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Accelerating AI and Data Strategy Transformation: Integrating Systems, Simplifying Financial Operations Integrating Company Systems to Accelerate Data Flow and Facilitate Real-Time Decision-Making

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ABSTRACT

The rapid advancement of artificial intelligence (AI) and data-driven technologies has intensified the need for organizations to integrate heterogeneous systems and redesign their data strategies to support real-time decision-making and financial efficiency. This study investigates how system integration accelerates AI and data strategy transformation and simplifies financial operations in the Energy and Utilities sector in the United States. Using a quantitative research design, data were collected from 250 professionals in 2024 through a structured questionnaire measured on a five-point Likert scale. The data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS 3) to examine the relationships among system integration, data architecture and integration, AI and business intelligence capability, real-time decision-making, and financial operational performance. The results reveal that system integration significantly enhances data integration and AI-enabled analytical capability, which in turn improves real-time decision-making. Real-time decision-making emerges as the strongest predictor of improved financial operational performance, particularly in budgeting and forecasting processes. Furthermore, the findings demonstrate that the impact of system integration on financial performance is largely mediated by data integration, AI and BI capability, and decision-making capability. This study contributes to the digital transformation literature by providing empirical evidence from a multi-cloud context and offers practical insights for Energy and Utilities organizations seeking to leverage AI and data strategies to achieve agile, data-driven financial management.

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1. INTRODUCTION

The acceleration of artificial intelligence (AI) and data-driven technologies has fundamentally reshaped how organizations design, operate, and govern their information systems. In an era characterized by increasing data volumes, velocity, and variety, organizations are no longer challenged by data scarcity but by their ability to integrate heterogeneous systems, manage complex data architectures, and translate data into actionable insights in real time [1], [2]. This challenge is particularly pronounced in the Energy and Utilities sector, where operational complexity, regulatory pressures, capital-intensive assets, and demand volatility require highly reliable and timely data-informed decision-making. Although substantial investments have been made in digital technologies, many organizations in this sector continue to operate within fragmented system environments, where legacy enterprise resource planning (ERP) systems, operational technology (OT), supervisory control and data acquisition (SCADA), financial platforms, and customer information systems remain loosely coupled or siloed. Such fragmentation results in delayed data flows [3], inconsistent information, and limited analytical visibility, thereby constraining the effectiveness of AI deployment, which relies heavily on integrated, high-quality, and near-real-time data. Consequently, the absence of robust data integration mechanisms undermines the strategic value of AI initiatives and hampers organizational agility, positioning AI and data strategy transformation as a strategic imperative rather than a mere technological option [4], [5].

System integration plays a pivotal role in addressing these challenges by enabling seamless data exchange across enterprise and operational domains. Technologies such as SOAP and REST APIs, middleware platforms, and service-oriented architectures facilitate standardized communication between disparate systems, supporting scalable and interoperable data ecosystems [6], [7]. When embedded within a well-defined data architecture and data strategy, these integration mechanisms enhance data consistency, accessibility, and reliability. In turn, they provide a critical foundation for business intelligence (BI) tools and AI-enabled analytics that support real-time operational monitoring, forecasting, and decision-making. However, empirical evidence on how system integration translates into tangible performance improvements—particularly in financial operations—remains limited.

Financial operations represent a critical domain in which the impact of AI and data integration is both measurable and strategically significant. In the Energy and Utilities sector, budgeting, forecasting, and financial planning processes are inherently complex due to long planning horizons, high capital intensity, fluctuating energy demand, and regulatory constraints, while traditional financial practices often rely on periodic and manually consolidated data that limit responsiveness to operational and market dynamics [8], [9]. In contrast, integrated data environments supported by AI-driven analytics enable dynamic forecasting, scenario analysis, and continuous financial insight, thereby simplifying financial operations and enhancing decision quality. From a theoretical perspective, this study is grounded in the intersection of digital transformation theory, the resource-based view of the firm, and data-driven decision-making frameworks, which conceptualize integrated information systems and AI capabilities as strategic organizational resources that enhance information processing capacity and operational efficiency [8], [10]. However, the value of these resources depends not merely on their adoption but on their alignment with organizational data strategy, data architecture, and analytical capabilities, underscoring the importance of empirical models that examine both direct and mediating relationships among system integration, AI-enabled data utilization, real-time decision-making, and financial operational performance.

Although prior studies have explored AI adoption, digital transformation, and business intelligence across various industries, research that specifically focuses on the Energy and Utilities sector—particularly using robust quantitative methods—remains limited. Existing literature often emphasizes technological potential or conceptual frameworks without empirically testing the structural relationships among system integration mechanisms, analytical capabilities, and financial outcomes. Moreover, only a small number of studies employ advanced multivariate techniques such as Structural Equation Modeling–Partial Least Squares (SEM-PLS) to capture the complex and multidimensional nature of AI and data strategy transformation. To address these gaps, this study investigates how system integration accelerates AI and data strategy transformation and simplifies financial operations by enabling efficient data flow and real-time decision-making in the Energy and Utilities sector in the United States. Using a quantitative research design, data were collected from industry professionals in 2024 through a structured Likert-scale questionnaire and analyzed using SEM-PLS 3 to examine both direct and indirect effects among the proposed constructs.

