VOLUME 05 ISSUE 05 Pages: 76-88

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# **Adaptive Governance of Intelligent Financial Systems: Integrating Historical Regulatory Lessons with Machine Intelligence for Robust Financial Stability**

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### ABSTRACT

The rapid integration of artificial intelligence (AI) and machine learning (ML) into financial systems has produced opportunities for efficiency, risk identification, and dynamic decision-making, while simultaneously introducing systemic, operational, and ethical challenges for regulators and institutions. This paper synthesizes lessons from historical banking failures and regulatory reforms with contemporary analyses of AI's role in finance to propose an adaptive governance framework for "intelligent financial systems." Drawing on the legacies of crisis-driven regulatory change, classical inquiries into bank failure, and emerging international guidance on model risk and AI deployment, the study maps the parallels and tensions between past regulatory interventions and present AI-driven disruptions (Acharya et al., 2011; Alston et al., 1994; Benston & Kaufman, 1997). It further collates contemporary institutional and scholarly perspectives on AI in financial services to inform a methodology for multi-policy analysis and model risk management (Bank of England, 2022; BoE-PRA, 2023; Aldasoro et al., 2024; Singh, 2025).

The paper's methodology uses a theory-driven synthesis and comparative regulatory-historical analysis combined with conceptual policy simulation to derive governance principles and operational controls appropriate for banks, central banks, and supervisory authorities. Results emphasize (a) the necessity of layered controls that combine traditional microprudential tools with machine-aware supervisory approaches, (b) the critical role of transparency and explainability in model governance, and (c) the importance of systemic scenario analysis that explicitly models AI-induced feedback loops and

Volume 05 Issue 05-2025

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









concentration risks (Bradford, 1935; Bratton, 2003; Bank of England & FCA, 2024). The discussion unpacks trade-offs between innovation and safety, the limits of rule-based versus principle-based regulation in AI contexts, and the institutional capacity-building required to implement adaptive regulation. Limitations are acknowledged regarding empirical calibration and evolving technological capacity; suggested future work includes empirical validation of the proposed governance taxonomy, development of sector-specific AI stress-testing protocols, and international cooperation mechanisms. The conclusion outlines actionable recommendations for policymakers and institutions to foster resilient, accountable, and innovationfriendly intelligent financial systems anchored in historical insight and modern model-risk practices.

**Keywords:** intelligent financial systems, model risk governance, adaptive regulation, financial stability, machine learning, supervisory frameworks

### Introduction

The global financial system has always evolved in response to technological innovation, economic shocks, and regulatory learning. From structural reforms enacted during the interwar period to the post-crisis legal architecture of the late twentieth and early twenty-first centuries, the interplay between market behavior and regulatory design has repeatedly reshaped how financial institutions operate and how supervisors seek to maintain safety and soundness (Bradford, 1935; Acharya et al., 2011; Benston & Kaufman, 1997). The contemporary inflection point is the pervasive incorporation of artificial intelligence and machine learning into financial decisionmaking, risk management, and service delivery. Al promises enhanced predictive power, process automation, and novel product offerings, but it also introduces new failure modes-algorithmic bias, opaque decisionmaking, automation-induced concentration, and adversarial vulnerabilities—that require

rethinking regulatory tools and supervisory tactics (Bank of England, 2022; Aldasoro et al., 2024; Bank of England & FCA, 2024).

Historical analyses of bank failures and regulatory reforms provide critical context for designing robust governance for AI in finance. Research on why banks failed in earlier eras points to a confluence of weak risk controls, information asymmetries, misaligned incentives, and gaps in supervisory capacity (Alston et al., 1994; Benston & Kaufman, 1997). Similarly, post-crisis evaluations emphasize the role of market failures and regulatory failures that amplify systemic risk in complex financial architectures (Acharya et al., 2011). These canonical findings suggest that the introduction of machine-intelligence into financial systems cannot be treated merely as a technical upgrade: demands fundamental a reassessment of governance principles grounded in historical lessons.

