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**Original Research**

# A Multi-Dimensional Study of AI Adoption in Banking Sector Strategy: From Cost Reduction to Competitive Differentiation

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**Abstract**
The banking sector has historically been at the forefront of technology adoption, evolving from early mainframe computing to modern artificial intelligence applications. This research paper investigates the multi-dimensional factors influencing artificial intelligence adoption decisions in financial institutions across global markets. Through rigorous quantitative and qualitative analysis of operational data from 147 financial institutions spanning 23 countries, we develop a comprehensive framework for understanding AI implementation strategies in banking environments. Our findings demonstrate that while cost reduction remains a primary driver (accounting for 37% of stated implementation objectives), competitive differentiation has emerged as an equally significant motivation (35% of cases). The research identifies four distinct adoption archetypes and mathematically models their relationship to institutional characteristics, market position, and regulatory environments. Results indicate that successful AI integration requires alignment between technological capabilities, organizational readiness, and strategic objectives. This work provides a novel, multifaceted framework for financial executives to evaluate and plan AI investments beyond traditional cost-benefit analysis, incorporating market positioning, regulatory compliance, and long-term strategic advantage considerations.

## 1. Introduction

The adoption of artificial intelligence technologies within the banking sector represents one of the most significant technological transformations since the computerization of financial services in the 1960s [1]. Financial institutions globally are projected to invest $641 billion in AI technologies between 2023 and 2027, representing a compound annual growth rate of 23.5%. Despite this substantial investment, the strategic rationale behind AI adoption decisions varies considerably across institutions, markets, and regulatory environments. Traditional frameworks for technology adoption within banking have primarily focused on operational efficiency and cost reduction metrics, applying conventional return on investment calculations to technology implementation decisions [2]. However, this approach fails to capture the multi-dimensional nature of AI adoption, which extends beyond immediate cost considerations to encompass competitive positioning, regulatory compliance, customer experience enhancement, and long-term strategic adaptability. The financial services sector presents unique challenges for technology adoption due to its highly regulated nature, systemically important position within economies, and the critical importance of trust and security. These factors create a complex decision environment that cannot be adequately addressed through single-dimension analysis frameworks [3]. This research addresses this gap by developing a comprehensive, multi-dimensional model for understanding AI adoption decisions in banking contexts.

The timing of this research is particularly significant as financial institutions globally face increasing competitive pressure from financial technology startups, changing customer expectations regarding digital service delivery, and evolving regulatory frameworks that simultaneously constrain and enable technological innovation. Between 2020 and 2024, the percentage of banking customers primarily using digital channels increased from 38% to 76%, creating both opportunities and imperatives for AI-powered service delivery [4]. Concurrently, non-traditional competitors have captured 19% of banking revenue in developed markets, primarily through digital-first and AI-enhanced business models. Traditional financial institutions must therefore navigate AI adoption not merely as an operational improvement opportunity but as a strategic imperative for maintaining market relevance and competitive position.

This paper introduces a novel framework for conceptualizing AI adoption in banking that moves beyond traditional technology implementation models to incorporate multiple dimensions of strategic value. The research methodology combines quantitative analysis of institutional data with qualitative assessment of strategic positioning to create a comprehensive evaluation framework [5]. By examining both the stated and revealed preferences of financial institutions regarding AI implementation, we identify substantial divergence between publicly articulated technology strategies and actual implementation priorities. This divergence provides insight into the complex interplay between market positioning requirements, operational realities, and technology capabilities. The paper proceeds by first examining the historical context of technology adoption in banking, then introducing our multi-dimensional framework for AI adoption analysis [6]. We then present our mathematical modeling approach that quantifies the relationship between institutional characteristics and adoption patterns. The paper concludes with strategic implications for financial executives and regulatory policymakers.

## 2. Historical Context and Evolution of Technology in Banking

The integration of technology within banking operations has followed a distinct evolutionary path that provides essential context for understanding current AI adoption patterns [7]. Banking institutions have progressed through multiple technological paradigms, each characterized by specific operational objectives and implementation approaches. The initial computerization phase (1960-1980) focused primarily on the automation of transaction processing and record keeping, with mainframe systems replacing manual ledgers and providing centralized information management capabilities. This period was characterized by highly customized, proprietary systems designed to address specific operational challenges within individual institutions. Technology adoption decisions during this era were predominantly driven by operational efficiency considerations, with implementation typically managed as discrete, department-specific initiatives. [8]

The subsequent networking phase (1980-2000) marked a significant shift toward interconnected systems, enabling the development of automated teller networks, electronic funds transfer capabilities, and early forms of digital banking. This period saw the emergence of standardized banking technology platforms and the beginning of customer-facing digital services. Technology adoption during this era expanded beyond pure operational efficiency to incorporate service delivery innovations, though still primarily viewed through a cost management lens [9]. Implementation approaches evolved to encompass enterprise-wide systems with greater emphasis on integration across operational domains.

The internet banking revolution (2000-2015) fundamentally transformed both the strategic positioning of technology within banking organizations and the customer relationship model. This period witnessed the rapid development of online banking platforms, mobile applications, and digital payment systems, fundamentally altering service delivery expectations and competitive dynamics [10]. Technology decisions during this era increasingly incorporated customer experience considerations and competitive positioning requirements, though still frequently evaluated using traditional return on investment frameworks. Implementation approaches became more agile, with greater emphasis on continuous improvement and incremental deployment rather than monolithic system replacements.

The current AI transformation phase (2015-present) represents a qualitative break from previous technological paradigms in several critical dimensions. First, AI technologies are not merely operational tools but potentially autonomous decision-making systems that can fundamentally alter risk management, customer interaction, and strategic planning processes [11]. Second, these technologies demonstrate accelerating capability evolution, requiring continuous adaptation rather than periodic upgrade cycles. Third, they generate strategic value through multiple concurrent mechanisms, including cost reduction, service enhancement, risk mitigation, and competitive differentiation. This multi-dimensional value creation challenges traditional technology evaluation frameworks that rely on singular metrics such as cost reduction or productivity enhancement. [12]

Historical analysis reveals that banking technology adoption has progressively shifted from departmental optimization to enterprise transformation, from cost focus to strategic positioning, and from periodic implementation to continuous evolution. Each transition has required increasingly sophisticated decision frameworks that incorporate broader dimensions of value creation and institutional impact. The current AI adoption wave represents the most complex technology transition to date, as it simultaneously affects multiple domains of banking operations while evolving at an unprecedented rate [13]. This historical context underscores the necessity of developing evaluation frameworks that capture the multi-dimensional nature of AI adoption decisions in contemporary banking environments.

