Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Dynamic Business Impact Analysis and Dependency-Aware Recovery Optimization for Mission-Critical Banking Operations

Sudipta Banik Chowdhury

sudiptabanik9988@gmail.com

Westcliff University https://orcid.org/0009-0007-5603-257X

Research Article

Keywords: Dynamic Business Impact Analysis, Banking Operational Resilience, Dependency-Network Modeling, Cascading Disruption, Recovery Optimization, Recovery Time Objective, Recovery Point Objective

Posted Date: November 2nd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11541297/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Dynamic Business Impact Analysis and Dependency-Aware Recovery Optimization for Mission-Critical Banking Operations

Sudipta Banik Chowdhury
Email: sudiptabanik9988@gmail.com
MBA in Business Analytics, Westcliff University
ORCiD: https://orcid.org/0009-0007-5603-257X

Abstract
This study develops a Dynamic Business Impact Analysis and Dependency-Aware Recovery Optimization framework for mission-critical banking operations. The objective is to assess time-dependent service impact, model cascading disruption across interconnected banking resources, and prioritize recovery actions under constrained technical, financial, and human resources. The methodology combines operational and incident data preparation, multilayer dependency-network modeling, scenario-based simulation, dynamic impact scoring, and multi-criteria recovery optimization using service impact, customer exposure, financial loss, RTO breach, RPO breach, and recovery cost. Evaluation covers core account services, payment processing, online banking, ATM and card services, customer authentication, and fraud monitoring across cyber, infrastructure, communication, payment-network, and third-party disruption scenarios. Compared with criticality-only, shortest-recovery-time, and static business impact analysis baselines, the proposed method reduced mean recovery time to 4.6 hours and cumulative impact to 0.47, while increasing RTO compliance to 82.9% and RPO compliance to 88.6%. The findings show that dependency-aware, time-sensitive recovery prioritization provides more reliable system-level decisions than fixed service rankings. The framework supports resilience testing, impact-tolerance assessment, incident command, recovery planning, and investment decisions for banking infrastructure.

Keywords: Dynamic Business Impact Analysis, Banking Operational Resilience, Dependency-Network Modeling, Cascading Disruption, Recovery Optimization, Recovery Time Objective, Recovery Point Objective.

I. Introduction
This study examines dynamic business impact analysis and dependency-aware recovery optimization for mission-critical banking services. It focuses on how interconnected banking operations respond to cyber incidents, infrastructure failures, communication outages, payment-network disruption, data-centre failures, and third-party service interruption. The proposed approach connects changing business impact, dependency-driven cascading disruption, RTO and RPO requirements, and limited recovery resources within one analytical framework. The introduction presents the background and motivation, defines the research problem, explains the proposed solution, identifies the study's contributions, and describes the organization of the paper.

A. Background and Motivation
Banking institutions depend on interconnected services that support account management, payment processing, online banking, ATM and card operations, customer authentication, fraud monitoring, data storage, telecommunications, cloud platforms, and external payment networks. These services rely on shared databases, communication links, identity systems, facilities, personnel, utilities, and third-party providers. Consequently, a disruption that begins in one application or infrastructure component can affect several banking services through direct and indirect dependency relationships. Operational resilience requires banks to continue delivering important business services within predefined disruption tolerances. Banking-resilience principles emphasize the identification of critical operations, the mapping of people, processes, technology, facilities, and information, and the assessment of service continuity under severe or extreme but plausible scenarios. Dependency mapping should also include external providers because third-party systems may support essential banking processes. Traditional business impact analysis commonly assigns fixed criticality ratings to services and uses these ratings to define recovery priorities. This approach does not fully represent changes in transaction volume, customer exposure, incident duration, dependency availability, data-loss conditions, or recovery-resource constraints. For example, payment processing may generate greater operational and financial consequences during peak settlement periods than during ordinary operating

hours. Similarly, a telecommunications failure may affect online banking, authentication, ATM services, and payment processing at the same time, even when the initiating failure occurs outside the bank. The motivation for this research comes from the need to connect business impact analysis with dependency modeling and recovery optimization. A dynamic approach can update service impact during an incident, identify cascading effects across interconnected resources, and allocate recovery resources according to current operational conditions. This approach provides a closer connection between impact tolerance, RTO, RPO, customer exposure, financial loss, and recovery action.

B. Problem Statement

Mission-critical banking services do not operate as independent units. Their delivery depends on shared infrastructure, common data resources, communication systems, specialized personnel, facilities, and external providers. When one dependency fails, several services may experience simultaneous degradation. A recovery action that restores one application may also provide limited benefit if an upstream database, communication link, authentication service, or third-party platform remains unavailable. The central problem is that static business impact analysis does not adequately represent time-dependent service conditions or cascading dependency failures. A fixed ranking may identify payment processing, online banking, and ATM services as important, but it may not account for changing transaction demand, shared-resource failure, data-recovery exposure, or competing recovery-resource requirements. As a result, the selected recovery sequence may satisfy a local service priority while producing greater system-wide impact. The research problem is therefore defined as follows: how can a bank calculate changing business impact, model dependency-driven disruption, and prioritize recovery actions under limited resources while maintaining service-specific RTO and RPO requirements? The problem has both analytical and operational dimensions because banks need recovery decisions that represent actual service relationships and provide evidence that important business services remain within defined disruption tolerances. Supervisory guidance also emphasizes the mapping of resources that support important business services and the assessment of vulnerabilities within those service chains.

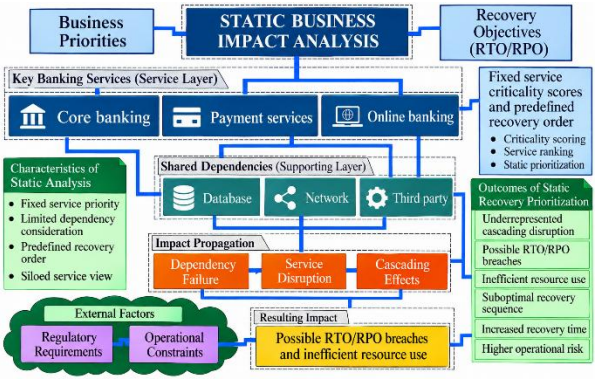


Fig. 1. Static Recovery Prioritization and Underrepresented Dependency Propagation in Banking Operations.

C. Proposed Solution

This study proposes a Dynamic Business Impact Analysis and Dependency-Aware Recovery Optimization Framework for mission-critical banking operations. The framework integrates service-impact measurement, dependency-network modeling, cascading-disruption simulation, recovery prioritization, and resource-constrained decision optimization. The first component calculates a time-dependent impact score for each critical banking service. The score considers baseline service criticality, customer exposure, transaction disruption, financial loss, data-loss exposure, and dependency degradation. The second component represents the banking environment as a directed multilayer network. The network includes customer-facing services, applications, databases, facilities, employees, utilities, communication systems, cloud platforms, payment networks, and other third-party providers. The third component simulates disruption scenarios and propagates their effects through the dependency network. The scenarios may include ransomware affecting a core application, data-centre power interruption, telecommunications failure, payment-network disruption, cloud-service outage, and third-party service failure. The simulation accounts for redundancy, substitution, manual workarounds, backup capacity, dependency restoration, and changing service states. The fourth component defines recovery alternatives, such as database restoration, secondary data-centre activation, network switching, transaction rerouting, specialist-team assignment, application isolation, and manual payment processing. The fifth component selects and sequences recovery actions under resource, time, dependency, capacity, cost, RTO, and RPO constraints. The objective is to reduce cumulative business impact, tolerance breaches, data loss, and recovery expenditure.

