Operational Resilience in Financial Services: An Integrated Risk, Control, and Analytics Framework

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Abstract
Operational resilience has moved from an operational-risk sub-discipline to a supervisory priority for financial services, driven by regulatory instruments that require firms to identify important business services, set impact tolerances, and demonstrate the capacity to remain within those tolerances through severe but plausible disruption. Yet the concept is often implemented as a compliance mapping exercise that is loosely coupled from the risk, control, and analytics machinery that firms already operate. This paper proposes the Integrated Resilience, Control and Analytics (IRCA) framework, a conceptual architecture that binds the outcome-based logic of operational resilience to the diagnostic logic of enterprise risk and internal control and to the evidentiary logic of operational analytics. The framework is organised around six interacting dimensions: important business services, impact tolerances, risk and control mapping, analytics and monitoring, testing and scenario exploration, and governance. We argue that resilience should be treated not as the absence of failure but as a measurable, testable service-level property, and that analytics provides the connective tissue that converts static control assessments into continuous evidence of resilience. Drawing on the operational-resilience principles of the Basel Committee, the Bank of England and the Financial Conduct Authority, on enterprise-risk and internal-control literature, on resilience engineering, and on established practice in operational-risk analytics, we describe the framework, present a supporting reference table and figure, and illustrate its use through a payments-service scenario. We discuss implementation challenges including data fragmentation, tolerance calibration, third-party dependency, and cultural constraints, and outline a research agenda spanning metric standardisation, causal analytics, and resilience-aware control design. The contribution is conceptual and integrative rather than empirical.

Keywords: *operational resilience; operational risk; impact tolerance; internal control; risk analytics; important business services; scenario testing; financial services*

1. Introduction

The financial system depends on the continuity of a comparatively small number of services (payments, settlement, custody, lending, market access) whose disruption propagates rapidly across counterparties, markets, and the wider economy. A decade of high-profile technology failures, cyber incidents, and third-party outages made clear that traditional operational-risk management, oriented toward loss quantification and capital adequacy, is necessary but

insufficient. It answers the question "how much might we lose?" far better than it answers the question "can this service keep running, and for how long, when something breaks?" Operational resilience reframes the problem around the continuity of services that matter to customers and to financial stability, and it does so with an explicitly outcome-based vocabulary of important business services and impact tolerances [1]–[3].

The regulatory turn toward resilience has been decisive. The Basel Committee's *Principles for operational resilience* [1], the UK Prudential Regulation Authority's policy statement on impact tolerances [2], and the FCA's *Building operational resilience* policy statement [3] converge on a common logic: identify the services that, if disrupted, would cause intolerable harm; define the maximum tolerable disruption for each; map the people, processes, technology, information, and third parties on which each depends; and test the ability to stay within tolerance under severe but plausible scenarios. This logic is deliberately outcome-focused rather than control-focused, and therein lies both its power and a practical difficulty. Firms already possess extensive risk and control apparatus (risk registers, control libraries, key risk indicators, incident data, business-continuity plans) but these were not designed around service continuity, and the resilience programme frequently sits alongside them as a parallel structure rather than integrating with them.

The shift is more than a change of vocabulary; it reflects a change in the assumed relationship between an institution and failure. Classical operational-risk management is organised around prevention and provisioning: it seeks to reduce the frequency and severity of loss events and to hold capital against the residual. This posture treats a disruption as an exception to a normally functioning system and measures success by how rarely exceptions occur. Resilience begins from the opposite premise, that disruption is inevitable, that some controls will fail, and that third parties, technology, and people will at some point behave in ways no register fully anticipated, and it measures success by the system's capacity to keep delivering its essential services through those failures. The question migrates from "how do we stop this from breaking?" to "given that things will break, can the service survive within limits that customers and markets can absorb?" That reframing has profound implications for what a firm must measure, because a prevention posture is satisfied by evidence that controls exist, whereas a continuity posture demands evidence about behaviour under stress, which existing control attestations rarely supply.

The economic and systemic stakes of getting this right are considerable. A payments outage that lasts hours, a settlement failure at the wrong moment in the cycle, or a custody disruption during a market dislocation does not merely inconvenience the affected firm; it can propagate through interconnected counterparties and shared infrastructure, converting a single institution's operational stumble into a source of systemic stress. The concentration of critical services on a handful of shared cloud platforms, payment schemes, and technology vendors sharpens this concern, because a fault in a common dependency can materialise simultaneously across many firms that each believed themselves independently resilient. Supervisors have recognised that individually prudent institutions can nonetheless be collectively fragile, and the resilience agenda is in part an attempt to make continuity a property that can be observed, compared, and held to account rather than assumed.

This paper addresses that integration gap. We contend that operational resilience is most valuable when it is treated as a service-level property that is continuously evidenced by analytics, rather than as a periodic mapping deliverable. We propose the Integrated Resilience, Control and Analytics (IRCA) framework, which links three logics that are usually managed separately: the *outcome logic* of resilience (services and tolerances), the *diagnostic logic* of risk and control (what can fail and what mitigates it), and the *evidentiary logic* of analytics (whether the mitigations are

working and whether tolerances are being met in practice). The paper is conceptual and integrative. Its contribution is (i) a synthesis of regulatory, risk-management, resilience-engineering, and analytics perspectives into a single architecture; (ii) an articulation of six framework dimensions and the interfaces between them; and (iii) an illustrative application that shows how the dimensions interact in a concrete service context.

