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a Magyar Tudomány Ünnepe alkalmából
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Sopron, 2025. november 6.
6 November 2025, Sopron

FEJLŐDÉSI PÁLYÁK ÉS ÚJ TÖRÉSVONALAK A FENNTARTHATÓSÁGI ÁTMENET IDŐSZAKÁBAN

DEVELOPMENT TRAJECTORIES AND NEW DIVIDES IN TIMES OF SUSTAINABILITY TRANSITIONS

Szerkesztők / Editors:
RESPERGER Richárd, SZÉLES Zsuzsanna, TÓTH Balázs István

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Regulatory AI as Catalyst: Framework for Sustainable Financial Transformation

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Abstract:
The growing dynamics of regulatory change in the financial sector demands adaptive and future-proof internal processes to safeguard banks against process and compliance risks. This paper presents a modular, conceptual Regulatory AI framework that acts as a catalyst to strengthen corporate governance and improve the resilience in digital financial transformation. Leveraging Natural Language Processing (NLP), Machine Learning (ML), and generative AI (GenAI), the framework screens regulatory sources in real-time, identifies relevant changes based on their impact on internal workflows (e.g., risk management, reporting, and compliance) and seamlessly integrates them into existing systems. It consists of four core components: Data Ingestion, Screening and Analysis, Process Integration, and Continuous Monitoring. By embedding principles of sustainable finance and responsible AI governance, the framework not only enhances regulatory responsiveness but also supports the alignment of financial institutions with long-term ESG objectives. Its implementation of the framework can reduce manual efforts and enhances process resilience. The approach promotes proactive adaptations regarding regulations such as the EBA (European Banking Authority) Guidelines or MaRisk (Minimum Requirements for Risk Management). Drawing on empirical implications from current developments, the framework provides a strategic foundation to link digital transformation with long-term operability.

Keywords: Regulatory AI, sustainable financial transformation, Machine Learning, Compliance-Screening, Process Resilience
JEL Codes: G28, O33, C55, D83, K23, M48

1. Introduction

The growing dynamics of regulatory change in the financial sector demand adaptive and future-proof internal processes to safeguard banks against process and compliance risks. Compliance-driven investments in technology, commonly referred to as RegTech, are growing rapidly as financial institutions respond to heightened regulatory challenges (Bakhos Douaihy & Rowe,

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2023; Charoenwong et al., 2024). Banks, particularly those in developing countries, struggle to maintain their reputations while facing escalating regulatory requirements (Bakhos Douaihy & Rowe, 2023). The need to adopt a holistic approach to risk assessment that combines financial and non-financial information, including Environmental, Social, and Governance (ESG) performance, has become increasingly apparent (Palmieri et al., 2024).

Digitalization offers significant opportunities as well as substantial challenges for risk management within commercial banks (Wang et al., 2024). Digital transformation extends beyond technological upgrades to encompass a complete reshaping of business concepts, organizational structures, and business processes. Research demonstrates that digitalization significantly curtails risk-taking on the balance sheet while concurrently escalating off-balance-sheet risk exposure (Wang et al., 2024). Using an InstructGPT-inspired deep learning model to develop a multidimensional bank digitalization index, empirical evidence has been provided of digitalization's dual effects on banking risk profiles (Wang et al., 2024). This finding underscores the complexity of managing digital transformation in financial institutions while maintaining robust risk management frameworks.

The integration of ESG criteria into banking operations represents a critical dimension of contemporary financial governance. An exploration of the joint effect of bank business models and their ESG pillar performance on banks' risk profiles, analyzing 639 European Union banks between 2013 and 2022, suggests that wholesale and retail banks could mitigate default risk by enhancing their environmental pillar performance (Palmieri et al., 2024). The study offers practical implications for banking supervisory authorities and practitioners, encouraging the adoption of diversified ESG investment strategies according to bank-specific business models (Palmieri et al., 2024). This demonstrates the increasing importance of integrating sustainability considerations into regulatory compliance frameworks.

In response to these multifaceted challenges, artificial intelligence (AI) technologies have experienced exponential growth, coupled with advanced algorithms and increased computational capacity, facilitating their widespread adoption across various industries including financial services (Issa et al., 2023). Natural language processing (NLP) and text mining techniques are being deployed to analyze regulatory communications and automate compliance processes. Text mining techniques have been employed to examine confidential letters sent from the Bank of England's Prudential Regulation Authority to supervised financial institutions, finding that letters to high-impact firms use more evaluative, judgment-based language and adopt a more forward-looking perspective (Bholat & Brookes, 2020). The analysis provides evidence that prudential regulatory authority letters differ significantly in their degree of forward-looking language and directiveness, reflecting the shift in supervisory approach following the 2007-2009 financial crisis (Bholat & Brookes, 2020).

Companies face pressure to streamline and automate regulatory compliance through digital workflows and specialized IT-based assistance systems (Thimm, 2023). An extensive conceptual data model has been developed that serves as a foundation for tailoring a generic method to perform relevance assessments of environmental regulatory announcements, considering site-specific individual environmental compliance facts. The proposed method uses heuristic data operations and various text processing techniques from the field of natural language understanding (Thimm, 2023). This approach demonstrates how NLP-based scoring methods can assess the relevance of regulatory announcements and support automated compliance monitoring.

