



Reimagining Financial Systems Through Adaptive Automation

Shashikala Valiki

Independent Researcher

shashikala.valiki.researcher@gmail.com

Abstract

Next-generation financial Cloud systems must meet the automation, operational pacing, and rapid-market-change demands of the digital economy, which cannot be supported by traditional automation paradigms. Intelligent automation, which employs appropriate AI technologies for different automation decision categories and business processes, is a concept with unprecedented potential. Seen as an enabler for next-generation financial Cloud systems, three critical aspects need serious consideration to seize this opportunity: the intelligent automation of internal operations, the governance and compliance of intelligent automation at a system level, and how companies can incrementally build intelligent automation capabilities. The first two aspects interact because the business case for intelligent automation is built on stakeholder demand for cost reduction. Filling gaps in these two areas provides a foundation for a roadmap of maturity phases or increments. Primary examples of intelligent automation in financial operations research illustrate its industrial relevance.

Keywords : Intelligent Automation, Financial Clouds, Automation Paradigms, Decision Automation, Robotic Process Automation, Explainable AI, Auditability of AI, Compliance Automation, RPA, Cloud Computing.

1. Introduction

Next-generation financial cloud systems are becoming cloud-native architectures. Intelligent Automation, a way to achieve the desired business outcomes for the cloud-based services in a robust, scalable, flexible, and easy-to-go manner by integrated AI/ML-based technologies, is not a separate technology, but the way that these systems will implement the technologies that are necessary for modern business requirements. Thus, Intelligent Automation and Decision Engineering along with the supporting components such as Robotic Process Automation, Decision Automation Engines, Rule Engines, and all the governance elements should be part of the overall architecture presented.

An Automation strategy and strategy roadmap that describes how Automation will be done, where the initial focus areas will be, and how those will evolve in time is key for successful Intelligent Automation. An initial maturity model is also required to see where the Automation capabilities are today and how those should evolve over the coming years to support the broader Intelligent Automation strategy and roadmap. As part of the Automation strategy and roadmap, specific Metrics/KPIs that track the success of Automation and ultimately assess the overall Return on Investment (ROI) achieved through it should be defined.

1.1. Research design

The study investigates automated and autonomous processing in the domain of financial cloud-based systems cognizant of risk and compliance requirements throughout. A focus on efficiency and scalability informs key patterns of financial cloud architecture before identifying a number of components that possess inherent intelligent decisioning and fulfilment capabilities, which can also provide intelligent support for automation of the remaining workflow processes. Maturity modelling supports implementation roadmaps capable of delivering incremental returns in available funding even when total funding is very limited. Industry case studies demonstrate both the benefits of automating such processes generally and the relevance and applicability of



intelligent automation particulars to such initiatives. The culmination of these efforts revolves around verifying the components of intelligent automation against SCL's long-established 4Cs of financial processing cloud computing systems.

The breadth of intelligent automation embraces all forms of automating and orchestrating tasks. Intelligent automation embodies incremental renewables of Robotic Desktop/Machine Process Automation, automating repetitive keyboard tasks usually taken on by humans. Intelligent Process Automation imprints decisioning on parasitically intelligent business processes, then feeding those decisions into the Robotic Process Automation together with human inputs where required. Intelligent Workflow Automation schedules the whole as per priority and fulfilment time. Decision Automation and orchestration include rule splitting and comparison enabled for very high-frequency environments. Capaci-temporal KPIs built into the rules manage such environments in real-time. Within a BaaS cloud, intelligent automation is a layered set of capabilities that apply to multiple application categories in a financial operating model. Automated testing and auditing tools can ensure that all decision-use cases created, modified, or removed comply with the necessary explainability and audit requirements.



Fig 1: Next-gen financial cloud automation architecture

1.2. Background and Significance

The intelligent automation of financial cloud systems is important because it supports the evolution of banking as a service (BaaS) with rich and complex offerings; adapts to the need for running multiple banking tenants on a single cloud; builds fraud detection and prevention into the cloud; and tackles the pressing issue of the industry talent shortage. Intelligent automation brings together the capability to automate decisions, operations, and processes across a cloud system, from onboarding and transaction processing to credit and compliance operations. To enable a higher degree of automation in financial cloud systems,



the role of artificial intelligence, machine learning, and robotic process automation is emphasized together with supporting architectures and the automation of compliance controls and risk management processes.

Intelligent automation combines robotic process automation (RPA), decision automation, and artificial intelligence and machine learning (AI/ML) components and applies them to workflow management, enterprise and business process management, and intelligent business process management systems.

Equation 1: Effort Saved by Automation

Let:

- E_m = manual effort before automation
- E_a = effort after automation
- E_s = effort saved

By definition,

$$E_s = E_m - E_a$$

Step-by-step derivation

Start from total work before automation:

$$\text{Total original effort} = E_m$$

After automation, some effort still remains:

$$\text{Remaining effort} = E_a$$

So the part removed by automation is:

$$\text{Effort saved} = \text{original effort} - \text{remaining effort}$$

Therefore,

$$\boxed{E_s = E_m - E_a}$$

Percentage effort saved

To normalize across teams or banks:



$$\%E_s = \frac{E_s}{E_m} \times 100$$

Substitute $E_s = E_m - E_a$:

$$\%E_s = \frac{E_m - E_a}{E_m} \times 100$$

$$\%E_s = \left(1 - \frac{E_a}{E_m}\right) 100$$

2. Core Concepts of Intelligent Automation in Financial Clouds

Cloud systems delivering services to the financial sector can be enabled to provide unprecedented levels of automation to the consumers of such services. Intelligent Automation encompasses a wide range of methodologies, models, and software components. Examples include Robotic Process Automation (RPA) that uses software robots executing business processes through graphical user interfaces, Decision Automation that captures decision-making knowledge and applies rules to discover the best outcomes using different scoring and simulation algorithms, and the wider use of emerging techniques such as Machine Learning and Artificial Intelligence on the vast amount of data flowing through payments and settlements systems. Hence, it brings benefits such as improved efficiency, increased throughput, reduced operational risk, and lower infrastructure spending. However, achieving full potential requires financial cloud systems that support next-generation Intelligent Automation by adopting Architectural Patterns that are evolved from the earliest cloud designs for the financial sector.