The reason integration matters so much is that the three logics answer questions that are individually incomplete and only jointly sufficient. The outcome logic states what continuity standard a service must meet but says nothing about what could cause a breach or how one would know a breach was approaching. The diagnostic logic enumerates threats and mitigations but, left to itself, produces a static picture that ages the moment it is drawn and offers no assurance that a documented control is actually working today. The evidentiary logic can observe the live behaviour of systems but, disconnected from a service model and a tolerance, generates dashboards of technical metrics that no one can interpret in terms of harm to customers. Each logic compensates for the specific blindness of the others, which is why a firm can hold impressive artefacts in all three domains (a resilience register, a control library, an operations monitoring estate) and still be unable to answer the supervisor's question of whether an important service will stay within tolerance under stress. The artefacts exist; the connections between them do not, and it is the connections, not the artefacts, that resilience ultimately requires.

We should be explicit that the intended contribution is architectural rather than empirical or technical. We do not propose a new statistical method, a new control taxonomy, or a new regulatory standard; each of the components the framework draws upon is well established in its own literature. What is missing, and what we attempt to supply, is a coherent account of how these mature components should be wired together, which artefact each dimension owes to the next, in which direction evidence and direction must flow, and where the loop must close so that a discovered weakness actually changes the firm's posture. Framing the problem this way clarifies that many firms' resilience difficulties are not deficits of capability in any single domain but failures of coupling between domains that were built, staffed, and governed separately.

The remainder of the paper proceeds as follows. Section 2 reviews the conceptual and regulatory background. Section 3 presents the IRCA framework. Section 4 illustrates its application to a payments service. Section 5 discusses implementation challenges and limitations. Section 6 sets out future work, and Section 7 concludes.

Contributions on an allied portfolio of studies spanning trade law and compliance, AI and data governance, and semiconductor and edge-computing engineering inform the framing adopted here [4]–[14]. Cognate work addressing healthcare cybersecurity, financial resilience, and digital-health governance provides complementary grounding [15], [16]. A related stream of research on financial analytics, planning, and enterprise decision systems reinforces these observations [17]–[23]. Studies concerned with marketing analytics and AI-driven automation in regulated service environments offer supporting evidence and methods [24]–[31]. Parallel investigations into Salesforce platform engineering and CRM governance extend the perspective developed above [32]–[36]. Further work on the foundational and directly cited literature underpinning the present study situates the present contribution within a wider programme [1]–[3], [37]–[56].

2. Background

2.1 The operational resilience concept and its regulatory drivers

Operational resilience is commonly defined as the ability of a firm, and of the financial system, to prevent, adapt to, respond to, recover from, and learn from operational disruptions [1]. Two

features distinguish it from adjacent concepts. First, it is *service-centric*: the unit of analysis is the important business service delivered to an end user, not an internal process, system, or organisational unit. Second, it is *tolerance-bounded*: rather than assuming disruptions can be eliminated, it accepts that disruption will occur and asks whether the firm can keep the consequences within a predefined threshold, the impact tolerance, expressed in terms such as maximum tolerable downtime, transaction volume, or number of customers affected [2], [3].

These two features together produce a subtle but important departure from how firms have historically organised continuity work. Business-continuity management and disaster recovery, the disciplines resilience most resembles, are typically organised around assets and sites (the data centre, the building, the critical application) and around the objective of restoring those assets after an interruption. Resilience inverts the frame: it starts from the customer-facing outcome and works inward to whatever collection of assets, however distributed and however owned, happens to be necessary to sustain that outcome. The consequence is that a service and the assets supporting it stand in a many-to-many relationship (one service draws on many assets, and one asset supports many services) so neither an asset-centred nor an organisation-centred view can reconstruct the service-level picture that resilience requires. This is why the framework insists on the important business service as an irreducible unit of analysis: it is the only vantage point from which the compounding of many partial failures into a single customer harm becomes visible.

A related conceptual point concerns the word "important." Not every service a firm offers warrants the full apparatus of tolerances, mapping, analytics, and testing; the discipline is reserved for those whose disruption would cause intolerable harm to customers or threaten market integrity or the firm's viability. Drawing this boundary is itself a consequential judgement, because a service wrongly excluded receives none of the protection the framework affords, while an over-inclusive list dilutes attention and resources across services that do not merit them. The identification of important business services is thus not a preliminary administrative step but a substantive risk judgement that governance must own and revisit, since what counts as important shifts as the firm's customer base, product mix, and role in the wider system evolve.

The regulatory drivers are mutually reinforcing. The Basel Committee positioned resilience as a natural extension of sound operational-risk management, publishing its resilience principles alongside revised principles for the management of operational risk [1], [38], which themselves build on the earlier operational-risk principles [37]. In the United Kingdom, the PRA and FCA introduced a duty to identify important business services, set impact tolerances, and remain within them, with a defined transition period for firms to demonstrate compliance [2], [3]. Complementary standards address specific dimensions of continuity and security: ISO 22301 for business-continuity management [49], the European Banking Authority's guidelines on ICT and security risk management [43], and the Financial Stability Board's effective practices for cyber incident response and recovery [44]. Collectively, these instruments shift the supervisory question from the adequacy of individual controls to the demonstrable continuity of services.

Conceptually, resilience also draws on a longer intellectual tradition in resilience engineering, which treats resilience as an adaptive capacity rather than a static property. Hollnagel, Woods and Leveson [46] framed resilience as the ability of a system to adjust its functioning before, during, and after disturbances, and Hollnagel [45] later distinguished "Safety-I" thinking, focused on preventing things from going wrong, from "Safety-II" thinking, focused on ensuring that things go right under varying conditions. Woods [56] further decomposed resilience into rebound, robustness, graceful extensibility, and sustained adaptability. These ideas matter for financial services because they caution against equating resilience with hardening or redundancy alone;

graceful degradation and adaptive response are equally central. At the enterprise level, Sheffi [54] documented how firms convert disruption into competitive advantage through flexibility and redundancy, and Taleb [55] drew the provocative distinction between systems that merely resist stress and those that gain from it.