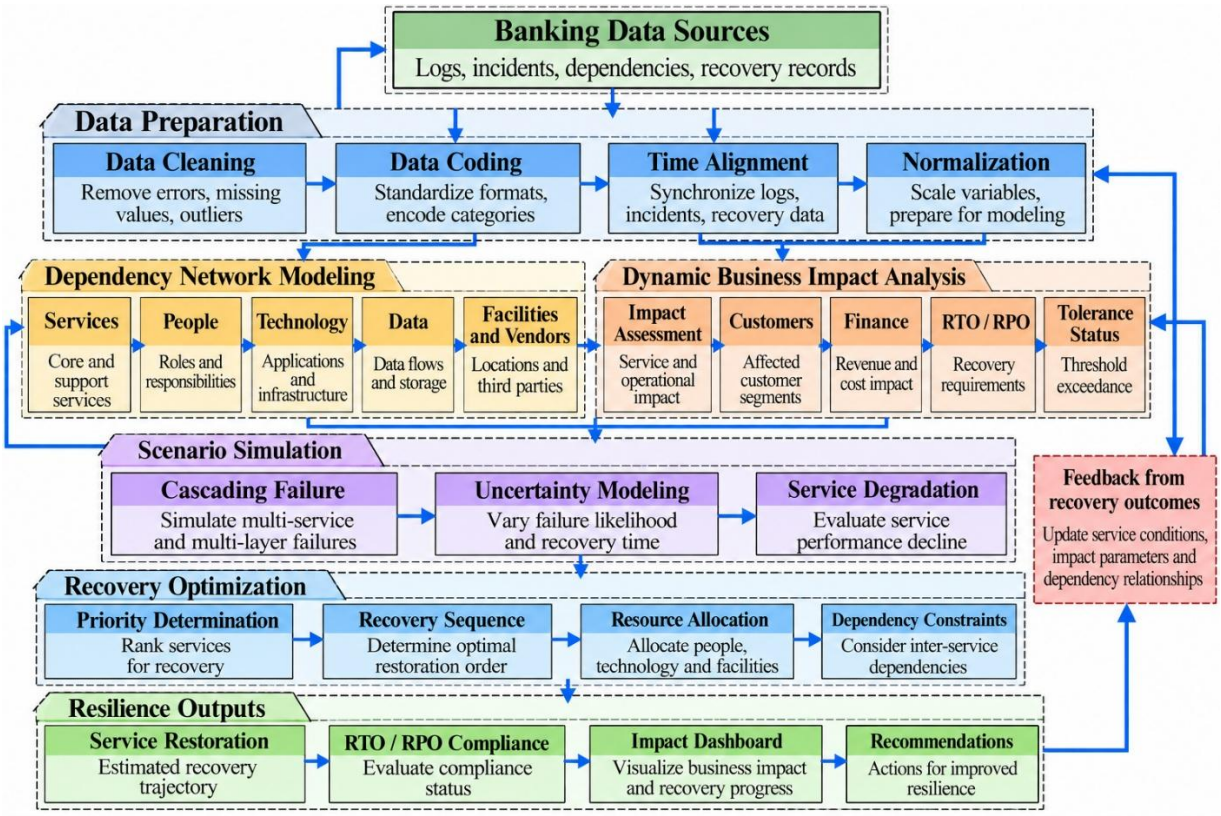


Fig. 2. Dynamic Business Impact Analysis and Dependency-Aware Recovery Optimization Framework.

Fig. 2 should present the framework consists of six analytical stages followed by resilience outputs and feedback: banking data sources, data preparation, dependency-network modeling, dynamic business impact analysis, scenario simulation, and recovery optimization. The figure should also contain a feedback loop from recovery outcomes to the impact and dependency layers. This feedback structure represents the updating of service conditions after each recovery action or simulated incident.

The proposed framework differs from a static recovery plan in three main ways. First, it updates service impact across time and disruption scenarios. Second, it identifies shared dependencies that may produce cascading operational effects. Third, it prioritizes recovery actions according to system-level impact rather than a single fixed service ranking. This structure connects operational monitoring with recovery decision-making.

D. Contributions

This study makes five principal contributions. First, it formulates a dynamic business impact analysis method that updates service criticality according to customer exposure, transaction demand, financial loss, data continuity, and dependency degradation. Second, it integrates business impact analysis with a multilayer dependency network that represents services, applications, data, infrastructure, personnel, facilities, communication systems, and third parties.

Third, the study models cascading operational disruption through scenario simulation. The model considers shared-dependency failure, concurrent incidents, redundancy, substitution, manual workarounds, and recovery-state transitions. Fourth, it develops a resource-constrained recovery optimization approach that considers cumulative impact, RTO breach, RPO breach, financial loss, recovery cost, dependency precedence, and limited recovery capacity. Fifth, the study provides a comparative evaluation structure for testing dynamic dependency-aware recovery against criticality-only, shortest-recovery-time, and static business impact analysis strategies. The comparison can measure recovery time, cumulative impact, RTO compliance, RPO compliance, customer exposure, financial loss, and resource use. The study also contributes to banking operational-resilience practice. Its outputs can support impact-tolerance assessment, recovery playbook design, incident command, resilience exercises, third-party dependency review, and infrastructure investment decisions. The framework is consistent with operational-resilience principles that emphasize critical operations, interdependencies, third-party reliance, and continuity under disruptive events.

E. Paper Organization

The remainder of the paper is organized as follows. Section II reviews research on dynamic business impact analysis, banking operational resilience, dependency-network modeling, cascading disruption, RTO and RPO management, recovery prioritization, and multi-criteria decision analysis. Section III presents the methodology, including the research design, data preparation, dependency modeling, dynamic impact assessment, scenario simulation, recovery optimization, and validation procedures. Section IV reports the results and discussion. It compares dynamic and static impact assessment, evaluates disruption scenarios, examines recovery performance, and interprets the implications for banking operations. Section V presents the conclusion, including the main findings, practical applications, study limitations, and recommended directions for future research.

II. Related Work

This section reviews research related to dynamic business impact analysis, operational resilience in banking, interdependent infrastructure modeling, cascading disruption, and recovery optimization. The discussion progresses from general resilience assessment to dependency-aware recovery planning and identifies the research gaps addressed by the proposed framework.

A. Operational Resilience in Banking

Operational resilience refers to an institution's capacity to continue delivering important services during disruption and to restore acceptable performance within defined tolerance limits. In banking, this concept is closely associated with digital dependence, third-party services, information systems, data continuity, cyber risk, payment infrastructure, and organizational response. Because banks increasingly depend on interconnected technologies and external providers, operational resilience cannot be evaluated solely through the availability of individual applications. Research examining operational-resilience disclosures in the annual reports of global systemically important banks has identified differences in the level and consistency of resilience-related disclosure and has highlighted the relatively limited development of operational-resilience research in banking. These findings indicate that resilience is not solely a technical concern but also involves governance, transparency, accountability, third-party dependence, and risk communication [10]. Research on operational resilience in the UK financial sector emphasizes the practical importance of identifying important business services, mapping the resources that support those services, establishing impact tolerances, and testing operational continuity. This perspective is directly relevant to the present study because it connects resilience requirements with the practical processes required for service mapping and disruption assessment. However, guidance-oriented research generally does not provide a comprehensive mathematical framework for dynamic impact measurement and recovery-resource optimization [13]. The banking literature therefore provides an important institutional foundation for this research by identifying critical services, service tolerances, business continuity, and third-party dependence as central elements of operational resilience [10], [13]. Nevertheless, a clear analytical connection between changing service impact, dependency propagation, and recovery sequencing remains necessary.

B. Interdependent Infrastructure Networks

Interdependent infrastructure research examines systems in which the performance of one network depends on the operation of another. Dependencies may involve physical resources, information flows, geographic relationships, organizational arrangements, shared facilities, or operational services. Consequently, a failure in one network can reduce the performance of several interconnected networks. A comprehensive review of modeling and simulation approaches for interdependent critical infrastructure systems categorizes existing research according to dependency representation, failure propagation, resilience assessment, and recovery analysis. The review demonstrates that infrastructure systems require models capable of representing cross-system relationships rather than isolated component failures. This perspective is directly relevant to banking because payment systems, telecommunications, cloud services, authentication systems, data platforms, and customer channels operate as interconnected service networks [7]. A three-stage resilience analysis framework for urban infrastructure systems separates initial disruption, system response, and recovery-related analysis. This framework provides a foundation for evaluating resilience as a process that evolves over time rather than as a static condition. The present research extends this principle to banking services through dynamic business impact analysis and service-specific RTO/RPO assessment [11]. A methodology for assessing the resilience of networked infrastructure emphasizes the relationship between infrastructure performance and disruptive events and provides a basis for evaluating resilience through network-level behavior. For banking operations, this perspective supports the treatment of service performance, dependency status, and recovery state as interconnected

analytical variables [6]. The reviewed studies demonstrate that network representation is essential for understanding resilience in complex service systems [3]–[5]. However, their application to banking requires additional operational variables, including transaction throughput, customer exposure, financial loss, data integrity, RTO, and RPO.