Contemporary institutional responses reflect this recognition. Central banks, supervisory authorities, and international standard-setters

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









have issued guidance and analysis on AI, model risk, and operational resilience—highlighting the need for explainability, robust model validation, and heightened cyber-security posture (Bank of England, 2022; BoE-PRA, 2023; Bank of England & FCA, 2024; Aldasoro et al., 2024). Industry bodies and actuarial associations have also begun to articulate practitioner-focused competencies and ethical considerations for AI use (Actuarial Association of Europe, 2024). At the same time, emerging research explores algorithmic governance, the influence of private industry on AI research directions, and the broader macro-financial implications of automation and generative AI (Ahmed et al., 2023; Aldasoro et al., 2024; Accenture, 2024).

This paper addresses a pressing gap: while regulators and researchers have identified discrete risks and recommended technical safeguards, there remains a need for an governance integrative framework synthesizes historical regulatory insight with modern model-risk principles and multi-policy analysis to guide the regulation of intelligent financial systems. Specifically, the paper asks: How can regulatory design principles learned from past crises be adapted to manage the unique risks posed by AI in finance? What institutional mechanisms and supervisory practices are necessary to mitigate systemlevel threats while preserving legitimate innovation? And how can multi-policy analysis supported by machine learning enhance adaptive regulation without exacerbating the very risks it seeks to control?

answer these questions, To the paper constructs a theoretical and conceptual governance model—Adaptive Governance for Intelligent Financial Systems (AGIFS)—that draws on historical evidence, supervisory guidance, and the latest academic and practicebased analyses. The AGIFS framework emphasizes layered risk controls, continuous model validation. cross-functional transparency, and macroprudential surveillance that explicitly incorporates AIrelated systemic channels. The intent is to provide a publication-ready, theory-rich contribution to policy debate and to offer practitioners actionable governance constructs grounded in extant literature.

#### **METHODOLOGY**

The methodological approach is deliberately theory-driven and integrative, combining historical-comparative analysis. literature synthesis, and conceptual policy modeling to generate governance prescriptions. Empirical data collection was intentionally limited to the literature provided by the commissioning author; thus, the study relies on careful exegesis of canonical regulatory histories, supervisory statements, working papers, and contemporary analyses. The methods used are outlined below.

Historical-Comparative Analysis: The study systematically reviews historical literature on bank failures and regulatory reforms to extract

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









enduring causal mechanisms and institutional responses. Key sources include analyses of bank failures in the 1920s, legislative reforms culminating in the Banking Act of 1935, and retrospective evaluations of regulatory performance (Alston et al., 1994; Bradford, 1935; Benston & Kaufman, 1997). The historical-comparative method treats these episodes not as exact analogues but as archetypes—illuminating instructive governance failures (information asymmetry, inadequate risk measurement) that are relevant to AI-era risks.

Regulatory Guidance Synthesis: Contemporary supervisory documents and institutional reports were analyzed to identify present-day supervisory priorities and emerging best practices for AI and model risk. These include Bank of England discussion papers, BoE-PRA supervisory statements on model management, BIS working papers on intelligent financial systems, and joint Bank of England and FCA reports on AI in UK financial services (Bank of England, 2022; BoE-PRA, 2023; Aldasoro et al., 2024; Bank of England & FCA, 2024). This synthesis identifies cross-cutting themes: explainability, governance, model validation, cyber resilience, and supervisory capability.

Conceptual Multi-Policy Modeling: Building on Singh (2025) and contemporary BIS analyses, the study develops a conceptual model of multipolicy analysis that treats AI systems as components of a complex socio-technical financial ecosystem. Multi-policy analysis here is not an empirical simulation but a structured conceptual exercise that maps how different policy levers—microprudential supervision, macroprudential policy, conduct regulation, and operational resilience standards—interact in the presence of AI-induced feedback effects. This approach leverages theoretical arguments about feedback loops, concentration risk, and procyclicality drawn from the literature (Acharya et al., 2011; Aldasoro et al., 2024).

Policy Taxonomy Development: Using findings from the historical and supervisory syntheses, the paper constructs a taxonomy of governance instruments tailored to intelligent financial systems. Each instrument is described in terms of its objective, mechanism, implementation prerequisites, and trade-offs. This taxonomy serves as the core of the AGIFS framework.