RegTech adoption for Anti-Money Laundering and Combating the Financing of Terrorism (AML/CFT) is notably employed for efficient screening of clients and monitoring of their transactions (Bakhos Douaihy & Rowe, 2023). However, RegTech presents several additional challenges that must be overcome for effective compliance, including finding the right vendors and ensuring data quality (Bakhos Douaihy & Rowe, 2023). The adoption of RegTech is mainly driven by coercive pressures, whereas the choice of RegTech solutions is highly dependent on mimetic and normative forces and occurs at a later stage (Bakhos Douaihy & Rowe, 2023).

This finding highlights the complex institutional dynamics that shape RegTech implementation in banking organizations.

Research on AI micro-decisions in FinTech firms reveals that three main themes - ambidexterity, data sovereignty, and model explainability - emerge as underpinnings for effective AI micro decision-making (Issa et al., 2023). These findings, derived from interviews and surveys conducted with FinTech firms across Europe, emphasize the importance of governance frameworks that balance innovation with accountability and transparency (Issa et al., 2023).

Despite the promising capabilities of AI-driven compliance technologies, significant integration challenges persist. It has been found that RegTech expenditures lead to increased IT budgets and reduced profits, especially at small firms, while acquisition activity and market concentration increase (Charoenwong et al., 2024). These expenditures enable complementary investments that are leveraged for non-compliance purposes, leading to modest savings from avoided customer complaints and misconduct (Charoenwong et al., 2024). This empirical evidence suggests that the relationship between RegTech investment and compliance outcomes is more nuanced than commonly assumed, with potential unintended consequences for market structure and firm profitability.

Research Question and Objectives

To address the identified research problem, this study is guided by the following main research question (MRQ) and three complementary research questions (RQ).

MRQ: What conceptual requirements must an AI-supported framework fulfill to assist banks in adaptively managing regulatory changes while simultaneously strengthening corporate governance and process resilience in digital financial transformation?

RQ1: What impacts do regulatory changes have on the compliance, risk management, and reporting processes of banks?

RQ2: What organizational approaches and processes do banks employ to identify, interpret, and implement regulatory changes, and what limitations do these approaches exhibit?

RQ3: What potential do AI technologies (NLP, Machine Learning, generative AI) offer for automating and optimizing regulatory management to strengthen corporate governance and process resilience?

The overarching objective of this study is the development of a conceptual approach for an AI-supported regulatory framework approach that assists banks in adaptively managing regulatory changes while simultaneously strengthening corporate governance and process resilience in digital financial transformation. The work thereby creates the scientific basis for the subsequent technical development of such a framework in a second study. To achieve the research objective, the following sub-objectives are pursued:

- *Objective 1: Systematic Analysis of the Impacts of Regulatory Changes:* Systematic investigation and documentation of the impacts of regulatory changes on the compliance, risk management, and reporting processes of banks. The emerging process and compliance risks shall be identified, categorized, and evaluated with regard to their relevance for process resilience. This objective creates the empirical foundation for deriving process-specific requirements for the AI framework.
- *Objective 2: Identification and Analysis of Organizational Response Patterns*: Capturing and analyzing the organizational approaches and processes that banks currently employ to identify, interpret, and implement regulatory changes. Through systematic examination of their characteristics and limitations, insights shall be gained that serve as a foundation for the conceptual design of the AI framework.
- *Objective 3: Systematization of AI Potential for Regulatory Management:* Creating a systematic overview of the deployment and potential of AI technologies (Natural Langu-

age Processing, Machine Learning, generative AI) for automating and optimizing regulatory management. Specific deployment possibilities for strengthening corporate governance and process resilience shall be identified and systematically presented.

- *Objective 4: Derivation of Conceptual Requirements:* Based on the findings from Objectives 1 through 3, the systematic derivation and structuring of conceptual requirements for an AI-supported regulatory framework approach shall be conducted. These requirements encompass functional, technological, organizational, and governance-related dimensions and constitute the central scientific result of the study.
- *Objective 5: Development of a Conceptual Framework Approach:* Development of a conceptual model for a modular regulatory AI framework that integrates the derived requirements. This conceptual model encompasses the specification of core components (data ingestion, screening and analysis, process integration, continuous monitoring), their conceptual functionality and interactions, as well as the embedding of principles of sustainable finance and responsible AI governance. The developed conceptual model forms the theoretical and structural foundation for technical development and implementation in a subsequent study.

2. Methodology

2.1. Research Design and Methodological Rationale

This study employs a systematic literature review to develop the conceptual foundation for an AI-supported regulatory framework approach in banking. A systematic review utilizes explicit, systematic methods to collate and synthesize findings of studies addressing a clearly formulated research question (Page et al., 2021). The methodological approach addresses the key research problems presented above.

The selection of a literature-based methodology is justified by the study's analytical and synthesizing objectives. The three complementary research questions require integration of fragmented knowledge across multiple disciplinary domains – regulatory compliance, organizational process management, and AI technologies – that currently exist in relative isolation. A systematic literature review enables the synthesis of diverse empirical findings, theoretical frameworks, and technological assessments into coherent conceptual requirements, which would not be achievable through context-specific primary research within individual banking institutions or regulatory jurisdictions (Boaye Belle & Zhao, 2023). Moreover, systematic reviews are essential for decision makers confronted by an overwhelming volume of research (Boaye Belle & Zhao, 2023; Page et al., 2021).

