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Integrating Hybrid Cloud And Ai Strategy: A Capability Maturity Model For Large Enterprises

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Abstract
The study presents an artificial intelligence (AI) alignment Capability Maturity Model (CMM) for large businesses offering hybrid cloud environments. Existing maturity models examine the development of cloud adoption and AI, but they do not adequately explain how these two domains evolve in relation to one another. The proposed model includes the elements of the Capability Maturity Model and contemporary AI maturity assessment models, creating a multi-level capability structure that spans the entire process of strategy development, the design of data architectures, the implementation of cloud architectural components, the engineering process for AI, defining the management framework, and the automation of operational systems processes. The framework enables scalable artificial intelligence workloads across hybrid cloud environments while ensuring regulatory compliance and reduced processing latency. Additionally, ModelOps and AIOps facilitate effective AI lifecycle governance and intelligent operational management throughout the hybrid infrastructure. The model is designed to be applicable across industries, enabling assessment, capability gap identification, and the formulation of transformation plans. The study proposes a step-by-step, capability-based framework for organizations to build resilient, scalable digital ecosystems and develop intelligent capabilities by closing the maturity gap between cloud and AI.

Keywords: Hybrid Cloud Computing; Artificial Intelligence Strategy; Capability Maturity Model; Enterprise Digital Transformation; ModelOps and AIOps; Cloud-AI Integration

1. INTRODUCTION

Hybrid cloud computing has emerged as a critical concept at the intersection of enterprise information systems (EIS) and artificial intelligence (AI) in contemporary digital transformation. A hybrid cloud architecture combines on-premises infrastructure with public and private cloud services to provide the flexibility and scalability required to meet workload distribution, performance, and regulatory compliance requirements. This is particularly important for AI workloads, which often require computational intensity, distributed data processing, and real-time inference [1-5]. AI has moved beyond its earlier role as an analytical tool and is now widely regarded as a strategic business asset that can generate insights, improve processes, and support decision-making across business functions. The Capability Maturity Model (CMM) remains one of the most widely used frameworks for evaluating and improving organizational processes through structured, incremental development. Contemporary AI maturity models build on this tradition by incorporating dimensions such as data readiness, algorithmic sophistication, governance, and organizational alignment. At the same time, AI deployment increasingly depends on hybrid cloud environments that can support scalable model training and inference while enabling efficient data management across distributed systems. ModelOps and AIOps serve as important operational enablers for coordinating AI lifecycle activities, as discussed in Section 2.3, and allow enterprises to govern model development, deployment, and continuous optimization at scale. Together, these developments highlight the need for organizations to adopt an integrated approach that aligns cloud infrastructure with AI capabilities in support of enterprise transformation and sustained innovation [1]-[3].

Though the literature is extensive on both cloud and AI individually, few studies have systematically examined how these two domains interact and co-evolve within enterprise transformation. The majority of AI maturity models focus on the organization's readiness, data governance, and analysis capabilities, while a few focus solely on the impact of cloud infrastructure on the support of scalable, production-grade AI systems [2], [4]. By contrast, cloud maturity models typically emphasize infrastructure evolution and service capabilities, including lifecycle management, advanced data processing, pipeline automation, and continuous deployment, rather than integrated AI capabilities. A key issue emerging from the literature is that the pace of AI adoption and the readiness of cloud infrastructure to support it are not always aligned; in many cases, organizations initiate AI-driven projects before adequate architectural, governance, and operational foundations are in place [5, 6]. This misalignment negatively affects system performance, increases technical debt, and heightens security, compliance, and data governance risks. Currently, most maturity models lack an appropriate methodology because they do not adhere to established criteria. Most frameworks are applied to descriptive and heuristic constructs, which must be empirically tested and proven in real business environments [6]. Determining enterprise readiness is more complex because companies require consistency across systems to integrate the strategy, technical, and operational systems. In this context, there is a strong need for a capability-based maturity classification system that integrates hybrid cloud and AI to address current shortcomings and strengthen enterprise maturity [7-13].

We will address today's research gaps by creating an integrated capability maturity model within a single evaluation system for both 'Hybrid cloud capability' and 'AI capability'. The model comprises eight capability dimensions spanning strategy alignment, data infrastructure, cloud architecture, AI engineering, governance and security, operating model, talent and culture, and automation and operations. It enables organizations with lower levels of maturity to identify missing capabilities and areas requiring development. Based on these insights, organizations can make informed decisions about their transformation priorities. The model offers a blueprint for organizations to follow, enabling a journey from experimentation to usable, efficient AI infrastructure in a hybrid world. The study develops a theoretical framework grounded in cloud computing principles that connects cloud concepts with AI maturity assessment and supports practical business strategies for executives leading digital transformation.

Research Questions:

1. How can hybrid cloud and AI capabilities be systematically integrated within a single maturity model?
- Which capability dimensions are required to assess enterprise readiness for AI-enabled hybrid cloud transformation?
- How does misalignment between cloud maturity and AI maturity affect enterprise scalability, governance, and operational performance?
- Which maturity levels best capture the progression toward fully AI-native hybrid enterprises?

1.1 Research Problem

Artificial Intelligence (AI) and the rapid transition to the cloud, each with its own dynamics, have resulted in an already complex and sometimes disjointed digital transformation landscape in the enterprise. Many organizations are investing in new AI-enabled capabilities for decision-making and automation while still relying on immature or insufficiently supported hybrid cloud foundations. The current maturity models study AI and cloud separately, which doesn't account for their interdependencies. The outcomes of this division include inconsistent competency measurement, limited scalability of AI solutions, and an increased risk of operational issues. In addition, organizations often face data fragmentation, data governance challenges, and inconsistent data lifecycle management, which increases the importance of ModelOps and AIOps capabilities. No single or capability-based maturity model exists that can be systematically applied to assess maturity, identify gaps, and tie technology investments to strategic goals. Therefore, we need a systematic, integrated approach to close the gap between hybrid cloud maturity and AI readiness and to support enterprises throughout their broader transformation journey.

Key Problem Dimensions:

- Lack of cohesive frameworks that embed the capabilities of the hybrid cloud and enterprise AI framework and operating cycle.
- There is a disconnect, and enterprise-level readiness of hybrid cloud is relatively behind the pace of AI implementation projects.
- Lack of a robust benchmarking approach, limited comparability across maturity assessments, and weak translation of assessment findings into decision-making.
- Poor end-to-end AI lifecycle management solution (ModelOps and AIOps) alignment with the existing cloud maturity models.
- Few official guidelines on how businesses can get beyond basic implementations of AI and construct scalable production-ready hybrid cloud solutions.

1.2 Research Objectives

This study proposes an extensible maturity model to help organizations achieve hybrid cloud objectives while standardizing the processes required to support enterprise-scale AI deployment. It develops an evaluation framework designed to address gaps in existing maturity models for cloud infrastructure, AI services, and associated operational processes. The proposed framework provides enterprises with a structured tool for assessing organizational maturity, identifying capability gaps, and prioritizing appropriate investments. It also serves as a baseline for evaluating progress as organizations move from isolated AI initiatives to AI-native hybrid ecosystems. More broadly, the paper contributes both theoretical and practical insights into maturity modeling by integrating strategy alignment, data infrastructure, governance, automation, and operational capabilities into a unified assessment approach.

Specific Objectives:

- Integrate the Capability Maturity Model with hybrid cloud capabilities, AI building blocks, and associated processes, management, and governance practices.
- Address the absence of integrated strategies and roadmaps across capability areas such as data infrastructure, governance, cloud architecture, and AI engineering.
- Support the gradual advancement of enterprise maturity through staged progression from early experimentation toward AI-native hybrid cloud environments.
- Examine the implications of misalignment between cloud maturity and AI readiness for enterprise governance, scalability, and performance.
- Provide structured and practical guidance for developing scalable and resilient hybrid cloud solutions.

1.3 Research Contributions

The study contributes to both academic research and managerial practice by introducing a unified maturity framework that integrates hybrid cloud and AI capabilities. Rather than evaluating these domains separately, the framework assesses enterprise readiness through a capability-driven approach that emphasizes interdependence across strategic, technological, and operational dimensions. Drawing on the logic of the CMM, the model organizes maturity into structured stages and associated capabilities, enabling organizations to assess their current state and plan future development. In doing so, the study provides decision-makers with a more coherent basis for aligning AI initiatives with cloud capabilities and broader transformation priorities.