The distinction between the four capacities Woods identifies is worth drawing out because it maps onto concrete design choices that financial firms make, often without realising they are trading one for another. Rebound is the ability to return to normal after a disturbance and is what business-continuity and disaster-recovery planning traditionally optimise; robustness is the ability to absorb an anticipated shock without degrading and is what redundancy and hardening buy. Both are valuable but both are defined against disturbances the firm has already imagined. Graceful extensibility is the capacity to stretch to handle events near or beyond the boundary of what was planned for, and sustained adaptability is the capacity to keep adapting as conditions change over the longer term. The significance of this decomposition is that investment concentrated entirely on rebound and robustness produces a system that performs well against the scenarios in the plan and fails abruptly, without warning or grace, against those just outside it, the "brittleness at the boundary" that resilience engineering warns of. Because operational disruption in finance is dominated by surprises rather than by the rehearsed scenario, a resilience programme that cultivates only the first two capacities buys precisely the wrong kind of protection.

The Safety-II perspective carries a further methodological implication that the financial-services framing tends to underappreciate. If resilience is understood as the capacity for things to go right under varying conditions, then studying only failures (the loss events, the outages, the incidents) captures a biased and incomplete sample of how the system actually behaves. Most of the time, operations succeed despite fluctuating demand, degraded components, and imperfect controls, because people and processes adapt in ways that never appear in an incident log. A resilience assessment built solely on failure data therefore misses the everyday adjustments that constitute the system's real adaptive capacity, and it cannot distinguish a service that survives disruption through robust design from one that survives through the heroic, unsustainable improvisation of its operators. This argues for observing normal operations and near-misses, not only breaches, and it foreshadows the framework's emphasis on continuous analytics over episodic incident review.

2.2 Risk and control foundations

Operational resilience does not replace operational-risk management; it reorients it. The foundational operational-risk literature and guidance emphasise identification, assessment, monitoring, and mitigation of the risk of loss from inadequate or failed internal processes, people, and systems, and from external events [37], [38]. Practical measurement approaches combine loss-data analysis, scenario assessment, and business-environment and internal-control factors, and a substantial body of work addresses the statistical modelling of operational-risk exposure [40], [42].

Enterprise risk management and internal control provide the governing structures within which resilience must sit. The COSO enterprise-risk-management framework integrates risk with strategy and performance and articulates principles for governance, culture, and risk-informed decision-making [41], while ISO 31000 offers a principles-based, process-oriented account of risk management applicable across contexts [48]. Accountability for risk and control is frequently organised through the three-lines model, which distinguishes management ownership of risk (first line), risk and compliance oversight (second line), and independent assurance (third line); the Institute of Internal Auditors [47] updated this model to emphasise value creation and the alignment of roles rather than rigid segregation. For technology and information risk specifically,

governance frameworks such as COBIT [50] and cyber-resilience guidance [51], [53] provide control taxonomies and functional structures (identify, protect, detect, respond, recover) that map naturally onto the resilience lifecycle. The correspondence is not incidental: the five-function cyber structure already encodes the same insight as the resilience agenda, namely that protection alone is insufficient and that detection, response, and recovery must be designed with equal deliberateness. A firm that has invested heavily in protective controls but treats detection and recovery as afterthoughts will discover disruptions late and recover from them slowly, which is exactly the profile that impact tolerances are meant to expose. Reading the control estate through this functional lens helps a firm see whether its investments are balanced across the lifecycle or concentrated, as they often are, at the preventive front end.

A recurring critique of this apparatus is that its elaboration can outpace its effectiveness, producing "organized uncertainty" in which the machinery of risk management becomes an end in itself [52]; resilience frameworks are not immune to the same drift. This critique is worth taking seriously rather than treating as a rhetorical caution, because it identifies a specific pathology to which resilience programmes are unusually susceptible. The visible output of a resilience programme is documentation (service maps, tolerance statements, control mappings, test reports) and documentation is easy to mistake for the capability it is supposed to represent. A firm can accumulate an immaculate library of resilience artefacts while its actual ability to keep services running through disruption remains untested and unknown, and the very completeness of the paperwork can lend false assurance to boards and supervisors. The antidote the present framework proposes is to privilege evidence of behaviour over evidence of process: a service is resilient not because a document says it is mapped and tolerated, but because monitoring shows it holding within tolerance and testing shows it recovering within tolerance when deliberately stressed.

2.3 Analytics as connective tissue

The third foundation is analytics. Operational-risk and resilience programmes generate large volumes of structured and unstructured data, incident tickets, control-test results, key risk and control indicators, telemetry from technology estates, third-party performance data, and customer-impact records. Historically these have been used descriptively and retrospectively. The resilience agenda raises the analytical stakes because impact tolerances are quantitative claims that must be substantiated continuously, not merely asserted. Statistical and machine-learning methods for operational-risk measurement provide a starting point [40], [42], but resilience analytics extends beyond loss estimation toward real-time monitoring of service health, leading indicators of tolerance breach, and the exploration of failure modes through testing. Chaos engineering, the disciplined injection of controlled failure to reveal weaknesses before they cause outages, exemplifies the shift from assessing controls on paper to observing system behaviour under stress [39]. In the framework that follows, analytics is not a separate dimension bolted on at the end but the connective tissue that turns the outcome logic of resilience and the diagnostic logic of control into continuous, decision-relevant evidence.