This research makes three key contributions. First, it provides empirical evidence on the role of system integration technologies—such as SOAP and REST APIs—within a comprehensive AI and data strategy framework tailored to the Energy and Utilities sector. Second, it extends the digital transformation literature by empirically demonstrating the mediating role of AI-enabled data utilization and real-time decision-making in linking system integration to financial operational efficiency, particularly in budgeting and forecasting processes. Third, the study offers practical insights for executives, data architects, and financial leaders seeking to design integrated, AI-ready systems that support agile and data-driven financial management [11]. By bridging technological, analytical, and financial perspectives, this research advances understanding of how organizations can effectively accelerate AI and data strategy transformation in complex and asset-intensive industries.

2. LITERATURE REVIEW

2.1. AI and Data Strategy Transformation

Artificial intelligence (AI) has become a central driver of digital transformation across industries by enabling organizations to automate processes, enhance analytical capabilities, and improve decision-making quality. In the context of organizational transformation, AI is increasingly understood not as a standalone technology but as an integral component of a broader data strategy that governs how data are collected, integrated, analyzed, and utilized for strategic purposes [12], [13]. A coherent data strategy aligns technological infrastructure, analytical tools, and organizational objectives to ensure that data-driven initiatives generate sustained value. Prior studies emphasize that successful AI and data strategy transformation requires close alignment among data governance, analytical capabilities, and organizational processes, suggesting that AI-driven value creation depends not only on algorithmic sophistication but also on the organization's ability to translate analytical insights into operational and financial decisions.

Within the Energy and Utilities sector, AI and data strategy transformation is particularly critical due to the sector's reliance on data-intensive activities such as energy generation, distribution monitoring, demand forecasting, and asset management [13], [14]. AI-driven analytics enable predictive maintenance, load forecasting, and operational optimization, while advanced data strategies support regulatory compliance and long-term investment planning. However, the effectiveness of these initiatives is highly contingent on the availability of integrated, high-quality data and a well-defined data architecture that supports scalable analytics. Without robust system integration and coherent data architecture, AI adoption risks becoming fragmented and underutilized, underscoring the role of system integration as a key enabler of AI-driven transformation in complex, asset-intensive industries.

2.2. *System Integration and Data Architecture*

System integration refers to the process of enabling communication and data exchange among heterogeneous information systems within an organization. In complex organizational environments, particularly in the Energy and Utilities sector, system landscapes typically comprise legacy enterprise systems, operational technology (OT), financial platforms, and customer-facing applications that are often developed independently, resulting in data silos and interoperability challenges [15], [16]. To address these issues, modern integration approaches increasingly rely on service-oriented architectures and standardized interfaces such as SOAP and REST APIs, which facilitate seamless data exchange across disparate systems. Supported by a robust data architecture that defines how data are structured, stored, governed, and accessed, system integration enables modularity, scalability, and real-time connectivity, forming the backbone of enterprise data platforms that support advanced analytics and AI applications [16], [17].

Empirical research suggests that integrated system environments significantly enhance data consistency, reduce redundancy, and improve data availability, thereby strengthening an organization's information processing capabilities. In contrast, the absence of effective integration often forces organizations to rely on manual data reconciliation processes, which increases operational complexity and delays decision-making. Such delays are particularly detrimental to AI and business intelligence applications, where analytical relevance and accuracy depend on timely, high-quality data [17], [18]. Consequently, effective system integration and data architecture are not merely technical enablers but critical organizational capabilities that underpin real-time analytics, informed decision-making, and AI-driven transformation in data-intensive sectors such as Energy and Utilities.

2.3. *Data Integration and Data Flow Efficiency*

Data integration is a critical outcome of effective system integration and refers to the consolidation of data from multiple sources into a unified and coherent view. Efficient data integration enables continuous data flow across organizational units, ensuring timely access to accurate and consistent information [19], [20]. In the Energy and Utilities sector, where operations depend heavily on real-time monitoring and coordination, data flow efficiency is essential for tracking operational performance, responding to demand fluctuations, and managing financial risks. By reducing data fragmentation and latency, integrated data environments support more responsive and informed operational and financial decision-making [20], [21].

Efficient data flow also enhances an organization's information processing capacity and supports the deployment of AI-driven analytics that rely on timely and high-quality inputs. Prior research in the information systems literature indicates that data integration improves analytical accuracy and reduces processing delays, enabling organizations to transition from periodic, batch-based reporting to real-time analytics [15], [22]. From a theoretical perspective, data flow efficiency functions as an intermediary capability that links technological infrastructure to organizational performance, allowing AI tools to transform raw data into actionable insights. Consequently, data integration serves as a foundational mechanism through which system integration influences downstream analytical capabilities and financial outcomes, particularly in budgeting and forecasting processes.

2.4. *Business Intelligence, AI Analytics, and Real-Time Decision-Making*

Business intelligence (BI) and AI-enabled analytics constitute the analytical layer of organizational data systems. BI tools primarily deliver descriptive and diagnostic insights through dashboards, reports, and visualizations, while AI-enabled analytics extend these capabilities by supporting predictive and prescriptive analysis [2], [23]. Together, BI and AI analytics enhance organizational decision-making by improving the quality, speed, and relevance of insights. In dynamic and data-intensive environments, real-time decision-making has become a critical organizational capability, particularly in the Energy and Utilities sector, where timely insights support operational control, demand response, and financial risk management [3], [24]. Integrated BI and AI systems enable decision-makers to access up-to-date information, conduct scenario simulations, and respond proactively to emerging operational and market conditions, positioning organizations to better manage uncertainty and complexity.