Apart from an underlying reliable Microservices architecture and Service Oriented Architecture (SOA) style, Intelligent Automation in Financial Clouds requires Service Level Agreements (SLAs) covering diverse types of Automation. Further, the automation decisions must be processed in real-time, captured accurately and performed well so that automation is effective and efficient. A key aspect of Financial Clouds driving the Intelligent Automation Engine is the Banking Cloud, which is supported by Corporate Banks and their ecosystem.

Intelligent Automation in Financial Clouds goes beyond a robust foundation of Microservices architecture and Service-Oriented Architecture (SOA) by requiring well-defined Service Level Agreements (SLAs) that address diverse automation scenarios across financial operations. These SLAs ensure that automation processes meet strict performance, reliability, and compliance standards essential in the financial domain. Additionally, automation decisions must be executed in real time, with high accuracy and minimal latency, enabling institutions to respond instantly to dynamic market conditions and customer needs. The effectiveness and efficiency of such automation depend on seamless data capture, precise decision-making, and optimized execution. At the core of this ecosystem lies the Banking Cloud, a critical driver of the Intelligent Automation Engine, supported by corporate banks and an interconnected financial ecosystem, which together enable scalable, secure, and intelligent financial services delivery.



Fig 2: Intelligent automation in financial clouds

2.1. Automation Paradigms and Decisioning

Automation can relieve the burden of mundane manual effort from knowledge and professional employees, freeing them for strategic work. Intelligent process automation (IPA) achieves real transformation of business operations by substituting human-level cognition and decision-making with mechanistic procedures based primarily upon scrutable reasons. Within the context of financial services clouds, a further distinction is made between scriptable and scrutable procedures, reflecting whether simply-defined rules are required or advanced Artificial Intelligence (AI) technologies may be deployed.

Above the IPA level, some processes are unable to evolve for complete automation, either becoming too expensive per switch to the on mode, or requiring human intuition and judgement on a regular basis, even if for a minority of cases. The aim then becomes enabling better, faster and/or cheaper human decision-making through advanced Data Visualisation (DV) and Decision Automation Facility (DAF) technologies. The concept of Decision Making as a Service (DMaaS) enables related products and content to be parametrised and offered as a cloud service.

2.2. Artificial Intelligence and Machine Learning in Financial Operations

For some process domains, the analytical capabilities of AI and ML enable intelligent decisioning functions to be integrated with automation stacks, thereby migrating additional work into hands-free execution modes. For other functional areas—especially high-volume, data-intensive activity—decisioning capabilities must be developed to deliver timely, accurate, and defensible predictions, scores, findings, or recommendations. ML models for such purposes may be developed for in-house use or



commissioned from third parties, and any work product can be adequately tested and validated in a controlled environment. By providing the requisite processing power, many clouds allow these types of predictive and prescriptive workloads to operate in near-real-time.

Other areas of cloud-based finance involve decisions that by their nature should be less automated and more bespoke. Nevertheless, for a significant number of decision-driven activities within risk management, credit operations, money-laundering detection, and other subjects hard-coded decision rules can be formulated to cover operationally simple, low-risk cases. The crafting, testing, and validation of such rules can even be gamified by presenting the decision business areas with competing scores. The champion can then be recommended for hands-free execution while additional, potentially more complex and risky cases are passed on for bespoke decisioning by case officers. With growing transaction volumes and the price wars in payments and settlements, specialized payment services offering competitive pricing have appeared, catering to a specific micro-segment of the payment market, capturing market share, and becoming acquirers for specialized payment gateways of smaller merchants. The SoA design pattern has seen renewed interest with the emergence of Blockchain and other Distributed Ledger Technologies (DLT).

Equation 2: Error Reduction Rate

Let:

- N_m = number of errors before automation
- N_a = number of errors after automation
- R_e = error reduction rate

By definition,

$$R_e = \frac{N_m - N_a}{N_m}$$

Step-by-step derivation

Original error count:

$$N_m$$

New error count after automation:

$$N_a$$

Reduction in errors:

$$\Delta N = N_m - N_a$$



To convert this to a rate relative to the original baseline:

$$R_e = \frac{\Delta N}{N_m}$$

Substitute ΔN :

$$R_e = \frac{N_m - N_a}{N_m}$$

$$R_e = \frac{N_m - N_a}{N_m}$$

Percentage form

$$\%R_e = \frac{N_m - N_a}{N_m} \times 100$$

$$\%R_e = \left(1 - \frac{N_a}{N_m}\right) 100$$

3. Architectural Patterns for Next-Gen Financial Clouds

Within the Intelligent Automation framework outlined earlier, the first three paradigms of Intelligent Automation address the capabilities and end-to-end life cycles of financial operations in the next-generation Financial Cloud systems. The remaining four paradigms map to the core architectural patterns underlying the shift from rule-based automation to Intelligent Automation in Financial Clouds. Being a fact-based presentation, the realization of Intelligent Automation in financial Clouds is attributed to the following four architectural patterns.