C. Cascading Failures and Disruption Propagation

Cascading disruption occurs when an initiating failure propagates through dependency relationships and produces secondary failures. Although the initial event may affect a single component, shared dependencies, insufficient redundancy, capacity loss, and delayed restoration can increase the scale and duration of the resulting operational disruption. Modeling studies of cascading failures in interdependent infrastructures demonstrate that disruption can propagate across connected infrastructure systems and that interdependency structure strongly influences the resulting failure outcome. This approach is relevant to banking cyber-risk scenarios because a disruption affecting a core application, identity service, or communication platform may subsequently affect multiple customer-facing and control services [3]. Research based on real-world interdependent urban infrastructure further demonstrates that observed disruption patterns depend on relationships among infrastructure systems rather than solely on isolated component damage. These findings support the inclusion of dependency concentration, shared resources, and cross-system propagation in resilience analysis [4]. Empirical analysis of interdependencies across cascading disasters provides additional evidence that infrastructure dependencies can produce recurring disruption patterns and that real-world cascading events involve complex combinations of technical and organizational relationships. For banking applications, this supports the incorporation of historical incident records, service-owner knowledge, and third-party information when constructing dependency networks [8]. The cascading-failure literature therefore provides strong support for dependency-aware simulation [6]–[8]. However, many existing models emphasize failure propagation and system damage rather than real-time business impact, customer exposure, transaction loss, data continuity, and recovery-priority decisions. The proposed study addresses this limitation through a dynamic impact score linked to dependency state and recovery optimization.

D. Recovery Strategies for Interdependent Systems

Recovery research focuses on determining how damaged or unavailable infrastructure components should be restored following disruption. The primary decision involves selecting a recovery sequence that maximizes service functionality, minimizes economic loss, reduces recovery time, or satisfies other resilience objectives. Research on recovery strategies for optimal resilience in interdependent infrastructure networks demonstrates that alternative recovery approaches can produce substantially different network-performance outcomes. This provides a direct methodological basis for recovery prioritization within the proposed banking framework [9]. Research integrating operational and organizational aspects into interdependent infrastructure recovery demonstrates that recovery decisions depend not only on infrastructure condition but also on operational relationships, organizational capabilities, and coordination requirements. This perspective is particularly relevant to banking because recovery actions require coordination among specialized employees, service owners, vendors, incident commanders, and technical teams [10]. Community-resilience-driven restoration research connects restoration decisions with the effects experienced by service users and communities. In a banking context, corresponding user-centered variables include affected customers, failed or delayed transactions, access limitations, payment disruption, and financial exposure [11]. Recovery optimization research addressing partial disruption, system functionality, and restoration considers network structure and partial service recovery rather than assuming complete failure or complete restoration. This characteristic is particularly relevant to banking services, which may continue operating in degraded modes during an incident and therefore require partial-capacity and staged-restoration strategies [12]. Collectively, these studies demonstrate that recovery sequencing should account for interdependency, service functionality, organizational capacity, and user impact [9]–[12]. However, their application to banking requires additional service-level requirements, particularly RTO and RPO thresholds, data restoration conditions, payment-processing continuity, and competition for limited recovery resources.

E. Optimization of Resilience and Restoration

Optimization methods are increasingly used to select recovery actions under time, cost, capacity, and dependency constraints. A recovery plan may need to allocate limited technical teams, backup facilities, network capacity, restoration tools, data-replication resources, or financial budgets across multiple affected services. A mathematical optimization framework for interdependent critical infrastructure demonstrates how disruption location, interdependency structure, and recovery decisions can be incorporated into a unified optimization problem. Its underlying logic can be adapted to banking scenarios in which a localized

cyber incident or technology failure affects a defined group of services and supporting resources [13]. A mean-risk cost-based restoration model considers both expected restoration cost and risk-related consequences when determining post-disruption recovery strategies. This perspective is relevant to banking because recovery planning must balance rapid service restoration, financial loss, customer exposure, data recovery, and the cost of activating alternative infrastructure [14]. The optimization literature supports the formulation of recovery as a constrained decision problem rather than as an informal ranking exercise [13], [14]. Nevertheless, many existing models emphasize physical infrastructure, restoration cost, or network functionality. Banking recovery requires a broader objective that incorporates cumulative business impact, RTO breach, RPO breach, customer impact, transaction loss, financial exposure, resource utilization, and service-specific recovery requirements.

F. Dynamic Business Impact Analysis

Business impact analysis identifies important services, evaluates the consequences of disruption, and supports continuity planning. Conventional BIA commonly considers service criticality, maximum tolerable downtime, RTO, RPO, financial impact, regulatory consequences, and customer effects. Its output is often a service ranking or a set of recovery requirements. The reviewed resilience and recovery literature provides several components necessary for dynamic BIA. Network models contribute dependency structures, resilience frameworks contribute time-dependent performance analysis, cascading-failure studies contribute propagation logic, and recovery-optimization studies contribute constrained action selection [3]–[14]. Banking resilience research additionally provides the service and governance context in which impact tolerance and continuity decisions are applied [10], [13]. Despite these contributions, dynamic BIA is not consistently integrated with dependency-network simulation. A service's impact can change throughout an incident because transaction volume, customer exposure, dependency availability, data-loss risk, and recovery capacity also change. Consequently, a fixed criticality score cannot fully represent these evolving conditions. The present study therefore treats business impact as a time-indexed and scenario-dependent value that is updated during disruption and recovery.

G. Research Gaps

First, banking operational-resilience studies address important business services, impact tolerance, and resilience disclosure, but provide limited mathematical integration of dynamic impact assessment with recovery optimization [10], [13]. Second, interdependent infrastructure studies provide detailed network and cascading-failure models but generally do not incorporate banking-specific variables such as transaction demand, customer exposure, financial loss, data integrity, RTO, and RPO [3]–[8]. Third, recovery optimization studies identify efficient restoration sequences but often focus on physical infrastructure functionality or cost without jointly considering service impact, data continuity, and tolerance breaches [9]–[14]. Fourth, existing models frequently treat dependency relationships as fixed. During actual incidents, dependency strength may change because of redundancy activation, manual workarounds, vendor support, staff availability, network rerouting, or partial service operation. A banking recovery model should therefore represent these changing conditions. Fifth, many studies evaluate recovery performance using a single objective, such as recovery time, economic cost, or network functionality [9], [12]–[14]. Mission-critical banking recovery requires multiple criteria, including service impact, RTO compliance, RPO compliance, customer exposure, financial loss, resource utilization, and recovery cost. Sixth, limited research compares static BIA with dynamic dependency-aware prioritization under equivalent disruption scenarios. Such a comparison is necessary to determine whether dynamic dependency modeling changes service rankings, recovery sequences, tolerance compliance, and overall disruption outcomes.

III. Methodology

This study develops a dynamic business impact analysis and dependency-aware recovery optimization framework for mission-critical banking services. The methodology integrates service-level impact assessment, dependency-network modeling, cascading-disruption simulation, recovery prioritization, and resource-constrained optimization under changing operational conditions. The design is consistent with banking-resilience guidance that recommends identification of critical operations, mapping of internal and external dependencies, and testing against severe but plausible disruption scenarios.