The methodological design follows a three-phase process aligned with the research objectives. The first phase, systematic literature identification and selection, ensures comprehensive, unbiased coverage of relevant scholarly knowledge across banking regulation, organizational responses, and AI applications, thereby supporting Research Objectives 1 through 3. The PRISMA guidelines provide a structured framework enhancing transparency and methodological rigor (Nezameslami et al., 2025). The second phase, thematic analysis and knowledge synthesis, extracts and categorizes findings from included studies according to the three research questions, identifying patterns, gaps, and convergent insights. The third phase, requirement derivation and conceptual modeling, transforms synthesized evidence into structured requirements and a conceptual framework model serving as the foundation for subsequent technical development, directly addressing Research Objectives 4 and 5. This phased approach ensures that derived requirements are grounded in existing evidence rather than speculative assumptions, thereby enhancing credibility and practical applicability (Nezameslami et al., 2025).

2.2. PRISMA-based Systematic Literature Review

The literature review adopts core principles from the PRISMA framework to ensure transparency, systematicity, and reproducibility. PRISMA provides a structured protocol for documenting search strategies, inclusion and exclusion criteria, study selection processes, and quality assessment procedures (Boaye Belle & Zhao, 2023; Page et al., 2021). While originally developed for systematic reviews of medical interventions, PRISMA's foundational principles of methodological transparency and reproducible research processes have been successfully adapted across diverse research domains, including information systems, management, and technology research (Kitchenham & Charters, 2007; Nezameslami et al., 2025; Okoli, 2015; Tranfield et al., 2003). Webster and Watson (2002) emphasize that a well-conducted literature review creates a firm foundation for advancing knowledge by facilitating theory development, closing areas where substantial research exists, and uncovering areas where research is needed. Systematic reviews in management and information systems research serve to synthesize the state of knowledge, identify research priorities, and inform evidence-based decision making (Tranfield et al., 2003; Webster & Watson, 2002).

Scope and Delimitation of the Research Field

The literature review encompasses three interconnected thematic domains corresponding to the research questions. The first domain examines regulatory change impacts on banking processes, including effects of Basel III/IV, MiFID II, GDPR, ESG disclosure regulations, and supervisory guidelines on compliance processes, risk management, and regulatory reporting systems, as well as emerging process and compliance risks.

The second domain addresses organizational responses to regulatory change, documenting practices, frameworks, and tools banks employ to identify, interpret, and implement regulatory requirements. This includes empirical research on compliance structures, governance frameworks, change management processes, and documented limitations banks encounter, with particular emphasis on best practices identifying gaps for AI-supported frameworks.

The third domain encompasses AI technological potential for regulatory compliance, including natural language processing for regulatory text analysis, machine learning (ML) for relevance assessment and impact prediction, and generative AI (GenAI) for decision support. This domain also covers RegTech implementations, responsible AI governance frameworks, and challenges of deploying AI in regulated environments requiring transparency and explainability.

The temporal scope spans 2010-2025, capturing post-financial-crisis regulatory intensification and AI technology maturation. The geographic scope encompasses diverse regulatory jurisdictions, particularly EU frameworks, US federal regulations, and international standards from the Basel Committee and Financial Stability Board. Publication types include peer-reviewed journals, top-tier conference proceedings, institutional working papers, and regulatory publications, following established quality criteria for literature inclusion in systematic reviews (Okoli, 2015; Tranfield et al., 2003).

Database Selection and Search Strategy

The systematic literature search is conducted across multiple databases selected to ensure comprehensive coverage of the interdisciplinary research field. Database selection follows established guidelines for systematic reviews in information systems and management research, prioritizing sources that provide access to peer-reviewed scholarly literature across relevant disciplines (Okoli, 2015; Webster & Watson, 2002). *Table 1* presents the selected databases along with their disciplinary coverage and rationale for inclusion.

Table 1: Database Selection

Database	Publisher/Provider	Disciplinary Coverage	Rationale for Inclusion
SciSpace	Typeset, Inc.	Multidisciplinary (Science, Technology, Engineering, Medicine, Social Sciences, Business)	Comprehensive AI-powered academic search engine with access to over 200 million papers; advanced semantic search capabilities for identifying AI and regulatory compliance literature; full-text search functionality enables precise identification of relevant European banking studies
Google Scholar	Google LLC	Multidisciplinary (all academic disciplines, gray literature, technical reports)	Broad coverage of academic and gray literature including working papers, conference proceedings, and institutional reports; captures regulatory documents from European banking authorities (EBA, ECB, BIS); essential for identifying practitioner-oriented RegTech and SupTech publications
arXiv	Cornell University	Computer Science, Quantitative Finance, Statistics, Electrical Engineering	Leading preprint repository for cutting-edge AI, machine learning, and computational finance research; provides early access to emerging techniques in NLP, deep learning, and explainable AI before formal peer review; critical for capturing latest developments in AI applications for regulatory compliance
PubMed	U.S. National Library of Medicine (NLM) / National Center for Biotechnology Information (NCBI)	Life Sciences, Biomedical Sciences, Health Informatics	Included for interdisciplinary research on AI ethics, algorithmic fairness, and responsible AI governance; captures health informatics literature relevant to AI risk management frameworks; provides access to studies on AI transparency and explainability applicable to financial services