However, the effectiveness of BI and AI analytics is highly dependent on the quality of the underlying data infrastructure. Fragmented systems, inconsistent data, and limited interoperability undermine analytical accuracy and erode decision-maker trust, reducing the practical value of advanced analytics [12], [25], [26]. As a result, real-time decision-making capability emerges not merely from the availability of analytical tools but from the integration of systems, data, and analytics within a coherent data strategy. This perspective underscores the mediating role of analytical capabilities in translating system integration into improved organizational performance, highlighting that the strategic value of BI and AI analytics is realized only when supported by robust data integration and governance mechanisms.

2.5. *Financial Operations, Budgeting, and Forecasting*

Financial operations, including budgeting, forecasting, and financial planning, are central to organizational performance and strategic control. In capital-intensive sectors such as Energy and Utilities, these processes are inherently complex due to long-term investment horizons, regulatory oversight, and demand uncertainty [27], [28]. Traditional financial planning approaches often rely on historical data and periodic updates, which constrain their ability to respond effectively to dynamic operational and market conditions. As a result, financial decision-making in such environments is frequently reactive rather than proactive, limiting organizational agility and strategic responsiveness [29], [30].

AI-enabled analytics and integrated data systems offer significant potential to transform financial operations by enabling dynamic forecasting, continuous planning, and scenario-based analysis. Integrated data architectures allow financial systems to draw directly from operational and market data, reducing manual intervention and improving accuracy [31], [32]. Beyond process automation, the simplification of financial operations also involves greater clarity, consistency, and decision support, as integrated AI-driven insights help reduce complexity, eliminate redundant processes, and enhance decision quality. This transformation aligns with broader digital finance trends that emphasize real-time visibility and data-driven financial management, enabling organizations to achieve more agile and resilient financial performance.

2.6. *Research Gap and Conceptual Foundation*

Despite growing interest in AI, data strategy, and digital transformation, several gaps remain in the literature. First, empirical studies examining the structural relationships among system integration, data integration, AI analytics, real-time decision-making, and financial operations are limited, particularly within the Energy and Utilities sector. Second, much of the existing research adopts conceptual or qualitative approaches, leaving a need for quantitative validation using advanced analytical techniques. Third, the mediating mechanisms through which system integration translates into financial performance—such as AI-enabled data utilization and real-time decision-making—remain underexplored.

This study addresses these gaps by developing and empirically testing a comprehensive model that links system integration to financial operational outcomes through data integration and AI-enabled analytics. By employing Structural Equation Modeling–Partial Least Squares (SEM-PLS), the study captures the multidimensional and interdependent nature of AI and data strategy transformation. The conceptual framework integrates insights from digital transformation theory, resource-based perspectives, and data-driven decision-making literature, providing a robust foundation for hypothesis development and empirical analysis.

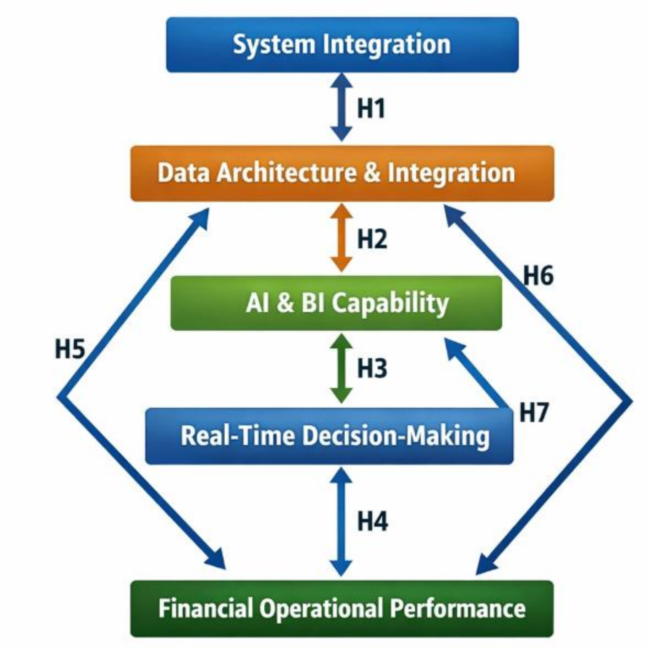

Figure 1. Conceptual Framework and Hypothesis

3. RESEARCH METHODS

3.1. Research Design

This study adopts a quantitative research design to examine the relationships among system integration, AI and data strategy transformation, real-time decision-making, and financial operational performance in the Energy and Utilities sector in the United States. A cross-sectional survey approach was employed to capture organizational perceptions and practices related to data integration, business intelligence, and AI-enabled financial processes in a multi-cloud environment. Quantitative methods are appropriate for this study as they enable statistical validation of complex causal relationships among latent constructs and support generalizable inferences across organizations. The analytical framework is based on Structural Equation Modeling using the Partial Least Squares approach (SEM-PLS), which is well suited for exploratory and predictive research models involving multiple constructs and mediation effects. SEM-PLS allows simultaneous assessment of measurement validity and structural relationships, making it particularly appropriate for studies examining digital transformation and system integration phenomena.