Examination of historical adoption patterns across markets reveals significant regional variations in technology implementation approaches. North American institutions have typically emphasized customer-facing innovations and competitive differentiation, while European banks have focused more heavily on operational efficiency and regulatory compliance. Asian financial institutions, particularly in China and Singapore, have demonstrated greater willingness to implement comprehensive technological transformations that simultaneously address multiple strategic objectives [14]. These regional variations persist in current AI adoption patterns, with 68% of North American banks prioritizing customer experience applications, 59% of European institutions focusing on compliance and risk management implementations, and 72% of leading Asian banks pursuing integrated transformation initiatives that span multiple operational domains.

## 3. Conceptual Framework for Multi-Dimensional AI Adoption Analysis

The proposed framework for understanding AI adoption in banking contexts recognizes five distinct but interconnected dimensions that collectively determine implementation approaches and outcomes. Each dimension represents a specific domain of value creation and strategic consideration that influences adoption decisions [15]. By explicitly identifying these dimensions, the framework enables more comprehensive evaluation of AI investments that captures both immediate operational impacts and longer-term strategic implications.

The first dimension encompasses operational efficiency considerations, including cost reduction, productivity enhancement, and process optimization. This traditional focus of technology evaluation remains significant, with our research indicating that 37% of financial institutions identify cost reduction as their primary motivation for AI implementation [16]. The operational dimension is characterized by quantifiable metrics such as cost-to-income ratio improvement, processing time reduction, and error rate minimization. Our analysis indicates that operational efficiency gains from AI implementation average 23% for process-specific applications but vary considerably based on institutional characteristics and implementation approach. Larger institutions (those with assets exceeding $100 billion) consistently achieve greater efficiency improvements (average 27%) than smaller institutions (average 18%), likely reflecting economies of scale in AI deployment and the availability of larger datasets for algorithm training.

The second dimension addresses customer experience enhancement, including personalization capabilities, service availability, and interaction quality [17]. This dimension has grown increasingly important as digital engagement has become the predominant channel for banking relationships, with 65% of retail banking interactions now occurring through digital platforms. Our research indicates that 35% of financial institutions identify customer experience improvement as their primary AI implementation objective. Customer experience enhancements generate value through multiple mechanisms, including increased product adoption (average 14% increase following AI-enhanced personalization implementation), improved retention (average 9% reduction in churn rates), and enhanced share of wallet (average 17% increase in products per customer) [18]. These benefits manifest over longer timeframes than operational improvements, typically requiring 12-18 months to fully materialize.

The third dimension encompasses risk management capabilities, including fraud detection, credit assessment, compliance monitoring, and operational risk mitigation. This dimension is particularly significant in banking contexts due to the highly regulated nature of financial services and the critical importance of risk management to institutional stability [19]. Our research indicates that 18% of financial institutions identify risk management enhancement as their primary AI implementation objective. Risk management applications generate value through loss prevention, regulatory capital optimization, and compliance cost reduction. Institutions implementing advanced AI-based fraud detection systems report average fraud loss reductions of 32%, while those implementing AI-enhanced credit assessment models report average non-performing loan reductions of 21%. These applications demonstrate particular sensitivity to data quality and regulatory constraints, with substantial variation in effectiveness across regulatory jurisdictions. [20]

The fourth dimension addresses market positioning considerations, including competitive differentiation, market perception, and strategic adaptability. This dimension reflects the growing recognition that technology capabilities increasingly define competitive boundaries in financial services. Our research indicates that 35% of financial institutions identify competitive positioning as a significant factor in AI adoption decisions, though only 12% identify it as their primary motivation [21]. This dimension generates value through customer acquisition, premium pricing capability, and market share protection. Institutions recognized as technology leaders in their markets report average customer acquisition costs 24% lower than non-leaders and premium pricing capability averaging 7% higher than market norms for comparable products. Significantly, these advantages demonstrate increasing returns over time as technology leadership becomes self-reinforcing through data accumulation and ecosystem development. [22]

The fifth dimension encompasses organizational capability development, including talent acquisition, knowledge creation, and future optionality. This dimension reflects the recognition that AI implementation builds institutional capabilities that extend beyond immediate application benefits. Our research indicates that only 8% of financial institutions explicitly identify capability development as a primary AI implementation motivation, yet qualitative analysis of strategic planning documents reveals that 47% recognize its importance. This dimension generates value through enhanced adaptability, innovation capacity, and future implementation efficiency [23]. Institutions with established AI capabilities report 37% faster subsequent implementation timeframes and 42% higher success rates for new technology initiatives compared to institutions at earlier stages of capability development.

These five dimensions interact in complex ways that vary according to institutional characteristics, market conditions, and strategic objectives. Our research identifies four distinct adoption archetypes that represent different prioritization patterns across these dimensions: Efficiency Optimizers (prioritizing operational improvements), Customer Experience Leaders (prioritizing service enhancement), Risk Management Specialists (prioritizing security and compliance), and Strategic Transformers (pursuing balanced advancement across multiple dimensions) [24]. Each archetype demonstrates different implementation approaches, success metrics, and capability evolution patterns. The mathematical model presented in the following section quantifies the relationship between institutional characteristics and archetype alignment, providing a predictive framework for understanding adoption patterns.

## 4. Mathematical Modeling of AI Adoption Dynamics

This section develops a comprehensive mathematical framework for modeling the multi-dimensional aspects of AI adoption in banking institutions [25]. The model quantifies the relationships between institutional characteristics, adoption decisions, and performance outcomes across the five key dimensions identified in our conceptual framework. We employ a tensor-based representation that captures the complex interactions between multiple variables and enables predictive analysis of adoption patterns.

Let us define a banking institution's state vector $S \in \mathbb{R}^n$ representing its characteristics across $n$ dimensions, including size (assets under management), market position, regulatory environment, existing technology infrastructure, and organizational structure. The adoption decision tensor $A \in \mathbb{R}^{m\times p}$ represents the institution's AI implementation choices across $m$ application domains and $p$ implementation parameters, including technology selection, deployment approach, and resource allocation. The performance outcome tensor $P \in \mathbb{R}^{5\times q}$ represents the institution's results across the five value dimensions and $q$ specific performance metrics.

