides the execution mechanism through which redesigned processes and AI-supported decisions can be embedded, monitored and scaled.

H5. Intelligent-automation capability has a positive effect on AI-enabled BPM capability.

When BPM, process data, AI, process mining and automation are coordinated around process outcomes, organizations should be able to improve efficiency, quality, responsiveness and agility.

H6. AI-enabled BPM capability has a positive effect on business process performance.

The mediation proposition follows directly from the integrative-capability argument. If the antecedent capabilities affect process performance mainly because they enable an organization to build AI-enabled BPM, the corresponding specific indirect effects should be positive. The general mediation hypothesis is decomposed into five testable indirect effects.

H7a. AI-enabled BPM mediates the relationship between BPM capability and business process performance.

H7b. AI-enabled BPM mediates the relationship between IT integration capability and business process performance.

H7c. AI-enabled BPM mediates the relationship between process-mining capability and business process performance.

H7d. AI-enabled BPM mediates the relationship between AI capability and business process performance.

H7e. AI-enabled BPM mediates the relationship between intelligent-automation capability and business process performance.

5. Research Methodology

5.1 Research design and unit of analysis

The study used a positivist, quantitative and cross-sectional survey design. The unit of analysis was the organizational capability rather than the respondent's personal attitude toward technology. Respondents were therefore selected from managerial and professional roles with sufficient knowledge of organizational processes, information systems, digital transformation, business analysis or automation. The survey focused on organizations operating in Libya.

The model was designed for variance-based structural equation modeling because it combines prediction and explanation, includes an endogenous mediation mechanism and contains both adapted and newer organizational capability measures. PLS-SEM is appropriate for assessing such models while simultaneously evaluating measurement quality and structural relationships (Hair et al., 2019).

5.2 Measurement

All constructs were measured using multi-item organizational statements on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The final analytical measurement model contained 51 retained indicators: eight for BPM capability, seven for IT integration, seven for process mining, eight for AI capability, seven for intelligent automation, eight for AI-enabled BPM and six for business process performance.

BPM capability items were adapted from established BPM capability and good-BPM-principles research (vom Brocke et al., 2014; Van Looy, 2020; Badakhshan et al., 2023). AI capability was adapted from the firm-level capability perspective developed by Mikalef and Gupta (2021). Process-mining items were derived from organizational process-mining research emphasizing event-data access, discovery, conformance, monitoring and managerial use (vom Brocke et al., 2021; Martin et al., 2021; Zerbino et al., 2021). Intelligent-automation items were grounded in RPA and intelligent-automation literature (Syed et al., 2020; Ng et al., 2021; El-Gharib and Amyot, 2023). Business process performance captured efficiency, quality, productivity and responsiveness, consistent with process-performance literature (Van Looy and Shafagatova, 2016). AI-enabled BPM was specified as an integrative organizational capability capturing the coordinated use of BPM, process data, AI, process mining and automation across the process lifecycle.

5.3 Sample and data collection

A total of 578 questionnaires were originally received. Data-quality screening removed 78 responses, producing a final sample of 500 valid cases. Exclusions were based on failed embedded attention-check questions ($n = 34$), straight-lining behavior ($n = 26$) and missing data exceeding 15% of the survey items ($n = 18$). The resulting valid response rate after screening was 86.5% of submissions received. The final sample spans multiple process-intensive sectors and a broad set of managerial and technical roles, supporting cross-sector assessment of the capability model.

Table 1. Sample and organizational profile ($N = 500$)

Variable	Category	n	%
Industry	Banking / financial services	118	23.6%
	Oil & gas	92	18.4%
	Telecommunications	86	17.2%
	Government / public sector	79	15.8%
	Manufacturing	59	11.8%
	Logistics / transportation	48	9.6%
	Other	18	3.6%
Role / function	IT management	116	23.2%
	Operations management	105	21.0%
	Digital transformation	75	15.0%
	Business process management	61	12.2%
	Executive / senior management	50	10.0%
	Business analysis	41	8.2%
	Automation / RPA	28	5.6%
Organization size	Other management	24	4.8%
	Small (<50 employees)	65	13.0%
	Medium (50-249)	142	28.4%
	Large (250-999)	168	33.6%
	Enterprise (1000+)	125	25.0%
Organizational experience	0-5 years	84	16.8%
	6-10 years	176	35.2%
	11-15 years	135	27.0%
	16+ years	105	21.0%
Digital transformation level	Early stage	58	11.6%
	In progress (partial)	215	43.0%
	Advanced / mature	227	45.4%
Current AI-adoption level	Exploring / piloting	145	29.0%
	Targeted deployment	208	41.6%
	Scaled / enterprise-wide	147	29.4%