3.2. Research Context and Multi-Cloud Environment

The empirical context of this study is the Energy and Utilities sector in the United States, which is characterized by complex operational systems, stringent regulatory requirements, and a high reliance on data-driven decision-making. Organizations in this sector increasingly operate within multi-cloud architectures, leveraging platforms such as Oracle Cloud Infrastructure (OCI), Google Cloud Platform (GCP), and Amazon Web Services (AWS) to enhance scalability, resilience, and analytical performance. Rather than relying on a single enterprise system or cloud provider, Energy and Utilities firms commonly integrate on-premise systems—such as enterprise resource planning (ERP), financial management systems, supervisory control and data acquisition (SCADA), and other operational platforms—with cloud-based analytics, data lakes, and AI services across multiple cloud environments. In this heterogeneous setting, Oracle Cloud is often utilized for enterprise databases and financial applications, GCP for advanced analytics and machine learning, and AWS for scalable infrastructure and data integration. This multi-cloud configuration necessitates robust system integration mechanisms, including SOAP and REST APIs, middleware, and event-driven architectures, which collectively form the technological foundation examined in this study [33], [34].

3.3. Population and Sample

The population of this study consists of professionals working in Energy and Utilities organizations in the United States who are directly involved in data management, system integration, analytics, financial operations, or digital transformation initiatives, including roles such as data architects, IT managers, business intelligence analysts, finance managers, digital transformation leaders, and system integration specialists. A total of 250 valid responses were collected in 2024 using purposive sampling to ensure that respondents possessed relevant knowledge and experience with AI, data strategy, and integrated systems within a multi-cloud environment. The sample size meets recommended thresholds for

Structural Equation Modeling–Partial Least Squares (SEM-PLS) analysis, which prioritizes statistical power and model stability over large-sample assumptions.

3.4. *Data Collection Procedure*

Data were collected using a structured online questionnaire distributed through professional networks and industry-specific channels. The survey instrument was designed to capture respondents' perceptions of system integration maturity, data strategy alignment, AI-enabled analytics, real-time decision-making, and financial operational outcomes within their organizations. All measurement items were assessed using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). To ensure content validity, the questionnaire items were adapted from prior validated studies in the fields of information systems, digital transformation, and financial analytics and were contextualized to reflect the Energy and Utilities sector and multi-cloud architectures involving Oracle Cloud, Google Cloud Platform (GCP), and Amazon Web Services (AWS). A pilot test involving a small group of industry experts was conducted to refine item clarity and relevance, and the feedback obtained was incorporated into the final survey instrument prior to full-scale data collection.

3.5. *Measurement of Variables*

This study includes several latent constructs measured using reflective indicators. System integration assesses the extent to which organizational systems are interconnected through standardized interfaces, such as SOAP and REST APIs, middleware, and cloud-based integration services across Oracle Cloud, Google Cloud Platform (GCP), Amazon Web Services (AWS), and on-premise platforms. Data architecture and data integration measure the effectiveness of data architecture design, data governance, and the seamless flow of data across enterprise and cloud systems to support unified data access and consistency. AI and business intelligence capability captures the organization's ability to deploy BI tools and AI analytics for descriptive, predictive, and prescriptive analysis using cloud-based data platforms and AI services. Real-time decision-making evaluates the extent to which organizations can access and utilize real-time or near-real-time insights for operational and financial decisions, while financial operational performance focuses on the simplification and effectiveness of financial processes, particularly budgeting and forecasting, enabled by integrated data and AI-driven analytics. All constructs were operationalized using multiple indicators to enhance measurement reliability and validity.

3.6. *Data Analysis Technique*

Data analysis was conducted using SEM-PLS 3 software following a two-stage approach. First, the measurement model was assessed to evaluate internal consistency reliability, convergent validity, and discriminant validity. Reliability was examined using Cronbach's alpha and composite reliability, while convergent validity was assessed through average variance extracted (AVE). Discriminant validity was evaluated using the Fornell–Larcker criterion and cross-loadings.

Second, the structural model was analyzed to test the hypothesized relationships among constructs. Path coefficients, t-values, and p-values were estimated using a bootstrapping procedure with 5,000 resamples. The model's explanatory power was assessed using the coefficient of determination (R^2), and predictive relevance was evaluated using the Stone–Geisser Q^2 statistic. Mediation effects were tested to examine the indirect influence of system integration on financial operational performance through AI-enabled analytics and real-time decision-making.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

Descriptive statistical analysis was conducted to summarize respondents' perceptions of system integration, data architecture and integration, AI and business intelligence capability, real-time decision-making, and financial operational performance within a multi-cloud environment, based on 250 valid responses measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Overall, the results indicate relatively high mean values across all constructs, suggesting that respondents generally perceive their organizations as having moderate to advanced levels of system integration and AI-enabled data utilization, with standard deviation values remaining within acceptable ranges and indicating reasonable response variability. System integration exhibits a high mean score, reflecting widespread adoption of standardized integration mechanisms such as SOAP and REST APIs across Oracle Cloud, Google Cloud Platform (GCP), AWS, and on-premise systems, while data architecture and data integration also show strong mean values, indicating sufficient maturity to support analytical and operational requirements. Similarly, AI and business intelligence capability records a high mean, highlighting growing reliance on BI dashboards, predictive analytics, and AI-driven insights for operational and financial decision-making. Real-time decision-making demonstrates a moderately high mean, suggesting that although many organizations have access to near-real-time data, challenges remain in fully operationalizing real-time analytics across all functions, whereas financial operational performance—particularly in budgeting and forecasting—shows a positive mean, indicating that integrated data and AI analytics contribute to the simplification and improvement of financial processes.