Source: Own elaboration

The search strategy employs structured Boolean search strings combining three concept clusters corresponding to the research domains, following systematic review protocols for transparent and reproducible search procedures (Page et al., 2021; Tranfield et al., 2003). The first concept cluster captures banking and financial institutions using terms including *bank*, *financial institution*, *credit institution*, *commercial bank*, *investment bank*, *universal bank*, *retail bank*, and *wholesale bank*, with appropriate truncation to capture plural and variant forms. The second concept cluster addresses regulatory change and compliance using terms including *regulatory change*, *regulation change*, *regulatory update*, *regulatory reform*, *regulatory compliance*, *compliance management*, *regulatory adaptation*, *regulatory implementation*, and specific regulation names including *Basel III*, *Basel IV*, *MiFID*, *MaRisk*, *EBA guideline*, *ESG regulation*, *ESG disclosure*, *sustainable finance*, *prudential regulation*, *conduct regulation*, *AML*, *anti-money laundering*, *KYC*, *know your customer*, *regulatory reporting*, and *supervisory expectation*. The third concept cluster captures AI technologies and RegTech using terms including *artificial intelligence*, *AI*, *machine learning*, *ML*, *deep learning*, *natural language processing*, *NLP*, *text mining*, *text analytics*, *generative AI*, *large language model*, *LLM*, *transformer model*, *RegTech*, *regulatory technology*, *SupTech*, *compliance technology*, *compliance automation*, *automated compliance*, and *intelligent automation*.

These three concept clusters are combined using Boolean AND operators to identify studies addressing banking contexts, regulatory change or compliance, and AI technologies simultaneously. Search strings are adapted to accommodate database-specific syntax and indexing structures. Supplementary search strategies complement database searches to ensure comprehensive coverage (Okoli, 2015; Webster & Watson, 2002). Backward citation chaining involves

reviewing reference lists of highly relevant included studies to identify additional sources not captured in database searches. Forward citation chaining utilizes citation tracking functions in Scopus, and Web of Science to identify more recent studies citing key included papers.

Selection Criteria

Inclusion criteria require studies demonstrating relevance to regulatory impacts on banking processes, organizational responses to regulatory change, or AI potential for compliance automation. Studies must focus on banking institutions or provide transferable insights from analogous regulated industries, demonstrate methodological transparency and quality, and be published between 2010-2025, with exceptions for seminal foundational works.

Exclusion criteria eliminate studies focusing solely on non-banking institutions without generalizable insights, purely technical AI research without regulatory application, AI banking applications unrelated to compliance (unless providing transferable governance insights), promotional materials lacking scholarly rigor, and studies addressing only market-level regulatory effects without examining process-level organizational impacts.

Quality assessment procedures follow established protocols for evaluating diverse study types in systematic reviews (Okoli, 2015; Tranfield et al., 2003). Empirical studies are evaluated based on methodological rigor including appropriateness of research design, transparency of data collection and analysis procedures, and discussion of limitations and validity threats. Conceptual papers are assessed based on theoretical coherence, grounding in existing literature, logical argumentation, and clarity of contribution. Technical studies are evaluated based on reproducibility of methods, validation procedures, performance evaluation, and discussion of practical applicability and limitations.

2.3. Data Extraction and Analysis

The analysis follows a structured process aligned with the research questions. Descriptive analysis constitutes the initial analytical step, involving systematic categorization of findings within each study according to predefined dimensions derived from the three research questions (Okoli, 2015; Tranfield et al., 2003; Webster & Watson, 2002). RQ1 categories capture types of regulatory impacts, affected process domains, and risk classifications. For RQ2, categories encompass types of organizational practices, tools and frameworks, and reported limitations. Regarding RQ3, categories capture AI technology types, application domains, demonstrated capabilities, and governance requirements. This descriptive analysis provides an organized representation of the content of each included study.

Thematic analysis builds on the descriptive foundation by identifying patterns, themes, and relationships across multiple studies within each research question domain (Thomas & Harden, 2008). Following established procedures for thematic synthesis in systematic reviews, this step involves comparing and contrasting findings across studies to identify convergent findings that appear consistently across multiple studies and contexts, suggesting robust evidence, as well as divergent findings that vary across contexts, suggesting context-dependent relationships (Thomas & Harden, 2008; Webster & Watson, 2002). Thematic analysis also identifies gaps where certain topics or questions are inadequately addressed in the existing literature, highlighting areas where the conceptual framework must make reasoned extrapolations or where future empirical research is needed (Okoli, 2015; Tranfield et al., 2003).

Integrative synthesis represents the final analytical step, involving cross-domain integration that identifies connections between regulatory impacts documented in RQ1-focused studies, organizational gaps identified in RQ2-focused studies, and AI solutions described in RQ3-focused studies (Torraco, 2016; Whittemore & Knafl, 2005). Following established procedures for integrative literature reviews, this synthetic analysis combines diverse methodologies and perspectives to generate new insights and frameworks beyond what individual studies provide

(Torraco, 2016). This forms the direct basis for requirement derivation by revealing how technological capabilities can address organizational limitations in responding to regulatory impacts (Tranfield et al., 2003; Webster & Watson, 2002). The integrative synthesis makes explicit the logical chains connecting evidence to requirements, ensuring traceability and enabling validation of the requirement derivation logic (Torraco, 2016).