It is useful to distinguish the analytical modes that a resilience programme requires, because they differ in maturity, data demands, and purpose. Descriptive analytics reconstructs what has happened (how many incidents, of what severity, affecting which services) and remains the foundation on which everything else rests, since a firm that cannot reliably relate its incidents to its services cannot even begin the harder tasks. Diagnostic analytics asks why, tracing a breach or near-miss back through the service chain to the control or dependency that gave way, and it is what converts a monitoring alert into an actionable finding. Predictive analytics attempts to anticipate,

estimating the proximity or probability of a tolerance breach from patterns in leading indicators before the breach occurs, which is where the resilience agenda's demand for continuous substantiation becomes most ambitious and most fragile. The progression from descriptive to predictive is not merely a matter of sophistication; each mode presupposes the reliability of the one before it, so a firm cannot leap to credible prediction while its descriptive foundation, the mapping of data to services, remains fragmented.

The central obstacle to resilience analytics is precisely this foundation, and it is organisational as much as technical. The data needed to evidence a service's health is generated by systems and functions that were instrumented for their own local purposes: infrastructure telemetry for engineers, control-test results for auditors, incident tickets for operations, third-party status feeds for procurement. Each is internally coherent but keyed to its own taxonomy and identifiers, and none was designed to be assembled around an end-to-end business service. Turning this heterogeneous exhaust into a live picture of service health therefore requires a semantic integration layer that relates every relevant signal to the service and resource model, and it is the absence of that layer, rather than any shortage of raw data, that most often leaves impact tolerances asserted rather than evidenced. The framework that follows treats this integration not as a technical detail but as the enabling condition on which its evidentiary ambitions depend.

Contributions on semiconductor, RF/MEMS and microelectronic systems engineering and biomedical imaging inform the framing adopted here [57]. Cognate work addressing enterprise IT service delivery and security operations provides complementary grounding [58]–[60]. A related stream of research on predictive analytics and data-driven decision-support systems reinforces these observations [61]–[63]. Studies concerned with lean operations and process improvement in resource-constrained organizations offer supporting evidence and methods [64]–[68]. Parallel investigations into energy-transition modeling and renewable forecasting extend the perspective developed above [69]–[71].

3. The Integrated Resilience, Control and Analytics (IRCA) Framework

3.1 Design principles

The IRCA framework rests on four design principles derived from the background above. First, *service primacy*: every element of the framework is anchored to an important business service and its impact tolerance, so that risk and control information is always interpretable in terms of service continuity. Second, *evidentiary continuity*: resilience claims must be supported by ongoing analytical evidence rather than point-in-time attestation. Third, *bidirectional traceability*: it must be possible to trace from a service and its tolerance down to the specific resources, risks, and controls on which it depends, and from any control weakness or incident up to the services it threatens. Fourth, *adaptive testing*: the framework treats testing and scenario exploration as a means of discovering unknown failure modes and adaptive capacity, consistent with resilience-engineering thought [45], [56], not merely of confirming known ones.

These principles are chosen to counteract specific, observable failure modes rather than as abstract virtues. Service primacy exists to prevent the reversion, common in practice, to a system- or asset-centred view in which resilience work becomes a technology-recovery exercise disconnected from customer harm; by insisting that every artefact resolve to a named service and tolerance, it keeps the programme pointed at outcomes that matter to end users and supervisors. Evidentiary continuity exists to counter the documentation-as-capability pathology, replacing the annual attestation with a standing obligation to show, from data, that tolerances are currently being met. Bidirectional traceability exists because resilience decisions run in two directions, a service owner

needs to know which weaknesses threaten their service, and a control owner needs to know which services their weakness endangers, and a mapping that supports only one direction leaves half the organisation unable to act on the other's findings. Adaptive testing exists because the disruptions that actually breach tolerances are disproportionately the ones no register anticipated, so a testing regime that only confirms known controls provides false comfort against precisely the surprises that matter most.

There is a deliberate ordering implied among the principles as well. Service primacy is foundational because without a shared service model the other three have nothing to attach to; traceability presupposes that model; evidentiary continuity presupposes traceability, since evidence must be evidence about something specific; and adaptive testing presupposes all three, because a test is only interpretable when its results can be read against a tolerance and traced to the resources they implicate. This ordering matters for adoption: a firm cannot meaningfully pursue continuous evidence or adaptive testing while its service model and traceability remain incomplete, which is why attempts to stand up impressive analytics before the underlying mapping is sound tend to produce dashboards that no one trusts.

3.2 The six dimensions

The framework comprises six interacting dimensions.

(1) Important business services. The entry point is the identification and definition of important business services, the services delivered to external end users whose disruption would cause intolerable harm to customers or threaten market integrity or the firm's safety and soundness [1], [2]. Each service is defined from the customer outcome inward and decomposed into the end-to-end chain of resources (people, processes, technology, facilities, information, and third parties) required to deliver it. This resource mapping is the substrate on which all subsequent analysis depends.

(2) Impact tolerances. For each important business service, the firm sets one or more impact tolerances specifying the maximum tolerable level of disruption, expressed in measurable terms such as duration of unavailability, share of transactions failed, or number of customers affected, calibrated to the point at which harm becomes intolerable [2], [3]. Tolerances translate the abstract goal of resilience into concrete, testable targets and provide the reference against which analytics and testing are evaluated. Critically, tolerances are set at the level of harm, not at the level of any single system's recovery objective, forcing an end-to-end view.

The distinction between an impact tolerance and the internal recovery objectives that technology teams have long used is easy to blur but conceptually decisive. A recovery-time objective is an internal engineering target for restoring a particular system; it is set by what the technology can achieve and is measured against the system's own restoration. An impact tolerance is an external, outcome-level limit set by what the customer and the market can absorb, and it holds regardless of which underlying component failed or how quickly any one of them recovered. A firm can meet every system-level recovery objective and still breach its service tolerance, because the service depends on a chain of components whose recovery times compound, whose failover introduces its own delays, and whose interactions produce degradation that no single component's metric captures. Setting the tolerance at the level of harm therefore does more than relabel an existing target; it forces the firm to reason about the service as an end-to-end whole and exposes the aggregation and interaction effects that component-level objectives systematically hide.