Key Contributions:

- Introduces an integrated assessment framework that addresses limitations in existing business maturity approaches by combining hybrid cloud and embedded AI capabilities within a single model.
- Extends the traditional concept of maturity modeling to encompass AI lifecycle management, hybrid cloud platforms, and enterprise-level operational integration.
- Demonstrates how strategic alignment, information systems, governance structures, and AI-enabled capabilities can be integrated within a single enterprise framework.
- Defines maturity stages that organizations can use to evaluate current performance, identify capability gaps, and prioritize transformation initiatives against structured benchmarks.
- Offers practical implementation guidance and decision support for leaders seeking to deploy hybrid cloud systems with AI in a secure, scalable, and operationally effective manner.

2. THEORETICAL FOUNDATIONS

The theoretical foundation of this study draws on maturity modeling, enterprise AI capability, and hybrid cloud architecture as complementary lenses for understanding enterprise digital transformation. Maturity models provide a structured means of assessing organizational capabilities through incremental improvements in processes, technologies, and governance. The CMM, in particular, offers a well-established framework for explaining how organizations evolve from ad hoc practices toward increasingly standardized and optimized systems [8]. AI capability research extends this perspective by highlighting that successful AI adoption depends not only on algorithmic sophistication but also on infrastructure, scalability, governance, and organizational readiness [9]. Hybrid cloud architecture provides a corresponding infrastructural perspective by offering a distributed and scalable environment capable of supporting heterogeneous workloads, data-locality requirements, and regulatory constraints [10]. These perspectives converge in a multidimensional space that requires coordination across strategy, technology, and operations. In addition, ModelOps and AIOps [11-16] underscore the importance of lifecycle management, automation, and observability in sustaining enterprise-scale AI. Although each of these theoretical streams is well developed individually, they remain insufficiently integrated. This study, therefore, uses them as the basis for a unified model of hybrid cloud and AI maturity.

2.1 Capability Maturity Models

Capability maturity models enable organizations to assess and improve processes in a staged manner, moving from unstructured practices to standardized, monitored, and continuously optimized systems. Originating in software engineering and process improvement, these models emphasize standardization, measurement, and governance as foundations of operational excellence. The CMM remains one of the best-known examples, providing a framework for assessing process predictability, efficiency, and quality of outcomes [8, 17-19]. Over time, maturity modeling has expanded beyond software development into areas such as enterprise architecture, cybersecurity, and IT service management (ITSM). In complex technological environments, maturity models are increasingly used as diagnostic tools to assess capabilities and guide developmental planning [12]. However, conventional maturity models tend to emphasize process standardization while providing limited attention to emerging technologies such as AI and hybrid cloud. They also face methodological limitations, including inconsistent validation approaches and a lack of standardization in evaluation procedures [13, 20-23]. Even so, maturity models remain highly valuable as a theory of organizational development and can be adapted to address new technological paradigms and evolving capability requirements.

2.2 AI Maturity and Enterprise AI Capability

AI maturity models have been developed primarily to assess how well organizations are prepared to design, implement, and scale AI-enabled solutions. These models typically evaluate dimensions such as data readiness, algorithmic capability, organizational culture, and governance. AI maturity is commonly understood as a progression from isolated experimentation to coordinated, enterprise-wide deployment and optimization [9, 24-29]. Critical elements of this progression include not only model development and inference but also access to high-quality real-time data and the supporting infrastructure required to process, integrate, and govern it effectively. Governance mechanisms are likewise central to the ethical use of AI, regulatory compliance, and risk management [14]. Recent studies [11] also emphasize the operationalization of AI through frameworks and tools that support model deployment, monitoring, retraining, and lifecycle management. However, most AI maturity models do not explicitly address the infrastructure dependencies of AI at enterprise scale, particularly in hybrid and multi-cloud environments. This omission limits their applicability in large organizations, where AI systems must operate across distributed and heterogeneous infrastructures [30-35]. As a result, there is a growing need to expand AI maturity models to reflect both organizational capabilities and the infrastructural conditions required for enterprise-scale deployment.

2.3 Hybrid Cloud Architecture and Integration

Hybrid cloud architecture, as discussed in Section 1, provides the scalable and flexible foundation needed to support distributed AI workloads while balancing performance, cost, and compliance requirements. It enables organizations to distribute workloads across on-premises, private, and public cloud environments based on operational needs and regulatory constraints. This flexibility is especially important for AI applications that involve distributed model training, real-time inference, large-scale data movement, and latency-sensitive decision-making. Hybrid cloud environments can also be extended through edge computing, which further reduces latency for time-critical applications. The evolution of hybrid cloud maturity typically reflects a shift from basic virtualization to highly orchestrated, multi-cloud environments with advanced automation and governance [15, 36, 37]. At the same time, integrating AI into hybrid cloud environments presents challenges related to data synchronization, interoperability, security, and workload coordination. Recent studies have therefore emphasized the role of automation, including AIOps, in addressing these challenges through intelligent monitoring, anomaly detection, and predictive maintenance [11].

3. LITERATURE REVIEW

Over the last 10 years, there has been a greater focus on hybrid cloud maturity, and a number of businesses have begun to consider how a hybrid approach, combined with the robust technology of AI, can digitally transform their business. However, most maturity assessments treat AI and cloud independently, producing a fragmented picture that fails to reflect their operational interdependence in real enterprise environments. The emerging literature focuses on issues of organizational maturity, data readiness, algorithm maturity, the role of governance bodies, and moving beyond a single initiative toward enterprise-wide AI use [15]. These studies share a common focus on the impact of data quality, ethical considerations in the use of AI, and the proper management of the AI model lifecycle, ensuring alignment with the organization for successful AI deployment. As noted in Section 2.2, most AI maturity models assume a stable, centralized IT environment and therefore fail to address the infrastructural complexity of operating AI across distributed, hybrid enterprise systems. Cloud maturity studies typically focus on the progression from virtualized environments to cloud-native, hybrid, and multi-cloud architectures, while emphasizing scalability, cost management, flexibility, and operational efficiency [16, 17]. Although these models are useful for assessing infrastructure modernization, they are not sufficient for evaluating hybrid cloud environments that must also support AI capabilities such as machine learning lifecycle management, distributed model deployment, real-time inference, and integration with ModelOps and intelligent automation. As businesses enter a high-growth phase, having infrastructure alone is insufficient; robust governance frameworks and operational strategies are equally essential to effectively scale AI capabilities. These limitations in the empirical literature help clarify the practical challenges organizations face, including workload orchestration, data synchronization, governance complexity, latency management, and operational scale in hybrid cloud environments. Furthermore, the studies [18] were conducted at varying degrees of maturity, which makes it difficult to compare their results and renders their practical application infeasible due to the lack of uniformity in maturity levels. In recent years [19], there has been a need for combined solution structures of AI and Cloud, but very few, if any, frameworks move beyond the conceptual level of application and are complete in demonstrated capability mapping (no known structure), the empowerment concept, and empirical validation. We believe the enterprise's additional acceleration on its AI journey is a key factor. Most of today's enterprise AI tools are based on distributed systems spanning public and private clouds, the edge, on-premises environments, and everything in between [38-42]. Accordingly, interoperability, regulatory compliance, workload migration, low-latency inference, intelligent orchestration, and operational monitoring must all be addressed within an integrated framework. As a result, existing capability maturity models fail to capture the full context of hybrid cloud-AI integration, particularly across governance, engineering, and operational dimensions simultaneously. This research addresses that gap by proposing a multidimensional capability model that links hybrid cloud operational maturity with broader enterprise maturity. Building on this foundation, the study extends AI capability development as a core element of enterprise hybrid cloud maturity and introduces a comprehensive model for guiding the development of integrated hybrid cloud-AI capabilities.

Table 1: Comparative Analysis of Existing Literature on AI and Cloud Maturity.