2.4. Requirement Derivation and Conceptual Modeling

The synthesized findings are systematically transformed into conceptual requirements through structured requirement mapping (Hevner et al., 2004; Peffers et al., 2007). Functional requirements derive from documented regulatory impacts and process risks (RQ1), defining framework capabilities for regulatory change detection, interpretation, impact assessment, and process adaptation support. Organizational requirements emerge from identified limitations in current practices (RQ2), addressing gaps in organizational processes, information flows, decision-making support, and change implementation to ensure the framework accounts for organizational realities. Technological requirements derive from demonstrated AI capabilities and constraints (RQ3), specifying contributions of natural language processing for regulatory text analysis, machine learning for relevance assessment, and generative AI for decision support, alongside necessary technical constraints and governance mechanisms for responsible deployment. Governance requirements emerge from cross-cutting themes on accountability, transparency, explainability, and responsible AI deployment, ensuring the framework incorporates principles essential in regulated banking environments where algorithmic decisions must be auditable.

Requirements are structured into a catalog organized by functional, technological, organizational, and governance dimensions, with each requirement explicitly linked to supporting literature evidence ensuring traceability. Based on this catalog, a conceptual framework model is developed specifying core components: data ingestion for regulatory source monitoring, screening and analysis for relevance and impact evaluation, process integration for embedding insights into workflows, and continuous monitoring for implementation tracking.

3. Results

This section presents the conceptual findings of the systematic literature review. Following the five research objectives and guiding questions, the review synthesized evidence from regulatory, RegTech, and AI literature as well as European supervisory publications. Based on the PRISMA-guided selection process, 570 studies were identified as relevant for the broader thematic landscape of AI-supported regulatory compliance (*Figure 1).* From these, 30 high-quality, representative sources were selected for detailed analysis in this Results chapter. This focused subset reflects the studies with the strongest conceptual alignment to the research objectives, the highest methodological rigor, and the greatest contribution to understanding how regulatory change affects banks, how organizations respond, and how AI can strengthen regulatory management and governance. Together, these sources provide an integrated and theoretically coherent foundation for the conceptual advancements developed in this chapter.

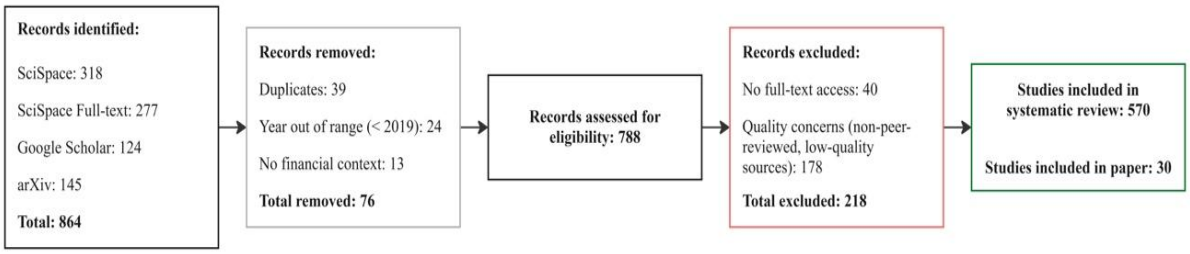

Figure 1: PRISMA flowchart
Source: Own elaboration

3.1. Impacts of Regulatory Changes on Banking Processes

The analysis shows that regulatory change has become a defining structural driver of operational, compliance, and risk-management complexity in European banks (EBA, 2021; Goldstein et al., 2019; Landi et al., 2022; Zetzsche et al., 2019). Since the 2007–2009 Global Financial Crisis, supervisors have expanded the depth and breadth of regulatory requirements, resulting in higher reporting granularity, more frequent updates, and increased prudential expectations (EBA, 2021; Lee, 2020; Wünsch et al., 2023; Zetzsche et al., 2019). The EBA (2021) describes these developments as "fast and continuous changes in regulations" that strain existing reporting, compliance, and oversight structures.

European banks face structurally higher regulatory-induced costs than U.S. peers, including higher capital requirements, more demanding supervisory processes, and significantly greater contributions to resolution and deposit-insurance funds. These differences create sustained pressure on profitability and resource allocation, which in turn affect banks' ability to maintain robust risk-management processes and overall process resilience (Goldstein et al., 2019; Landi et al., 2022; Wünsch et al., 2023).

Across the literature, several process and compliance risks emerge. Banks frequently struggle with data fragmentation, as regulatory data often reside in heterogeneous systems, leading to inconsistent data definitions, manual reconciliation efforts, and higher error potential (EBA, 2021; Goldstein et al., 2019; Lee, 2020). Regulatory requirements also intensify operational complexity, as compliance functions must produce extensive documentation, coordinate across functions, and update controls and models under tight supervisory timelines (EBA, 2021; Wünsch et al., 2023). Furthermore, traditional AML detection approaches increasingly fail to cope with the scale and sophistication of financial crime, generating high false-positive rates and inefficient monitoring processes (EBF, 2021).

3.2. Organizational Response Patterns and Their Limitations

Banks have developed a variety of organizational practices to manage regulatory change, yet consistent structural limitations remain. The literature indicates that regulatory interpretation is often handled through decentralized processes, with legal, compliance, risk, and business units conducting their analyses independently. The EBA (2021) highlights that this decentralization produces heterogeneous interpretations, duplicated analytical work, and inconsistent quality in compliance submissions.