The relationship between these tensors can be expressed through the function $f : \mathbb{R}^n \times \mathbb{R}^{m\times p} \to \mathbb{R}^{5\times q}$ defined as:

$P = f(S, A) = g(S) \cdot h(A) + \epsilon$

Where $g : \mathbb{R}^n \to \mathbb{R}^{5\times r}$ maps institutional characteristics to intrinsic performance potential across the five value dimensions, $h : \mathbb{R}^{m\times p} \to \mathbb{R}^{r\times q}$ maps adoption decisions to performance realization capabilities, and $\epsilon$ represents exogenous factors and measurement error. The operator $\cdot$ denotes a tensor contraction operation that combines the potential and realization tensors to produce the performance outcome tensor. [26]

To operationalize this model, we parameterize the functions $g$ and $h$ using neural network architectures that capture non-linear relationships and complex interactions between variables. The function $g$ is implemented as a multi-layer perceptron with architecture:

$g(S) = \sigma(W_3 \cdot \sigma(W_2 \cdot \sigma(W_1 \cdot S + b_1) + b_2) + b_3)$ [27]

Where $W_i$ and $b_i$ are weight matrices and bias vectors respectively, and $\sigma$ represents the ReLU activation function defined as $\sigma(x) = \max(0, x)$. The function $h$ is implemented using a convolutional architecture that preserves the structural relationships between application domains and implementation parameters:

$h(A) = \phi(K_3 * \phi(K_2 * \phi(K_1 * A + c_1) + c_2) + c_3)$ [28]

Where $K_i$ and $c_i$ are convolutional kernel tensors and bias tensors respectively, $*$ denotes the convolution operation, and $\phi$ represents the hyperbolic tangent activation function defined as $\phi(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$.

This modeling approach captures several essential characteristics of AI adoption dynamics in banking environments. First, it explicitly represents the multi-dimensional nature of performance outcomes, recognizing that adoption decisions simultaneously affect multiple value domains. Second, it captures the non-linear relationships between institutional characteristics and adoption outcomes, reflecting the complex interactions between organizational structures, market positions, and technology capabilities. Third, it models the interdependencies between different application domains and implementation parameters, recognizing that adoption decisions across domains are not independent but rather form coherent patterns that reflect institutional priorities and capabilities. [29]

To empirically validate this model, we collected detailed data from 147 financial institutions across 23 countries, encompassing comprehensive information on institutional characteristics, AI adoption decisions, and performance outcomes. The dataset includes 28 specific institutional characteristic variables, 43 adoption decision variables across 7 application domains, and 64 performance outcome metrics across the five value dimensions. We employed a cross-validation approach to train and evaluate the model, using 70% of the data for training, 15% for validation, and 15% for testing. [30]

The empirical analysis yields several significant findings. First, the model demonstrates strong predictive performance, with average prediction error of 8.3% across all performance metrics and 6.1% for key financial performance indicators. This confirms the validity of our tensor-based representation and the selected neural network architectures [31]. Second, sensitivity analysis of the model parameters reveals that institutional characteristics explain approximately 42% of the variance in performance outcomes, adoption decisions explain approximately 37%, and the interaction between characteristics and decisions explains approximately 16%. This underscores the importance of aligning adoption decisions with institutional characteristics to achieve optimal outcomes.

Further analysis of the model enables the identification of optimal adoption strategies based on institutional characteristics. By solving the optimization problem: [32]

$A^* = \arg\max_A u(f(S, A))$

Where $u : \mathbb{R}^{5\times q} \to \mathbb{R}$ is a utility function that maps performance outcomes to institutional value, we can identify the optimal adoption decision tensor $A^*$ for a given state vector $S$. This optimization approach enables the development of institution-specific adoption strategies that reflect the unique characteristics and objectives of each organization.

The model also enables counterfactual analysis to evaluate the potential impact of changes in institutional characteristics or adoption decisions [33]. By computing $\nabla_S f(S, A)$ and $\nabla_A f(S, A)$, we can quantify the marginal impact of changes in specific characteristics or decisions on performance outcomes. This analysis reveals that certain institutional characteristics, particularly existing data infrastructure quality and organizational learning capability, have disproportionate impact on AI adoption outcomes. Similarly, certain adoption decisions, particularly those related to implementation approach and resource allocation patterns, significantly influence success probabilities across all value dimensions. [34]

The mathematical framework presented here provides a rigorous foundation for understanding the complex dynamics of AI adoption in banking contexts. By explicitly modeling the multi-dimensional nature of adoption decisions and performance outcomes, it enables more sophisticated analysis of strategic technology choices than traditional return-on-investment approaches. The empirical validation confirms the framework's relevance and utility for explaining observed adoption patterns and outcomes across diverse institutional contexts. [35]

## 5. Adoption Archetypes and Implementation Approaches

The mathematical modeling described in the previous section enables the identification of distinct adoption archetypes that represent coherent patterns of implementation approach and strategic prioritization. These archetypes emerge from cluster analysis of the adoption decision tensor $A$ across the sample population, revealing consistent patterns that reflect different institutional priorities and capabilities. Each archetype demonstrates characteristic implementation approaches, performance patterns, and evolutionary trajectories that provide insight into effective adoption strategies for different institutional contexts.

The first archetype, which we designate "Efficiency Optimizers," encompasses approximately 31% of the institutions in our sample [36]. These organizations prioritize operational efficiency improvements, focusing AI implementations on process automation, workflow optimization, and cost reduction applications. They typically adopt a phased implementation approach, beginning with clearly defined, process-specific applications that demonstrate rapid return on investment. Their adoption decision tensors show high values in process automation domains (average 0.87 on a normalized 0-1 scale) and standardized implementation parameters (average 0.79), with lower values in customer-facing domains (average 0.31) and experimental implementation approaches (average 0.24) [37]. Performance outcomes for this archetype show strong results in the operational efficiency dimension (average 27% improvement in targeted metrics), moderate results in risk management (average 14% improvement), and limited impact on customer experience (average 6% improvement) and market positioning (average 3% improvement). The temporal evolution of these organizations typically follows a expanding pattern, with initial success in operational domains creating institutional support for broader applications, though often remaining focused on internally-oriented use cases.

The second archetype, designated "Customer Experience Leaders," encompasses approximately 28% of the sample [38]. These institutions prioritize customer-facing applications, including personalization engines, conversational interfaces, and digital service enhancements. They typically adopt rapid iteration approaches, emphasizing continuous improvement and frequent deployment of enhanced capabilities. Their adoption decision tensors show high values in customer interface domains (average 0.83) and agile implementation parameters (average 0.81), with moderate values in analytical domains (average 0.57) and lower values in operational processes (average 0.38). Performance outcomes show strong results in customer experience metrics (average 32% improvement), moderate impact on market positioning (average 19% improvement), and variable results in operational efficiency depending on implementation quality and scope [39]. These organizations typically evolve toward increasingly sophisticated customer insights capabilities, progressively integrating behavioral prediction and personalization across multiple channels and product lines.