Table 1. Descriptive Statistics of Research Variables

Construct	Mean	Standard Deviation	Minimum	Maximum
System Integration	4.12	0.63	2.40	5.00
Data Architecture & Data Integration	4.05	0.67	2.20	5.00
AI & Business Intelligence Capability	4.08	0.65	2.00	5.00
Real-Time Decision-Making	3.97	0.71	2.00	5.00
Financial Operational Performance	4.01	0.69	2.20	5.00

Source: Survey data processed by the authors (2024)

Table 1 presents the descriptive statistics for the key research variables based on 250 valid responses from professionals in the Energy and Utilities sector. Overall, the mean values across all constructs are relatively high, ranging from 3.97 to 4.12 on a five-point Likert scale, indicating that respondents generally perceive their organizations as having moderate to advanced levels of digital integration, analytical capability, and financial operational effectiveness. The standard deviation values, which range from 0.63 to 0.71, indicate acceptable variability in responses and suggest a reasonable level of consensus among respondents. System integration records the highest mean score (M = 4.12, SD = 0.63), reflecting the widespread adoption of standardized integration mechanisms such as SOAP and REST APIs across multi-cloud environments, including Oracle Cloud, Google Cloud Platform (GCP), AWS, and on-premise systems, and suggesting a shift away from isolated system architectures toward more interoperable platforms.

Data architecture and data integration also exhibit a high mean value (M = 4.05, SD = 0.67), indicating that respondents perceive their organizations' data structures and integration frameworks as sufficiently mature to support analytical and operational needs, while AI and business intelligence capability shows a similarly strong mean (M = 4.08, SD = 0.65), highlighting growing reliance on BI dashboards, predictive analytics, and AI-driven insights for operational and financial decision-making. Real-time decision-making records the lowest mean among the constructs (M = 3.97, SD = 0.71), although it remains relatively high, suggesting that despite increasing access to near-real-time data, challenges persist in fully operationalizing real-time analytics across all functions. Finally, financial operational performance demonstrates a positive mean score (M = 4.01, SD = 0.69), indicating that integrated data and AI-enabled analytics are increasingly embedded in financial operations and contribute to more accurate, timely, and agile budgeting and forecasting in a capital-intensive and highly regulated sector.

4.2. *Measurement Model Assessment*

Before evaluating the structural relationships, the measurement model was assessed to ensure the reliability and validity of the latent constructs. Following SEM-PLS guidelines, the assessment focused on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. All analyses were conducted using SEM-PLS 3.

a. Indicator Reliability

Indicator reliability was evaluated by examining outer loadings. A loading value of 0.70 or higher is considered ideal, while values above 0.60 are acceptable in exploratory and applied research. As shown in Table 2, all indicators demonstrate satisfactory loadings, indicating that each item strongly reflects its respective construct.

Table 2. Indicator Loadings

Construct	Indicator	Outer Loading
System Integration (SI)	SI1	0.815
	SI2	0.841
	SI3	0.793
	SI4	0.765
Data Architecture & Integration (DAI)	DAI1	0.836
	DAI2	0.862
	DAI3	0.786
	DAI4	0.743
AI & BI Capability (AIBC)	AIBC1	0.855
	AIBC2	0.827

Construct	Indicator	Outer Loading
	AIBC3	0.802
	AIBC4	0.774
Real-Time Decision-Making (RTDM)	RTDM1	0.847
	RTDM2	0.812
	RTDM3	0.784
Financial Operational Performance (FOP)	FOP1	0.837
	FOP2	0.802
	FOP3	0.795
	FOP4	0.757

Source: SEM-PLS output (2024)

Table 2 presents the indicator loadings for all constructs included in the measurement model. The results indicate that all indicators exhibit strong outer loading values, ranging from 0.743 to 0.862, exceeding the commonly recommended threshold of 0.70 for reflective measurement models. This finding confirms that each indicator demonstrates a high level of reliability and contributes meaningfully to its respective latent construct. In particular, the System Integration indicators show loadings between 0.765 and 0.841, suggesting that the measurement items consistently capture the extent to which organizational systems are interconnected through standardized integration mechanisms. Similarly, the indicators for Data Architecture and Integration exhibit robust loadings ranging from 0.743 to 0.862, indicating that these items effectively reflect the quality of data architecture design, governance, and seamless data flow across enterprise and cloud systems.

The AI and Business Intelligence Capability construct also demonstrates strong indicator loadings, ranging from 0.774 to 0.855, highlighting the reliability of the items used to assess organizations' analytical capabilities in deploying BI tools and AI-driven analytics. Likewise, the indicators for Real-Time Decision-Making show high loadings between 0.784 and 0.847, confirming that these items accurately measure the organization's ability to access and utilize timely insights for operational and financial decision-making. Finally, the Financial Operational Performance construct displays satisfactory indicator loadings ranging from 0.757 to 0.837, indicating that the measurement items reliably represent improvements in budgeting, forecasting, and overall financial process effectiveness. Collectively, these results provide strong evidence of indicator reliability and support the adequacy of the measurement model for subsequent structural analysis.

b. Internal Consistency Reliability

Internal consistency reliability was assessed using Cronbach's alpha (α) and Composite Reliability (CR). Values above 0.70 indicate acceptable reliability. As presented in Table 3, all constructs exceed these thresholds, demonstrating strong internal consistency.