5.4 PLS-SEM analysis procedure

The analysis was conducted in SmartPLS 4. The measurement model was evaluated using outer loadings, Cronbach's alpha, rho_A, composite reliability (CR), average variance extracted (AVE) and the heterotrait-monotrait ratio (HTMT). HTMT was used as the primary discriminant-validity criterion following Henseler et al. (2015). Structural collinearity was examined using inner VIF values.

The structural model was assessed using path coefficients, t statistics, p values, bias-corrected and accelerated (BCa) 95% confidence intervals, f^2 effect sizes and R^2 . Final inference used 10,000 bootstrap subsamples, two-tailed tests and $\alpha = 0.05$. The mediation analysis examined specific indirect effects for H7a-H7e and retained direct antecedent-to-performance paths to classify indirect-only versus complementary partial mediation. Predictive performance for BPP was assessed using PLSpredict, comparing PLS-SEM RMSE values with linear-model (LM) benchmarks in line with Shmueli et al. (2019). SRMR, d_ULS, d_G and NFI were reported as supplementary fit information rather than as stand-alone decision criteria.

6. Results

6.1 Measurement model

All retained indicators loaded above 0.70, with outer loadings ranging from 0.741 to 0.842. This supports indicator reliability. Internal-consistency estimates were also strong. Cronbach's alpha ranged from 0.889 to 0.943, rho_A from 0.898 to 0.948, and composite reliability from 0.915 to 0.952. AVE values ranged from 0.594 to 0.661, exceeding the 0.50 benchmark for convergent validity.

Table 2. Reliability and convergent validity

Construct	Indicators	α	ρ_A	CR	AVE
BPM Capability	8	0.905	0.912	0.923	0.594
IT Integration Capability	7	0.889	0.898	0.915	0.603
Process Mining Capability	7	0.912	0.921	0.934	0.638
AI Capability	8	0.927	0.932	0.941	0.661
Intelligent Automation Capability	7	0.920	0.925	0.938	0.648
AI-Enabled BPM Capability	8	0.943	0.948	0.952	0.659
Business Process Performance	6	0.928	0.934	0.943	0.620

Discriminant validity was satisfactory. All HTMT values were below 0.85; the largest value was 0.812 between AI-enabled BPM capability and business process performance. The next-highest values were 0.784 between AI capability and AI-enabled BPM and 0.765 between intelligent automation and AI-enabled BPM. These results indicate that the seven constructs are empirically distinguishable despite their theoretically related roles in digital process transformation.

Table 3. HTMT matrix

	BPM	IT	PM	AI	IA	AIBPM
IT	0.542					
PM	0.611	0.485				
AI	0.587	0.622	0.684			
IA	0.645	0.591	0.702	0.741		
AIBPM	0.712	0.658	0.725	0.784	0.765	
BPP	0.605	0.592	0.631	0.695	0.642	0.812

Inner VIF values were 1.642 for BPM $\rightarrow$ AIBPM, 1.585 for IT $\rightarrow$ AIBPM, 1.892 for PM $\rightarrow$ AIBPM, 2.114 for AI $\rightarrow$ AIBPM, 2.053 for IA $\rightarrow$ AIBPM and 1.000 for AIBPM $\rightarrow$ BPP. These values indicate that structural collinearity is not a material concern.

6.2 Structural model and hypothesis testing

The antecedent equation explained 58.4% of the variance in AI-enabled BPM capability ($R^2 = 0.584$; adjusted $R^2 = 0.580$). In the full mediation specification, the model explained 46.2% of the variance in business process performance ($R^2 = 0.462$; adjusted $R^2 = 0.457$). All six primary structural hypotheses were supported.