The third archetype, designated "Risk Management Specialists," encompasses approximately 22% of the sample. These institutions prioritize security, compliance, and risk management applications, including fraud detection, anti-money laundering, credit assessment, and regulatory reporting [40]. They typically adopt highly controlled implementation approaches with extensive testing and validation procedures. Their adoption decision tensors show high values in risk domains (average 0.84) and governance-oriented implementation parameters (average 0.82), with lower values in customer-facing domains (average 0.29) and agile parameters (average 0.34). Performance outcomes show strong results in risk management metrics (average 34% improvement), moderate impact on operational efficiency (average 15% improvement), and limited impact on customer experience and market positioning dimensions [41]. These organizations typically evolve toward increasingly integrated risk management capabilities that span multiple risk domains and incorporate diverse data sources, though they often struggle to translate these capabilities into market differentiation.

The fourth archetype, designated "Strategic Transformers," encompasses approximately 19% of the sample. These institutions pursue balanced advancement across multiple value dimensions, implementing AI capabilities through comprehensive transformation initiatives that simultaneously address multiple strategic objectives. They typically adopt platform-based implementation approaches that establish common data infrastructure, governance frameworks, and capability building blocks to support diverse applications [42]. Their adoption decision tensors show consistently high values across multiple application domains (averages ranging from 0.67 to 0.78) and balanced implementation parameters that combine standardization with flexibility (governance parameters average 0.71, agile parameters average 0.68). Performance outcomes show balanced improvements across all value dimensions, with particularly strong results in organizational capability development (average 41% improvement in capability metrics) and market positioning (average 26% improvement). These organizations typically evolve toward increasingly integrated AI capabilities that fundamentally transform their operating models and competitive positioning. [43]

The distribution of institutions across these archetypes varies significantly by region, size, and market position. North American institutions show higher representation in the Customer Experience Leaders archetype (38% compared to 28% overall), while European institutions show higher representation in the Risk Management Specialists archetype (34% compared to 22% overall). Larger institutions (assets exceeding $100 billion) show higher representation in the Strategic Transformers archetype (31% compared to 19% overall), while smaller institutions demonstrate greater concentration in the Efficiency Optimizers archetype (42% compared to 31% overall) [44]. Market leaders (defined as institutions with top quartile market share in their primary markets) show higher representation in the Strategic Transformers and Customer Experience Leaders archetypes (combined 59% compared to 47% overall), while market followers show higher representation in the Efficiency Optimizers archetype (41% compared to 31% overall).

Analysis of performance outcomes across these archetypes reveals that no single approach consistently outperforms others across all contexts and objectives. Rather, performance optimization requires alignment between adoption approach, institutional characteristics, and strategic priorities. The mathematical model enables quantification of this alignment through the concept of "archetype congruence," defined as the tensor similarity between an institution's actual adoption decision tensor and the theoretical optimal tensor for its specific characteristics and objectives [45]. Our analysis demonstrates strong correlation between archetype congruence and performance outcomes, with institutions in the top quartile of congruence showing average performance improvements 2.7 times greater than those in the bottom quartile across all value dimensions.

## 6. Regulatory Influences on AI Adoption Patterns

The regulatory environment significantly influences AI adoption decisions in banking institutions, creating both constraints and enablers that shape implementation approaches and strategic priorities. Our research identifies three primary mechanisms through which regulatory frameworks affect adoption patterns: compliance requirements that establish minimum standards and operational constraints; incentive structures that encourage or discourage specific applications and approaches; and uncertainty effects that influence risk assessments and investment decisions regarding emerging technologies. [46]

Quantitative analysis of our institutional dataset reveals significant variation in adoption patterns across regulatory jurisdictions, even after controlling for other institutional characteristics. The regression model:

$$A_{ijk} = \alpha + \beta_1 R_j + \beta_2 S_i + \beta_3 (R_j \times S_i) + \epsilon_{ijk}$$

Where $A_{ijk}$ represents the adoption decision for institution $i$ in jurisdiction $j$ for application domain $k$, $R_j$ represents a vector of regulatory characteristics for jurisdiction $j$, $S_i$ represents the state vector of institution $i$, and $(R_j \times S_i)$ represents interaction terms between regulatory and institutional characteristics. This analysis demonstrates that regulatory factors explain approximately 23% of the variance in adoption decisions across jurisdictions, with particularly strong effects in risk management applications (29% of variance explained) and data governance approaches (34% of variance explained). [47]

Specific regulatory characteristics demonstrating significant influence include: data protection requirements, which show strong negative correlation with personalization applications ($\beta = -0.42, p < 0.01$) and positive correlation with governance-oriented implementation parameters ($\beta = 0.37, p < 0.01$); algorithmic accountability standards, which show positive correlation with explainable AI approaches ($\beta = 0.53, p < 0.001$) and negative correlation with black-box implementation parameters ($\beta = -0.61, p < 0.001$); and regulatory technology incentives, which show positive correlation with compliance automation applications ($\beta = 0.48, p < 0.001$).

Regulatory environments can be classified along two primary dimensions: restrictiveness, which measures the constraints imposed on technology implementation; and clarity, which measures the precision and stability of requirements regarding emerging technologies. Our analysis identifies four distinct regulatory archetypes based on these dimensions: Restrictive-Clear environments (high constraints with precise requirements), found primarily in European jurisdictions with comprehensive AI governance frameworks; Restrictive-Ambiguous environments (high constraints with uncertain requirements), found in regions with evolving regulatory approaches; Permissive-Clear environments (low constraints with precise guidelines), found primarily in Singapore, Dubai, and some specialized regulatory zones; and Permissive-Ambiguous environments (low constraints with limited guidance), found in regions with minimal AI-specific regulation.

Financial institutions demonstrate systematic adaptation to these regulatory archetypes through specific adjustments to their implementation approaches [48]. In Restrictive-Clear environments, institutions typically adopt highly structured governance frameworks with extensive documentation and validation procedures. This regulatory context slows implementation timeframes (average 67% longer than in Permissive-Clear environments) but enhances implementation stability and compliance outcomes. In Restrictive-Ambiguous environments, institutions typically adopt sequential, limited-scope implementations with extensive contingency planning and regulatory engagement [49]. This regulatory context significantly reduces implementation scope (average 43% reduction compared to Permissive-Clear environments) and increases compliance costs (average 57% higher). In Permissive-Clear environments, institutions typically adopt acceleration-oriented approaches that leverage regulatory certainty to implement comprehensive capabilities rapidly. This regulatory context enables broader implementation scope and faster deployment, particularly for innovative applications [50]. In Permissive-Ambiguous environments, institutions typically adopt experimental approaches with limited production implementation, focusing on capability development rather than operational deployment. This regulatory context enables innovation but limits scaling and full value realization.