Study Focus	**Domain**	**Key Contributions**	**Limitations**	**Relevance to Proposed Study**

AI adoption stages and enterprise transformation [15]	AI Maturity	Defines progression from experimentation to enterprise-scale AI deployment	Limited focus on infrastructure dependencies	Highlights need to integrate AI maturity with cloud capabilities
Cloud maturity evolution models [16]	Cloud Computing	Explains the transition from traditional IT to hybrid and multi-cloud architectures	Does not incorporate AI lifecycle or data intelligence aspects	Supports the infrastructure dimension of the proposed model
AI-cloud misalignment in enterprises [17]	AI + Cloud	Identifies performance and governance challenges due to maturity gaps	Lacks a structured maturity framework for integration	Validates the need for a unified maturity model
Maturity model development methodologies [18]	General Maturity Models	Reviews methodological inconsistencies and lack of validation in maturity frameworks	Does not address AI or hybrid cloud specifically	Provides a basis for improving methodological rigor
Integrated AI-cloud frameworks (conceptual) [19]	AI + Cloud Integration	Proposes initial concepts for aligning AI and cloud strategies	Lacks empirical validation and capability mapping	Directly motivates the development of the proposed framework
Data governance in AI systems [20]	AI Governance	Emphasizes the importance of data quality, compliance, and ethical AI	Limited integration with infrastructure and cloud models	Supports the governance dimension of the proposed model
Multi-cloud and hybrid cloud strategies [21]	Cloud Architecture	Discusses scalability, flexibility, and distributed system benefits	Does not address AI-specific operational requirements	Strengthens the hybrid cloud architecture foundation
ModelOps and AI lifecycle management [22]	AI Operations	Highlights the need for continuous deployment, monitoring, and retraining of AI models	Often treated independently from cloud maturity frameworks	Reinforces the operational dimension of the proposed model

The literature analyzed makes it evident that Hybrid Cloud and AI are not only individually significant to enterprise digitalization but are also deeply interdependent; their combined maturity determines a company's capacity for sustainable digital transformation. The literature has previously recognized the importance of powerful data infrastructure, appropriate governance, and scalable computing solutions for the effective use of AI [15][20][43]. Studies of cloud maturity highlight that, both within the organization and in terms of return on investment, flexibility, scalability, and cost reduction can only be achieved with hybrid/multi-cloud solutions [16, 21]. There is one more classical one: 'Governance and operational mechanisms and lifecycle management', and the other, the newly created 'ModelOps', which is intended to ensure that AI systems are dependable and sustainable [22]. Strategic alignment and "inter-area collaboration and integration", not to mention being culturally appropriate, should be part of the organizational maturity as well, aside from technology, the researcher says. There is a broad consensus in the literature on a cross-sectoral approach to maturity, intended to span three levels: Strategy, Infrastructure, and Data/Ops.

Although the literature addresses these topics extensively, the available studies still provide limited coverage of diverse business scenarios and operational contexts. Another drawback of the research is the lack of standardized approaches across individual AI and cloud maturity frameworks (e.g., [17, 19]) for integration and adoption. Existing AI and cloud maturity frameworks are often narrow in scope and do not adequately explain how business processes influence operationalization and integration with cloud environments [23-26]. In addition, many frameworks emphasize algorithmic complexity and technical readiness, while cloud maturity models focus on capabilities such as data analytics, virtualization, scalability, and service orchestration, without fully connecting these elements across domains. These limitations are particularly significant for enterprises operating in distributed, multi-cloud, and hybrid environments that require runtime orchestration, intelligent automation, and end-to-end lifecycle management, including continuous monitoring [27-35]. There are no definitive measures of readiness for enterprise AI transformation, making it challenging to define comprehensive frameworks. The current frameworks still lack sufficient readiness for enterprise AI transformation [36-38]. The proposed framework adopts a hybrid cloud-AI perspective, introduces AI engineering as a dedicated capability, and integrates it with governance and operational digitalization within the capability assessment framework. ModelOps/AIOps are consistent across the same CAF, enabling massive enterprise-scale AI.

Table 2: Comparative Analysis of Existing Maturity Models and Proposed Framework

Feature / Capability	Traditional AI Maturity Models	Cloud Maturity Models	Existing Integrated Frameworks	Proposed Hybrid Cloud-AI Maturity Model
AI Governance [33]	Supported	Not Supported	Partially Supported	Fully Supported
Cloud Infrastructure Assessment [5]	Not Supported	Supported	Partially Supported	Fully Supported
Hybrid Cloud Integration [7]	Not Supported	Limited Support	Partial Support	Fully Supported
AI Lifecycle Management (ModelOps) [29]	Not Supported	Not Supported	Limited Support	Fully Supported
Intelligent Operations (AIOps) [11]	Not Supported	Not Supported	Not Supported	Fully Supported

Distributed AI Workload Support [38]	Not Supported	Limited Support	Partial Support	Fully Supported
Real-Time Data Processing Capability [30]	Limited Support	Limited Support	Partial Support	Fully Supported
Governance & Compliance Integration [14]	Limited Support	Limited Support	Partial Support	Fully Supported
Cross-Domain Capability Mapping [18]	Not Supported	Not Supported	Not Supported	Fully Supported
Enterprise AI-Cloud Alignment [19]	Not Supported	Not Supported	Conceptual Support	Fully Supported
Quantitative Maturity Progression [1]	Limited Support	Limited Support	Not Supported	Fully Supported

4. RESEARCH METHODOLOGY

This paper employs Design Science Research (DSR) to develop a capability maturity model for hybrid cloud and AI integration in large enterprises. The methodology, iterative stages, and design principles are elaborated in Section 4.1. Core capability dimensions are identified through secondary sources, including peer-reviewed literature, industry publications, and existing maturity frameworks. A comparative analysis of AI and cloud maturity models is used to identify recurring constructs as well as integration gaps. The resulting model is organized into multidimensional capability areas and associated maturity levels. The study does not seek empirical validation at this stage; rather, it focuses on conceptual validation through alignment with existing theoretical constructs and the demonstration of cross-domain consistency. This approach is intended to produce a rigorous, extensible framework suitable for future real-world testing in enterprise settings.

4.1 Research Design and Approach

Design Science Research (DSR) is adopted as the primary methodology because it is well-suited to the development of complex artifacts, such as maturity models and transformation frameworks, that are both theoretically grounded and practically relevant to enterprise environments. In this study, the proposed Integrated Cloud-AI Maturity Model (I-CMM) is treated as a research artifact intended to unify hybrid cloud infrastructure and AI capabilities within a single enterprise transformation assessment framework.

The research process is divided into six stages: problem identification, objective definition, artifact design and development, demonstration, evaluation, and communication of results. The problem identification stage begins with a systematic literature review (SLR) to identify research gaps and establish the absence of integrated AI and cloud maturity perspectives in existing enterprise transformation research. The objective definition stage then translates these gaps into research goals centered on a capability-driven approach to enterprise digital transformation.

In the design and development stage, theoretical constructs are translated into a practical maturity model that integrates AI capability frameworks, cloud maturity principles, hybrid cloud architecture, governance mechanisms, and operational automation, including AIOps and ModelOps. The demonstration stage shows how the proposed I-CMM can be used by enterprises to assess and plan digital transformation across different organizational contexts. The evaluation stage focuses on theoretical consistency, comparison with existing maturity models, cross-domain applicability, and preliminary validation through enterprise capability indicators and transformation measures. Finally, the communication stage presents the research findings, the framework structure, the maturity dimensions, and the implications for enterprise transformation practice. The proposed framework scales maturity dimensions progressively across capability stages, including process standardization, process automation, governance maturity, and intelligent optimization of operations. This staged approach helps organizations move systematically from basic digital capabilities toward advanced operational intelligence supported by AI. Together, these six stages ensure the framework is both theoretically grounded and practically extensible across diverse enterprise transformation contexts.

4.2 Data Collection and Synthesis

The study relies primarily on secondary sources to provide broad and in-depth insight into the field from multiple perspectives. Data are collected through a systematic review of scholarly articles, industry white papers, and publicly available maturity models related to AI, cloud computing, and enterprise transformation. Sources include peer-reviewed journal articles, conference proceedings, and publications from major technology organizations. Qualitative synthesis is then used to identify recurring themes, capability dimensions, and maturity attributes across the literature, with particular attention to strategy, data infrastructure, governance, and operational processes. These constructs are grouped and integrated into a unified set of capability domains. The synthesis process also identifies gaps, overlaps, and inconsistencies across existing models, which inform the development of the integrated framework.