A second barrier arises from siloed technology architectures. Empirical studies report that compliance-relevant data frequently reside in isolated legacy systems, limiting interoperability and obstructing automation efforts (Diener & Špaček, 2021; Goldstein et al., 2019; Grassi & Lanfranchi, 2022). Banks also exhibit a largely reactive approach to regulatory implementation (Ayling & Chapman, 2022; Diener & Špaček, 2021; Paleti, 2022). As reported by the EBA (2021) and Wünsch et al. (2023), regulatory implementation is frequently reactive, with

transformation efforts often occurring only once regulatory texts are finalized, compressing implementation timelines and increasing operational strain. Recent studies underline that limited organizational readiness, fragmented governance structures, and inadequate digital capabilities further reinforce reactive compliance behavior (Diener & Špaček, 2021; Do et al., 2022; Mäntymäki et al., 2022; Sood et al., 2023).

In addition, several studies point to skills gaps, particularly in AI, data science, and digital regulatory technologies, that limit the effective adoption of modernized regulatory processes (Biju et al., 2024; EBF, 2021). An industry-wide analysis confirms persistent shortages in AI, analytics, and RegTech competencies, which constrain modernization efforts (Singh, 2024).

Current organizational response patterns are marked by fragmented interpretation processes and siloed system architectures, which increase manual coordination efforts and reinforce reactive compliance behavior. This underscores the need for integrated workflows, harmonized data structures, and AI-supported regulatory interpretation.

3.3. Potential of AI for Regulatory Management

The literature shows substantial potential for AI technologies, to enhance regulatory management in areas where regulatory complexity and data intensity are highest. NLP-based models demonstrate strong capabilities in structuring, classifying, and extracting regulatory obligations. Prior research on regulatory text processing shows that AI can assess regulatory relevance, map obligations to internal controls, and detect overlaps between regulatory updates (Thimm, 2023). Recent work demonstrates that transformer-based NLP models achieve high accuracy in extracting obligations from supervisory texts and significantly reduce manual review time (Battu, 2025; Fritz-Morgenthal et al., 2022; Pattnaik et al., 2024).

Techniques based on ML have also proven effective in compliance monitoring. The EBF (2021) reports significant improvements in AML detection accuracy compared to rule-based systems, particularly with regard to reducing false positives. Multiple empirical evaluations confirm substantial improvements in AML detection, particularly in reducing false positives and identifying complex laundering networks (Gandhi et al., 2024; Kute et al., 2021; Paleti, 2022). In parallel, AI-based ESG risk-modelling can integrate multidimensional indicators and support scenario analysis for environmental and governance-related risks (Goel & Maheshwari, 2025; Xu, 2024). AI can also support climate-risk modelling, automated ESG scoring, and sustainable investment screening, expanding the role of AI in sustainable finance beyond traditional compliance applications (Musleh Al-Sartawi et al., 2022).

GenAI is increasingly applied to narrative reporting, regulatory text synthesis, and supervisory documentation support. These applications are expected to streamline compliance and reporting processes, particularly in sustainability and ESG disclosure reporting, where Large Language Model (LLM)-based text generation can automate narrative sections of reports while raising concerns about authenticity and verification requirements (De Villiers et al., 2024).

This aligns with broader AI-governance frameworks emphasizing fairness, transparency, and accountability as necessary safeguards for high-risk AI systems in regulated sectors (Fritz-Morgenthal et al., 2022; Truby, 2020). The EU AI Act requires providers of high-risk AI systems to implement lifecycle risk-management processes, ensure human oversight, maintain comprehensive technical documentation, and comply with data-governance and transparency obligations (FLI, 2024). Recent analyses highlight that GenAI systems can automate narrative regulatory summaries and supervisory documentation while requiring strict compliance with EU regulations (Ayling & Chapman, 2022; Botunac et al., 2024). In the ESG domain, AI supports climate risk modeling, automated ESG scoring, and sustainability disclosures (Landi et al., 2022).

3.4. Conceptual Requirements for an AI-Supported Regulatory Framework

The synthesis of the identified challenges and technological potentials enables the derivation of the conceptual requirements for an AI-supported regulatory framework. From a functional perspective, such a framework must systematically ingest, structure, and interpret regulatory texts. This includes the automated identification of regulatory obligations, the mapping of these obligations to internal controls, policies, and risk indicators, and the continuous detection of compliance deviations or emerging risks.

From a technological perspective, harmonized data models, standardized taxonomies, and secure, traceable data pipelines are required to ensure integrity across the regulatory lifecycle. Interoperability layers must enable the integration of legacy infrastructures with AI-enabled components in order to reduce architectural fragmentation and support end-to-end automation (Diener & Špaček, 2021; Grassi & Lanfranchi, 2022). As supervisory expectations increasingly incorporate sustainability-related dimensions, the architecture must additionally be capable of integrating ESG-related datasets and supporting AI-based scenario analyses (Landi et al., 2022; Musleh Al-Sartawi et al., 2022).