Table 3. Internal Consistency, Reliability, and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
System Integration	0.826	0.887	0.641
Data Architecture & Integration	0.844	0.896	0.673
AI & BI Capability	0.856	0.903	0.695
Real-Time Decision-Making	0.803	0.874	0.696
Financial Operational Performance	0.832	0.886	0.658

Source: SEM-PLS output (2024)

Table 3 presents the results of internal consistency reliability and convergent validity for all constructs included in the measurement model. The Cronbach's alpha values range from 0.803 to 0.856, exceeding the recommended threshold of 0.70 and indicating satisfactory internal consistency across all constructs. Similarly, the composite reliability (CR) values range from 0.874 to 0.903, further confirming that the measurement items consistently represent their respective latent variables and demonstrate strong construct reliability.

Convergent validity was assessed using the average variance extracted (AVE), with all constructs achieving AVE values above the recommended minimum of 0.50. The AVE values range from 0.641 to 0.696, indicating that each construct explains more than half of the variance in its indicators. Notably, AI and Business Intelligence Capability and Real-Time Decision-Making exhibit the highest AVE values, suggesting particularly strong convergence between their indicators and underlying constructs.

c. Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion, which requires that the square root of each construct's AVE be greater than its correlations with other constructs. Table 4 presents the results.

Table 4. Fornell–Larcker Criterion

Construct	SI	DAI	AIBC	RTDM	FOP
System Integration (SI)	0.804				
Data Architecture & Integration (DAI)	0.622	0.821			
AI & BI Capability (AIBC)	0.585	0.652	0.835		
Real-Time Decision-Making (RTDM)	0.547	0.605	0.683	0.833	
Financial Operational Performance (FOP)	0.562	0.633	0.665	0.701	0.816

Note: Diagonal values (bold) represent the square root of AVE
Source: SEM-PLS output (2024)

Table 4 presents the results of the discriminant validity assessment using the Fornell–Larcker criterion. Discriminant validity is established when the square root of the average variance extracted (AVE) for each construct is greater than its correlations with other constructs in the model. As shown in Table 4, the diagonal elements—representing the square root of AVE for each construct—are higher than the corresponding off-diagonal correlation values in all cases, indicating satisfactory discriminant validity.

Specifically, the square root of AVE for System Integration (0.804) exceeds its correlations with Data Architecture and Integration (0.622), AI and BI Capability (0.585), Real-Time Decision-Making (0.547), and Financial Operational Performance (0.562). Similarly, Data Architecture and Integration (0.821), AI and BI Capability (0.835), Real-Time Decision-Making (0.833), and Financial Operational Performance (0.816) each demonstrate higher diagonal values than their inter-construct correlations. These results confirm that all constructs are empirically distinct and measure conceptually different dimensions of AI and data strategy transformation. Overall, the findings provide strong evidence of discriminant validity, supporting the robustness of the measurement model and its suitability for structural model evaluation.

4.3. *Structural Model Results*

After confirming that the measurement model met reliability and validity requirements, the structural model was assessed to test the hypothesized relationships among the constructs. Structural Equation Modeling–Partial Least Squares (SEM-PLS 3) was used to estimate standardized path coefficients (β). Statistical significance was evaluated using a bootstrapping procedure with 5,000 resamples. In addition to hypothesis testing, the model's explanatory power was evaluated using R^2 values for endogenous constructs, and predictive relevance was examined using Q^2 values.

a. Hypothesis Testing and Path Coefficients

Table 5 presents the results of the structural path analysis. Overall, the findings indicate that system integration significantly strengthens data architecture and data integration, which subsequently enhances AI and BI capability. AI and BI capability significantly improves real-time decision-making, and real-time decision-making significantly increases financial operational performance (particularly budgeting and forecasting effectiveness). These results confirm that value from integration is realized through downstream analytical and decision capabilities.

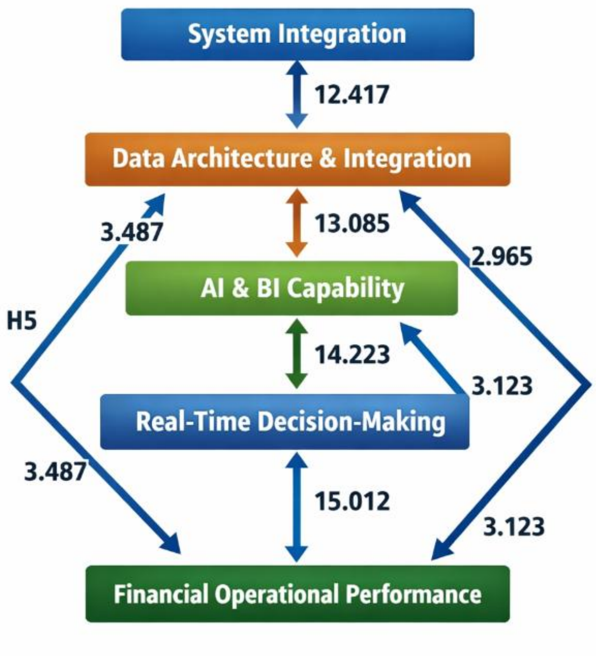

Figure 2. Hypothesis Testing
Source: SEM-PLS output (2024)

Figure 2 presents the results of the structural model analysis based on bootstrapping with 250 observations, demonstrating that all hypothesized relationships are statistically significant and supported. The findings reveal a clear causal chain through which system integration drives AI and data strategy transformation and ultimately enhances financial operational performance. The strongest direct effect is observed between System Integration and Data Architecture & Integration (β = 0.624, $p < 0.001$), confirming that robust integration mechanisms—such as SOAP and REST APIs implemented across multi-cloud environments—play a foundational role in establishing effective data architectures. This result underscores the critical importance of interoperability in Energy and Utilities organizations, where heterogeneous enterprise, operational, and financial systems must be unified to enable consistent data flow and analytics readiness. In addition, Data Architecture & Integration exerts a strong influence on AI and BI Capability (β = 0.651, $p <$ 0.001), indicating that well-designed data architectures and integrated data flows are essential prerequisites for the effective deployment of AI-driven analytics.