Analytical Rationale and Triangulation: While the study does not include primary empirical testing, it triangulates insights across historical records, supervisory guidance, and contemporary scholarship to strengthen the plausibility of the governance recommendations. Every major claim in the paper is anchored to specific references to ensure fidelity to the source material and to permit readers to trace the evidentiary basis of the arguments.

Ethical and Institutional Constraints: The methodology recognizes normative and institutional constraints on regulatory action, including legal limits, industry capacity, and the global coordination challenges inherent in

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









cross-border financial activities (Bratton, 2003; Benston & Kaufman, 1997). These constraints inform the discussion of feasibility and implementation.

Limitations of Methodology: The chosen methods prioritize depth of conceptual integration over empirical generalizability. The absence of novel quantitative data or simulation outputs is mitigated by a comprehensive literature base, but the framework requires future empirical validation and operational pilot testing by supervisory authorities and institutions.

#### **RESULTS**

The study's principal output is the Adaptive Governance for Intelligent Financial Systems (AGIFS) framework and its supporting taxonomy. Results are presented as descriptive findings, synthesizing historical lessons with contemporary regulatory guidance and multipolicy conceptual mapping.

1. Core Principles for AI-Aware Financial Governance

From the historical and supervisory literature, the paper extracts six core governance principles applicable to intelligent financial systems: a. Layered Controls and Redundancy. Historical episodes reveal that single-point failures—often due to overreliance on narrow risk metrics or unvalidated models—magnify systemic fragility (Alston et al., 1994; Acharya et al., 2011). For AI, this implies the need for redundancy: parallel risk measures, fallback manual controls. and cross-checking mechanisms that validate algorithmic outputs against independent indicators (BoE-PRA, 2023; Aldasoro et al., 2024).

b. Transparency and Explainability. The opacity of decision-making was a recurrent problem in past crises when stakeholders could not interpret underlying drivers of fragility (Benston & Kaufman, 1997). For ML models, explainability is essential for internal governance and supervisory oversight: regulators now emphasize model documentation, lineage, and interpretable outputs (Bank of England, 2022; Bank of England & FCA, 2024).

c.Dynamic Supervision and Continuous Validation. Past regulatory lapses often stemmed from static supervisory rules that failed to adapt to evolving practices (Bradford, 1935; Acharya et al., 2011). Al systems require ongoing validation across their lifecycle, with continuous monitoring for performance degradation, drift, and emergent biases (BoE-PRA, 2023; Actuarial Association of Europe, 2024).

d. Systemic Awareness and Macroprudential Integration. Historical regulatory reforms after crises foregrounded the importance of systemic surveillance. Al's potential to create correlated exposures across institutions (e.g., through common model suppliers or shared data) necessitates macroprudential lenses that track concentration and common-mode failure risks (Acharya et al., 2011; Aldasoro et al., 2024).

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









- e. Accountability and Incentive Alignment. Regulatory failures have often been magnified by misaligned incentives within firms (Bratton, 2003). AI governance requires explicit accountability structures—clear ownership of models, performance-linked incentives that penalize risky automation, and effective oversight of third-party providers (Bank of England & FCA, 2024; Accenture, 2024).
- Cyber-Operational Resilience. The digitization of finance increases cyber-attack surfaces: the literature highlights intersection between model risk and cyber risk, particularly for generative AI and systems that depend on large datasets or model-serving infrastructure (Aldasoro et al., 2024; Aldasoro et al., 2024 BIS Papers).

### 2. Taxonomy of Governance Instruments

Based on the above principles, the AGIFS taxonomy categorizes governance instruments into five broad domains: Institutional Model Lifecycle Governance. Controls. Supervisory Practices, Macroprudential Tools, and Legal/Conduct Measures. Each domain is described below with illustrative instruments and operational considerations.

Institutional Governance: Instruments include risk committees, model board-level AI ownership registries, and cross-functional review bodies that include compliance, risk, IT, and business units. The historical record underscores the need for governance structures that can exert real authority within firms (Benston & Kaufman, 1997; Bragg, 2006).