Microservices and service-oriented architectures (SoA) have been widely adopted in financial Clouds in recent years, enabling rapid business development and support of heterogeneous platforms across Clouds. The microservices paradigm promotes rapid development of large composite business services spanning multiple technology platforms by assembling SoA-style application service components deployed in public and private Clouds.

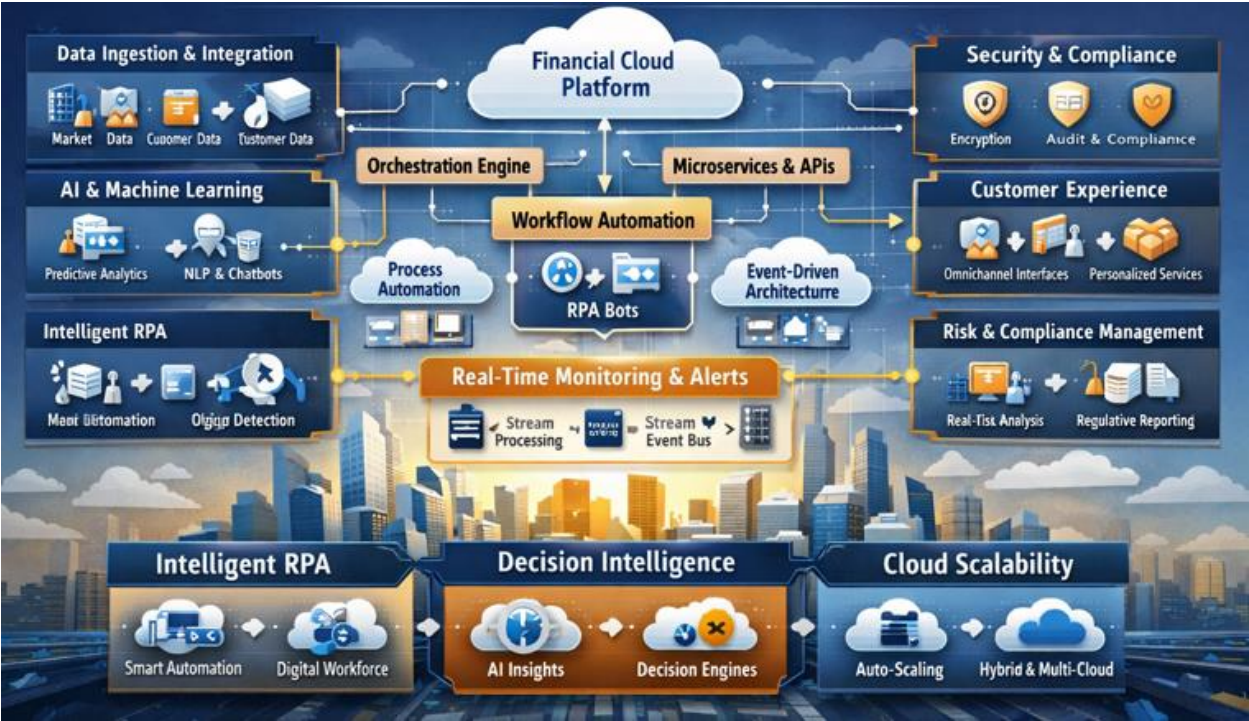


Fig 3:Architectural patterns for financial clouds

3.1. Microservices and Service-Oriented Architectures

Microservices and service-oriented architectural (SOA) patterns simplify the development and delivery of reliable applications by dividing functionality into smaller, independently deployable modules that are scaled up and down based on demand, tested with minimal overhead, and combined into larger components or packaged as containers for easier management. In cloud-based financial services, some operations with low complexity and high-risk impact adopt BAU (business-as-usual) development methods and supporting micro websites or applications, while others consume services through SOA without source code dependencies.

The cognitive characteristics of consumer decisions (extensive versus intensive) drive distinct patterns of decision automation; extensive decisions can often be automated using defined algorithms, based on machine learning and/or neural network analyses of outcome data within business microservices, processes, or autopilot systems. These cloud services enable volumes of in-series transactions to be automated within clear regulatory requirements, aided by pre-built intelligent-automation models, process-workflow engines, and process repositories.

Paradigm	Primary function in article	Typical financial use
RPA	Automates repetitive operational tasks and support activities	Back-office processing, monitoring, workflow execution



Decision Automation	Applies structured rules and decision logic	Risk control points, approvals, policy-based routing
AI / ML	Generates predictive or prescriptive insight	Fraud detection, credit scoring, forecasting, anomaly detection
Workflow Orchestration	Coordinates work among humans, bots, and services	Task dispatch, handoffs, SLA tracking, prioritization
Compliance Automation	Embeds audit, policy, and control checks	Monitoring, reporting, control management, explainability
Real-Time Event Processing	Responds to streaming events quickly	Fraud alerts, payment events, high-risk transaction triggers

Table 1: Derived table: core automation paradigms

3.2. Event-Driven and Real-Time Processing

The managed nature of cloud infrastructures enables data and workloads to be processed in proximity. Event-driven architectures built on publish/subscribe messaging patterns are ideal for decoupling components and facilitating parallel processing. State preservation via external engines rather than in-app memory offers scale-out capabilities beyond transient processing payloads and complexities. Conversely, delivered at scale, the volume of generated messages can become both a source of noise and a hindrance to fast decision making (e.g. ultrafast trading).