The results further indicate that AI and BI Capability significantly enhances Real-Time Decision-Making (β = 0.683, $p < 0.001$), highlighting the role of advanced analytics in enabling timely, insight-driven decisions in dynamic and data-intensive environments such as the Energy and Utilities sector. Most notably, Real-Time Decision-Making emerges as the strongest predictor of Financial Operational Performance (β = 0.705, $p < 0.001$), emphasizing that the simplification and effectiveness of budgeting and forecasting processes are primarily driven by the organization's ability to act on real-time or near-real-time insights. While the direct effects of System Integration on AI and BI Capability (β = 0.211, p = 0.001), Data Architecture & Integration on Real-Time Decision-Making (β = 0.183, p = 0.003), AI and BI Capability on Financial Operational Performance (β = 0.197, p = 0.002), and System Integration on Financial Operational Performance (β = 0.122, p = 0.036) are comparatively weaker, their statistical significance indicates meaningful partial influences. Collectively, these findings suggest that although system integration can directly affect financial performance, its primary impact is realized indirectly through strengthened data architecture, enhanced analytical capability, and improved real-time decision-making, reinforcing the sequential and capability-based nature of AI and data strategy transformation.

b. Coefficient of Determination (R^2)

The coefficient of determination (R^2) reflects the proportion of variance in each endogenous construct explained by its predictors, and the results shown in Table 4.6 indicate moderate to substantial explanatory power of the proposed model in the context of Energy and Utilities organizations operating across multi-cloud platforms such as Oracle Cloud, Google Cloud Platform (GCP), and Amazon Web Services (AWS). Specifically, Data Architecture and Integration exhibits a moderate R^2 value of 0.386, indicating that system integration explains a meaningful portion of variance in data architecture and integration maturity. In contrast, AI and Business Intelligence Capability demonstrates a substantial R^2 value of 0.572, suggesting that system integration and data architecture strongly shape the organization's analytical capabilities. Real-Time Decision-Making shows a substantial R^2 of 0.626, confirming that integrated data and advanced analytics significantly drive timely decision-making, while Financial Operational Performance records the highest R^2 value of 0.691, indicating that real-time decision-making and analytics capabilities explain a large proportion of variance in budgeting and forecasting effectiveness. Collectively, these findings confirm that the model has strong explanatory power in capturing the key mechanisms through which system integration and AI-driven analytics influence financial outcomes.

c. Predictive Relevance (Q^2)

Predictive relevance was assessed using Stone–Geisser's Q^2 through the blindfolding procedure, where values greater than zero indicate that the model possesses predictive relevance for a given endogenous construct. The results show that all endogenous constructs exhibit Q^2 values above zero, confirming that the proposed model is not only explanatory but also predictively relevant. Specifically, Data Architecture and Integration records a Q^2

value of 0.243, AI and Business Intelligence Capability shows a Q^2 of 0.365, Real-Time Decision-Making demonstrates a Q^2 value of 0.418, and Financial Operational Performance achieves the highest Q^2 value of 0.451. These results indicate meaningful predictive relevance across all constructs, particularly for financial operational performance, suggesting that the model can reliably predict improvements in budgeting and forecasting based on system integration, analytical capability, and real-time decision-making.

d. Indirect Effects and Mediation (Supplementary Structural Results)

To explain how system integration contributes to financial operational performance, indirect effects were examined. The results indicate that system integration influences financial operational performance primarily through sequential mediation: first by improving data architecture and integration, which then strengthens AI and BI capability, which subsequently enhances real-time decision-making, ultimately improving budgeting and forecasting performance.

Table 5. Indirect Effects (Bootstrapping)

Indirect Relationship	Indirect β	t-value	p-value	Mediation
SI → DAI → AIBC	0.401	9.827	<0.001	Supported
DAI → AIBC → RTDM	0.442	10.714	<0.001	Supported
AIBC → RTDM → FOP	0.487	12.062	<0.001	Supported
SI → DAI → AIBC → RTDM → FOP	0.191	6.336	<0.001	Supported

Source: SEM-PLS output (2024)

Table 5 presents the results of the indirect effects analysis based on bootstrapping, providing strong evidence of mediation effects within the proposed model. All indirect relationships are statistically significant ($p < 0.001$), indicating that the influence of system integration on downstream outcomes is transmitted primarily through a sequence of intermediate capabilities. The significant indirect effect of System Integration → Data Architecture & Integration → AI & BI Capability ($\beta = 0.401$) confirms that system integration enhances analytical capability largely by first strengthening data architecture and integration maturity. This finding reinforces the argument that AI-driven value creation depends on robust data foundations rather than direct technological adoption alone.