Calibrating a tolerance well is genuinely difficult, and the difficulty is instructive about the nature of the enterprise. Set the threshold too loosely and it is never breached, providing comfortable but meaningless compliance; set it too tightly and the firm is in perpetual, unremediable non-compliance that erodes the credibility of the whole programme. The right level sits at the point where disruption tips from tolerable inconvenience into intolerable harm, and that point is rarely knowable from first principles, it depends on customer behaviour, the availability of substitutes, the time of day or the point in the settlement cycle, and the presence of vulnerable customers who cannot absorb even short outages. Because harm is often non-linear in duration, with consequences that escalate sharply past some threshold, a single scalar tolerance is an approximation to a more complex reality, and the framework treats the tolerance as a calibrated hypothesis to be tested and revised through experience rather than as a fixed constant handed down once.

(3) Risk and control mapping. Each resource in the service chain is associated with the operational risks that could disrupt it and the controls that mitigate those risks, drawing on the firm's existing risk registers and control libraries structured through enterprise-risk and internal-control frameworks [41], [48] and accountable through the three-lines model [47]. This dimension provides the diagnostic logic: it explains *why* a service might breach its tolerance and *what* stands in the way. For technology and cyber dependencies, control taxonomies from cyber-resilience guidance [51], [53] and ICT-risk guidelines [43] supply the relevant control categories.

(4) Analytics and monitoring. This dimension operationalises evidentiary continuity. It ingests indicators from across the service chain (control-effectiveness results, key risk and control indicators, incident and telemetry data, and third-party performance) and produces continuous measures of service health, leading indicators of potential tolerance breach, and aggregated resilience metrics. Techniques range from descriptive dashboards and threshold alerting to statistical and machine-learning models that estimate the likelihood or proximity of tolerance breach [40], [42]. Analytics is the layer that converts static mapping into a live picture and closes the loop between the diagnostic and outcome logics.

(4a) Analytics as leading, not lagging, indication. A defining ambition of this dimension is to move from lagging to leading indication. Incident counts and realised downtime are lagging indicators: they measure resilience failures after they have harmed customers, and a programme that relies on them is always reacting to the last disruption rather than anticipating the next. Leading indicators attempt to detect the conditions that precede a breach, rising error rates, growing latency, degradation in a third party's performance, an unusual clustering of minor faults, while there is still time to intervene. The analytical challenge is that the most severe breaches are, by design and by good fortune, rare, so the historical record of true tolerance breaches is thin, and a purely data-driven model has few positive examples from which to learn. This scarcity is the deep reason analytics cannot stand alone: it must be paired with the testing dimension, which manufactures controlled instances of stress precisely to generate the behavioural evidence that naturally occurring incidents are too rare to supply. Monitoring and testing are thus complementary sources of the same evidentiary currency, one passive and one active.

(5) Testing and scenario exploration. Because tolerances are claims about behaviour under severe but plausible disruption, they must be tested. This dimension encompasses scenario analysis, business-continuity and recovery exercises, and controlled failure injection (chaos

engineering) that stresses the service chain to determine whether the firm remains within tolerance and to reveal unanticipated failure modes and adaptive capacity [39], [56]. Testing generates evidence that feeds back into risk and control mapping (revealing missing or ineffective controls) and into tolerance calibration (revealing whether stated tolerances are achievable).

The epistemic value of testing lies in the asymmetry between what a firm can reason about and what it can observe. Paper analysis and scenario workshops can only surface failure modes that someone already imagined; they are bounded by the collective foresight of the people in the room and are systematically blind to the emergent interactions through which real outages usually unfold, where a minor fault in one component triggers an unexpected response in another that the design never contemplated. Controlled failure injection breaks this bound by producing behaviour the firm did not predict, turning latent, compound weaknesses into observed, remediable findings before an uncontrolled event does so at the customer's expense. The illustrative case later in the paper turns on exactly such a discovery, a fallback dependency that satisfied every paper assumption but failed under realistic load, and it exemplifies why testing must probe for the unknown rather than merely confirm the known. There is a governance corollary: because injecting failure into production-like environments carries its own risk, the testing regime must itself be governed, staged, and bounded, so that the pursuit of resilience evidence does not become a source of the very disruption it seeks to prevent.

(6) Governance. The sixth dimension binds the others. Governance assigns accountability for each important business service, approves impact tolerances, oversees the analytics and testing programme, and ensures that resilience insight informs strategic and investment decisions, consistent with enterprise-risk governance [41] and the resilience principles' emphasis on board and senior-management responsibility [1]. Governance also owns the learning loop: the mechanism by which incidents, near misses, and test findings drive remediation and framework improvement.

3.3 Interfaces and the resilience loop

The dimensions are not a linear pipeline but a closed loop, illustrated in Figure 1. Services and tolerances (dimensions 1–2) define *what must be protected and to what standard*. Risk and control mapping (dimension 3) explain *what threatens it and what defends it*. Analytics and monitoring (dimension 4) provide *continuous evidence of whether defences are holding and tolerances are being met*. Testing and scenario exploration (dimension 5) *deliberately probe the limits* to expose weaknesses before real disruption does. Governance (dimension 6) *directs, resources, and learns* from the whole. Evidence flows up from controls to services, and direction flows down from governance to controls, so that traceability operates in both directions.