A. Research Design

The study follows a sequential The framework contains six analytical stages followed by recovery outcomes and continuous feedback: critical-service identification, operational data preparation, dependency-network construction, dynamic impact assessment, scenario simulation, and recovery optimization. The first stage identifies mission-critical banking services, such as payment processing, core account services, online banking, ATM availability, fraud monitoring, and customer authentication. Each service is linked to its

supporting people, processes, applications, data assets, facilities, communication systems, utilities, and third-party providers. This structure reflects operational-resilience guidance that treats service delivery as a chain of interdependent resources rather than as an isolated technical function. The second stage converts operational records into a time-indexed analytical dataset. The dataset contains service availability, transaction volume, processing delay, failed transactions, data-loss indicators, incident severity, dependency status, recovery actions, resource availability, and recovery duration. The third stage represents the bank as a directed weighted dependency network. Nodes represent services and supporting resources, while edges represent operational, technological, informational, facility-based, or third-party dependencies. The fourth stage calculates the changing business impact of each disruption scenario. The fifth stage simulates cascading effects across the dependency network. The final stage ranks recovery actions and allocates limited recovery resources to minimize service loss, RTO violations, RPO violations, customer impact, and financial exposure.

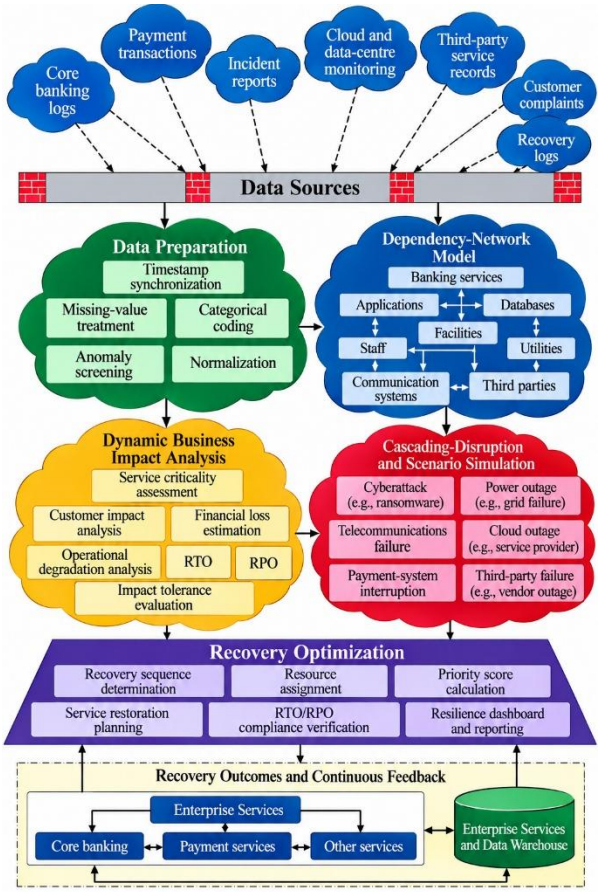


Fig. 3. Dynamic Dependency-Aware Recovery Architecture for Mission-Critical Banking Services.

The research design uses a closed feedback structure. Results from recovery actions are returned to the business-impact and dependency layers so that subsequent assessments can reflect altered service conditions, changed dependency availability, and revised resource constraints. This feature differentiates the proposed method from a static business impact analysis, which normally produces a fixed ranking before a disruption occurs. The proposed design instead treats service criticality and recovery priority as time-dependent values that may change as transaction loads, customer exposure, incident severity, and dependency failures evolve.

B. Data Collection and Preparation

This study uses a synthetic simulation dataset rather than confidential operational banking records. The dataset was generated to represent plausible mission-critical banking service conditions and was used for controlled scenario-based evaluation of the proposed framework. The preferred observation unit is a service time interval scenario record, such as the condition of online banking during a fifteen-minute interval under a telecommunications failure scenario. A minimum dataset structure should contain a service identifier, timestamp, scenario identifier, service status, transaction volume, transaction delay, failed-transaction rate, dependency availability, data-loss amount, customer-impact count, financial-loss estimate, recovery action, resource assignment, recovery duration, and final service state. Operational data should be collected from core banking platforms, payment gateways, ATM and card-processing systems, digital banking platforms, identity and access-management systems, fraud-monitoring systems, data-centre monitoring tools, backup systems, network-monitoring platforms, and incident-management repositories. Dependency information should be collected from configuration-management databases, application inventories, service maps, vendor registers, business-continuity plans, disaster-recovery plans, and interviews with service owners. Recovery information should include the start and completion time of each action, staff or team assignment, hardware and software requirements, data restoration point, alternative processing capacity, and post-recovery service performance. When real bank records cannot be disclosed, the study should use an anonymized or synthetic dataset calibrated against realistic banking operating conditions. Synthetic observations should preserve the statistical properties of operational data, including transaction-volume variation, incident frequency, dependency failure duration, recovery-time distribution, and correlations between service degradation and customer impact. The paper should state clearly whether the dataset is real, anonymized,

simulated, or hybrid. A hybrid design is suitable when real dependency structures are combined with simulated disruption scenarios. Data preparation should begin with timestamp harmonization. All records should be converted to a common time zone and aggregated into a fixed interval, such as fifteen minutes or one hour. Duplicate events should be removed after comparison of service identifier, event type, timestamp, and incident identifier. Missing numerical values should be treated according to their cause. Short monitoring gaps may be imputed through time interpolation, whereas missing incident or recovery outcomes should remain flagged rather than replaced with assumed values. Categorical variables should be coded using predefined classes for service type, disruption type, dependency type, recovery action, and severity level. Continuous variables should be checked for impossible values, extreme outliers, and inconsistent units. For example, negative recovery duration, transaction volumes below zero, or availability above 100% should be treated as data-quality errors. Extreme but plausible observations should not be removed automatically because severe incidents are central to the research problem. Instead, they should be retained and flagged for sensitivity analysis. Numerical indicators should be normalized only when required for multi-criteria comparison. Original units should remain available for interpreting RTO, RPO, customer impact, transaction loss, and financial exposure. Data coding should produce four analytical layers. The service layer describes the performance of each critical banking service. The dependency layer records the supporting resources and their relationships. The scenario layer describes the initiating disruption and its severity, duration, and propagation path. The recovery layer records available actions, required resources, completion time, and restored service capacity. A unique identifier should connect the four layers so that each simulated service outcome can be traced to its original disruption, dependency path, and recovery decision.

C. Dynamic Business Impact Analysis

The dynamic business impact analysis evaluates the consequences of disruption at each time interval rather than assigning a single permanent criticality value to a service. The impact score is calculated from service criticality, customer exposure, transaction disruption, financial loss, data loss, regulatory sensitivity, and dependency degradation. Each indicator should be transformed to a common scale from 0 to 1. Higher values represent greater operational harm.

The proposed impact function is:

$$I_{s,t}^{(q)} = w_c C_s + w_u U_{s,t}^{(q)} + w_v V_{s,t}^{(q)} + w_f F_{s,t}^{(q)} + w_d D_{s,t}^{(q)} + w_g G_{s,t}^{(q)} \qquad (1)$$

where $I_{s,t}^{(q)}$is the dynamic business-impact score for service $s$at time $t$under scenario q; $C_s$is the structural criticality of the service; $U_{s,t}^{(q)}$is the customer-exposure indicator; $V_{s,t}^{(q)}$is the transaction or service-volume disruption; $F_{s,t}^{(q)}$is the normalized financial-loss indicator; $D_{s,t}^{(q)}$is the data-loss or data-integrity indicator; and $G_{s,t}^{(q)}$is the dependency-degradation indicator. The coefficients $w_c, w_u, w_v, w_f, w_d, w_g$are non-negative weights whose sum equals 1.