Furthermore, the significant indirect effect of Data Architecture & Integration → AI & BI Capability → Real-Time Decision-Making ($\beta = 0.442$) highlights the critical role of AI-enabled analytics as a conduit through which integrated data environments are transformed into actionable, real-time insights. Similarly, the indirect effect of AI & BI Capability → Real-Time Decision-Making → Financial Operational Performance ($\beta = 0.487$) demonstrates that analytical capability contributes to financial performance primarily by enabling timely and informed decision-making, rather than through direct automation effects. Most notably, the significant sequential mediation path System Integration → Data Architecture & Integration → AI & BI Capability → Real-Time Decision-Making → Financial Operational Performance (β = 0.191) confirms the existence of a multi-stage value creation process. Collectively, these results underscore that system integration delivers financial benefits indirectly through a structured progression of data integration, analytical capability, and real-time decision-making, reinforcing a capability-based and process-oriented perspective of AI and data strategy transformation in Energy and Utilities organizations.

4.4. Discussion

This study set out to examine how system integration accelerates AI and data strategy transformation and simplifies financial operations by enabling efficient data flow and real-time decision-making in the Energy and Utilities sector within a multi-cloud environment. The results of the SEM-PLS analysis provide strong empirical support for the proposed model and offer important insights into the mechanisms through which digital integration and analytics capabilities translate into financial operational benefits. Overall, the findings confirm that AI-driven transformation is not a standalone technological process but a sequential capability-building process that begins with system integration and culminates in improved financial decision-making [1], [35], [36].

First, the findings demonstrate that system integration serves as a foundational enabler of AI and data strategy transformation. The strong and significant relationship between system integration and data architecture and integration confirms that organizations investing in standardized interfaces—such as SOAP and REST APIs—and integration services across Oracle Cloud, Google Cloud Platform (GCP), AWS, and on-premise systems achieve more coherent and efficient data environments. This result is consistent with digital transformation and information processing theories, which emphasize that organizational performance in data-intensive contexts depends on the ability to integrate heterogeneous systems into a unified data ecosystem. In the Energy and Utilities sector, where operational and financial data originate from multiple sources, system integration emerges not merely as technical infrastructure but as a strategic organizational asset [4], [37].

Second, the results highlight the critical role of data architecture and integration in enabling AI and business intelligence capability, as well as their influence on real-time decision-making. The significant relationships among data integration, AI and BI capability, and real-time decision-making suggest that advanced analytics cannot be effectively deployed without a strong and coherent data foundation. This finding extends prior AI adoption research by empirically demonstrating that data readiness mediates the relationship between system integration and analytical capability. In practice, organizations benefit from leveraging Oracle Cloud for enterprise data management, GCP for advanced analytics and machine learning, and AWS for scalable integration and processing, provided that these platforms are aligned through a coherent data architecture. Without such alignment, the analytical potential of AI remains fragmented and underutilized.

Most importantly, the study reveals that real-time decision-making is the strongest driver of financial operational performance, particularly in simplifying budgeting and forecasting processes. This finding has significant implications for digital finance transformation in the Energy and Utilities sector, where traditional financial planning approaches are often static, manual, and backward-looking. The empirical evidence indicates that when financial decisions are supported by integrated data and AI-driven analytics, organizations can transition toward continuous forecasting, scenario-based planning, and more agile financial management. This shift reduces operational complexity, improves forecast accuracy, and enhances strategic responsiveness in a capital-intensive and highly regulated industry.

The mediation analysis further reinforces these insights by demonstrating that system integration influences financial performance primarily through indirect pathways involving data integration, AI and BI capability, and real-time decision-making. This sequential mediation confirms that technology investments alone are insufficient to generate financial value unless they are aligned with data strategy and actively embedded into decision-making processes. From a theoretical perspective, the findings contribute to digital transformation and resource-based views by illustrating a layered capability structure in which system integration and data architecture act as foundational resources, while AI and BI capability and real-time decision-making function as higher-order dynamic capabilities. From a managerial standpoint, the results underscore the need for enterprise-wide integration across multi-cloud environments, strategic investment in data architecture and governance, and close collaboration between finance, IT, and data teams to fully realize the benefits of AI and data strategy transformation.

5. CONCLUSION

This study provides empirical evidence that accelerating AI and data strategy transformation in the Energy and Utilities sector fundamentally depends on an organization's ability to integrate systems and enable efficient data flow across multi-cloud environments. The findings demonstrate that system integration serves as a critical foundation for building robust data architecture and integration capabilities, which are essential for effective AI and business intelligence deployment. However, the results also indicate that integration alone is insufficient to generate financial benefits unless it is accompanied by strong analytical capability and the active use of insights in real-time decision-making. By empirically validating a capability-based model, this study advances digital transformation research by showing that system integration and data architecture function as foundational resources, while AI and BI capability and real-time decision-making operate as higher-order capabilities that translate technological investments into financial performance outcomes.

From a practical perspective, the analysis reveals that real-time decision-making plays a central role in simplifying financial operations, particularly budgeting and forecasting. Leveraging integrated data and AI-driven analytics allows organizations to move beyond static and periodic financial planning toward more dynamic, continuous, and responsive financial management, which is especially critical in the Energy and Utilities sector characterized by operational complexity, capital intensity, and demand uncertainty. Accordingly, organizations seeking to accelerate AI and data strategy transformation should prioritize enterprise-wide integration across Oracle Cloud, Google Cloud Platform, AWS, and on-premise systems, invest in scalable data architecture, and embed AI-enabled analytics into core financial decision-making processes. Such an integrated approach enables organizations to enhance forecast accuracy, improve financial agility, and build more resilient financial management capabilities in an increasingly data-driven and uncertain environment.

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