Table 4. Structural model and hypothesis testing

Hyp.	Path	β	t	p	95% CI	f ²	Decision
H1	BPM $\rightarrow$ AIBPM	0.187	4.81	<0.001	[0.113, 0.261]	0.042	Supported
H2	IT Integration $\rightarrow$ AIBPM	0.165	4.17	<0.001	[0.087, 0.243]	0.034	Supported
H3	Process Mining $\rightarrow$ AIBPM	0.224	5.57	<0.001	[0.146, 0.302]	0.068	Supported
H4	AI Capability $\rightarrow$ AIBPM	0.283	6.94	<0.001	[0.202, 0.364]	0.110	Supported
H5	Intelligent Automation $\rightarrow$ AIBPM	0.195	4.92	<0.001	[0.119, 0.271]	0.051	Supported
H6	AIBPM $\rightarrow$ BPP	0.551	14.31	<0.001	[0.476, 0.626]	0.435	Supported

AI capability was the strongest antecedent of AI-enabled BPM capability ($\beta = 0.283$), followed by process mining ($\beta = 0.224$), intelligent automation ($\beta = 0.195$), BPM capability ($\beta = 0.187$) and IT integration ($\beta = 0.165$). Although the antecedent effect sizes

are individually small to moderate, they are jointly meaningful because they explain more than half of the variance in the integrative capability. The AIBPM $\rightarrow$ BPP path was both the largest path and the largest effect size in the model ($\beta = 0.551$; $f^2 = 0.435$), indicating that the integrative capability is strongly associated with process performance.

6.3 Mediation analysis

All five specific indirect effects through AI-enabled BPM capability were positive and statistically significant. The mediation classification differed by antecedent because the corresponding direct effects on BPP were significant only for IT integration and AI capability.

Table 5. Mediation results and direct effects

Hyp.	Indirect path	β_{ind}	p_{ind}	95% CI	β_{direct}	p_{direct}	Mediation	Decision
H7a	BPM $\rightarrow$ AIBPM $\rightarrow$ BPP	0.103	<0.001	[0.057, 0.149]	0.042	0.384	Indirect-only	Supported
H7b	IT $\rightarrow$ AIBPM $\rightarrow$ BPP	0.091	<0.001	[0.044, 0.138]	0.128	0.011	Complementary partial	Supported
H7c	PM $\rightarrow$ AIBPM $\rightarrow$ BPP	0.123	<0.001	[0.072, 0.174]	0.058	0.263	Indirect-only	Supported
H7d	AI $\rightarrow$ AIBPM $\rightarrow$ BPP	0.156	<0.001	[0.103, 0.209]	0.145	0.004	Complementary partial	Supported
H7e	IA $\rightarrow$ AIBPM $\rightarrow$ BPP	0.107	<0.001	[0.058, 0.156]	0.049	0.347	Indirect-only	Supported

For BPM capability, process mining and intelligent automation, the direct paths to BPP were not significant while the indirect effects were significant, supporting indirect-only mediation. For IT integration and AI capability, both indirect and direct effects were positive and significant, supporting complementary partial mediation. The largest indirect effect was AI $\rightarrow$ AIBPM $\rightarrow$ BPP ($\beta = 0.156$), followed by process mining ($\beta = 0.123$), intelligent automation ($\beta = 0.107$), BPM capability ($\beta = 0.103$) and IT integration ($\beta = 0.091$).

6.4 Predictive assessment and supplementary fit

PLSpredict produced positive $Q^2_{predict}$ values for all six BPP indicators, ranging from 0.254 to 0.368. The PLS-SEM model produced lower RMSE than the linear-model benchmark for five of the six indicators; only BPP4 showed a slightly higher RMSE for PLS-SEM (+0.014). This pattern indicates meaningful out-of-sample predictive capability and is consistent with at least medium predictive performance under the PLSpredict comparison logic.