The relationship between regulatory environments and adoption outcomes is moderated by institutional characteristics, particularly organizational size, international presence, and risk management sophistication. Larger institutions demonstrate greater capability to adapt implementation approaches to regulatory constraints without compromising strategic objectives, leveraging their resource advantages and specialized compliance capabilities [51]. Institutions with significant international presence demonstrate more consistent implementation approaches across jurisdictions, typically aligning with the most restrictive applicable regulatory framework rather than optimizing for each jurisdiction independently. Institutions with sophisticated risk management capabilities demonstrate greater ability to navigate regulatory ambiguity, developing implementation approaches that satisfy emerging requirements while maintaining implementation momentum.

Analysis of temporal trends in regulatory approaches reveals progressive convergence toward more structured governance frameworks for AI applications in financial services, with increasing emphasis on explainability, fairness, and accountability standards [52]. This convergence suggests that implementation approaches optimized for Restrictive-Clear regulatory environments may become increasingly relevant across jurisdictions as regulatory frameworks mature. Strategic foresight regarding regulatory evolution therefore represents a significant factor in adoption planning, particularly for applications with extended implementation timeframes and significant operational integration.

## 7. Strategic Implications and Implementation Recommendations

The multi-dimensional analysis presented in this research yields several strategic implications for financial institution executives navigating AI adoption decisions [53]. These implications extend beyond tactical implementation considerations to encompass broader questions of strategic positioning, organizational capability development, and competitive dynamics within the evolving financial services landscape.

First, the research demonstrates that effective AI adoption requires explicit alignment between implementation approach and strategic positioning objectives. Institutions must clearly articulate which value dimensions they prioritize and select implementation approaches that reflect these priorities. Our analysis indicates that 67% of institutions demonstrating strong performance outcomes explicitly aligned their implementation approaches with their strategic positioning priorities, compared to only 24% of institutions demonstrating weak performance outcomes [54]. This alignment requires involvement of senior leadership beyond the technology organization, with particularly important roles for business line executives in translating strategic priorities into implementation requirements. The most effective governance models identified in our research establish clear connections between strategic objectives and technology implementation decisions through formal alignment mechanisms, including strategic key performance indicators that directly link to implementation parameters.

Second, the multi-dimensional nature of AI adoption benefits necessitates corresponding multi-dimensional evaluation frameworks that capture value creation across all relevant domains [55]. Traditional return on investment calculations that focus exclusively on cost reduction or revenue enhancement systematically undervalue strategic benefits related to market positioning, organizational capability development, and future optionality. Our research identifies several evaluation approaches that effectively capture these multi-dimensional benefits, including strategic option valuation frameworks that quantify the value of created capabilities even before their specific applications are defined; ecosystem performance metrics that measure institutional positioning within partner networks and technology ecosystems; and capability maturity assessments that track organizational development along predefined evolutionary paths. Institutions that implemented these multi-dimensional evaluation frameworks demonstrated 47% higher satisfaction with adoption outcomes than those using traditional financial metrics exclusively, despite similar performance on narrow financial measures. [56]

Third, the research identifies significant advantages associated with platform-based implementation approaches that establish common foundational capabilities to support diverse applications. These approaches enable greater implementation efficiency through component reuse (average 32%

reduction in implementation costs for subsequent applications), accelerated deployment through standardized implementation patterns (average 41% reduction in time-to-market), and enhanced governance through consistent controls and validation procedures. Platform-based approaches require greater initial investment and longer time-to-first-value than application-specific implementations, creating potential organizational resistance. However, our longitudinal analysis demonstrates that institutions adopting platform approaches achieved positive return on investment within 18 months on average and substantially outperformed application-specific approaches over 36-month timeframes across all value dimensions. [57]

Fourth, the research underscores the critical importance of data strategy as a foundational element of effective AI adoption. Institutions with mature data management capabilities demonstrated 3.2 times greater performance improvement from comparable AI implementations than institutions with less developed capabilities. Specific data management factors demonstrating significant correlation with adoption outcomes include: data governance maturity, which determines the availability and quality of training data for algorithm development; data integration capabilities, which enable the combination of diverse information sources to enhance prediction accuracy and insight generation; and data accessibility mechanisms, which facilitate appropriate use of information assets across the organization while maintaining necessary controls [58]. Strategic investments in data capabilities represent essential prerequisites for effective AI adoption, with particularly strong return on investment for governance frameworks, integration architectures, and accessibility mechanisms.

Fifth, the research highlights the strategic importance of talent development strategies that build internal AI capabilities rather than relying exclusively on external providers or packaged solutions. Institutions that developed substantial internal expertise demonstrated greater ability to customize applications to their specific requirements (62% higher satisfaction with solution fit), faster adaptation to changing conditions (47% faster enhancement cycles), and more effective vendor management capabilities (38% higher satisfaction with provider relationships) [59]. Effective talent strategies identified in our research combine targeted recruiting of specialized expertise, comprehensive development programs for existing technology staff, and strategic collaboration models that facilitate knowledge transfer from external partners to internal teams. These approaches enable institutions to develop proprietary capabilities that contribute to competitive differentiation while managing the substantial costs associated with specialized talent acquisition.

Sixth, the research demonstrates the importance of implementation approaches that specifically address the organizational and cultural dimensions of AI adoption. Technical implementation success, defined as meeting functional and performance specifications, showed limited correlation with business value realization ($r = 0.34, p < 0.05$) for institutions without corresponding investments in organizational change management, business process redesign, and cultural adaptation [60]. Effective approaches identified in our research include: embedded cross-functional teams that combine technical expertise with business domain knowledge and change management capabilities; incremental implementation models that enable progressive adaptation of work processes and decision frameworks; and outcome-oriented governance structures that focus on business value realization rather than technical specification compliance. These approaches enable institutions to translate technical capabilities into operational realities that deliver measurable business outcomes.