Contemporary supervisory documents emphasize clear responsibilities and escalation protocols (BoE-PRA, 2023).

Model Lifecycle Controls: These encompass standards model development (data provenance, training documentation), independent validation, performance monitoring, and retirement policies. The BoE-PRA supervisory statement provides guidance on model risk management that aligns closely with these lifecycle controls (BoE-PRA, 2023). The actuarial profession emphasizes competency and record-keeping standards for models used in pricing and reserving (Actuarial Association of Europe, 2024).

Supervisory Practices: Practical supervisory instruments include enhanced model audits, deployment of supervisory machine-learning toolkits, requirement for model inventories and lineage reporting, and thematic reviews of AI use cases that pose high systemic risk. The Bank of England and FCA's joint report highlights the need for supervisors to upgrade capabilities to assess complex models and to coordinate crossborder supervision (Bank of England & FCA, 2024).

Macroprudential Tools: These are designed to address systemic effects from AI adoption capital buffers for AI-related operational risk exposures, concentration limits for critical third-party providers, and stress testing that integrates algorithmic failure scenarios. Acharya et al. (2011) emphasize that regulatory interventions must consider systemic channels;

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









BIS and Bank of England analyses similarly call for macro-level surveillance of AI-induced concentration risks (Aldasoro et al., 2024; Bank of England, 2022).

Legal/Conduct Measures: Instruments include transparency obligations for consumers (explainability in retail decisions), constraints on opaque automated decision-making in highstakes contexts, and obligations around thirdparty vendor management. The literature on Sarbanes-Oxley-era reforms and conduct regulation provides historical precedent for such legal measures (Bratton, 2003; Bragg, 2006).

#### 3. Multi-Policy Interaction Mapping

The conceptual multi-policy modeling reveals several non-linear interactions among policy levers. For instance. a stringent microprudential regime that imposes heavy documentation and validation requirements could, if poorly designed, create compliance bottlenecks that push institutions toward outsourced model solutions, increasing concentration risk—a classic regulationinduced unintended consequence historically observed in other domains (Benston & Kaufman, 1997; Acharya et al., 2011). Conversely, well-calibrated macroprudential measures, by addressing systemic channels (e.g., common provider risk), can complement microprudential controls to prevent correlated failures.

Short-Term 4.Operational Priorities and Actions

Synthesizing supervisory guidance and historical lessons yields operational priorities for immediate action by institutions and supervisors:

- Inventory and classification of AI models by systemic importance and potential consumer harm (BoE-PRA, 2023; Bank of England & FCA, 2024).
- Implementation of rigorous model validation frameworks and independent validation units (BoE-PRA, 2023).
- Development of explainability protocols and documentation standards to enable supervisory review (Bank of England, 2022; Actuarial Association of Europe, 2024).
- Strengthening third-party risk management and contractual terms with model vendors to ensure audit rights and continuity planning (Aldasoro et al., 2024).
- Adoption of scenario-based macroprudential stress testing that includes AI failure modes and common model drift scenarios (Aldasoro et al., 2024; Acharya et al., 2011).
- 5. Anticipated Trade-offs and **Systemic** Considerations

The framework highlights trade-offs inherent choices. governance For example, transparency requirements improve interpretability but can expose proprietary model details and create intellectual property tensions (Bratton, 2003; Bank of England & FCA, 2024). Similarly, rigorous validation

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









processes may raise operational costs and slow innovation, potentially disadvantaging smaller firms with fewer compliance resources. Historical regulatory experience suggests that cost burdens concentrated in specific industry segments can reshape market structure in ways that have long-term systemic implications (Benston & Kaufman, 1997; Bradford, 1935).

#### DISCUSSION

The AGIFS framework and taxonomy illuminate how a synthesis of historical regulatory learning and contemporary supervisory guidance can inform robust governance of AI in finance. This discussion delves into interpretive nuances, explores counter-arguments, and outlines the implications for regulators, financial institutions, and other stakeholders.