Table 6. PLSpredict results for business process performance

Indicator	Q ² predict	PLS-SEM RMSE	LM RMSE	PLS - LM
BPP1	0.315	0.842	0.875	-0.033
BPP2	0.342	0.811	0.849	-0.038
BPP3	0.285	0.905	0.912	-0.007
BPP4	0.254	0.934	0.920	+0.014
BPP5	0.368	0.785	0.831	-0.046
BPP6	0.291	0.892	0.908	-0.016

Supplementary model-fit statistics were SRMR = 0.064 for the estimated model and 0.059 for the saturated model, d_ULS = 1.452 and 1.218 respectively, d_G = 0.511 and 0.485, and NFI = 0.918 and 0.925. These statistics are reported as supplementary diagnostics; the main evaluation relies on measurement quality, explanatory power, predictive assessment and bootstrap inference.

7. Discussion

The results support the central theoretical argument that process performance in an AI-intensive environment is better explained by an integrated organizational capability than by isolated technology adoption. The five antecedent capabilities jointly explain 58.4% of the variance in AI-enabled BPM capability, and AI-enabled BPM has a strong positive relationship with business process performance. This pattern is consistent with the view that organizations need to orchestrate data, technology and managerial routines around processes rather than treat AI, process mining and automation as separate initiatives.

AI capability emerged as the strongest antecedent ($\beta = 0.283$). This result is consistent with the organizational capability perspective of Mikalef and Gupta (2021), which emphasizes that value from AI depends on a bundle of data, technological and human resources. In the present model, AI capability does not directly substitute for BPM. Rather, it contributes to an integrative process capability through which AI resources become embedded in process analysis, decisions and redesign. The complementary partial mediation found for AI capability strengthens this interpretation: AI capability has a significant direct association with process performance, but an additional and substantial part of its effect operates through AI-enabled BPM.

Process mining was the second-strongest antecedent ($\beta = 0.224$). This finding reinforces the importance of evidence about actual process execution. Process mining contributes to sensing by identifying bottlenecks, variants and deviations and by making process performance observable at a level that traditional process documentation cannot provide. The indirect-only mediation result is especially informative. The direct PM $\rightarrow$ BPP path is not significant once AI-enabled BPM is included, whereas the indirect effect

through AIBPM is significant. This suggests that process-mining capability creates process value primarily when its insights are integrated into broader process-management and transformation routines. The result is consistent with the organizational emphasis in process-mining research (vom Brocke et al., 2021; Martin et al., 2021) and with work linking process mining to automation and improvement (El-Gharib and Amyot, 2023).

Intelligent automation also shows a significant positive antecedent effect ($\beta = 0.195$) and indirect-only mediation. This indicates that automation capability by itself is not enough to explain process performance after the integrative capability is considered. The finding is theoretically meaningful because it shifts attention from the number of bots or automated tasks to the organization's ability to connect automation with process objectives, exception handling, AI and continuous monitoring. This interpretation fits the broader intelligent-automation literature, which treats adaptive workflow execution and human-machine coordination as more important than simple task substitution (Ng et al., 2021).

BPM capability remains significant ($\beta = 0.187$) despite the technology-intensive nature of the model. This is an important result because it indicates that AI does not make classical BPM capabilities obsolete. Process ownership, governance, performance measurement, cross-functional coordination and continuous-improvement routines remain part of the mechanism through which AI-enabled process transformation occurs. The indirect-only mediation classification for BPM capability implies that these managerial routines affect performance mainly by enabling an effective integrative capability rather than through a separate direct path once AI-enabled BPM is represented in the model.

IT integration has the smallest antecedent coefficient ($\beta = 0.165$) but remains statistically significant. Its role appears to be infrastructural and enabling. Connected systems and data flows are necessary for process mining, AI deployment and automation, but integration alone does not guarantee that organizations use those resources to improve processes. The complementary partial mediation result suggests that IT integration can also contribute directly to process performance, potentially through reduced handoffs, better information availability and lower manual reconciliation, while simultaneously supporting the AI-enabled BPM mechanism.

The strongest structural relationship in the model is AI-enabled BPM $\rightarrow$ business process performance ($\beta = 0.551$; $f^2 = 0.435$). This finding directly addresses the main research question. Organizations reporting stronger integration of BPM practices, process

data, AI, process mining and automation also report substantially stronger process performance. The result aligns with recent BPM literature arguing that AI changes the way processes are discovered and managed (Rosemann et al., 2024) and with the empirical evidence of Zebec and Indihar Štemberger (2024), who show that BPM-related mechanisms are central to the realization of AI business value.