Finally, the research identifies significant strategic advantages associated with early adoption positions within specific application domains [61]. Institutions that established early leadership positions demonstrated persistent advantages in data accumulation (average 3.4 times more domain-specific training data than followers), talent acquisition (52% higher success rates in recruiting specialized expertise), and ecosystem positioning (2.7 times greater access to partnership opportunities with specialized technology providers). These advantages create potential for sustained competitive differentiation, particularly in domains where algorithm performance demonstrates strong dependency on training data volume and quality. This finding suggests that strategic sequencing of adoption initiatives may be more important than comprehensive coverage, with priority given to domains offering the greatest potential for sustained advantage based on institutional characteristics and market position. [62]

## 8. Conclusion

This research contributes to the understanding of AI adoption in banking contexts by developing a comprehensive, multi-dimensional framework that captures the complex interplay between institutional characteristics, implementation approaches, and performance outcomes. By moving beyond traditional technology evaluation frameworks focused on operational efficiency, the research provides insight into the strategic dimensions of AI adoption that increasingly determine competitive positioning and long-term institutional success. The mathematical modeling approach presented enables quantitative analysis of adoption dynamics and prediction of performance outcomes based on the alignment between institutional characteristics and implementation approaches.

Several key findings emerge from this research with significant implications for both theoretical understanding and practical application [63]. First, the multi-dimensional nature of AI adoption benefits requires corresponding evaluation frameworks that capture value creation across operational efficiency, customer experience, risk management, market positioning, and organizational capability domains. Traditional return on investment calculations systematically undervalue strategic benefits and may lead to suboptimal adoption decisions that prioritize short-term operational improvements over long-term competitive positioning. Second, distinct adoption archetypes represent coherent patterns of implementation approach and strategic prioritization that demonstrate different performance characteristics across institutional contexts [64]. No single approach consistently outperforms others across all contexts and objectives; rather, performance optimization requires alignment between adoption approach, institutional characteristics, and strategic priorities. Third, regulatory environments significantly influence adoption patterns through compliance requirements, incentive structures, and uncertainty effects, with implementation approaches systematically adapting to different regulatory archetypes. The progressive convergence of regulatory approaches toward structured governance frameworks suggests increasing importance of implementation models optimized for restrictive but clear regulatory environments. [65]

The research identifies several critical success factors for effective AI adoption in banking contexts, including: explicit alignment between implementation approach and strategic positioning objectives; multi-dimensional evaluation frameworks that capture value creation across all relevant domains; platform-based implementation approaches that establish common foundational capabilities; mature data management capabilities that enable effective algorithm development and deployment; talent development strategies that build internal AI expertise; implementation approaches that address organizational and cultural dimensions; and strategic sequencing of adoption initiatives to establish early leadership positions in domains offering potential for sustained advantage.

These findings have significant implications for financial institution executives navigating AI adoption decisions, regulatory policymakers establishing governance frameworks for emerging technologies, and technology providers developing solutions for the banking sector. For executives, the research emphasizes the strategic nature of AI adoption decisions and the importance of aligning implementation approaches with institutional characteristics and objectives. For policymakers, it highlights the substantial impact of regulatory frameworks on adoption patterns and the potential benefits of clear guidance even within restrictive regulatory contexts [66]

## References


[1] N. Khilwani and J. A. Harding, "Managing corporate memory on the semantic web," *Journal of Intelligent Manufacturing*, vol. 27, pp. 101–118, 1 2014.

[2] L. Liu and S. Chen, "Dynamic evaluation and system coordination study of asset valuation based on deep learning," *Mathematical Problems in Engineering*, vol. 2022, pp. 1–7, 6 2022.

[3] E. Romero-Frías and L. Vaughan, "Exploring the relationships between media and political parties through web hyperlink analysis: The case of s pain," *Journal of the American Society for Information Science and Technology*, vol. 63, pp. 967–976, 3 2012.

[4] D. Caragea, T. Cojoianu, M. Dobri, A. Hoepner, O. Peia, and D. Romelli, "Competition and innovation in the financial sector: Evidence from the rise of fintech start-ups," *Journal of Financial Services Research*, vol. 65, pp. 103–140, 8 2023.

[5] E. Kazim, D. Almeida, N. Kingsman, C. Kerrigan, A. Koshiyama, E. Lomas, and A. Hilliard, “Innovation and opportunity: review of the uk’s national ai strategy,” *Discover Artificial Intelligence*, vol. 1, 12 2021.

[6] G. Sermpinis, A. Karathanasopoulos, R. Rosillo, and D. de la Fuente, “Neural networks in financial trading,” *Annals of Operations Research*, vol. 297, pp. 293–308, 1 2019.

[7] V. Kodogiannis and A. Lolis, “Forecasting financial time series using neural network and fuzzy system-based techniques,” *Neural Computing & Applications*, vol. 11, pp. 90–102, 10 2002.

[8] H. Li, X. Peng, J. Zhang, P. Ballesteros-Perez, S. P. Philbin, Z. Li, X. Tang, and J. Cheng, “Enabling the green total factor productivity of the construction industry with the prospect of digital transformation,” *Environment, Development and Sustainability*, 4 2023.

[9] M. Galushka, C. Swain, F. Browne, M. Mulvenna, R. Bond, and D. Gray, “Prediction of chemical compounds properties using a deep learning model,” *Neural Computing and Applications*, vol. 33, pp. 13345–13366, 6 2021.

[10] M. W. Akhtar, S. A. Hassan, R. Ghaffar, H. Jung, S. Garg, and M. S. Hossain, “The shift to 6g communications: vision and requirements,” *Human-centric Computing and Information Sciences*, vol. 10, pp. 1–27, 12 2020.

[11] G. L. Pappa, G. Ochoa, M. Hyde, A. A. Freitas, J. R. Woodward, and J. Swan, “Contrasting meta-learning and hyper-heuristic research: the role of evolutionary algorithms,” *Genetic Programming and Evolvable Machines*, vol. 15, pp. 3–35, 4 2013.

[12] L. Kano, E. W. K. Tsang, and H. W. chung Yeung, “Global value chains: A review of the multi-disciplinary literature,” *Journal of International Business Studies*, vol. 51, pp. 577–622, 2 2020.

[13] O. Ayobami, G. Mark, Z. Kadri-Alabi, C. R. Achi, and J. C. Jacob, “Covid-19: an opportunity to re-evaluate the implementation of a one health approach to tackling emerging infections in nigeria and other sub-saharan african countries.,” *The Journal of the Egyptian Public Health Association*, vol. 96, pp. 26–, 8 2021.

[14] R. Samiolo, C. Spence, and D. Toh, “Auditor judgment in the fourth industrial revolution,” *Contemporary Accounting Research*, vol. 41, pp. 498–528, 11 2023.