From an organizational and governance perspective, effective implementation requires clearly defined decision-making structures, explicit lines of accountability, and close collaboration between compliance, risk management, IT, and the business. The literature highlights that the expansion of digital and analytical competencies in the areas of AI, data governance, and RegTech constitutes an essential prerequisite for the operationalization of modernized regulatory workflows (Biju et al., 2024). In addition, the framework must include robust AI-governance mechanisms that ensure explainability, traceability, human oversight, and fairness in model outputs (Fritz-Morgenthal et al., 2022; Truby, 2020). Beyond high-level ethical principles, recent studies emphasize the need for practical AI-governance tools and implementation frameworks that translate ethical and regulatory expectations into operational processes (Biju et al., 2024; Fritz-Morgenthal et al., 2022; Musleh Al-Sartawi et al., 2022). These requirements align with emerging regulatory expectations under the EU AI Act as well as Europe's broader sustainability-oriented regulatory agenda, particularly in the areas of corporate sustainability reporting and corporate sustainability due-diligence obligations.

3.5. Conceptual Framework for a Regulatory AI System

The synthesized findings indicate four interrelated components: data ingestion, analytical screening, process integration, and continuous monitoring. Taken collectively, these components constitute the architecture of the proposed framework illustrated in *Figure 2*.

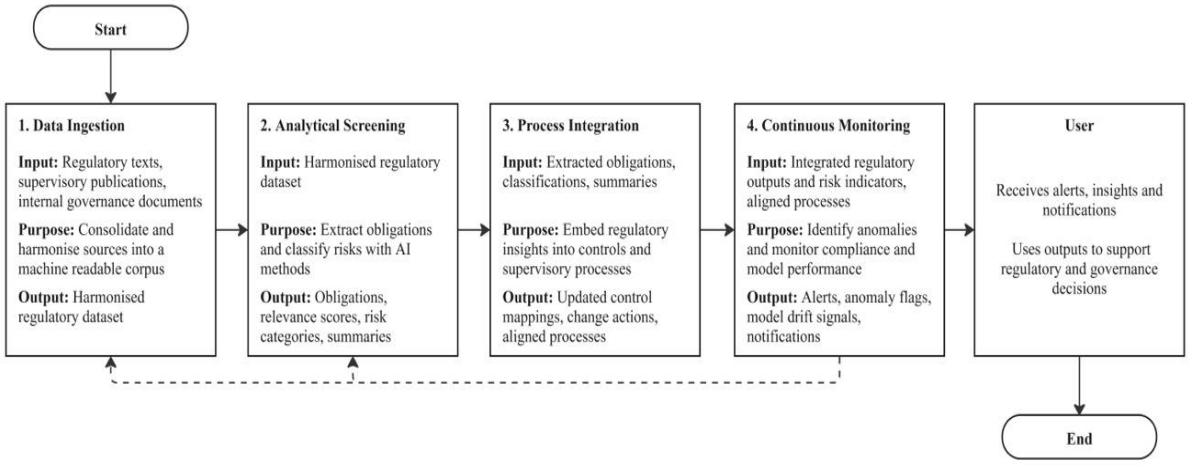

Figure 2: Architecture of the automated Regulatory AI Framework
Source: Own elaboration

The data ingestion component consolidates regulatory documents, supervisory communications, and internal governance data into a harmonized, machine-readable format. This directly mitigates data fragmentation and establishes a unified regulatory data layer that supports consistent and traceable information flows across the organization. By providing high-quality and structured inputs, it creates the foundation for AI-enabled analysis and enables the subsequent analytical screening component to extract, classify, and interpret regulatory requirements.

The screening and analysis component applies NLP, ML, and GenAI to identify relevant regulatory changes, extract requirements, classify risks, and generate interpretive summaries (Battu, 2025; Pattnaik et al., 2024; Thimm, 2023). Research on regulatory text mining shows that NLP-based relevance scoring and classification can reduce manual interpretation efforts and improve the consistency of analytical outcomes (Battu, 2025; Kute et al., 2021; Thimm, 2023).

The process integration component embeds regulatory insights into operational workflows. It links regulatory obligations with internal controls, orchestrates change-management tasks, and aligns outputs with key supervisory and risk-management processes, including internal capital and liquidity assessment activities, supervisory evaluation procedures, as well as AML and ESG-related activities. This component directly addresses organizational fragmentation and enhances interoperability (Grassi & Lanfranchi, 2022; Mazayo et al., 2023).

The continuous monitoring component provides real-time surveillance of compliance indicators, model performance, AML anomalies, and ESG-related risks (Kute et al., 2021; Paleti, 2022). It incorporates ML-based anomaly detection, model-drift monitoring (to identify performance degradation over time), and automated reporting (Alkhalili et al., 2021). These monitoring functions are consistent with supervisory expectations and supported by evidence of AI effectiveness in risk detection, particularly in AML and ESG contexts (EBF, 2021; Goel & Maheshwari, 2025; Landi et al., 2022; Musleh Al-Sartawi et al., 2022).

4. Discussion

Addressing RQ1 and Objective 1, the empirical evidence indicates that regulatory change has emerged as a fundamental structural driver of operational and organizational complexity within contemporary banking systems. Regulatory updates increasingly affect compliance workflows, risk-management procedures, and reporting obligations, generating a continuous need for reinterpretation, adaptation, and internal coordination. The results indicate that the rising frequency of supervisory changes, the growing granularity of reporting obligations, and new sustainability-related disclosure requirements collectively introduce process and compliance risks that challenge operational stability. Fragmented data landscapes, inconsistent data definitions, and siloed documentation practices further reinforce these vulnerabilities. The Discussion therefore underscores that regulatory change has shifted from being episodic to persistent, constituting a central driver of process fragility and highlighting the need for more adaptive, integrated, and technology-supported regulatory management capabilities.