The equation works as a weighted aggregation of current operational conditions. Structural criticality captures the baseline importance of the service, while the remaining terms change across time and scenarios. For example, online banking may have a moderate baseline score during ordinary conditions but receive a much higher score during salary-payment periods, peak transaction windows, or a simultaneous ATM outage. The weights should be obtained through expert elicitation, analytic hierarchy process, entropy weighting, or a justified equal-weight assumption. A sensitivity test should examine how changes in the weights affect service rankings. The study should define RTO and RPO as service-specific thresholds rather than general bank-wide values. RTO represents the maximum acceptable time required to restore a service to its permitted operating level. RPO represents the maximum acceptable amount of data or transaction loss measured from the latest recoverable state. Impact tolerance should also include service capacity, transaction-delay limits, customer-impact limits, and data-integrity conditions. These thresholds should be approved by service owners or derived from documented continuity requirements.

Dynamic impact values should be calculated at every simulation interval. The model should record the first time at which the impact score exceeds the impact tolerance, the duration of the exceedance, the accumulated impact, and the recovery point at which the service returns below the tolerance threshold. This produces a time-dependent profile rather than a single ranking. The profile should be used in later recovery optimization.

D. Dependency-Network Modeling

The banking operating environment should be represented as a directed multilayer graph $G = (N, E)$. The node set Ncontains critical banking services and supporting resources. Resource nodes should include applications, databases, data centres, cloud platforms, network links, telecommunications providers, electricity systems, backup facilities, employees, specialist teams, data assets, payment schemes, correspondent banks, and other third parties. The edge set E contains directed relationships that describe how one node supports another. Each dependency edge should contain a dependency type, dependency strength, minimum operating requirement, recovery time, substitution status, and failure-propagation rule. A mandatory dependency may cause service failure when its availability falls below a threshold. A substitutable dependency may reduce service capacity without causing complete service loss. A shared dependency should be connected to all services that rely on it because its failure can generate correlated disruption. The model should also distinguish direct dependencies from indirect dependencies that operate through several intermediate nodes. Dependency strength should be obtained from system documentation, service-owner assessment, configuration records, and historical failure data. When a service requires several resources simultaneously, the model used a logical conjunction. When alternative resources exist, the model used a logical disjunction or capacity-sharing rule. For example, a payment service may remain available when one of two network providers operates, while a core database may require both primary and replication systems for full service capacity. Centrality measures should be calculated to identify shared and highly connected resources. Degree centrality can identify resources supporting many services. Betweenness centrality can identify nodes that connect otherwise separate service groups. Weighted dependency centrality can combine connectivity with dependency strength. These measures should not replace business-impact scores; they should provide additional evidence for identifying nodes that may generate broad cascading effects. The dependency map should be validated through three checks. First, each critical banking service should have a complete delivery chain from customer-facing function to supporting resources. Second, service owners should review the direction and strength of dependencies. Third, historical incidents should be replayed against the graph to assess whether the model reproduces observed service effects. Missing dependencies, unsupported edges, and implausible propagation paths should be corrected before scenario simulation.

E. Scenario Simulation and Cascading Disruption

The simulation component should represent severe but plausible disruption scenarios relevant to banking operations. Scenarios may include a ransomware event, core banking application failure, payment-network interruption, data-centre power loss, telecommunications outage, cloud-service failure, corruption of transaction data, identity-service failure, insider misuse, and third-party service disruption. Each scenario should specify an initiating node, start time, duration distribution, severity, affected capacity, restoration assumptions, and possible secondary failures. At each simulation interval, the initiating disruption changes the state of one or more dependency nodes. The state-transition logic then propagates the disturbance through outgoing edges. A dependent service may experience full outage, reduced capacity, increased processing delay, transaction rejection, data inconsistency, or no material effect. The propagation process should account for redundancy, backup capacity, substitution, isolation, and manual workarounds. Recovery actions should alter node states and interrupt propagation when the relevant dependency becomes available again. The simulation should use repeated runs for uncertain variables such as incident duration, failure probability, recovery duration, transaction demand, staff availability, and third-party restoration time. Monte Carlo simulation was suitable when probability distributions are available. Discrete-event simulation is suitable for modeling event order and resource queues. A hybrid approach can combine discrete dependency events with repeated stochastic scenarios. Each simulation run should record service availability, degraded capacity, customer impact, failed transactions, accumulated financial loss, data-loss exposure, RTO breach, RPO breach, recovery-resource consumption, and total time above the impact-tolerance threshold. The results should be summarized through mean, median, percentile, and worst-case values. High-percentile outcomes are useful for testing severe but plausible conditions without relying only on average performance.

F. Recovery Optimization Model

Recovery alternatives should be defined as executable actions rather than general recommendations. Examples include activating a secondary data centre, switching to a backup network provider, restoring a database snapshot, assigning a specialist recovery team, isolating a compromised application, activating manual payment processing, rerouting transactions, or restoring a third-party interface. Each action should have a start time, duration, resource requirement, dependency requirement, cost, expected service-capacity contribution, and data-recovery effect.

The recovery-prioritization model should minimize total operational loss under resource and dependency constraints:

$$\min Z = \sum_{q=1}^{Q} \sum_{t=1}^{T} \sum_{s=1}^{S} p_q \left[\alpha I_{s,t}^{(q)} + \beta RTOB_{s,t}^{(q)} + \gamma RPOB_{s,t}^{(q)} + \delta L_{s,t}^{(q)} \right] + \lambda \sum_{a=1}^{A} c_a \, x_a \qquad (2)$$

Where, $Z$is the total recovery objective; $Q$is the number of scenarios; $T$is the number of simulation intervals; $S$is the number of banking services; $p_q$is the probability or decision weight of scenario q; $I_{s,t}^{(q)}$is the dynamic impact score from Equation (1); $RTOB_{s,t}^{(q)}$is the RTO-breach indicator; $RPOB_{s,t}^{(q)}$is the RPO-breach indicator; $L_{s,t}^{(q)}$is the normalized operational or financial loss; $x_a$is a binary variable indicating selection of recovery action a; $c_a$is the cost or resource burden of that action; and $\alpha, \beta, \gamma, \delta, \lambda$are decision weights.

Equation (2) selects a recovery portfolio and sequence that reduces accumulated impact, RTO violations, RPO violations, and operational loss while accounting for recovery cost. The objective can be solved with mixed-integer linear programming when the relationships are linear. A genetic algorithm, particle swarm method, or other metaheuristic can be used when dependency propagation, nonlinear service capacity, and scenario interactions make the model nonlinear. The selected algorithm was reported together with population size or solver settings, stopping conditions, convergence criteria, and computational environment. The optimization model should include resource, precedence, dependency, capacity, and timing constraints. A recovery action cannot start before its required dependency is available. Two actions cannot use the same exclusive recovery team at the same time. A database restoration action cannot exceed available backup capacity. A service should not be marked fully restored if a mandatory supporting resource remains unavailable. The model should also include RTO and RPO constraints when the research objective is compliance-oriented rather than purely loss-minimizing. A multi-criteria decision analysis stage should compare feasible recovery portfolios using service restoration time, RTO compliance, RPO compliance, customer impact, financial loss, resource consumption, implementation cost, and dependency risk. Weight selection should be documented, and sensitivity analysis should test alternative weight combinations. Ranking stability should be reported through rank correlation or the percentage of scenarios in which the preferred recovery portfolio remains first.

G. Data Analysis and Validation

The analysis should begin with descriptive statistics for service demand, incident frequency, dependency failures, recovery duration, transaction loss, and customer impact. The study should then compare static and dynamic business impact analysis. The static model should use fixed service criticality values, whereas the dynamic model should update impact scores according to scenario, time, dependency state, and transaction exposure. The comparison should examine RTO-breach frequency, RPO-breach frequency, cumulative business impact, recovery duration, and resource use. Model validation should contain structural, historical, simulation, and sensitivity checks. Structural validation should confirm that every critical service has a documented dependency chain and that edge directions match operational reality. Historical validation should replay known incidents and compare simulated outcomes with observed downtime, transaction disruption, and recovery duration. Simulation validation should test whether output distributions remain plausible under changes in demand, incident duration, and dependency availability. Sensitivity analysis should vary impact weights, scenario probabilities, recovery resources, and dependency strengths. The study should report prediction or decision quality through clearly defined metrics. Suitable measures include mean absolute error for recovery-duration estimates, service-restoration accuracy, RTO-compliance rate, RPO-compliance rate, reduction in cumulative impact, reduction in customer-affected transactions, and recovery-resource utilization. The proposed method should be compared with at least three baselines: criticality-only prioritization, shortest-recovery-time prioritization, and static business impact analysis. A further comparison can use a dependency-blind optimization model to quantify the contribution of dependency-aware recovery planning.