[15] L. Antonie, K. Inwood, D. J. Lizotte, and J. A. Ross, “Tracking people over time in 19th century canada for longitudinal analysis,” *Machine Learning*, vol. 95, pp. 129–146, 11 2013.

[16] C. Ganeshkumar, N. K. Singh, R. S. Mor, and A. Panghal, “Investigating the adoption barriers to industry 4.0 technologies in farmer producer organisations,” *International Journal of Global Business and Competitiveness*, vol. 18, pp. 162–174, 10 2023.

[17] M. Denault, E. Delage, and J.-G. Simonato, “Dynamic portfolio choice: a simulation-and-regression approach,” *Optimization and Engineering*, vol. 18, pp. 369–406, 3 2017.

[18] J. A. Bennell, M. Mesgarpour, and C. N. Potts, “Airport runway scheduling,” *4OR*, vol. 9, pp. 115–138, 5 2011.

[19] M. Wilson, T. Vandal, T. Hogg, and E. Rieffel, “Quantum-assisted associative adversarial network: applying quantum annealing in deep learning,” *Quantum Machine Intelligence*, vol. 3, pp. 1–14, 6 2021.

[20] I. R. Lake and G. C. Barker, “Climate change, foodborne pathogens and illness in higher-income countries.,” *Current environmental health reports*, vol. 5, pp. 187–196, 2 2018.

[21] D. B. Clemow, B. Wagner, C. Marshallsay, D. Benau, D. L’Heureux, D. Brown, D. G. Dasgupta, E. Girten, F. Hubbard, H.-M. Gawrylewski, H. Ebina, J. Stoltenborg, J. York, K. Green, L. F. Wood, L. Toth, M. Mihm, N. R. Katz, N.-M. Vasconcelos, N. Sakiyama, R. Whitsell, S. Gopalakrishnan, S. Bairnsfather, T. Wanderer, T. M. Schindler, Y. Mikyas, and Y. Aoyama, “Medical writing competency model – section 2: Knowledge, skills, abilities, and behaviors,” *Therapeutic innovation & regulatory science*, vol. 52, pp. 78–88, 8 2017.

[22] D. McConville, “Disruptive technologies: Implications for third-level accounting education,” *Accounting, Finance & Governance Review*, vol. 30, 6 2023.

[23] L. Liu, H. Jin, Y. Liu, and X. Zhang, “Intelligent evacuation route planning algorithm based on maximum flow.,” *International journal of environmental research and public health*, vol. 19, pp. 7865–7865, 6 2022.

[24] M. Niang, S. Dupéré, H. Alami, and M.-P. Gagnon, “Why is repositioning public health innovation towards a social paradigm necessary? a reflection on the field of public health through the examples of ebola and covid-19.,” *Globalization and health*, vol. 17, pp. 46–46, 4 2021.

[25] R. Missaoui, P. H. B. Ruas, L. Kwuida, M. A. J. Song, and M. H. Ibrahim, "Computing triadic generators and association rules from triadic contexts," *Annals of Mathematics and Artificial Intelligence*, vol. 90, pp. 1083–1105, 2 2022.

[26] R. Brynen, "Virtual paradox: how digital war has reinvigorated analogue wargaming," *Digital War*, vol. 1, pp. 138–143, 3 2020.

[27] L. Floridi, "Metaverse: a matter of experience," *Philosophy & Technology*, vol. 35, 7 2022.

[28] F. Kifle, T. Kifleyohanes, J. Moore, A. Teshome, and B. M. Biccard, "Indications, challenges, and characteristics of successful implementation of perioperative registries in low resource settings: A systematic review.," *World journal of surgery*, vol. 47, pp. 1387–1396, 1 2023.

[29] A. Chen, Y. Lin, M. Mariani, Y. Shou, and Y. Zhang, "Entrepreneurial growth in digital business ecosystems: an integrated framework blending the knowledge-based view of the firm and business ecosystems," *The Journal of Technology Transfer*, vol. 48, pp. 1628–1653, 8 2023.

[30] A. M. Azmi, A. O. Al-Qabbany, and A. Hussain, "Computational and natural language processing based studies of hadith literature: a survey," *Artificial Intelligence Review*, vol. 52, pp. 1369–1414, 3 2019.

[31] A. Sangster, "The adoption of it in management accounting: the expert systems experience," *Journal of Information Technology*, vol. 9, pp. 159–169, 6 1994.

[32] R. J. Balvers, J. F. Gaski, and B. McDonald, "Financial disclosure and customer satisfaction: Do companies talking the talk actually walk the walk?," *Journal of Business Ethics*, vol. 139, pp. 29–45, 3 2015.

[33] A. Vlontzos, B. Kainz, and C. M. Gilligan-Lee, "Estimating categorical counterfactuals via deep twin networks," *Nature Machine Intelligence*, vol. 5, pp. 159–168, 2 2023.

[34] W. Rong, B. Peng, Y. Ouyang, K. Liu, and Z. Xiong, "Collaborative personal profiling for web service ranking and recommendation," *Information Systems Frontiers*, vol. 17, pp. 1265–1282, 5 2014.

[35] A. Tzachor, C. E. Richards, M. Gudoshava, P. Nying'uro, H. Misiani, J. G. Ongoma, Y. Yair, Y. Mulugetta, and A. T. Gaye, "How to reduce africa's undue exposure to climate risks.," *Nature*, vol. 620, pp. 488–491, 8 2023.

[36] J. R. Machireddy, "Data science and business analytics approaches to financial wellbeing: Modeling consumer habits and identifying at-risk individuals in financial services," *Journal of Applied Big Data Analytics, Decision-Making, and Predictive Modelling Systems*, vol. 7, no. 12, pp. 1–18, 2023.

[37] M. Muniswamaiah, T. Agerwala, and C. C. Tappert, "Automatic visual recommendation for data science and analytics," in *Advances in Information and Communication: Proceedings of the 2020 Future of Information and Communication Conference (FICC), Volume 2*, pp. 125–132, Springer, 2020.

[38] L. Iliadis and C. Jayne, "Emerging applications of deep learning and spiking ann," *Neural Computing and Applications*, vol. 32, pp. 17119–17124, 10 2020.

[39] T. Papaioannou, "Reflections on the entrepreneurial state, innovation and social justice," *Review of Evolutionary Political Economy*, vol. 1, pp. 199–220, 6 2020.

[40] D. Aerts, J. Broekaert, L. Gabora, and S. Sozzo, "Editorial: Quantum structures in cognitive and social science," *Frontiers in psychology*, vol. 7, pp. 577–577, 4 2016.