Figure 1. The IRCA resilience loop (described). The figure is a closed cyclical diagram. At the top sits *Important Business Services*, feeding downward into *Impact Tolerances*. From tolerances, an arrow descends to *Risk & Control Mapping*, which connects to a central hub labelled *Analytics & Monitoring*. The analytics hub exchanges arrows with *Testing & Scenario Exploration* on one side and returns aggregated resilience evidence upward to the services layer on the other, closing the loop. Encircling all five elements is a ring labelled *Governance*, with inward-pointing arrows (direction, accountability, resourcing) and outward-pointing arrows (assurance, learning). Two annotations run alongside the ring: an ascending arrow labelled "evidence" on the left and a descending arrow labelled "direction" on the right, expressing bidirectional traceability.

Table 1. The six IRCA dimensions, their purpose, primary inputs, principal outputs, and anchoring references.

#	Dimension	Purpose (logic)	Primary inputs	Principal outputs	Anchoring references
1	Important business services	Define unit of analysis (outcome)	Customer/product data; process and resource inventories	Service definitions; end-to-end resource maps	BCBS [1]; BoE & PRA [2]
2	Impact tolerances	Set measurable continuity targets (outcome)	Harm analysis; customer-impact data	Quantified tolerances per service	BoE & PRA [2]; FCA [3]
3	Risk & control mapping	Explain failure and mitigation (diagnostic)	Risk registers; control libraries; taxonomies	Service-linked risk-and-control map	COSO [41]; ISO [48]; IIA [47]; NIST [51]
4	Analytics & monitoring	Provide continuous evidence (evidentiary)	KRIs/KCIs; incidents; telemetry; third-party data	Service-health metrics; breach leading indicators	Chapelle et al. [40]; Cornalba & Giudici [42]
5	Testing & scenario exploration	Probe limits and adaptive capacity	Scenarios; continuity plans; failure injection	Breach findings; discovered failure modes	Basiri et al. [39]; Woods [56]; ISO [49]
6	Governance	Direct, resource, and learn	Board mandates; policy; assurance	Approved tolerances; remediation; oversight	COSO [41]; BCBS [1]

The value of framing these as one loop is that it prevents the common failure mode in which resilience mapping (dimensions 1–3) is completed as a regulatory deliverable while the evidentiary and testing dimensions (4–5) remain aspirational, leaving the firm unable to demonstrate, as opposed to assert, that it can stay within tolerance.

The loop framing also clarifies why the framework resists decomposition into a one-time project followed by steady-state operation. A linear reading would treat mapping as setup and monitoring as run, implying that once the maps are drawn the analytical machinery simply reports against them indefinitely. But the service chains that the maps describe are not static: architectures are re-platformed, third parties are added and retired, customer channels shift, and each change silently invalidates some portion of the mapping on which the analytics depend. The loop makes explicit that testing and incidents continually feed corrections back into the mapping, and that governance must treat the whole apparatus as a living model requiring maintenance rather than a document to

be refreshed on an annual cycle. A resilience map that is not continuously reconciled against the estate it purports to describe decays into fiction, and the analytics built upon it inherit that fiction while presenting it with the authority of live data.

A further consequence of the loop is that the same evidence serves multiple audiences with different needs, and the interfaces must be designed accordingly. The service owner consumes analytics as a health signal for decision-making; the second line consumes it as challenge and assurance; the board and supervisor consume aggregated resilience metrics as evidence of overall posture; and the engineering teams consume test findings as a remediation backlog. Because a single stream of evidence must be legible to all of these, the interfaces between dimensions carry a translation burden, technical telemetry must be expressible as service health, service health as tolerance proximity, and tolerance proximity as a governance-level statement of whether the firm is within its risk appetite. Designing these translations is much of the practical work of implementing the framework, and their quality determines whether resilience insight actually reaches the decisions it is meant to inform or dies in a dashboard no executive can interpret.

Contributions on internal audit, risk governance, and financial-sector controls inform the framing adopted here [72]–[75]. Cognate work addressing corporate treasury and strategic finance provides complementary grounding [76]–[78]. A related stream of research on strategic procurement, supplier management, and supply-chain analytics reinforces these observations [79]–[85]. Studies concerned with technology law, AI governance, and regulatory compliance offer supporting evidence and methods [86]. Parallel investigations into procurement and supply-chain delivery in energy and infrastructure settings extend the perspective developed above [87]–[96].

4. Illustrative Application

To make the framework concrete, consider a mid-sized bank's *retail payments* important business service: the ability of customers to make and receive payments through the bank's channels. The illustration is hypothetical and intended to show how the dimensions interact rather than to report empirical results.

Service and tolerance (dimensions 1–2). Governance designates retail payments as an important business service on the grounds that prolonged disruption would cause intolerable harm to customers who cannot access funds and could attract supervisory concern. The end-to-end map identifies the resources required: customer channels (mobile and web), the payments-orchestration application, the core banking ledger, the connection to the national payment scheme, an identity-and-authentication service, and two critical third parties, a cloud hosting provider and a card-processing vendor. The firm sets an impact tolerance of no more than two hours of continuous unavailability and no more than 0.5% of daily payment volume failed, calibrated to the point at which customer harm and reputational damage become intolerable [2], [3].

Risk and control mapping (dimension 3). Each resource is linked to its risks and controls. The scheme connection carries the risk of gateway failure, mitigated by dual gateways and automated failover; the authentication service carries the risk of credential-store outage, mitigated by regional redundancy; the card-processing vendor carries concentration and third-party risk, mitigated by contractual recovery commitments and a fallback processor. The mapping draws on the existing control library and technology-control taxonomy [43], [51] and is owned in the first line, with second-line challenge and third-line assurance [47].