### 1. Interpretation of Historical Lessons in an AI Context

Historical episodes of regulatory failure whether from the interwar period or more recent banking crises—are often invoked as cautionary tales emphasizing the perils of lax oversight, opaque risk practices, and regulatory capture (Bradford, 1935; Acharya et al., 2011; Bratton, 2003). In the AI context, these lessons translate into an appreciation that novel technologies can magnify pre-existing governance weaknesses. For example, if a banking sector already exhibits weak vendor oversight or insufficient IT controls. introducing AI models without structural reforms will likely exacerbate systemic fragility (Benston & Kaufman, 1997). Equally, the historical record underscores the value of structural changes—legally enforcing duties, improving disclosure regimes, and building supervisory capacity—that must be adapted rather than merely transplanted to the AI era.

Counter-argument and nuance: Some commentators argue that technological progress reduces the need for intrusive regulation because automated systems can be more precise and objective than human judgment (Anson, 2001; Accenture, 2024). While automation can reduce certain human errors, relying solely on that premise ignores algorithmic bias, data quality issues, and adversarial manipulations. Historical evidence shows that technological solutions without governance often create novel failure modes (Bratton, 2003). Therefore, the advocates for principled augmentation of governance—embracing helpful automation while safeguarding against machine-specific risks.

#### 2. Rule-Based versus Principle-Based Regulation

The literature on regulatory design includes debates around rule-based (bright-line rules) principle-based (outcomes-oriented) regimes (Bragg, 2006; Bratton, 2003). AI raises the stakes of this debate. Rule-based standards mandatory documentation formats, prescribed validation tests) can create clarity and parity, but they risk being rapidly outpaced by evolving ML techniques. Conversely, principle-based approaches (e.g., requirements

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









for demonstrable explainability and risk mitigation) can adapt to innovation but may create supervisory discretion challenges and uneven compliance.

The AGIFS framework recommends a hybrid minimum approach: employ rule-like standards for baseline governance (model independent validation, loss inventories. reporting) while using principle-based expectations for higher-order objectives (transparency, fairness, systemic resilience). This combination reflects both historical regulatory success in setting statutory minima and supervisory guidance that emphasizes principles (BoE-PRA, 2023; Bank of England & FCA, 2024). The hybrid approach mitigates the risk of over-prescription while ensuring a minimum governance floor.

3. Supervisory Capability and Knowledge Gaps

One persistent theme across the literature is the gap between industry innovation and supervisory capability (Aldasoro et al., 2024; Bank of England, 2022). Building effective governance requires supervisors to develop technical skills to assess model integrity, understand data provenance, and evaluate operational resilience. Historical reforms highlight the consequences when supervisory institutions lag behind market innovation they become reactive rather than prophylactic (Acharya et al., 2011).

Operationalizing supervision requires investment in supervisory toolkits (including supervisory models). disciplinary staffing (data scientists embedded in supervision teams), and international coordination mechanisms to handle crossborder models and third-party providers (Bank of England & FCA, 2024; Aldasoro et al., 2024). Capacity building should also involve publicprivate exchanges where supervisors can obtain sanitized model artifacts or run controlled experiments to gain first-hand understanding.

4. Macroprudential Dimensions and Systemic Risk

The AGIFS taxonomy stresses macroprudential integration because AI can magnify correlated exposures. For instance, the adoption of a market-dominant scoring model across multiple financial institutions could create procyclical credit allocation patterns that amplify shocks (Acharya et al., 2011; Aldasoro et al., 2024). Additionally, common suppliers for training data or model infrastructure increase the risk of cascade failures in the event of outages or coordinated attacks.

Macroprudential tools must therefore account for AI-specific channels: concentration metrics for model suppliers. cross-institutional dependency mapping, and scenario-based stress tests that include model failure and adversarial manipulation. The historical record indicates that systemic reforms are often most effective when they are anticipatory and

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









structural rather than purely corrective; embedding macroprudential safeguards in AI governance is consistent with that lesson (Benston & Kaufman, 1997).

#### 5. Practical Trade-offs: Innovation. Competition, and Costs

Regulation inevitably influences innovation and competition. Overly burdensome rules can raise costs and stifle small entrants, potentially reducing competition. Conversely, regulation can allow dominant incumbents to exploit AI advantages to entrench market analyses show power. Historical regulatory design affects industry structure: for example. post-crisis reforms sometimes unintentionally advantaged larger firms that could absorb compliance costs (Benston & Kaufman, 1997).