Event-driven architectures can be a good option for sophisticated cloudified native applications spanning across clouds; cloud-native allows the use of a generic enterprise view on event-driven driven microservices allowing a more practical (and reusable) design but must consider “clear use cases and bounded integration to allow for software support”.

Real-time data feeds, steered to processing pipelines and complex event-processing engines, can be leveraged to react automatically to specific events that might indicate fraud, high-risk transactions or other key patterns, steering alerts or pausing other workstreams. Meanwhile, (supervised-learning) AI and ML applications can generate lists of crumbling (or resilient) bonds and companies and provide them on inception to participants’ feeds (“notification”), enhancing both risk processing and decisioning pipelines with real-time intelligence.

4. Intelligent Automation Components and Orchestration

An intelligent automation architecture for enterprise cloud systems consists of four major components: performing, supporting, and decision-automation engines and the intelligent business process orchestrator, which governs the interactions among them. The performing component consists of the machines and humans carrying out the core business operations and functions. These operations and the interactions among them are governed and orchestrated by the intelligent business process orchestrator that defines the workflows of the operations, dispatches work to the performing component, monitors progress and status, and governs handoffs among different operations, especially between human and machine. These workflows change continuously, often in real time, based on the changing demand and supply situation in the business environment. The supporting component includes the shared services and systems within the enterprise used in the business operations. Their workload is sometimes substantial in volume, repetitive, and routine. Robotic process automation (RPA) using computer programs or bots on these operation-supporting functions can bring substantial cost savings and efficiency gains to an enterprise.



components of most financial supplier platforms (SSPs) can already be automated to such an extent that designs can be rendered compliance-by-implementation ready. Consequently, these now substantively automatic elements can be pre-modeled and delivered "as-is" via all servicing-economy agreements.

Further, RCAs can address, and accelerate, otherwise non-mandated decisions. For example, while FSB guidance does not formally mandate automated monitoring, "non-failure" status inherently defines monitoring as risk-weighted capital does not cover its level of inherent latent risk exposure. Monitoring is indeed the clearly cheapest-level police-work of all, regardless of market structural form, yet hosting-outwards deployment is invariably limited as cost-take-out (CTO) benefits accrue only for DE-LEVERED banks or when acting as natural-bias-picking proposal specialists. Patently, however, the naturally bias-picking proposal-substantive element is, and can be, fully-compliance-embedded.

Equation 3: Throughput Improvement Equation

Let:

- T_m = manual throughput (transactions per hour/day)
- T_a = automated throughput
- G_t = throughput gain ratio

By definition,

$$G_t = \frac{T_a}{T_m}$$

Step-by-step derivation

Suppose before automation:

$$\text{Throughput} = T_m$$

After automation:

$$\text{Throughput} = T_a$$

To compare improvement, use ratio:

$$G_t = \frac{\text{new throughput}}{\text{old throughput}}$$

Hence,



$$G_t = \frac{T_a}{T_m}$$

Percentage throughput increase

The increase itself is:

$$\Delta T = T_a - T_m$$

Relative improvement:

$$\%I_t = \frac{\Delta T}{T_m} \times 100$$

Substitute ΔT :

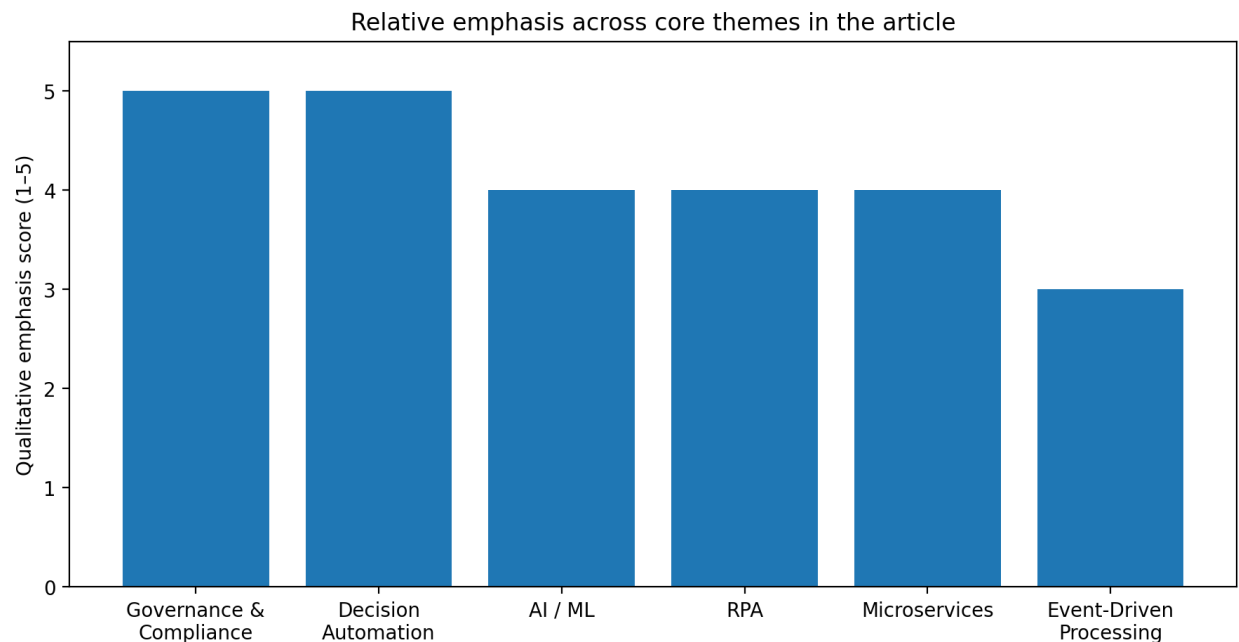
$$\%I_t = \frac{T_a - T_m}{T_m} \times 100$$