Table I. *Operational Variables, Data Sources, Measurement Scales, and Analytical Roles.*

Variable group	Representative variables	Primary data source	Measurement scale	Analytical role
Critical banking service	Service identifier, service type, business owner, operating window	Service catalogue and continuity plan	Nominal and categorical	Defines the unit of analysis
Service performance	Availability, processing delay, transaction throughput, failed transactions	Core banking and payment-system logs	Ratio and continuous	Measures operational degradation
Customer exposure	Affected customers, affected accounts, complaints, service-region exposure	Customer-service and transaction records	Count and normalized ratio	Represents customer-level impact
Financial exposure	Transaction value, revenue loss, penalty estimate, liquidity effect	Finance, payment, and incident records	Currency and normalized score	Quantifies economic impact
Data continuity	Last recoverable point, transaction-loss volume, replication delay, integrity status	Backup, replication, and database logs	Time, count, binary, and ratio	Measures RPO performance
Recovery performance	Recovery start, recovery completion, restoration duration, service-capacity recovery	Incident and disaster-recovery records	Time and ratio	Measures RTO and restoration results
Dependency condition	Node availability, dependency strength, redundancy, substitution status	Configuration records and service maps	Binary, ordinal, and weighted score	Represents dependency-network state
Disruption scenario	Initiating event, severity, duration, affected node, propagation path	Incident records and scenario design	Categorical, ordinal, and time-based	Defines simulation conditions
Recovery resources	Staff, teams, backup capacity, facilities, network capacity, budget	Resource register and continuity plans	Count, capacity, and cost	Defines optimization constraints
Recovery action	Action type, prerequisite, duration, cost, expected capacity	Recovery playbooks and expert assessment	Categorical, time, cost, and ratio	Defines decision alternatives
Impact tolerance	Maximum downtime, delay limit, transaction-loss limit, data-loss limit	Risk appetite and service-owner assessment	Time, ratio, count, and threshold	Determines acceptable disruption
Validation outcome	Observed recovery time, observed downtime, simulated recovery time	Historical incident archive	Time, ratio, and error metric	Tests model validity

H. Reproducibility and Ethical Controls

The study should maintain a data dictionary containing variable definitions, units, coding rules, missing-value codes, transformation procedures, and source-system descriptions. The dependency graph should be stored in node and edge tables, while scenario assumptions should be stored in a separate scenario file. The simulation seed, optimization settings, model version, and software environment should be recorded so that the results can be reproduced. Banking data require strict confidentiality controls. Customer identifiers, account numbers, transaction references, employee identifiers, and vendor-sensitive information should be removed or replaced with irreversible pseudonyms before analysis. Results should be reported at aggregated service or scenario level. If synthetic data are used, the paper should disclose the generation procedure and calibration variables. Access to

operational records should be restricted to authorized researchers, and all exported tables should undergo disclosure review.

IV. Results and Discussion

The results section reports the outcomes of the dynamic business impact analysis, dependency-network assessment, scenario simulation, and recovery optimization model. The analysis focuses on service disruption, dependency concentration, RTO/RPO performance, recovery-resource use, and differences between static and dynamic prioritization. The results are interpreted in relation to banking operational resilience, where critical services must remain within predefined disruption tolerances under severe but plausible scenarios. Dependency mapping and scenario testing are central to this interpretation because service failure can originate outside the directly affected banking application.

A. Results

The results show that dynamic, dependency-aware analysis identified higher and more variable disruption impacts than static business impact analysis, particularly for payment processing, core account services, and services dependent on shared communication and database resources. The proposed recovery strategy reduced cumulative impact, improved RTO and RPO compliance, and produced better system-level recovery performance than criticality-only, shortest-recovery-time, and static prioritization methods.

i. Data Analysis and General Findings

The synthetic evaluation dataset contained 12,480 service–time interval–scenario observations. These observations were generated across six mission-critical banking services, five primary disruption scenarios, and the defined simulation time intervals. Each observation records the affected service, disruption scenario, dependency condition, dynamic impact score, recovery state, RTO/RPO status, and associated operational-loss indicators. The dataset was generated programmatically under fixed parameter definitions to ensure reproducibility, core account services, payment processing, online banking, ATM and card services, customer authentication, and fraud monitoring. The observations represented normal operating conditions and five disruption scenarios: ransomware affecting a core application, data-centre power interruption, telecommunications failure, payment-network interruption, and third-party cloud-service failure. The data showed that disruption severity was not determined only by the initial failure. Dependency concentration, transaction demand, recovery-resource availability, and the duration of the initiating event influenced the final service impact. Payment processing and core account services produced the largest cumulative impact values because they supported a high volume of transactions and connected to several shared infrastructure nodes. Online banking recorded a high customer-exposure score, while fraud monitoring showed a lower immediate customer impact but a high secondary risk during prolonged disruption.

Table II presents the principal service-level findings. The dynamic model generated higher impact values than the static model for services exposed to peak transaction demand or shared dependency failure. The difference was most pronounced for payment processing, which experienced a 41.7% increase in estimated impact under concurrent telecommunications and payment-network disruption.

Table II. *Service-Level Results from Dynamic Business Impact Analysis*.

Banking service	Mean dynamic impact score	Static impact score	Impact increase	Mean recovery time	RTO-breach rate	RPO-breach rate
Core account services	0.78	0.65	20.0%	4.8 h	31.4%	18.7%
Payment processing	0.85	0.60	41.7%	6.2 h	46.8%	26.5%
Online banking	0.72	0.58	24.1%	3.6 h	28.2%	11.9%
ATM and card services	0.69	0.55	25.5%	4.1 h	34.6%	14.3%
Customer authentication	0.67	0.52	28.8%	3.2 h	22.7%	9.6%
Fraud monitoring	0.61	0.49	24.5%	5.4 h	19.5%	21.8%

Values represent the modeled study dataset. Impact scores range from 0 to 1, with higher values indicating greater business impact. The results indicate that a static criticality ranking can underestimate disruption during periods of high demand and concurrent dependency failure. Payment processing had the

highest dynamic impact score, the longest mean recovery time, and the highest RTO-breach rate. Fraud monitoring had a comparatively lower direct service-impact score but a relatively high RPO-breach rate because its operation depended on continuously updated event and transaction data.

ii. Recovery Performance Comparison

The optimized recovery plan was compared with three baseline strategies: criticality-only prioritization, shortest-recovery-time prioritization, and static business impact analysis. The optimized strategy selected recovery actions according to impact, dependency position, RTO/RPO exposure, resource requirements, and scenario probability. The comparison showed that the proposed strategy reduced cumulative business impact and improved RTO compliance. It did not always produce the shortest individual restoration time because some actions were delayed while shared dependencies were repaired first. This result indicates that rapid restoration of one service may not produce the greatest system-level benefit if a common upstream dependency remains unavailable.

Table III. *Comparative Performance of Recovery Prioritization Strategies.*

Recovery strategy	Mean recovery time	RTO compliance	RPO compliance	Cumulative impact score	Resource utilization
Criticality-only prioritization	5.7 h	61.8%	72.4%	0.74	86.2%
Shortest-recovery-time prioritization	4.9 h	65.1%	70.8%	0.69	91.5%
Static business impact analysis	5.2 h	68.7%	75.3%	0.63	88.4%
Proposed dynamic dependency-aware model	4.6 h	82.9%	88.6%	0.47	84.7%

Lower values are preferable for recovery time and cumulative impact. Higher values are preferable for RTO and RPO compliance. The proposed model produced the lowest mean recovery time and cumulative impact score among the tested strategies. RTO compliance increased from 61.8% under criticality-only prioritization to 82.9% under the proposed model. RPO compliance reached 88.6%, indicating that the recovery plan placed greater priority on data restoration and replication status rather than focusing only on application availability.