4.3 Model Development and Validation

The proposed maturity model is developed through a systematic process of synthesis and conceptual structuring grounded in the theoretical foundations reviewed earlier. Core capability dimensions, including strategy, data infrastructure, cloud architecture, AI engineering, governance, and operations, are derived from the literature and treated as thematic building blocks of the model. These dimensions are then translated into a descriptive framework that defines the characteristics of enterprise capability at different stages of development. A sequence of maturity stages is subsequently introduced to represent the progression organizations may follow as they develop toward an integrated, AI-enabled hybrid enterprise. Each capability dimension is cross-mapped against these maturity levels to produce an overall capability-maturity matrix. Conceptual validation is conducted by comparing the model with existing maturity frameworks and assessing the consistency of its dimensions and levels. Although the model has a strong theoretical basis, empirical testing remains a priority for future research.

Model Development Steps:

- Conduct a structured literature review to identify core capability dimensions and define their characteristics.
- Assess enterprise capabilities in relation to their developmental progression across maturity stages.
- Map capability dimensions to maturity levels and integrate them into a combined framework.
- Conduct conceptual validation by assessing internal consistency and cross-domain applicability.

5. PROPOSED CAPABILITY DIMENSIONS

Before an integrated capability maturity model can be developed, the key dimensions that shape hybrid cloud and AI capability must be clearly identified. This study draws on maturity modeling and enterprise architecture to conceptualize capability as a multidimensional construct encompassing strategic, technological, and operational aspects of enterprise development. These dimensions are used to capture the interdependencies between enterprise AI functionality and hybrid cloud infrastructure and to assess overall organizational maturity. Effective scaling of AI within hybrid cloud environments depends not only on algorithms, but also on data sharing, infrastructure design, operational automation, and interoperability [24]. The proposed model, therefore, integrates a range of enabling factors, extending beyond organizational readiness and talent to include lifecycle management, ModelOps, AIOps, governance, and security. The addition of governance and security as a dedicated dimension is particularly important in light of growing regulatory demands, ethical concerns surrounding AI, and enterprise risk management requirements. Taken together, these dimensions provide the basis for assessing maturity, identifying capability gaps, and guiding strategic transformation. They represent the core axes of the proposed maturity model and the principal areas in which large enterprises must build scalable hybrid cloud-AI capability.

Table 3: Proposed Capability Dimensions for Hybrid Cloud-AI Maturity Model

Capability Dimension	Description	Key Components	Relevance to Hybrid Cloud-AI Integration
Strategy Alignment [23]	Alignment of AI and cloud initiatives with enterprise business goals and digital transformation strategies	Vision, leadership commitment, investment planning, business-AI alignment	Ensures cohesive integration of AI and cloud initiatives with organizational objectives
Data Infrastructure [23][25]	Availability, quality, and integration of data across hybrid environments to support AI workflows	Data lakes, data pipelines, real-time processing, data governance	Enables seamless data flow and supports scalable AI model training and inference
Cloud Architecture [24]	Design and orchestration of hybrid and multi-cloud environments to support distributed workloads	Hybrid cloud setup, multi-cloud orchestration, edge integration, scalability	Provides the infrastructure backbone for AI deployment and workload distribution
AI Engineering [23]	Development, deployment, and optimization of AI/ML models within enterprise systems	ML pipelines, model development, testing, and deployment frameworks	Facilitates scalable and production-ready AI implementation
Governance & Security [26]	Policies and mechanisms ensuring compliance, ethical AI use, and risk management	Data privacy, regulatory compliance, AI ethics, cybersecurity controls	Ensures secure and responsible AI deployment across hybrid environments
Operating Model [25]	Organizational structure and processes supporting AI and cloud operations	Center of Excellence (CoE), cross-functional teams, DevOps integration	Enhances coordination and efficiency in managing AI and cloud capabilities
Talent & Culture [23]	Workforce skills, AI literacy, and organizational culture supporting digital transformation	Training programs, skill development, change management, and collaboration	Drives adoption and effective utilization of AI and cloud technologies

Automation & Operations [25]	Integration of automation frameworks for managing AI and cloud operations	AIOps, ModelOps, monitoring, continuous deployment, feedback loops	Enables efficient lifecycle management and operational scalability

6. PROPOSED MATURITY MODEL

The proposed maturity model conceptualizes hybrid cloud and AI adoption as a coherent, staged evolution of enterprise capabilities, with each stage building on the previous one. In this respect, it aligns with the logic of the CMM while extending maturity analysis beyond process control to include infrastructure, data ecosystems, AI lifecycle management, governance, and intelligent operations. Unlike traditional maturity models that assess isolated technological domains, this framework is capability-based and systems-oriented. It recognizes that successful technology adoption depends not only on technical implementation but also on strategic vision, architectural design, governance, and organizational execution. By integrating AI maturity concepts with hybrid cloud evolution, the model captures both vertical progression in capability depth and horizontal integration across enterprise domains. The maturity levels represent increasingly consistent, automated, and intelligent forms of enterprise capability. ModelOps and AIOps, discussed in Section 2.3, are positioned as critical enablers of sustainable AI deployment through continuous monitoring, retraining, and optimization across distributed environments [23], [25]. Governance and security are treated as cross-cutting concerns that remain relevant across all maturity stages, especially in relation to legal compliance, ethical AI use, and risk management in hybrid infrastructures [26]. Overall, the model provides a step-by-step, theory-informed framework for assessing enterprise maturity and identifying the gaps that must be addressed on the path toward an AI-native hybrid enterprise

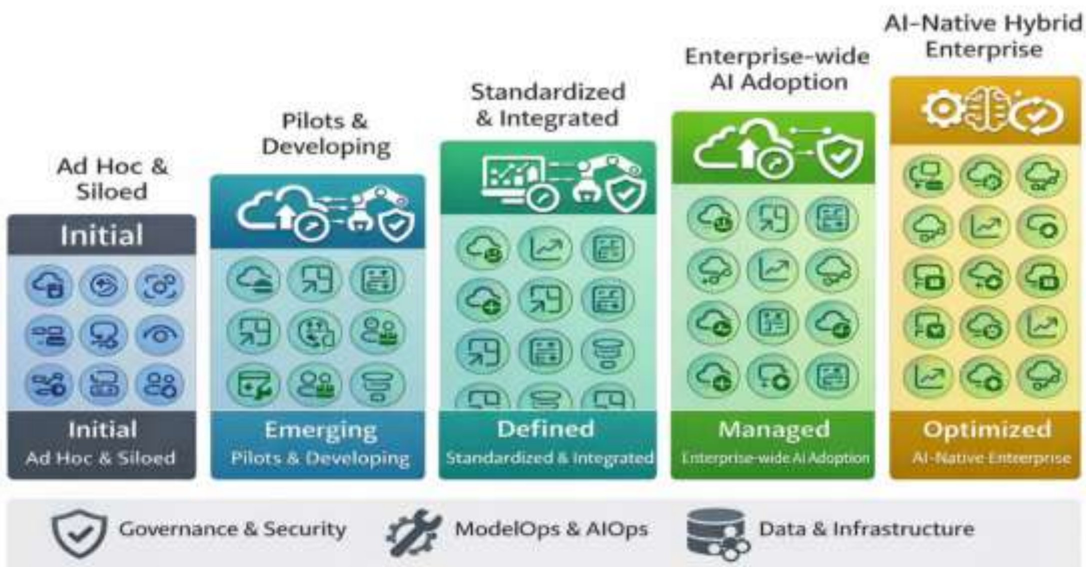

Figure 1: Hybrid Cloud-AI Capability Maturity Model

The maturity structure consists of a cumulative five-level hierarchy in which each level is defined by a distinct configuration of capabilities across one or more dimensions. Each successive level represents a higher degree of enterprise sophistication and builds on the capabilities established at lower levels. Importantly, the maturation of AI engineering is neither linear nor independent. Its development depends heavily on the maturity of data infrastructure and hybrid cloud architecture, while governance mechanisms must evolve in parallel to address increasing system complexity and regulatory demands. The hierarchical structure, therefore, serves two functions: it allows organizations to assess their current maturity state and provides a pathway for planning transformation. More broadly, the model emphasizes a shift from process-oriented operations toward intelligence-oriented systems in which decision-making is augmented or automated through embedded AI capabilities. As organizations progress through the maturity stages, they move toward adaptive and self-optimizing systems characterized by continuous feedback, real-time analytics, and dynamic resource coordination across hybrid cloud environments. This progression reflects not only technological advancement but also a bigger change in organizational culture, skills, governance systems, and strategic orientation.