$$\%I_t = \left(\frac{T_a}{T_m} - 1 \right) 100$$

4.2. Decision Automation and Rule Engines

The operational automation offered by RPA introduces a new layer of potential risk. Potentially unsafe or unethical decisions now reside within the automated mundane processing layer. The stakes are much higher than simply dealing with a delay for a customer while a bank spends two months sorting out its muddle. There is therefore a clear argument for automating the rule-based decisioning process as well. A well-established technology that is part of the broader Intelligent Automation toolkit is Decision Automation, often implemented through Rule Engines and/or Business Process Management (BPM) engines. Decision Automation combines both types of technology to support end-to-end process automation across both mundane process execution and automated business control decision making.

In its strictest sense, Decision Automation automates decision-making that is routine but non-automatic; if an RPA robot executes the routine mundane part of a process but a variable or indicator has also crossed a trigger point of some type, then a risk needs to be handled. A well-defined Risk Control Point will highlight this, allowing a human user to take a decision, thereby addressing the risk. Decision Automation uses a well-defined set of business rules continuously, in a structured format, which can be dynamically applied to determine readiness for risk-control decisions; but in an unstructured way, with variation, for less well-defined exceptions and edge cases.



5. Governance, Compliance, and Risk Management

Financial businesses operate in a highly regulated environment with strict governance requirements. The need for compliance and awareness of operation-related risks cannot be overstated; banks require around 12% of their staff merely to cater to regulatory requirements and operating risks, according to estimates by the BBC. Governance frameworks, policies, and procedures are often viewed as overheads, hindering organizational speed and agility. Yet, an increase in the approval cycles for a new offering or product from one day to one week can erode significant amounts of business—not only in terms of opportunity costs but also hard-dollar impacts from trade dislocations.

The cost of governance can, however, be minimized by adopting a compliance-by-design approach in automation design. Components used for the automation can be pre-checked, classified, and certified in a compliance registry repository, complete with due diligence checklists and ensuring that the functional and non-functional requirements imposed for the cloud environment are duly followed. Process design patterns—including aspects such as approval controls, separation of duties, regulatory reporting, information security, data leakage protection, and trade surveillance—form a compliance design catalog that early-stage automation developers can leverage. Adoption of low-code development techniques additionally aids non-coders in building code-free automation implementations while ensuring compliance with the bank's data governance and privacy requirements; related KPIs include the percentage of business-managed automation implementation and revenue contribution from such automation.



Compliance units' tasks, since it can help achieve a more comprehensive audit and monitoring mechanism, support defining Governance & Compliance Risk Policies, and provide assurance for detecting non-compliance situations.

It is common practice to consider Compliance as an oversight process that allows responding to the risks defined by the Governance unit and ensuring that the organization's executive processes are aligned with the established internal regulations. In an ideal situation, the executives' operational processes would be expressed as System Procedures and specifically implemented by an IA Decisioning Engine. Nevertheless, in cloud environments, Compliance must go beyond a conceptual framework and supervision task. The complexity of these business lines requires that Compliance be treated as a full cycle, which includes Risk Definition, Monitoring, and Response. Additionally, Consideration of Regulatory Pressure, Internal Governance, Business Risk Exposure, and Capacity of Prevention or Detection must be embedded in the Cloud Automation before executing any organizational service. Compliance Automation can be divided into four main aspects: Audit and Monitoring Automation; Control and Control Management Automation; Policy and Procedure Definition and Management Automation; and Risk Definition Automation. The Support of these aspects fully covers the Compliance Life Cycle in an Organization.

5.2. Auditing, Explainability, and Trust in Automated Processes

Auditing, Explainability, and Trust in Automated Processes When undertaking sensitive operational activities in financial organizations, compliance with regulations, governance policies, and accurate reporting are crucial. Such credibility for manual operations comes from extensive internal and external audit processes to provide verification and validation of the activity. Compliance, correctness, and accuracy for automated solutions need to be similarly ensured, albeit in ways and timescales that are appropriate for automation and that do not detract from the benefits that automation brings. It is here that appropriate levels of auditing, explainability, and trust come into play.

Auditing is mainly conducted for risk assessment, compliance tracking, and internal control monitoring. An audit log that records every operational transaction created by an intelligent automation flow can be fed into an intelligent auditing engine to evaluate and maintain compliance. Such an intelligent engine would assess whether the right decisions at the right times were taken, whether the automated solutions were working as expected, and if the results met regulatory needs, service-level agreements of the external or internal customers, and internal policies and procedures. Only these levels of assurance would provide the required credibility for intelligent automation. For example, Exhibition 7 shows the auditing system used in the intelligent automation flow of batch payments in a large private sector bank, where risk, service-level agreement, transaction, and regulatory criteria were set for each transaction, alerting the relevant users when any criteria fell below or rose above tolerance.