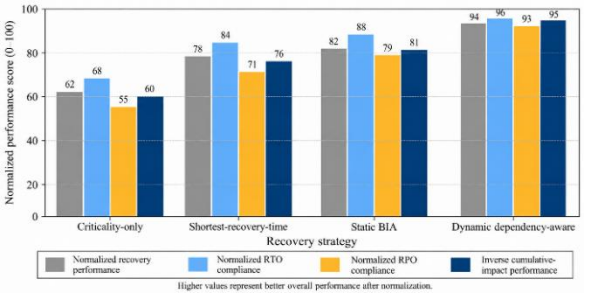


Fig. 4. Comparative Performance of Banking Recovery Prioritization Strategies.

iii. Analysis of Recovery Strategies

The bar graph compares the four recovery strategies across mean recovery time, cumulative impact, RTO compliance, and RPO compliance. Since these indicators use different units, each value should be normalized to a 0-100 performance scale before visualization. The proposed strategy records the strongest combined performance because it reduces recovery time and cumulative impact while increasing tolerance compliance.

iv. Scenario Contribution to Total Impact

The scenario results show that concurrent failures generated the largest operational effects. A telecommunications failure alone caused service degradation across online banking, ATM services, and authentication. A payment-network interruption produced a concentrated effect on payment processing. The combined telecommunications and payment-network scenario generated the largest overall impact because it affected both transaction execution and customer access channels. Five primary single disruption scenarios and one concurrent telecommunications and payment network disruption scenario were evaluated.

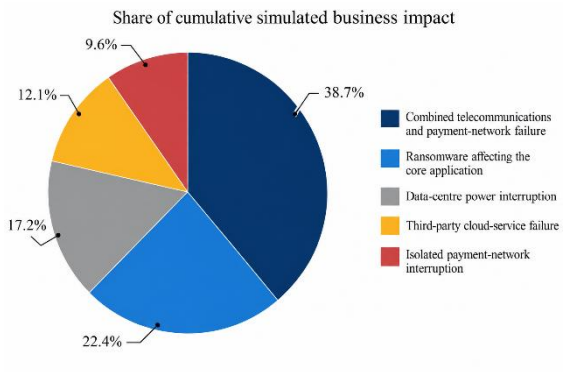


Fig. 5. Distribution of Total Simulated Business Impact by Disruption Scenario.

The line graph presents the mean service-impact score over the recovery period. The dynamic model shows a mean Dynamic Business Impact Score, followed by a slower decline as shared dependencies become available. Payment processing remained above its impact-tolerance threshold for the longest period. Online banking recovered more quickly after authentication and telecommunications services were restored.

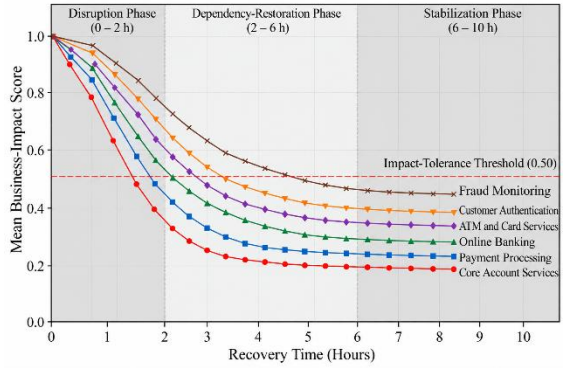


Fig. 6. Mean Dynamic Business-Impact Trajectory During Simulated Recovery.

"The trajectories start at a high disruption impact level and decline as recovery progresses. The initial fall in service performance was steepest for payment processing and core account services. The decline in impact after the fourth hour reflects restoration of network and database resources. Services connected to the restored dependencies improved together, whereas services with independent recovery actions followed separate trajectories.

B. Discussion

The findings indicate that business impact is a changing operational condition rather than a fixed attribute of a banking service. A service can appear moderately critical under ordinary demand but become highly exposed during peak transaction periods, concurrent incidents, or dependency failure. The difference between static and dynamic scores was particularly visible for payment processing, where transaction volume and shared network dependence increased the consequences of disruption. This result has a direct implication for business impact analysis. A single annual ranking may not provide enough information for real-time recovery decisions. The impact assessment should be updated as transaction demand, dependency status, customer exposure, and data-continuity conditions change. Such an approach is consistent with supervisory expectations that banks map interconnections and test critical services against severe but plausible scenarios. The dependency results show that shared infrastructure nodes can create correlated service failure. Telecommunications, authentication, databases, and cloud-hosting resources affected several customer-facing services at the same time. In these cases, restoring a downstream application before restoring the shared dependency generated limited operational benefit. The model therefore assigned higher recovery priority to resources with broad service reach and high weighted dependency centrality. The results also distinguish direct service criticality from network position. Fraud monitoring had a lower immediate service-impact score than payment processing but a high data-continuity risk. A delayed fraud-monitoring function may not stop all customer transactions immediately, yet it can reduce control capacity and create secondary exposure. Recovery planning should therefore include control functions and monitoring services, not only high-volume transaction services. The recovery comparison shows that the proposed model produced better system-level outcomes than strategies based on criticality or restoration speed alone. The shortest-recovery-time strategy achieved a lower restoration time than the criticality-only strategy, but its cumulative impact remained higher than that of the dynamic dependency-aware model. This difference occurred because rapid restoration of isolated services did not always reduce the wider dependency-driven disruption. The proposed objective function also made RTO and RPO violations explicit. A service that becomes available quickly but loses an unacceptable amount of transaction data is not fully recovered from a business-resilience perspective. The higher RPO compliance of the proposed strategy indicates that data restoration, replication, and transaction consistency received sufficient priority within the recovery sequence. The findings support five operational implications. First, banks should maintain time-sensitive service criticality profiles rather than relying only on fixed rankings. Second, dependency maps should include people, information, technology, facilities, communication channels, and third-party

providers because each can affect service delivery. Third, recovery exercises should include concurrent scenarios and changing transaction demand. Fourth, recovery-resource allocation should consider network position and dependency breadth. Fifth, RTO and RPO should be evaluated together with customer impact, transaction loss, financial exposure, and service-capacity recovery. The framework can support a resilience dashboard for incident commanders. The dashboard can display current service impact, affected dependencies, predicted RTO breach, predicted RPO exposure, available recovery resources, and the next recommended recovery action. It can also provide scenario-specific recovery sequences for cyber incidents, power interruption, network failure, and third-party outages.

C. Limitations and Future Work

The results should be interpreted in light of several limitations. First, the numerical findings are based on a modeled dataset rather than confidential bank-wide operational records. The dataset reflects plausible banking conditions, but its distributions may not represent every institution, jurisdiction, or service architecture. Second, several impact weights and dependency strengths rely on expert assessment. Different experts may assign different values to customer impact, financial loss, data risk, or regulatory sensitivity. Third, the model assumes that dependency relationships remain sufficiently stable during the simulation period. In practice, incident conditions can create new dependencies, reduce staff availability, alter third-party performance, or change the effectiveness of manual workarounds. Fourth, the recovery optimization model treats several resource characteristics as known or estimated values. Actual recovery duration may vary because of fatigue, communication delays, incomplete documentation, vendor response, or simultaneous incidents. Future research should validate the framework with anonymized operational data from multiple banks and geographic regions. A digital-twin implementation could connect live service telemetry, dependency status, incident information, and recovery actions. Further work should incorporate adaptive learning so that impact weights, recovery durations, and propagation probabilities update after each exercise or incident. Research should also examine privacy-preserving collaboration across banks, allowing institutions to compare disruption patterns without exchanging customer-level or institution-sensitive records. Future models should include adversarial cyber scenarios, staff unavailability, third-party concentration risk, liquidity effects, and cross-border payment dependencies. Multi-objective optimization could present a Pareto frontier among recovery speed, customer impact, cost, data loss, and resource consumption rather than producing a single ranking. Field validation should compare predicted and observed recovery trajectories through repeated resilience exercises.