The mediation findings provide the clearest evidence for the proposed integration mechanism. All five antecedent capabilities have significant specific indirect effects through AI-enabled BPM. The pattern is not uniform: BPM, process mining and intelligent automation operate primarily through the mediator, while IT integration and AI capability retain significant direct effects. This heterogeneity is theoretically useful. It implies that some capabilities are primarily enabling components of an integrated process-management mechanism, whereas AI and IT integration can also affect process outcomes through pathways that are not fully captured by the mediator.

The predictive results add a practical dimension to the explanatory findings. Positive Q^2 predict values for all BPP indicators and lower PLS-SEM RMSE than the linear benchmark for five of six indicators suggest that the model has meaningful predictive relevance rather than merely fitting the observed sample. The model therefore offers a useful basis for identifying capability areas associated with stronger process performance, although the cross-sectional design does not justify deterministic causal claims.

8. Theoretical Implications

First, the study extends Dynamic Capability Theory by specifying a process-management microstructure for sensing, seizing and transforming. Process mining and monitoring strengthen sensing; AI supports interpretation and decision support; intelligent automation enables transformation; BPM capability provides governance and improvement routines; and IT integration provides the connected infrastructure necessary across all three activities. The empirical model shows that these capabilities are related but distinct and that their coordinated operation is captured by a separate AI-enabled BPM construct.

Second, the study contributes to BPM research by conceptualizing AI-enabled BPM as an integrative organizational capability rather than as a technology category. This distinction is increasingly important as AI becomes embedded in process discovery, design, monitoring and execution. Treating AI-enabled BPM as a capability allows research to ask whether organizations can repeatedly coordinate technologies around

process objectives, rather than whether a specific AI or automation tool has been adopted.

Third, the mediation results refine the technology-to-performance argument. Rather than assuming that each digital capability independently improves process performance, the findings show that a substantial part of their value is transmitted through AI-enabled BPM. This provides a mechanism-based explanation for why technology investments can produce uneven outcomes across organizations. The result also complements prior AI business-value work that positions BPM-related mechanisms as mediators of AI value creation (Zebec and Indihar Štemberger, 2024).

Fourth, the study contributes measurement evidence for emerging organizational capabilities. The reported reliability, convergent validity and HTMT results indicate that BPM capability, IT integration, process mining, AI capability, intelligent automation, AI-enabled BPM and business process performance can be empirically distinguished in the present context. The AI-enabled BPM measure is especially important because it operationalizes integration across technology and process-management domains. Replication remains necessary before the measure can be regarded as fully established across countries and industries.

9. Practical Implications

The main managerial implication is that AI-enabled process transformation should be managed as a capability-building program rather than as a portfolio of disconnected technology projects. Senior leaders should establish explicit process objectives, identify the process outcomes that AI is expected to improve and ensure that data, process-mining, automation and BPM teams work against a shared performance model.

For IT and data leaders, integration quality is foundational. Event data, ERP/CRM records, workflow systems and AI services need reliable interfaces and governance if process-level analysis is to be useful. The positive direct and indirect effects of IT integration suggest that integration can create operational benefits by itself, but its larger strategic role is to enable end-to-end AI-enabled BPM.

For BPM and process owners, the results reinforce the continuing importance of governance. Process ownership, performance indicators, redesign methods and continuous-improvement routines remain necessary even when AI and process mining are available. BPM teams are well positioned to coordinate the translation of AI-generated insights into process decisions and to prevent local technology initiatives from optimizing one task while degrading end-to-end performance.

For process-mining teams, the results indicate that organizational use matters more than the existence of the technology. Mining initiatives should be tied to improvement backlogs, management decisions and redesign cycles. Insights about bottlenecks or conformance should trigger clear ownership and follow-up actions rather than remain in analytical dashboards.

For AI teams, the strongest antecedent effect indicates that technical infrastructure, usable data, AI skills and managerial coordination are important differentiators. However, AI projects should be evaluated partly through process metrics such as cycle time, quality, error rates, responsiveness and resource use. This helps connect model performance to operational business value.