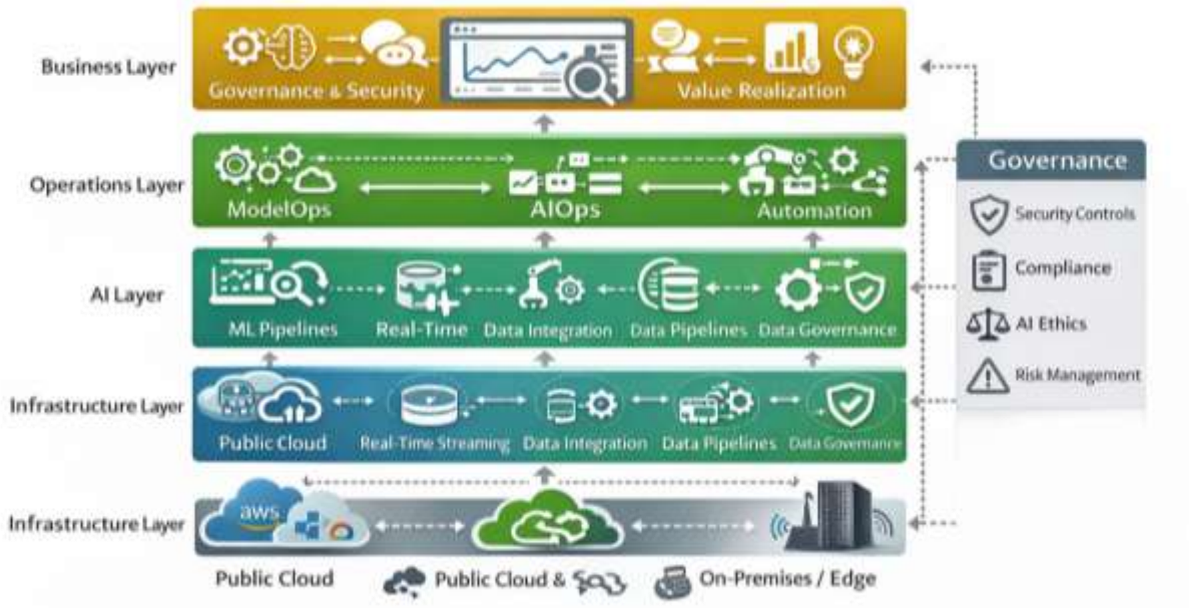

Figure 2: Implementation Architecture for Hybrid Cloud-AI Integration

The proposed maturity model also implies a layered implementation architecture that supports the progressive development of infrastructure, data, AI, and operational capabilities across the enterprise. The foundational layer is the infrastructure layer, which enables hybrid cloud deployment by linking on-premises resources with public and private cloud services, providing scalability, flexibility, and resilience. Built on this foundation is the data layer, which supports the storage and processing of structured and unstructured data across distributed systems while maintaining data quality, coherence, and availability for AI applications. The AI layer introduces standardized engineering pipelines that support model design, training, validation, deployment, and optimization. This layer must also connect with operational frameworks such as ModelOps and AIOps, which support continuous monitoring, deployment, anomaly detection, predictive maintenance, and broader AI management capabilities across hybrid infrastructure. The business layer sits at the top of the architecture and translates technical outputs into business insights, strategic decisions, and organizational value. Taken together, this multi-layer implementation model helps ensure that hybrid cloud and AI capabilities become not only scalable and intelligent, but also operationalized throughout the enterprise.

6.1 Maturity Levels

The proposed framework defines five sequential maturity levels that reflect the development of enterprise capabilities for hybrid cloud and AI integration. These levels are qualitative and vary in the degree of standardization, automation, intelligence, and institutionalization achieved across the key dimensions. Progression is cumulative: advancement to a higher level assumes that the capabilities associated with earlier levels have become stable and embedded in organizational practice. At the lower end of the model, organizations exhibit fragmented experimentation and limited coordination between AI and cloud initiatives. As maturity increases, organizations develop formal processes, integrated data platforms, and hybrid cloud architectures that support enterprise-scale AI use. At the higher levels, enterprises achieve coordinated integration, real-time data processing, and advanced operational models such as ModelOps and AIOps.

Ultimately, the model describes a progression from early experimentation to an AI-enabled hybrid enterprise characterized by adaptive optimization and intelligent operations. In this sense, the maturity levels provide a methodological reference point for capability benchmarking and for assessing readiness to build a resilient and intelligent digital environment [23]-[26].

- Level 1- Initial (Ad Hoc): Organizations conduct isolated AI experiments on legacy or non-cloud-based systems and lack standardized processes for managing AI operations.
- Level 2- Emerging: Organizations begin implementing cloud infrastructure, piloting AI initiatives, and connecting data systems across selected departments.
- Level 3- Defined: Organizations establish a hybrid cloud environment aligned with AI development processes and formalized operational management procedures.
- Level 4- Managed: Enterprises implement centralized data systems, governance controls, monitoring tools, and performance indicators to assess and improve system effectiveness.
- Level 5- Optimized (AI-Native Hybrid Enterprise): Organizations achieve self-learning, adaptive, and highly automated systems capable of intelligently managing hybrid cloud environments and AI-driven operations.

6.2 Capability Mapping Across Maturity Levels

The capability mapping framework supports the communication and visualization of the "stepped up" transformation, step by step, of each enterprise capability in the hybrid cloud and "Artificial Intelligence" (AI) world. The mapping structure represents the relationships (connections) among the maturity steps and strategic, technological, governance, and operational characteristics. These are expressed in a range of more or less mature implementations: lower-maturity implementations, more fragmented and reactive, and higher-maturity implementations, more integrated, automated, and intelligent, enterprise-wide. It also covers cross-cutting aspects of dimensions such as the maturity level of data infrastructure (and the ecosystems used to build it), data governance, and hybrid cloud architecture, which are vital enablers for AI engineering and the application of AI to operations. Based on the maturity levels and gaps identified in the Capability mapping stage and on enterprise readiness, we designed an AI-native hybrid ecosystems model framework to best support the enterprise AI transformation journey. In addition, it offers the opportunity to review measurable progress indicators across all bands and to conduct a comparative assessment of this element in the mapping.

Table 4: Capability Mapping Across Maturity Levels for Hybrid Cloud-AI Integration

Capability Dimension	Level 1- Initial	Level 2- Emerging	Level 3- Defined	Level 4- Managed	Level 5- Optimized
Strategy Alignment	Reactive and isolated AI initiatives with minimal business alignment	Partial alignment between IT and business objectives	Formalized enterprise AI-cloud strategy	Enterprise-wide governance and KPI-driven alignment	Adaptive AI-driven strategic optimization
Data Infrastructure	Siloed and inconsistent enterprise data	Partial data integration with limited governance	Unified enterprise data pipelines and governance	Real-time analytics and scalable distributed data systems	Intelligent autonomous data orchestration and optimization

Cloud Architecture	Legacy on-premise systems with minimal cloud adoption	Basic cloud deployment without orchestration	Integrated hybrid cloud environment with workload distribution	Multi-cloud orchestration with scalable infrastructure management	Autonomous and self-optimizing intelligent cloud ecosystem
AI Engineering	Experimental AI pilots with isolated model development	Department-level AI deployment with limited scalability	Standardized ML development and deployment pipelines	Enterprise-scale AI lifecycle monitoring and optimization	Autonomous self-learning and adaptive AI systems
Governance & Security	Reactive governance and limited compliance mechanisms	Basic security and policy controls	Defined governance, compliance, and ethical AI policies	Continuous auditing, monitoring, and risk management	AI-driven adaptive governance and automated compliance
Operations & Automation	Predominantly manual operations and monitoring	Semi-automated operational workflows	Integrated DevOps and initial ModelOps implementation	Advanced AIOps and predictive operational management	Fully autonomous self-healing and continuously optimized operations
Talent & Culture	Limited AI and cloud expertise across teams	Initial workforce training and awareness programs	Cross-functional collaboration and digital capability development	Enterprise-wide AI literacy and innovation culture	Continuous learning ecosystem with an AI-driven decision culture
ModelOps & AIOps Integration	No lifecycle management or operational intelligence	Basic monitoring and deployment automation	Structured model deployment and monitoring practices	Integrated predictive monitoring and automated optimization	Fully autonomous AI lifecycle orchestration and intelligent operations

7. DISCUSSION

The proposed hybrid cloud-AI capability maturity model offers an integrated framework for understanding how enterprises evolve within an increasingly complex digital environment. A central insight of the study is that AI maturity cannot be achieved without corresponding readiness in cloud infrastructure. At the same time, progress depends on coordinated capability development across multiple layers, including strategy, data, architecture, governance, and operations. The model underscores that it is difficult to scale enterprise AI without strengthening the hybrid cloud environment that supports it, particularly in areas such as data integration, workload orchestration, and lifecycle management. It also highlights the importance of aligning AI engineering with related domains such as data infrastructure and governance. The inclusion of operational constructs such as ModelOps and AIOps further emphasizes the shift toward intelligence-driven operations characterized by continuous monitoring, real-time optimization, and adaptive decision support. More broadly, the results suggest that maturity development is not purely technological, but also organizational, requiring alignment between leadership vision, workforce capability, and cultural readiness. In this sense, enterprise transformation is best understood as a socio-technical process shaped by the interaction of organizational adaptation and technological innovation.