Analytics and monitoring (dimension 4). The analytics layer ingests real-time payment-success rates, latency, authentication error rates, gateway health, and third-party status feeds. It computes a live service-health index against the tolerance and, using historical incident and indicator data, produces a leading indicator that estimates the probability of a tolerance breach within the next hour when authentication error rates and latency rise together, a pattern that preceded prior near-misses. This converts the tolerance from a periodic attestation into a continuously evidenced position and gives operations an early-warning signal [40].

Testing and scenario exploration (dimension 5). The firm runs a severe-but-plausible scenario in which the primary cloud region hosting the orchestration application becomes unavailable. Rather than reasoning about it on paper, it injects a controlled regional failover in a production-like environment [39] and measures the actual recovery time. The exercise reveals that failover completes within 90 minutes, inside the two-hour tolerance, but that the fallback card processor requires manual re-keying that would breach the 0.5% failed-volume tolerance under peak load. This is precisely the kind of unanticipated failure mode that a mapping-only approach would miss, and it illustrates the resilience-engineering point that testing reveals adaptive capacity and its limits [56].

Governance and the learning loop (dimension 6). The test finding flows up to the service owner and risk committee, which fund automation of the fallback re-keying process and adjust the risk-and-control map to reflect the newly discovered dependency. The leading indicator is added to the standing operational-resilience dashboard. The loop closes: a discovered weakness has driven remediation, an updated map, and improved monitoring, and the firm can now evidence, not merely assert, that retail payments remains within tolerance under the tested scenario.

The illustration repays a second reading for what it reveals about the interaction between the dimensions, because the value of the framework lies precisely there rather than in any single dimension acting alone. The mapping identified the fallback processor as a mitigant, and on paper the service appeared adequately protected; the analytics provided reassuring live health metrics under normal conditions; and yet neither would have surfaced the manual-re-keying weakness, because it lay dormant until the specific combination of a regional failover under peak load activated it. Only testing exposed it, only the mapping made the discovered dependency intelligible in terms of the service, only the tolerance made its severity assessable as a breach rather than a curiosity, and only governance converted the finding into funded remediation and an updated map. Remove any one dimension and the weakness either goes undiscovered, or is discovered but not understood, or is understood but not acted upon. This is the concrete meaning of the claim that resilience is a property of the coupled system rather than of any component: the failure mode was invisible to each dimension in isolation and visible only to their interaction.

It is also worth noting how the episode reframes the firm's compliance position. Before the test, the firm could assert, truthfully as far as it knew, that retail payments was mapped, tolerated, controlled, and monitored, a posture that would have satisfied a documentation-based review. After the test, it knew that this posture was in one respect false, and it could either conceal or remediate the gap. The framework's insistence on adaptive testing thus deliberately manufactures uncomfortable knowledge, trading the comfort of untested assertion for the discomfort of demonstrated weakness, on the premise that a weakness known and remediated is far preferable to one that first announces itself during a live customer-facing outage. A firm that embraces this trade will appear, on paper, to have more findings and more open remediation than one that does not,

which is a perverse incentive the governance dimension must actively counteract by rewarding discovery rather than penalising it.

Contributions on cybersecurity, data governance, and IT-risk management inform the framing adopted here [97]–[109]. Cognate work addressing enterprise IT systems, cloud migration, and service management provides complementary grounding [110]–[114]. A related stream of research on blockchain-enabled cross-border payment systems reinforces these observations [115]. Studies concerned with public-sector accounting, audit, and financial reporting offer supporting evidence and methods [116], [117]. Parallel investigations into pharmaceutical regulatory science and supply-chain governance extend the perspective developed above [118], [119].

5. Discussion

5.1 Implementation challenges

Several challenges condition the framework's practical adoption. The first is *data fragmentation*. The analytics dimension presumes that indicators, incident records, control results, and telemetry can be related to a common service model, yet in most firms these live in separate systems with inconsistent identifiers and taxonomies. Without an integration layer that keys data to services and resources, evidentiary continuity remains aspirational. The second is *tolerance calibration*. Setting a tolerance at the point of intolerable harm is conceptually clear but empirically hard; firms must avoid both complacent tolerances that are never breached and unattainable tolerances that invite perpetual non-compliance [2], [3]. The illustrative case shows that testing is often the only reliable way to discover whether a stated tolerance is achievable.

The third challenge is *third-party and concentration risk*. Important business services increasingly depend on a small number of cloud and technology providers whose internal controls the firm cannot fully observe, complicating both mapping and monitoring [43], [44]. The difficulty is twofold. Observability is limited, because the firm sees a provider's service through a contractual interface rather than through its internal telemetry, so the analytics dimension is partially blind exactly where dependency is greatest; the firm must rely on status feeds and contractual attestations that may not reveal degradation until it has already propagated. Concentration compounds this, because the same handful of providers underpins the same critical services across much of the industry, so a fault that a single firm treats as an idiosyncratic third-party risk is in fact a correlated exposure shared by many, capable of breaching tolerances simultaneously across firms that each mapped the dependency in isolation. The framework can represent the dependency and monitor its observable signals, but it cannot by itself resolve the underlying structural concentration, which is properly a matter for supervisory and macroprudential attention.

The fourth is *cultural and organisational*. Resilience cuts across business lines, technology, risk, and continuity functions that are conventionally siloed, and the three-lines model must be applied to encourage genuine ownership rather than defensive box-ticking [47], [52]. The framework's demand for a single service model that spans these functions is, in effect, a demand that organisations which have optimised locally for years agree on a shared object and a shared vocabulary, and the resistance this provokes is not irrational: each function's existing taxonomy encodes real local knowledge, and mapping it to a common service model imposes cost while threatening established boundaries of ownership. Where accountability for an important business service is genuinely assigned to a named owner with authority over the end-to-end chain, the coupling the framework requires can be achieved; where such ownership is diffuse, the service map becomes a contested artefact that no one function will maintain, and the loop breaks at its most fragile joint. A fifth challenge concerns *analytics maturity*: leading indicators of breach

require sufficient history of incidents and near-misses, which, fortunately for the firm but awkwardly for the model, may be sparse for the most severe events, so analytics must be complemented by, not substituted for, scenario reasoning. This scarcity creates a standing temptation to overfit models to the minor incidents that are plentiful while remaining silent about the severe events that actually threaten tolerances, and the framework must guard against the resulting illusion that a well-tuned dashboard of common faults constitutes evidence of resilience against rare catastrophic ones.