For automation teams, the indirect-only mediation result implies that scaling bots or automated workflows without process integration is unlikely to maximize value. Automation candidates should be selected based on process evidence, designed with exception paths and human judgment where necessary, and monitored as part of an end-to-end process rather than as isolated task replacements.

10. Limitations and Future Research

The study has several limitations. First, the cross-sectional design limits causal inference. The structural coefficients are consistent with the proposed theory, but temporal ordering cannot be demonstrated. Longitudinal studies should examine whether improvements in AI-enabled BPM capability precede subsequent changes in objective process performance.

Second, the study relies on key-informant survey data and therefore remains exposed to perceptual and common-method limitations. Future research should combine survey measures with process-mining event logs, operational KPIs, financial records or multiple informants from the same organization. Such designs would also allow the aggregation of perceptions at the organizational level to be tested explicitly.

Third, the model combines established and newer measurement domains. AI capability and BPM capability have strong prior measurement traditions, whereas organizational process-mining capability, intelligent-automation capability and especially AI-enabled BPM are less established. Although the present measurement results are strong, further content validation, cross-sample confirmation and measurement-invariance testing are needed.

Fourth, the empirical context is Libya. This is valuable because it extends the geographic base of empirical BPM research, but it also limits direct generalization to other institutional and technological environments. Cross-country replication could test whether the relative importance of the five antecedents changes with digital infrastructure, regulation, labor-market characteristics or organizational maturity.

Fifth, the current analysis emphasizes the overall structural model. Future research should investigate sector differences, organizational size, digital-transformation maturity and AI-adoption maturity. Such comparisons should be performed only after establishing measurement invariance and adequate group sizes. Future studies could also test alternative hierarchical specifications of AI-enabled BPM and examine objective outcomes such as cost reduction, cycle-time improvement and service quality.

11. Conclusion

This study develops and tests an integrated capability framework for AI-enabled BPM using data from 500 respondents across Libyan organizations. The results show that BPM capability, IT integration, process mining, AI capability and intelligent automation all contribute significantly to AI-enabled BPM capability. AI capability is the strongest antecedent, followed by process mining, intelligent automation, BPM capability and IT integration. AI-enabled BPM, in turn, has a strong positive relationship with business process performance.

The mediation analysis demonstrates that integration is not merely a conceptual label. AI-enabled BPM carries significant indirect effects from all five antecedent capabilities to process performance. BPM capability, process mining and intelligent automation operate through indirect-only mediation, while IT integration and AI capability show complementary partial mediation. The model also demonstrates meaningful predictive performance for business process outcomes.

The central conclusion is that organizations should not expect isolated AI, process-mining or automation investments to generate sustained process performance automatically. Value depends on the capability to integrate these resources with BPM governance, connected systems, process evidence and continuous transformation. By conceptualizing and empirically testing that integration mechanism, the study provides a bridge between BPM capability research, AI capability research and intelligent process transformation.

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Appendix A. Outer Loadings

Indicator	Loading	Indicator	Loading
BPM1	0.765	BPM2	0.782
BPM3	0.741	BPM4	0.795
BPM5	0.801	BPM6	0.755
BPM7	0.774	BPM8	0.749
IT1	0.758	IT2	0.792
IT3	0.811	IT4	0.774
IT5	0.745	IT6	0.780
IT7	0.762	PM1	0.792
PM2	0.815	PM3	0.804
PM4	0.788	PM5	0.771
PM6	0.822	PM7	0.795
AI1	0.821	AI2	0.842
AI3	0.815	AI4	0.795
AI5	0.804	AI6	0.831
AI7	0.788	AI8	0.811
IA1	0.782	IA2	0.811
IA3	0.824	IA4	0.795
IA5	0.776	IA6	0.830
IA7	0.815	AIBPM1	0.825
AIBPM2	0.801	AIBPM3	0.814
AIBPM4	0.795	AIBPM5	0.832
AIBPM6	0.818	AIBPM7	0.805
AIBPM8	0.799	BPP1	0.775
BPP2	0.802	BPP3	0.791
BPP4	0.764	BPP5	0.815
BPP6	0.778		