The proposed maturity model also has important implications for enterprise decision-makers, particularly for strategic planning and investment prioritization. Capability mapping can help organizations clarify their current position, identify the most significant gaps, and establish a practical roadmap for reaching the next level of maturity. For large enterprises, this is especially valuable because transformation often requires balancing competing priorities across infrastructure, data, and AI programs. The framework also supports benchmarking by enabling organizations to compare their maturity with industry patterns and identify areas requiring further development. The emphasis on governance and security is particularly relevant in light of increasingly stringent regulatory expectations related to responsible AI, distributed cloud environments, and enterprise risk management. At the same time, the study has important limitations. The model is theoretical and therefore requires empirical validation before broader generalization can be claimed. In addition, both AI and cloud technologies are evolving rapidly, which means that capability dimensions and maturity criteria may change over time and require periodic revision. Despite these limitations, the model offers a useful conceptual foundation for future research and a practical starting point for organizations pursuing integrated hybrid cloud and AI transformation.

8. CASE STUDY: APPLICATION OF THE HYBRID CLOUD-AI MATURITY MODEL

In the following section, a conceptual case study is presented to demonstrate the application of the proposed maturity model within a large enterprise undergoing digital transformation by adopting hybrid cloud and Artificial Intelligence (AI). The case study reflects the characteristics of data-intensive, highly regulated sectors, including banking, healthcare, and retail, where scalable infrastructure, governance, and AI-driven operations are critical for enterprise modernization. The scenario illustrates how organizations can apply the proposed framework to evaluate capability gaps, strengthen operational readiness, and support scalable AI-enabled hybrid cloud transformation. At this stage, the organization has not yet completed several critical steps, including integrating its IT systems, eliminating data silos, and scaling AI adoption in a meaningful way. The organization begins to make decisions based more consistently on data rather than intuition or isolated experience, while progressively implementing the proposed capability dimensions. Around this time, an organization can use a maturity-model-based diagnostic to evaluate its current state and the path to desired maturity levels, while identifying gaps and detailing the path to maturity. The case study highlights the value of an integrated solution that combines data architecture, cloud-based storage and processing, AI-enabled innovation, and strong governance and operations to ensure enterprise transformation is sustainable, coherent, and scalable, rather than a one-off initiative. Supporting distributed data processing applications and deploying AI within them in a hybrid cloud has been addressed as mentioned above [28], and for MLOps and AIOps support and operations automation, a hybrid cloud has been proposed [29].

8.1 Initial State Assessment and Capability Gaps

In its initial state, the organization can be characterized as operating between Level 1 (Initial) and Level 2 (Emerging) maturity. Its IT environment is dominated by legacy on-premises systems with limited virtualization and little integration with public cloud platforms. Data remains fragmented across silos, with varying levels of quality, consistency, and accessibility depending on departmental needs. AI activity is limited to a small number of pilot initiatives conducted within individual departments, and these efforts are not yet standardized, scalable, or strategically aligned. Governance structures are underdeveloped, with reactive controls, incomplete processes, and limited implementation of data security, compliance, and ethical AI practices. Operational processes remain largely manual, with only minimal automation. Applying the maturity model across capability dimensions makes it possible to identify major gaps, including the absence of a unified data infrastructure, limited hybrid cloud deployment, weak AI engineering practices, and insufficient governance mechanisms. Additional constraints include skills shortages, limited cross-functional collaboration, and cultural resistance to change. These findings are consistent with prior research identifying data fragmentation and technical debt as major barriers to enterprise AI adoption [30].

8.2 Transformation Strategy and Capability Development

Transformation begins by extending existing on-premises systems to a hybrid cloud configuration, establishing the scalable, flexible infrastructure foundation required for AI deployment [28]. At the same time, the organization adopts an integrated data strategy centered on data lakes and real-time data pipelines to ensure data access and consistency across business units. Unified AI development pipelines support the consistent development and deployment of machine learning models, thereby improving scalability and reproducibility. Governance systems are established to address data protection, regulatory, and ethical challenges to AI, and to develop AI policies and monitoring. The company's strategy is to build human resources, help staff deepen their understanding of AI, and foster a collaborative, innovative work culture. DevOps practices are introduced to strengthen operational capabilities and establish the groundwork for a gradual transition toward ModelOps [29]. During this stage, a range of improvements in interdepartmental coordination, business and IT strategies, and operational effectiveness can be measured.

8.3 Outcomes and Maturity Advancement

The progression of capability maturity illustrates the practical value of the Hybrid Cloud-AI Capability Maturity Model (AI-HCMM), drawing on reported enterprise gains associated with cloud transformation, AI operations, DevOps automation, ModelOps, AIOps, and data-driven digital transformation studies [39]-[43]. It is important to note that the results presented here do not constitute a direct empirical assessment; rather, they serve as an illustration of how organizational performance indicators may evolve across successive stages of maturity, as shown in the figure. This analysis is based on an organization transitioning from level 2, where AI efforts remain fragmented and only partially integrated with cloud resources, to level 4, where AI capabilities, cloud infrastructure, governance mechanisms, and operational processes are implemented and optimized systematically.

The effect on the illustrative qualitative and operational performance indicators is substantial. For example, automated CI/CD pipelines can reduce AI model build and deployment cycles from as long as 12 days to as little as 4 days. Intelligent management of hybrid cloud workloads, including workload optimization and infrastructure placement, can improve infrastructure efficiency for hybrid cloud workloads by approximately 22% to 42% [42, 43]. The most efficient architecture for real-time data processing is the integrated data platform and scalable cloud-native architectures, which deliver efficiencies of between 65% and 88% [42, 43]. Operational automation can increase to 80% through improvements enabled by workflow automation, DevOps practices, and AIOps-inspired operational management [39] [40]. Scalability to support business growth and larger workloads can improve incrementally from 55% to 87% without requiring a proportionate increase in operational complexity. For governance and compliance, the adoption of enterprise AI and cloud-based systems with centralized policy enforcement, monitoring, and automated auditing can improve efficiency by 27%. In fact, incident prediction and resolution times can be reduced significantly through the use of AIOps platforms with predictive analytics, anomaly detection, and automated remediation [39, 41]. In addition, 86% of enterprises become interoperable and coordinate workloads across platforms, cloud services, enterprise applications, and AI-powered business processes, all working seamlessly together [42] [43].

There is also evidence that continuous maturity development within the proposed framework can improve organizational adaptability, governance effectiveness, business agility, and overall responsiveness through more effective use of technology [39]-[43]. The results corroborate the theory that to be successful, the journey towards a hybrid cloud using AI needs to be undertaken together in a coordinated manner, that is, full-stack development following the hybrid cloud model that involves both infrastructure and data, as well as operations, governance, and organizational capabilities. The goal of scaling AI use for enterprises is a significant step toward intelligent automation, adaptive decision-making, and the vision of fully integrated, AI-native hybrid cloud architectures [40]-[43] becoming more of a reality.

9. COMPARATIVE ANALYSIS OF HYBRID CLOUD AND AI CAPABILITY MATURITY

This section reviews and compares findings from the academic literature, capability maturity models, and industry reports on hybrid cloud adoption and AI capability development. The purpose of this review is to identify common maturity indicators, implementation patterns, and best practices reported in prior studies and industry frameworks. Rather than validating the results of individual studies, this analysis synthesizes existing evidence to better understand the relationship between hybrid cloud capabilities and the progression of AI maturity within enterprises. The insights gathered from these sources provide a foundation for examining how cloud infrastructure readiness can support and influence an organization's AI transformation journey.