RQ2 and Objective 2 addressed how banks currently interpret and implement regulatory changes and which structural limitations characterize these approaches. The analysis shows that regulatory interpretation and implementation remain highly decentralized across compliance, risk, legal, and business functions. This fragmentation results in heterogeneous interpretations, duplicated analytical work, and variation in the quality of regulatory assessments. Legacy IT infrastructures, insufficient interoperability, and gaps in digital competencies exacerbate these challenges, reinforcing reactive, compliance-driven behavior. The findings further reveal that structured mechanisms for early regulatory monitoring and cross-functional coordination are often lacking. As a consequence, organizational response patterns remain misaligned with the accelerating regulatory pace, underscoring the need for a framework that automates regulatory interpretation and embeds outputs within harmonized workflows and governance structures.

Addressing RQ3 and Objective 3, the findings demonstrate that AI technologies, notably NLP, ML, and GenAI, exhibit considerable transformative potential for regulatory management optimization. NLP methods enable the systematic ingestion, classification and extraction of regulatory obligations and thereby reduce the manual effort associated with screening and interpreting complex regulatory texts. ML techniques show potential for relevance assessment, anomaly detection and risk modelling, especially in AML, ESG and operational risk contexts. GenAI can support narrative synthesis, interpretive reasoning and the preparation of supervisory documentation. These potentials, however, can only be realized if implementation is supported by governance arrangements that ensure explainability, traceability, fairness and human oversight. AI therefore supplements and strengthens rather than replaces existing governance structures. The Discussion emphasizes that AI supported regulatory management should be conceptualized as an enabler of accountable decision making rather than a mechanism for automated compliance.

Objectives 4 and 5 required the derivation of conceptual requirements and the development of a modular framework that integrates the insights from RQ1 through RQ3. The synthesized results indicate that an effective regulatory AI framework must incorporate functional capabilities for regulatory text ingestion, classification, interpretation and impact assessment. It must also include technological foundations such as harmonized data models, interoperable architectures and secure and auditable AI pipelines. In addition, organizational requirements arise including cross functional governance structures, clearly allocated responsibilities and strengthened digital competencies. Governance requirements further include transparency, explainability, human oversight and alignment with supervisory expectations. These dimensions are reflected in four interrelated components, namely data ingestion, analytical screening, process integration and continuous monitoring. Each component addresses specific limitations in current regulatory management practices and demonstrates how AI based analytics can be embedded into regulatory workflows. The model thus links regulatory intelligence, organizational processes and governance mechanisms into a coherent system.

Viewed in relation to the overarching objective and the main research question, the findings collectively indicate that AI supported regulatory frameworks can help financial institutions move from reactive and fragmented compliance processes toward proactive and integrated regulatory adaptation. The analysis shows that such a framework can enhance corporate governance by improving the consistency, auditability and transparency of regulatory interpretation and implementation. At the same time, it strengthens process resilience by reducing manual dependencies, harmonizing data flows and enabling continuous monitoring of risks and compliance deviations. These developments support the argument that AI should be regarded as a structural catalyst for transforming regulatory management in line with the requirements of digital financial transformation.

5. Future Research Directions

This paper establishes a conceptual basis and approach for the subsequent stage: developing and thoroughly evaluating a practical prototype as part of a Design Science Research project. The primary focus of this next phase will be the technical realization of the proposed modular Regulatory AI framework into a fully operational system. The four principal components - Data Ingestion, Screening & Analysis, Process Integration, and Continuous Monitoring - will be implemented as an integrated prototype and assessed with both real-world and simulated regulatory scenarios (such as the Basel III final reforms transition period beginning July 2025, inaugural CSRD application in 2025/26, new EBA guidelines on ESG risks, or amendments to MaRisk).

The main objective is to provide empirical evidence that the framework substantially decreases the time required for manual analysis and interpretation of new regulations. It also enhances the consistency and auditability of regulatory assessments, supports seamless integration

into current compliance and risk management processes, and fully complies with responsible AI governance requirements, including the EU AI Act, explainability, and human oversight.

The prototype is developed with a focus on modularity, ensuring it can be adapted to various bank sizes, legacy infrastructures, and specific regulatory requirements. A concurrent comparative analysis of leading commercial RegTech solutions will underscore the unique benefits of this approach, with particular emphasis on its flexibility, data sovereignty, compliance with EU regulations, and its capacity to support proactive and resilient regulatory management strategies.

By leveraging advanced AI-driven regulatory frameworks, financial institutions are empowered to proactively anticipate and respond to evolving supervisory demands, aligning compliance initiatives with broader organizational objectives and long-term value creation. This paradigm not only elevates the strategic importance of regulatory management but also positions compliance capabilities as a foundation for innovation, competitive differentiation, and enhanced stakeholder trust. As the sector navigates increasingly complex regulatory landscapes, such integrated approaches are essential for fostering adaptability, ensuring regulatory integrity, and supporting the continuous evolution of the financial ecosystem.

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