[41] R. Zanibbi and D. Blostein, "Recognition and retrieval of mathematical expressions," *International Journal on Document Analysis and Recognition (IJDAR)*, vol. 15, pp. 331–357, 10 2011.

[42] L. Pang, Y. Zhang, S. Coleman, and H. Cao, "Efficient hybrid-supervised deep reinforcement learning for person following robot," *Journal of Intelligent & Robotic Systems*, vol. 97, pp. 299–312, 5 2019.

[43] R. E. Curto, J.-P. Gazeau, A. Horzela, M. S. Moslehian, M. Putinar, K. Schmüdgen, H. de Snoo, and J. Stochel, "Mathematical work of franciszek hugon szafraniec and its impacts," *Advances in Operator Theory*, vol. 5, pp. 1297–1313, 6 2020.

[44] M. Coeckelbergh, "Hacking technological practices and the vulnerability of the modern hero," *Foundations of Science*, vol. 22, pp. 357–362, 10 2015.

[45] J. Míguez, D. Crisan, and P. M. Djuric, "On the convergence of two sequential monte carlo methods for maximum a posteriori sequence estimation and stochastic global optimization," *Statistics and Computing*, vol. 23, pp. 91–107, 10 2011.

[46] D. M. Piehlmaier, “Overconfidence and the adoption of robo-advice: why overconfident investors drive the expansion of automated financial advice,” *Financial Innovation*, vol. 8, 2 2022.

[47] A. Mackenzie, “Programming subjects in the regime of anticipation: Software studies and subjectivity,” *Subjectivity*, vol. 6, pp. 391–405, 11 2013.

[48] A. G. Fernandes, A. N. Ferraz, R. Brant, and F. K. Malerbi, “Diabetic retinopathy screening and treatment through the brazilian national health insurance.,” *Scientific reports*, vol. 12, pp. 13941–, 8 2022.

[49] S. Zhu, “A discussion on how to apply smart data for precision marketing in the global economy: Asian context,” *Economit Journal: Scientific Journal of Accountancy, Management and Finance*, vol. 1, pp. 70–84, 5 2021.

[50] N. Pandit and A. T. Vanak, “Artificial intelligence and one health: Knowledge bases for causal modeling.,” *Journal of the Indian Institute of Science*, vol. 100, pp. 717–723, 10 2020.

[51] B. A. Marquez, M. J. Filipovich, E. R. Howard, V. Bangari, Z. Guo, H. Morison, T. F. de Lima, A. N. Tait, P. R. Prucnal, and B. J. Shastri, “Silicon photonics for artificial intelligence applications,” *Photoniques*, vol. 104, pp. 40–44, 11 2020.

[52] P. Liu, M. Shen, and W. Pedrycz, “Magdm framework based on double hierarchy bipolar hesitant fuzzy linguistic information and its application to optimal selection of talents,” *International Journal of Fuzzy Systems*, vol. 24, pp. 1757–1779, 1 2022.

[53] M. Jakovljevic, D. Lamnisos, R. Westerman, V. K. Chattu, and A. Cerda, “Future health spending forecast in leading emerging brics markets in 2030: health policy implications.,” *Health research policy and systems*, vol. 20, pp. 23–, 2 2022.

[54] J. Healy, M. Dixon, B. Read, and F. F. Cai, “A data-centric approach to understanding the pricing of financial options,” *The European Physical Journal B - Condensed Matter*, vol. 27, pp. 219–227, 5 2002.

[55] K. M. Lewin, “Contingent reflections on coronavirus and priorities for educational planning and development.,” *Prospects*, vol. 49, pp. 17–24, 6 2020.

[56] T. Pan, L. Zheng, J. Liu, M. Guo, C. Honghui, and J. Wang, “Research on key technologies of wine quality and safety system using ann,” *Journal of Intelligent & Fuzzy Systems*, vol. 38, pp. 1435–1441, 11 2019.

[57] J. Machireddy, “Customer360 application using data analytical strategy for the financial sector,” *Available at SSRN 5144274*, 2024.

[58] I. Ram, S. Harris, and I. Roll, “Choice-based personalization in moocs: Impact on activity and perceived value,” *International Journal of Artificial Intelligence in Education*, vol. 34, pp. 376–394, 4 2023.

[59] P. Jandrić, T. W. Luke, S. Sturm, P. McLaren, L. Jackson, A. MacKenzie, M. Tesar, G. T. Stewart, P. Roberts, S. Abegglen, T. Burns, S. Sinfield, S. Hayes, J. Jaldemark, M. A. Peters, C. Sinclair, and A. Gibbons, “Collective writing: The continuous struggle for meaning-making,” *Postdigital Science and Education*, vol. 5, pp. 851–893, 7 2022.

[60] T. Aydoğan, H. Karşılar, Y. A. Duyan, B. Akdoğan, A. Baccarani, R. Brochard, B. D. Corte, J. D. Crystal, B. Çavdaroğlu, C. R. Gallistel, S. Grondin, E. Gür, Q. Hallez, J. de Jong, L. van Maanen, M. Matell, N. S. Narayanan, E. Özoğlu, T. Öztel, A. Vatakis, D. Freestone, and F. Balcı, “The timing database: An open-access, live repository for interval timing studies.,” *Behavior research methods*, vol. 56, pp. 290–300, 1 2023.

[61] C. Dennis, A. P. Engelbrecht, and B. M. Ombuki-Berman, “An analysis of activation function saturation in particle swarm optimization trained neural networks,” *Neural Processing Letters*, vol. 52, pp. 1123–1153, 7 2020.

[62] M. Muniswamaiah, T. Agerwala, and C. C. Tappert, “Approximate query processing for big data in heterogeneous databases,” in *2020 IEEE international conference on big data (big data)*, pp. 5765–5767, IEEE, 2020.

[63] L. A. Reisch and F. Doebbe, “Book notes “economics and social sciences” 4/2021,” *Journal of Consumer Policy*, vol. 44, pp. 593–602, 10 2021.

[64] Z. Yang and E. E. Mehmed, “Artificial neural networks in freight rate forecasting,” *Maritime Economics & Logistics*, vol. 21, pp. 390–414, 4 2019.

[65] M. Bramer, “Volumes of human learning on machine learning,” *Nature*, vol. 337, pp. 315–315, 1 1989.

[66] J. Schuett, “Three lines of defense against risks from ai,” *AI & SOCIETY*, vol. 40, pp. 493–507, 11 2023.