5.2 Limitations

This paper is conceptual and integrative, and its claims are correspondingly bounded. The IRCA framework is a synthesis of existing regulatory, risk-management, resilience-engineering, and analytics ideas rather than a novel empirical instrument, and it has not been validated through implementation or comparative study; the illustrative application is hypothetical. The framework is deliberately general and does not prescribe specific tolerance values, indicator sets, or modelling techniques, which will vary by firm, service, and jurisdiction. It inherits the well-known critiques of formal risk-management systems, that elaboration can substitute for effectiveness and that measurement can create a false sense of control [52], and its emphasis on analytics could, if misapplied, exacerbate rather than mitigate this tendency. Finally, the framework focuses on the firm level; system-wide resilience, including the correlated failure of shared third parties across many firms, raises questions of macroprudential coordination that lie beyond its scope [44].

Contributions on operational-technology and critical-infrastructure security inform the framing adopted here [120]–[123]. Cognate work addressing financial analytics, audit, IT-risk and governance across the wider research portfolio provides complementary grounding [124]–[203]. A related stream of research on predictive analytics for retail, finance, and operations reinforces these observations [204]–[208]. Studies concerned with health-system strategy, financing, and data-driven transformation offer supporting evidence and methods [209]–[212]. Parallel investigations into pharmaceutical care, diagnostics, and medicine access extend the perspective developed above [213].

6. Future Work

Three lines of future work follow directly. The first is *metric standardisation*. The framework would benefit from an agreed vocabulary of resilience metrics (service-health indices, time-to-recovery distributions, and breach-proximity indicators) that are comparable across firms and legible to supervisors, extending operational-risk measurement practice [40], [42] toward continuity outcomes. Standardisation would deliver a benefit beyond convenience: because the most dangerous exposures are concentrated in shared third parties and common infrastructure, resilience metrics that are comparable across firms would let supervisors aggregate a system-wide picture that no single firm can assemble from its own vantage point, turning a collection of local self-assessments into a genuine view of correlated fragility. The obstacle is that firms differ in architecture, service definition, and data maturity, so a standard must be prescriptive enough to be comparable yet flexible enough to fit heterogeneous estates, a tension that any serious standardisation effort will have to negotiate.

The second is *causal and predictive analytics*. Current monitoring is largely correlational; advancing toward causal models of how control failures propagate to tolerance breaches, and toward validated leading indicators, would strengthen the evidentiary dimension and support anticipatory rather than reactive response. The distinction is practically important because a

correlational indicator can signal that a breach is likely without revealing which intervention would prevent it, whereas a causal model of the propagation from component fault to service breach can tell an operator where to act and with what expected effect. Building such models is hard in a domain where severe events are rare and where the system is continually changing beneath the model, and it may prove more tractable to learn causal structure from the abundant controlled disruptions that the testing dimension can generate than from the scarce naturally occurring breaches, which links this research direction directly to the maturation of chaos-engineering practice. The third is *resilience-aware control design*, integrating the framework with architectural practices, graceful degradation, redundancy, and controlled failure injection [39], [56], so that resilience is engineered into services rather than assessed after the fact. This is the most consequential long-run direction, because a framework that only observes and tests resilience is ultimately parasitic on how well services were built; embedding resilience objectives into architectural decisions, designing services to degrade gracefully, to fail over cleanly, and to expose the telemetry that monitoring requires, would shift the framework from diagnosis toward prevention and close the gap between assessing resilience and producing it. Empirical validation through case studies and, ideally, cross-firm comparison would test whether integrated frameworks such as IRCA actually improve the ability to remain within impact tolerances relative to compliance-oriented approaches. Extending the model to system-level and third-party-concentration resilience is a further, more ambitious direction.

Contributions on enterprise cybersecurity and cyber-defense engineering inform the framing adopted here [214]–[217]. Cognate work addressing financial-fraud detection, audit analytics, and risk analytics provides complementary grounding [218]–[220]. A related stream of research on supply-chain management, ESG auditing, and sustainable procurement reinforces these observations [221]–[226]. Studies concerned with artificial intelligence in education, learning, and digital health offer supporting evidence and methods [227], [228]. Parallel investigations into the broader external academic literature on analytics, machine learning, security, and digital systems extend the perspective developed above [229]–[314].

7. Conclusion

Operational resilience represents a genuine advance in how financial firms and their supervisors think about disruption: it shifts attention from the loss consequences of failure to the continuity of the services that customers and the financial system depend on, and it makes that continuity measurable through impact tolerances. But the promise of resilience is undercut when it is implemented as a standalone mapping exercise disconnected from the risk, control, and analytics capabilities a firm already possesses. This paper has argued for integration and offered the IRCA framework as a way to achieve it, binding the outcome logic of services and tolerances, the diagnostic logic of risk and control, and the evidentiary logic of analytics into a single governed loop. Its central claim is modest but consequential: resilience should be continuously evidenced and deliberately tested, not periodically asserted. Analytics is the connective tissue that makes this possible, and testing is the discipline that keeps tolerances honest. The framework is conceptual and awaits empirical validation, but it offers practitioners a structure for moving from compliance with resilience requirements toward demonstrable resilience in fact.

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