The ability to navigate a hybrid transformation and successfully implement technologies such as AI is also always a key component, but the emphasis in the literature has shifted toward technologies, governance, and strategic alignment with the technology to be successful. According to Arroyabe et al. [32], several factors are relevant when considering AI adoption, internal capabilities related to organizations' digitalization capabilities are more well interrelated with innovative capacity and external factors. AI utilization can also be categorized into distinct levels of maturity, which progress over time as organizations address challenges related to technology, infrastructure, data management, data governance, and organizational readiness. This gradual evolution of AI capabilities is reflected in the maturity models proposed by M. Sonntag et al. [33] and Lukas Weiss et al. [34].Moreover, according to findings of Anthropic [35], there are regional and organizational variations with regard to AI application patterns, and when assessing the level of AI maturity, adapting to the measurements of the diverse types of Enterprise contexts seems like the proper approach to take.

In addition, the study found that Hybrid cloud is the enabling technology that enables scaling and maintains the integration of Artificial Intelligence. As part of the digital revolution, hybrid cloud solutions integrate public and private cloud resources with on-premises infrastructure, providing users with the strength, agility, and data access necessary for sophisticated AI initiatives. The study conducted by X. Stiensmeier and B. Barua [36, 37] highlights the benefits of moving to a hybrid cloud environment: improved processing power, better resource utilization, and greater operational scalability for AI tasks. Furthermore, according to D. Chen et al. [38], hybrid cloud and AI technology can lead to improvements for an organization's performance, governance, and resilience. Such results and conclusions suggest a considerable relationship between the status of the AI maturity and the status of the technologies, the operational and organizational capability to deploy them in a hybrid fashion, strongly emphasizing the importance of structuring the development of both of these at the same time.

Table 5: Hybrid Cloud and AI Capability Maturity: Comparative Analysis Based on Published Literature

Dimension	Study / Source	Empirical Evidence	Key Insight	Implication
Digital Capability	Arroyabe et al. [32]	Large-scale firm analysis (European SMEs)	Internal digital capability drives AI adoption	Build strong foundational IT & data systems
AI Maturity Models	Sonntag et al. [33]	Structured maturity framework validation	AI capability evolves in stages	Adopt a phased maturity approach
AI Maturity Models	Weiss et al. [34]	SME-based maturity model application	Non-linear and context-dependent maturity	Customize maturity models to the enterprise context
Adoption Patterns	Appel et al. [35]	Observational AI usage data	AI adoption is uneven across regions & tasks	Need flexible, adaptive maturity frameworks

Hybrid Cloud Architecture	Stiensmeier et al. [36]	Use-case driven architecture study	Hybrid cloud supports scalable AI workloads	Hybrid cloud is foundational for AI systems
Resource Optimization	Barua & Kaiser [37]	AI-driven microservices allocation	Improves efficiency and workload distribution	Integrate AI with cloud orchestration
AI + Cloud Integration	Chen et al. [38]	Large-scale system architecture research	Enhances performance, governance, and scalability	Use a hybrid cloud for enterprise AI deployment

10. LIMITATIONS AND CHALLENGES

The proposed hybrid cloud-AI capability maturity model offers a relatively holistic view of enterprise transformation, but it is important to recognize its limitations and implementation challenges. First, the model is conceptual and synthesizes existing maturity, hybrid cloud, and AI capability frameworks rather than being derived from large-scale empirical validation. As a result, it cannot yet be assumed to apply uniformly across organizations of different sizes, industries, regulatory settings, or levels of technological maturity. Second, the rapid evolution of AI and cloud technologies introduces instability in both the identified capability dimensions and the progression of maturity itself, making continuous refinement necessary. Third, several dimensions, such as governance, culture, and strategic alignment, are inherently qualitative and may be difficult to assess consistently. The interdependence of the dimensions also increases implementation complexity, since progress in one area, such as AI engineering, often depends on advancement in others, such as data infrastructure and cloud architecture. Resource constraints, legacy systems, and differing organizational interpretations of maturity may further complicate stepwise progression. Nevertheless, despite these challenges, the model offers a structured basis for assessing capability and planning transformation.

10.1 Conceptual and Methodological Limitations

The major limitation of the work is its reliance on a conceptual and design-based research model, which is well-established theoretically but has not been tested through quantitative analysis or a large-scale case study. There is no uniformity in maturity-level scales, which adds subjectivity to the assessment process and creates variations in the "maturity level" that organizations perceive. Furthermore, the literature on maturity models has revealed that methodological heterogeneity, whether in the notion of maturity levels, in the definition of competencies or domains, or in the set of tests used to assess competencies, can be enormous, influencing the appropriateness of the proposed maturity model. This is because the combination of Hybrid clouds and AI can make the approaches more complex, involving the integration of multiple operational paradigms and theoretical models. Besides, it does not include a formal scoring system or a quantitative maturity index; thus, its use as a benchmarking and comparison tool is not straightforward. Further research should focus on standardizing, validating, and testing the measurement protocol across a variety of enterprise contexts to improve its reliability and generalizability.

10.2 Technological and Infrastructure Challenges

Many organizations still rely on monolithic legacy systems and outdated infrastructure that are only partially integrated with distributed cloud environments, thereby increasing technical debt and making transformation more difficult. Hybrid environments also pose challenges for data synchronization, particularly when organizations seek to support low-latency, high-availability AI applications across multiple locations. Limited interoperability across cloud platforms, operational tools, and AI systems can further complicate implementation and increase the risk of vendor lock-in. In addition, AI workloads often require dynamic resource allocation, a capability that may be difficult to achieve in partially mature hybrid environments. Edge computing introduces further complexity, especially in scenarios where low latency is essential.

10.3 Organizational and Cultural Barriers

Organizational and cultural factors are the key drivers of maturity progression and have a greater impact than technological constraints. The transition to hybrid cloud-AI operating models requires significant changes in organizational mindset, practices, and collaboration patterns. Traditional siloed IT structures and functionally isolated decision-making processes must be replaced with more collaborative, data-driven, and innovation-oriented operating practices. The challenge of resistance to change is highlighted, particularly in large companies, where processes and organizational structures create obstacles. Furthermore, the organization is losing out on advanced capabilities and scalability due to the need for skilled professionals in AI, cloud computing, and data engineering. The fact that the business and IT efforts are misaligned results in disorganized initiatives and a lack of resource allocation, making these matters even more difficult. For integrated solutions to be a reality, cross-functional collaboration among data scientists, engineers, and business stakeholders is likely to be the key driver of success. Moreover, cultural inertia can be an obstacle to adopting agile and continuous improvement practices needed to progress toward maturity.

10.4 Governance, Security, and Compliance Risks

Governance, security, and compliance challenges are often more acute in large, established enterprises with legacy systems, distributed operations, and complex regulatory obligations. The core of the decentralization of hybrid clouds has created additional attack surfaces and risks for information exposure, intrusions, and data leakage. However, when data is spread across different clouds and regions and located in other countries, data privacy and data sovereignty become even more complex, as each country has its own laws and standards. One of the novel effects of AI on governance is the issue of algorithmic discrimination, transparency, and accountability for algorithmic decisions. As AI is implemented in large enterprises, the risk of errors and incidents increases, and these risks must be reduced through effective risk management and monitoring systems. Current governance structures may not accommodate AI's dynamism and adaptability, and new, more open and adaptable governance models should be developed. These risks must be mitigated through a security-by-design approach, constant monitoring, and automatic compliance measures.

11. FUTURE RESEARCH DIRECTIONS

The hybrid cloud-AI capability maturity model provides a foundation for several future research directions. As AI and cloud technologies continue to evolve rapidly, further studies should aim to refine, validate, and extend the framework to enable its application across a wider range of organizational and technological contexts. One important priority is large-scale empirical testing, including case studies and quantitative validation, to assess the robustness and generalizability of the model. Emerging technologies such as edge computing, federated learning, and generative AI are also likely to influence maturity requirements and may necessitate revision of capability dimensions and progression stages. In addition, sector-specific variants of the model may be needed to reflect the distinctive legal, technical, and informational requirements of industries such as healthcare, finance, and manufacturing. Finally, future research could explore the use of analytics and decision-support systems to make maturity assessment more precise, adaptive, and actionable.