Equation 4: ROI of Intelligent Automation

Let:

- B = total benefit from automation
- C = total automation investment cost
- ROI = return on investment

Standard ROI is:



$$ROI = \frac{B - C}{C}$$

Step-by-step derivation

Net gain from automation is:

$$\text{Net gain} = B - C$$

Return on investment compares net gain against the amount invested:

$$ROI = \frac{\text{Net gain}}{\text{Investment}}$$

Substitute:

$$ROI = \frac{B - C}{C}$$

$$\boxed{ROI = \frac{B - C}{C}}$$

Percentage form

$$\%ROI = \frac{B - C}{C} \times 100$$

$$\boxed{\%ROI = \left(\frac{B}{C} - 1\right) 100}$$

Expanded benefit form

From the article, benefits can come from effort savings, error reduction, faster decisions, and reduced compliance loss. So write:

$$B = B_{\text{labor}} + B_{\text{error}} + B_{\text{speed}} + B_{\text{compliance}}$$

Then,

$$ROI = \frac{B_{\text{labor}} + B_{\text{error}} + B_{\text{speed}} + B_{\text{compliance}} - C}{C}$$

$$\boxed{ROI = \frac{B_{\text{labor}} + B_{\text{error}} + B_{\text{speed}} + B_{\text{compliance}} - C}{C}}$$

6. Implementation Considerations and Maturity Models

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Implementation of intelligent automation architectures follows standard system development methodologies of additional techniques such as Roadmapping, maturity assessments, OKRs, and KPIs can accelerate time-to-benefit while highlighting present business pains. A roadmap articulates a logical sequence of capability development that will maximize benefit realization. The roadmap does not prescribe every assignment but instead provides information that should enhance course decisions. Planning the sequence of automating operations that are merely complex together with areas demanding frequent exceptions can appear logical. Yet these elements are often attended by low demand. Serious business loss or harm can also result from infrequent, anticipated complexity that is inadequately supported. A maturity model is a framework for defining and assessing the essential capabilities needed for maturity in a particular domain. Creating an intelligent automation maturity model incorporates careful research, industry benchmarking, and consideration of future industry directions and trends. Leading players within the financial cloud ecosystem can benefit from tracking their own maturity progress as well as that of partners and competitors.

IDEAL, an integrated process enabling process automation at Enterprise level, enables banks to fast ramp up Straight-through Processing STP of transactions at 100 percent hit-rate, with 0 defects and 24 by 7 enablement, along with monitoring and support capabilities. Enterprise payments monitoring solutions enable payment orchestration and support manage payments across the bank, automate transactions across multiple routes, settle cross-border payments in local currency, monitor and manage risks, and integrate back-office systems through APIs. Radically new approaches to maintain risk thresholds for trading include removal of people from the trading process. Tools support risk mitigation in real-time but will spark new strategies, with different underlying trading clients in the financial markets domain. Intelligent automation becomes a game changer for business leaders, enabling organizations to do things differently and enter new market spaces through industry change, even reinventing business models.

IDEAL, as an integrated enterprise-level automation framework, represents a transformative shift in how financial institutions, particularly banks, approach transaction processing and operational efficiency. By enabling rapid adoption of Straight-through Processing (STP) with near-perfect accuracy, zero defects, and continuous 24/7 availability, it significantly reduces manual intervention and operational bottlenecks. This capability is further strengthened by advanced monitoring and support systems that ensure seamless oversight and quick issue resolution. Complementing this, enterprise payment monitoring solutions bring a new level of orchestration across banking systems, allowing institutions to intelligently route transactions, handle cross-border payments in local currencies, and maintain compliance while minimizing risk. Through robust API integrations, these systems unify front-end and back-office operations, creating a cohesive and agile financial ecosystem. At the same time, the evolution of trading risk management is moving toward automation-driven models where human intervention is minimized, enabling real-time risk mitigation and adaptive strategy development. Such tools not only enhance precision and responsiveness but also pave the way for innovative trading approaches tailored to diverse market participants. Ultimately, intelligent automation emerges as a strategic enabler for business leaders, empowering organizations to reimagine processes, unlock new market opportunities, and even redefine traditional business models in an increasingly digital and competitive financial landscape.

The paradigm captures hyper-data from real-time transactions, detects anomalies in real-time payments and settlement operations, automated the approval process as per Bank Policies and Procedures, and executes in accordance with the bank's Risk Policy to mitigate any breach in Banks' Risk appetite that potentially hampers Compliance Guidelines. With the use of Intelligent Automation based BPS, Banks are able to consume more than 90% of transaction volume in an automated manner with an approval based on thresholds, thereby reducing effort enormously.



Fig 6: Intelligent automation in financial cloud systems

6.1. Roadmapping and Capability Incrementalism

Automating manual, time-consuming processes brings immediate efficiency gains in terms of transaction speed, volume handling and cost reduction, but hides a larger potential for improvement using decision, data and process automation. However, including decision automation from the beginning is the only way of building it by design and not as an afterthought. Migration roads, frameworks and capability matrices are indispensable for developing intelligent automation incrementally, with the budgets available for cloud migration as the leading driver. Evaluation parameters, KPIs and methods for determination of ROI projections measure not just the savings achieved but the additional potential that could be realised using intelligent automation.

Roadmapping cloud deployment and development of the requisite decision-making and governance capabilities is essential for realising the full potential of cloud automation. The deployment of intelligent bots automating frequent, high-volume, time-consuming and error-prone processes offers easily measurable returns on investment. However, the greatest upside comes from the automation of decisions supporting process execution and risk assessment. Both sets of activities are distinct yet complementary. Process automation increases the volume of transactions that can be executed in accordance with established guidelines and frees up staff to focus on risk assessment and problem-solving. Decision automation becomes critical at the cloud scale, especially for functions such as risk management, credit assessment, cyber security and fraud detection that can swing business profitability from year to year. Making a leading factor either the cloud costs or the migration of manual processes to the cloud provides an opportunity to set much of the remaining activity on an intelligent automation roadmap.