Policymakers should therefore consider proportionality: calibration of requirements based on systemic importance, activity risk, and consumer impact. For smaller firms, regulatory sandboxes, shared validation resources, or standardized model-testing platforms might lower barriers without compromising safety (Bank of England, 2022; Bank of England & FCA, 2024). International coordination on baseline standards can prevent regulatory arbitrage and help level the playing field globally.

#### 6. Third-Party Risk and Contractual Architecture

The tendency to outsource complex AI development to specialized vendors raises contractual and operational considerations. Contracts must ensure auditability. lineage, and continuity planning while balancing intellectual property concerns (Aldasoro et al., 2024). Historical lessons on vendor oversight and operational resilience such as continuity planning mandates from prior regulatory frameworks—remain relevant and should be extended to AI suppliers (Benston & Kaufman, 1997; Bragg, 2006).

### 7. Ethical and Social Considerations

Beyond safety and stability, AI governance touches ethical concerns: fairness in credit decisions, privacy in data use, and the social impact of automation. Regulators must therefore coordinate with consumer protection agencies and privacy authorities to ensure that Al deployment respects broader societal norms (Actuarial Association of Europe, 2024; Bank of England & FCA, 2024). The AGIFS framework includes conduct-oriented instruments to address these dimensions—disclosure obligations, algorithmic fairness audits, and redress mechanisms for consumers affected by automated decisions.

#### 8. Limitations of the Framework

Several limitations warrant acknowledgement. First, the framework is conceptual and requires empirical testing and pilot studies. The absence of primary data constrains precise calibration of policy instruments (e.g., the magnitude of capital buffers for AI-related operational risk). Second, technological evolution may introduce failure modes not anticipated by current

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









literature; governance design must therefore cross-jurisdictional be iterative. Third. complexities—different legal systems, data protection supervisory regimes, and capacities—complicate international harmonization.

#### 9. Future Research Directions

The paper identifies several promising avenues for future research: empirical measurement of Al concentration risks in financial services: development of standardized explainability metrics applicable across models; pilot studies of supervisory ML toolkits; and experimental stress tests that incorporate adversarial attacks on financial models. Additionally, research into incentive structures that align developer and institutional objectives with social welfare would complement governance design.

#### CONCLUSION

The integration of AI and machine learning into financial systems presents both transformative potential and systemic risk. Historical experience with banking failures and regulatory responses offers vital lessons: governance must be layered, transparent, adaptive, and attentive to systemic channels. Contemporary supervisory guidance converges on similar priorities—model risk management, continuous validation, and enhanced supervisory capability—yet the scale and specificities of AI demand an integrative governance approach.

This paper proposes the Adaptive Governance for Intelligent Financial Systems (AGIFS) framework, which synthesizes historical lessons, supervisory guidance, and multi-policy analysis into a taxonomy of governance instruments tailored to AI-era risks. AGIFS emphasizes hybrid regulatory approaches that combine rule-based minimums with principlebased objectives, macroprudential integration, robust institutional governance, and capacity building for supervisors. Operational recommendations include model inventories, independent validation units, scenario stress testing for AI failure modes, strengthened third-party oversight, and proportionate regulatory measures that balance innovation with stability.

Implementation of AGIFS requires coordinated action: firms must upgrade internal governance and validation practices; supervisors must invest in technical capabilities and crossborder cooperation; and policymakers must legal frameworks enforce craft that accountability while preserving innovation. The approach also requires iteration—regular revisitation of standards as technology and market practices evolve.

Ultimately, safeguarding financial stability and protecting consumers in an era of intelligent financial systems will hinge on our ability to learn from the past, rigorously govern models in the present, and design adaptive, forwardlooking institutions for the future. The governance choices made today will determine

VOLUME 05 ISSUE 05 Pages: 76-88

OCLC - 1368736135









whether AI amplifies resilience or accelerates fragility in the global financial system.

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Volume 05 Issue 05-2025

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