11.1 Empirical validation and quantitative model.

To demonstrate its applicability, a capability assessment approach guided by a quantitative method is illustrated: the proposed AI-Hybrid Cloud Capability Maturity Model (AI-HCMM). The assessment framework focuses on capabilities with standard attributes across AI Adoption, Hybrid Cloud transformation, Enterprise Architecture, Governance, Digital Transformation, and Operational automation, which they have already worked on and experienced. The model is intended to demonstrate, in a quantitative fashion, the levels of maturity of an organization's capabilities across a number of areas. Avoid providing the results of an empirical primary investigation, but rather a systematic way to evaluate a defined maturity modeling approach, which relies on outcomes reported in the literature.

Overall maturity index (M), Maturity is calculated as a weighted sum of capability scores in the other dimensions of organizational maturity (Maturity is a capability score across all the organizational dimensions):

$$M = \sum_{i=1}^{n} w_i C_i$$

where:

- **M** represents the overall enterprise maturity index;
- **Ci** represents the normalized capability score of dimension i (ranging from 0 to 1);
- **wi** represents the weighting factor assigned to dimension i according to its relative strategic and operational importance.
- **n** denotes the total number of capability dimensions included in the assessment.

Each capacity score (C_i) is the result of scoring indicators within the dimension, then aggregated and scaled to the 0-1 range. The weighting factor (wi) signifies the effect of a capability dimension in the enterprise-wide AI-powered transformation to hybrid cloud. Conversely, "scalability," "operational performance," "governance effectiveness," "automation capability", and "recognition of business value" have a greater impact when considering lengths. Evidence for the weights comes from existing maturity frameworks or enterprise transformation studies, with the weights normalized such that:

$$\sum_{i=1}^{n} w_i = 1$$

The weight factors to apply and the performance levels (Illustrative) are given in Table 6 and should be referenced when assessing the impact of the operation and capability score dimension. The operational impact percentage gives an idea of the contribution of a capability to the organization's performance, and the weighting factor is applied directly to the calculation of the maturity index. This is akin to the weights, with a strategic dimension increasing its influence on the final maturity score if it has good capability performance.

The framework for enabling hybrid cloud transformations with AI adoption seeks to shift the emphasis to the concept of "preparedness" for enterprise transformation, which is a multi-dimensional challenge. Although technological readiness is clearly important, there are factors beyond technical considerations that can impact organizational readiness to adopt AI, including strategic alignment, organizational governance effectiveness, interoperability, operational and maintenance automation, maintaining AI models throughout their lifecycle, and more. Thus, the model allows for a structured process of determining strengths, documenting capability gaps, ranking investments, and evidence-based planning of transformation processes, as well as continuous maturity enhancement for all of them.

Derivation of Weighting Factors (wi)

The weighting factors reflect the relative importance of each capability dimension to enterprise hybrid cloud-AI transformation. In line with the DSR methodology adopted in this study, weights are derived from a structured literature synthesis rather than from primary data collection. Each dimension was assessed against two criteria: (i) the frequency with which it was identified as a critical success factor across the reviewed studies [15, 17, 19, 22, 32-34], and (ii) the magnitude of operational impact attributed to it in enterprise transformation contexts [23, 25, 29, 38]. Dimensions consistently cited as primary enablers, Data Infrastructure, Operations and Automation, and Cloud Architecture, were assigned higher weights (0.14-0.15), while contextually variable dimensions such as Governance and Strategy Alignment received moderate weights (0.10). All weights are normalized such that $\Sigma wi = 1.00$. Future empirical work should validate and refine these weights using the Analytic Hierarchy Process (AHP) or a Delphi expert-panel study.

Derivation of Capability Scores (Ci)

Each capability score Ci is a normalized measure of a dimension's maturity attainment, mapped directly to the five-level structure defined in Table 4. A linear scoring rubric is applied: Level 1= 0.0-0.2, Level 2 = 0.2-0.4, Level 3 = 0.4-0.6, Level 4 = 0.6-0.8, and Level 5 = 0.8-1.0. Within each band, the score is refined by evaluating observable indicators, policy formalization, automation coverage, cross-functional integration, and evidence of continuous improvement against the descriptors in Table 4. The illustrative scores in Table 6 were assigned by mapping published enterprise transformation benchmarks [39-43] to this rubric. In applied assessments, Ci would be derived from structured questionnaires in which practitioners rate dimension-specific indicators on a five-point Likert scale, with responses aggregated and linearly normalized to [0, 1].

Table 6: Quantitative Enterprise Capability Assessment for Hybrid Cloud-AI Maturity

Capability Dimension	Capability Score ((C_i))	Weight Factor (w_i)	Operational Impact (%)	Maturity Contribution
Strategy Alignment	0.72	0.10	18%	High
Data Infrastructure	0.81	0.15	24%	Very High
Cloud Architecture	0.78	0.14	22%	High
AI Engineering	0.75	0.13	20%	High
Governance & Security	0.69	0.10	16%	Moderate
Operations & Automation	0.84	0.15	28%	Very High
ModelOps & AIOps Integration	0.79	0.13	25%	High
Enterprise Interoperability	0.73	0.10	19%	High
Total	-	**1.00**	-	-

Using the values from Table 6:

$M=(0.10\times0.72)+(0.15\times0.81)+(0.14\times0.78)+(0.13\times0.75)+(0.10\times0.69)+(0.15\times0.84)+(0.13\times0.79)+(0.10\times0.73)$
$\mathbf{M=0.772}$

Thus, the illustrative organization achieves an overall maturity score of 0.772 (77.2%), corresponding to an advanced maturity level within the proposed AI-Hybrid Cloud Capability Maturity Model.

11.2 Interoperation with developing technologies.

Emerging technologies create important opportunities for extending the proposed maturity model. Future versions of the framework may need to explicitly account for edge computing, federated learning, the Internet of Things (IoT), and generative AI, all of which introduce new capability requirements, such as decentralized processing, privacy-preserving learning, and real-time decision-making at the edge. These technologies are likely to affect both infrastructure and operational dimensions of maturity, and their convergence with hybrid cloud environments will require the framework to evolve accordingly.

11.3 Specific Adaptation and Customization to the Industry

Although the proposed model is intentionally generic, future research should develop industry-specific variants that address sectoral requirements more precisely. Differences in data sensitivity, regulatory constraints, infrastructure complexity, and operational risk mean that hybrid cloud and AI adoption will vary significantly across industries. For example, financial services may require greater emphasis on risk management and real-time analytics, while healthcare organizations must address stringent privacy requirements and clinical data governance. Industry-specific customization could therefore improve the practical relevance of the model and enable more meaningful comparisons across sectors.

11.4 Intelligent and Adaptive Maturity Assessment Systems

Another promising direction is the development of intelligent systems for automated maturity assessment and decision support. Advanced analytics and AI could be used to evaluate organizational readiness, simulate transformation scenarios, and recommend architecture or investment decisions in real time. Integrating such capabilities with enterprise data would transform maturity models from static diagnostic tools into dynamic systems that support continuous transformation management.

CONCLUSION

This study proposed an AI-based Hybrid Cloud Capability Maturity Model (AI-HCMM) to help enterprises navigate the transition toward more intelligent and distributed digital environments. Although hybrid cloud and AI each offer significant value independently, the proposed framework integrates them within a single maturity structure, thereby providing organizations with a more coherent means of assessing readiness for transformation. The framework identifies enterprise capability dimensions such as hybrid cloud infrastructure, data intelligence, AI engineering, ModelOps, and AIOps, governance and security, and organizational readiness as critical enablers of scalable AI deployment in hybrid cloud settings. The study also shows that challenges related to scalability, operational efficiency, governance, and business value creation often stem from uneven development across technological and organizational capabilities, making parallel development essential. In response, the framework defines a five-stage maturity continuum that spans the progression from isolated experimentation to fully AI-native hybrid enterprise capability. It also highlights the importance of ModelOps, AIOps, governance, and organizational culture in enabling organizations to derive sustained value from these technologies while managing risk and supporting intelligent decision-making. Although the model remains conceptual and requires empirical validation across industries, it offers a strong theoretical foundation for future maturity assessment research and practical implementation. In this way, it helps bridge the gap between cloud maturity and AI maturity perspectives and offers a more holistic basis for evaluating enterprise readiness.

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