6.2. Metrics, KPIs, and ROI Assessment

To derive business value from intelligent automation investment, financial industry firms need to establish metrics and KPIs aligned with their operational strategy and technology portfolio. Financial institutions are also adopting new approaches to analyse the quantitative aspects of intelligent automation to optimise their strategy. Successful implementations improve the return on investment (ROI).

Automation maturity could be evaluated based on three quantifiable criteria: efforts saved, error reduction rate, and direct value derived from automation. Efforts saved would evaluate the overall bank-wide efforts saved by automation across geographies and units for example, CUFA bank, could assess the automation productivity by measuring the number of ITOps engineers required to support production operations.

The delivered error reduction rate could measure the overall level of effort reduction across different premises such as booking of trades, risk reporting, P&L generation, etc. Efforts derived from such error reduction throughout a stipulated time frame would substantiate the direct value of automation.

Pattern	Reason it matters	Article linkage
Microservices / SOA	Independent deployment, scalability, modular service composition	Supports rapid development of cloud-native financial services
Event-driven processing	Decouples components and enables parallel processing	Useful for payments, alerts, and real-time reactions
Cloud-native data pipelines	Near-real-time analytics and automated reactions	Supports predictive workloads and streaming decisions
Externalized state / orchestration	Improves scale-out and control over workflows	Keeps automation manageable across multiple services
Compliance-by-design	Bakes governance into architecture from the start	Reduces audit and regulatory friction in automation

Table 2: architectural patterns

7. Case Studies and Industrial Relevance

Any architectural pattern for cloud systems is best illustrated through case studies that demonstrate its suitability for particular domains. Given the importance of intelligent automation in financial clouds, the most relevant paradigms are those used in Banking-as-a-Service offerings, particularly in areas that require real-time transaction processing. Payments and settlement operations are naturally the most advanced due to their transactional nature, while complex credit and risk management functions of financial services companies entail an extensive degree of human-based decision-making. Several automation solutions based on Artificial Intelligence and Machine Learning have emerged in these domains. Hence, it is time to turn to financial cloud systems and explore some pioneering BaaS offerings, their scope and rapidly-evolving nature.

The Payments and Settlements Automation case study illustrates three aspects that highlight its category as an Intelligent Automation solution: decision automation, new task allocation paradigms, and assurance of compliance through an audit trail. The operators of payments and settlement systems have thus deployed Intelligence Automation paradigms that automate the transactions of Payments and Settlement Operations in real-time.



7.1. Payments and Settlement Automation

Traditional payments are increasingly threatened by digital-only players offering payment services through simple mobile-based interfaces with lower fees compared to traditional financial institutions. Furthermore, cross-border payments in a delivered-at-place model ceaselessly increase, stressing existing payment networks designed in a pre-internet economy. Cloud-based natively hosted payment systems offer a way out. Why not combine these advantages with intelligent automation?

The era of cloud computing provides opportunities to rethink payments and settlement systems. New models based-on the microservices architectural pattern for Internet applications and event-driven architectures enable creating cloud-based systems that can scale horizontally in terms of transaction volume across geographic borders while providing reliability of service and cost advantages. Such systems, by delivering and collecting payments asynchronously, challenge existing payment rail infrastructures by offering new levels of responsiveness and convenience. However, like any cloud application, the construction of such systems requires a no-compromise approach to governance and risk management, supported at all times by supervision and control features. This no-compromise rule is paramount in financial cloud applications. Automated systems that autonomously execute financial transactions and make instantaneous or very low delay decisions affecting people's financial health must not only be powerful but also auditable, explainable, and understandable. The ability to prove that an automated financial decision corresponds to rules and guidelines diligently mapped, stored, exposed, and constantly monitored is essential and should be considered from the beginning. Any financial cloud system qualifies for a compliance-by-design approach.

Equation 5: Compliance / Risk Exposure Score

A natural quantitative compliance-risk model is:

- p_i = probability of violation i
- s_i = severity of violation i
- R = total expected risk exposure

Then:

$$R = \sum_{i=1}^n p_i s_i$$

Step-by-step derivation

For one compliance event:

$$\text{Expected risk for event } i = p_i \cdot s_i$$

If there are n independent risk categories, total expected risk is the sum:

$$R = p_1 s_1 + p_2 s_2 + \dots + p_n s_n$$

In sigma notation:



$$R = \sum_{i=1}^n p_i s_i$$

Compliance threshold condition

If the organization defines a maximum acceptable risk $R_{\max}$, then:

- compliant when

$$R \leq R_{\max}$$

- non-compliant or escalated when

$$R > R_{\max}$$

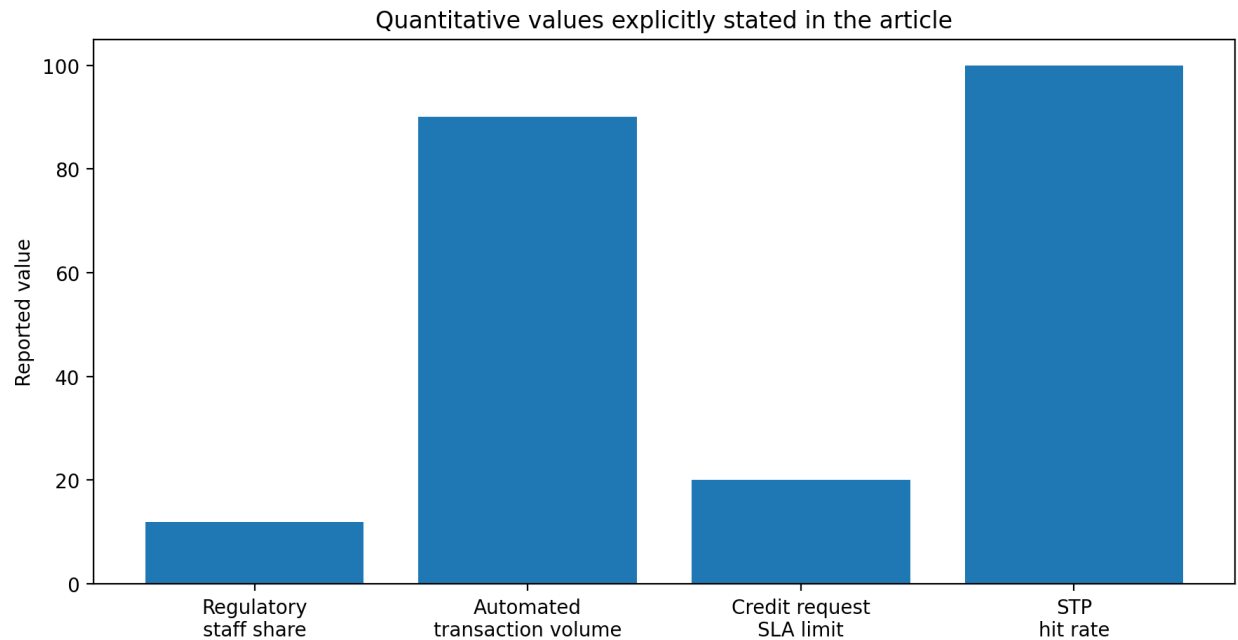
So the control rule becomes:

$$\text{System acceptable if } \sum_{i=1}^n p_i s_i \leq R_{\max}$$

7.2. Risk and Credit Operations Automation

A major cloud service provider introduced an internal credit decisioning platform spanning multiple cloud solutions with the parallel goals of reducing processing time and improving availability remote work favoured by pandemic. The existing rubber-stamp Crowd credit decision solution lingered over installation long past its original 4 months target, as many merchants loans had to be declined within an SLA lasting less than 20min. Following earlier studies theme of offering layer of Intelligent Automation as a service, the credit offering was split into reusable components and stepwise ported to the new cloud without then re-implementing Crowd solution code – although differences in business rules prevented joint operation. The Credit Operations Intelligent Automation Layer lowered both the operational and time-to-decision for providing credit limits to merchants in specifically credit card issuance-focused payment ecosystems, estimated earlier as being 25% of total payment market and expected to disappear in next 3 years. With merchants processing Payments via deployed Cloud solution rather than 3rd party platform, and business rules for support enabled using test-driven development, such Cloud credit decisioning offered incremental availability at less than 20min SLA per credit request.

Parallel internal efforts by financial cloud service provider on automating Inactive Risk with a layer of Intelligent Automation reported more errorless resourcing of alert. An earlier review showed a general lack of low-hanging fruit: solutions tend to have such automated successfully much earlier, both on results positively offering significant ROI & not good enough opportunities turning into hidden scams in knowledge of affected actor, yet opening such no- or de-minimis cost possibility.



8. Conclusion

The proposed architectural patterns and components support Cognitive Intelligent Automation Capability maps for financial cloud environments and provide a starting point to determine cloud automation maturity and readiness for advanced intelligent automation adoption. Intelligent automation enables more end-to-end process automation, allowing financial institutions to shift towards self-adaptive, self-learning, and self-healing process ecosystems.

Next-generation banking clouds have the potential to produce significantly positive return on investment by directly creating new, and enhancing existing, cloud service offerings. Intelligent automation is a fundamental enabler of such new cloud services and improved financial cloud offerings. However, the decisioning needs for intelligent automation services require careful consideration.

9. List of important References

Fintech processes exhibit a number of distinctive characteristics that drive their intelligent automation. They are usually based upon digital transactional information; integrated across functional silos; focus on establishment of state; require high throughputs; are subject for decision logic; and are compliance-sensitive, risk-governed and audited. In the context of the next-generation Financial Clouds definition, intelligent automation comprises the elements of automation execution (solving “how”),



decisioning (solving “what”), learning and reasoning (solving “why”) and iterative improvement (solving “how well”). Intelligent automation corresponds to the performing, deciding, learning and improving quadrants of the FinOps stack.

Four Cloud Maturity Models are relevant for intelligent automation solutions for the financial industry. Firstly, Process Intelligence supports the mapping of existing financial processes as a prerequisite for automation. Secondly, RPA Maturity measures the degree to which an organisation is automating manual processes for the execution of rules. Thirdly, Decision Automation Maturity assesses the incrementality and embeddedness of decision automation, auditing and compliance-by-design. Finally, Process Intelligence provides a roadmap and supporting toolkit for the realisation of a “Digital FinOps Assistant”.

Lifecycle component	Purpose	Examples from article
Risk definition	Specify risks and controls before execution	Risk appetite, regulatory pressure, prevention/detection capacity
Monitoring & audit	Observe automated activity continuously	Audit logs, intelligent auditing engines, SLA checks
Control management	Enforce approvals and separation of duties	Approval controls, surveillance, reporting requirements
Policy & procedure automation	Translate governance into executable logic	Decision rules, procedures, low-code implementations
Response	Trigger action when tolerance breaches occur	Alerts, human escalation, pause workstreams

Table 3 : compliance life cycle

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