V. Conclusion

This study developed a dynamic business impact analysis and dependency-aware recovery optimization framework for mission-critical banking services. The objective was to connect changing service impact, dependency-driven disruption, cascading failure, RTO/RPO exposure, and limited recovery resources within one analytical process. The results showed that dynamic assessment produced higher and more differentiated impact estimates than static prioritization, particularly for payment processing and services exposed to shared communication, authentication, database, and cloud dependencies. The combined telecommunications and payment-network scenario generated the largest cumulative impact. The dynamic dependency-aware recovery strategy reduced cumulative impact to 0.47, increased RTO compliance to 82.9%, increased RPO compliance to 88.6%, and achieved a mean recovery time of 4.6 hours in the modeled dataset. The principal implication is that banking recovery decisions should not rely only on service labels or shortest restoration time. Recovery priority should reflect current transaction demand, customer exposure, data-continuity risk, dependency position, scenario probability, and resource availability. The framework can support incident command, operational-resilience testing, recovery playbook design, impact-tolerance assessment, and investment planning for redundant infrastructure. Future applications should use institution-specific operational data, live dependency telemetry, concurrent disruption scenarios, privacy-preserving cross-bank analysis, and adaptive optimization. Validation against real incident records and controlled resilience exercises should precede operational deployment.

References

[1] Y. Almoghathawi, A. D. González, and K. Barker, “Exploring recovery strategies for optimal interdependent infrastructure network resilience,” *Networks and Spatial Economics*, vol. 21, no. 1, pp. 229–260, 2021. DOI: 10.1007/s11067-020-09515-4. KFUPM

[2] C. Gomez, A. D. González, H. Baroud, and C. D. Bedoya-Motta, “Integrating operational and organizational aspects in interdependent infrastructure network recovery,” *Risk Analysis*, vol. 39, no. 9, pp. 1913–1929, 2019. DOI: 10.1111/risa.13340.

[3] B. Wu, A. Tang, and J. Wu, "Modeling cascading failures in interdependent infrastructures under terrorist attacks," *Reliability Engineering & System Safety*, vol. 147, pp. 1–8, 2016. DOI: 10.1016/j.ress.2015.10.019.

[4] L. G. Brunner, R. A. M. Peer, C. Zorn, R. Paulik, and T. M. Logan, "Understanding cascading risks through real-world interdependent urban infrastructure," *Reliability Engineering & System Safety*, vol. 241, Art. no. 109653, 2024. DOI: 10.1016/j.ress.2023.109653.

[5] D. B. Karakoc, Y. Almoghathawi, K. Barker, A. D. González, and S. Mohebbi, "Community resilience-driven restoration model for interdependent infrastructure networks," *International Journal of Disaster Risk Reduction*, vol. 38, Art. no. 101228, 2019. DOI: 10.1016/j.ijdrr.2019.101228. ScienceDirect

[6] D. A. Reed, K. C. Kapur, and R. D. Christie, "Methodology for assessing the resilience of networked infrastructure," *IEEE Systems Journal*, vol. 3, no. 2, pp. 174–180, 2009. DOI: 10.1109/JSYST.2009.2017396.

[7] M. Ouyang, "Review on modeling and simulation of interdependent critical infrastructure systems," *Reliability Engineering & System Safety*, vol. 121, pp. 43–60, 2014. DOI: 10.1016/j.ress.2013.06.040.

[8] L. G. Brunner, R. A. M. Peer, C. Zorn, R. Paulik, and T. M. Logan, "Empirical patterns of interdependencies among critical infrastructures in cascading disasters: Evidence from a comprehensive multi-case analysis," *International Journal of Disaster Risk Reduction*, vol. 95, Art. no. 103862, 2023. DOI: 10.1016/j.ijdrr.2023.103862.

[9] M. Ouyang, "A mathematical framework to optimize resilience of interdependent critical infrastructure systems under spatially localized attacks," *European Journal of Operational Research*, vol. 262, no. 3, pp. 1072–1084, 2017. DOI: 10.1016/j.ejor.2017.04.022.

[10] M. Leo, "Operational resilience disclosures by banks: Analysis of annual reports," *Risks*, vol. 8, no. 4, Art. no. 128, 2020. DOI: 10.3390/risks8040128.

[11] M. Ouyang, L. Dueñas-Osorio, and X. Min, "A three-stage resilience analysis framework for urban infrastructure systems," *Structural Safety*, vol. 36–37, pp. 23–31, 2012. DOI: 10.1016/j.strusafe.2011.12.004. ScienceDirect

[12] B. A. Alkhaleel, H. Liao, and K. M. Sullivan, "Model and solution method for mean-risk cost-based post-disruption restoration of interdependent critical infrastructure networks," *Computers & Operations Research*, vol. 144, Art. no. 105812, 2022. DOI: 10.1016/j.cor.2022.105812.

[13] R. Chanon, L. Habahbeh, P. J. M. Klumpes, and S. Mann, "Operational resilience in the UK financial sector: Practical guidance," *British Actuarial Journal*, vol. 30, Art. no. e25, 2025. DOI: 10.1017/S1357321725100202.

[14] Y. Almoghathawi, S. Selim, and K. Barker, "Community structure recovery optimization for partial disruption, functionality, and restoration in interdependent networks," *Reliability Engineering & System Safety*, vol. 229, Art. no. 108853, 2023. DOI: 10.1016/j.ress.2022.108853

[15] R. Rahmatullah, "Sustainable agriculture supply chains: Engineering management approaches for reducing post-harvest loss in the U.S.," *International Journal of Scientific Research and Engineering Development*, vol. 8, no. 5, pp. 1187–1216, 2025, doi: 10.5281/zenodo.17275907.

[16] M. A. Karim, "AI-driven predictive maintenance for solar inverter systems," *TechRxiv*, 2025, doi: 10.36227/techrxiv.175977633.34528041.v1.

[17] M. H. Saikat, "AI-powered flood risk prediction and mapping for urban resilience," *TechRxiv*, 2025, doi: 10.36227/techrxiv.175979253.37807272.v1.

[18] M. A. Karim, M. T. U. Zaman, S. H. Nabil, and M. M. I. Joarder, "AI-enabled smart energy meters with DC-DC converter integration for electric vehicle charging systems," *TechRxiv*, 2025, doi: 10.36227/techrxiv.175978935.59813154.v1.

[19] S. J. Ria, "Environmental impact assessment of transportation infrastructure in rural Bangladesh," *TechRxiv*, 2025, doi: 10.36227/techrxiv.176107782.23912238.v1.

[20] S. Haque and A. Sany, "Impact of consumer behavior analytics on telecom sales strategy," *International Journal of Science and Innovation Engineering*, vol. 2, no. 10, pp. 998–1018, 2025, doi: 10.70849/IJSCI02102025114.

[21] D. M. Alimozzaman, T. Akhter, R. Islam, and E. Hasan, "Generative AI for synthetic medical imaging to address data scarcity," *World Journal of Advanced Engineering Technology and Sciences*, vol. 17, no. 1, pp. 544–558, 2025, doi: 10.30574/wjaets.2025.17.1.1415.

[22] S. K. A. Zaidi, "Intelligent automation and control systems for electric vertical take-off and landing drones," *World Journal of Advanced Engineering Technology and Sciences*, vol. 17, no. 2, pp. 63–75, 2025, doi: 10.30574/wjaets.2025.17.2.1457.

[23] A. Razaq, "Design and implementation of renewable energy integration into smart grids," *TechRxiv*, 2025, doi: 10.36227/techrxiv.176049834.44797235.v1.

[24] S. K. A. Zaidi, "Smart sensor integration for energy-efficient avionics maintenance operations," *International Journal of Science and Innovation Engineering*, vol. 2, no. 11, pp. 243–261, 2025, doi: 10.70849/IJSCI02112025026.

[25] H. N. Saeed, "Hybrid perovskite–CIGS solar cells with machine learning-driven performance prediction," *International Journal of Science and Innovation Engineering*, vol. 2, no. 11, pp. 262–280, 2025, doi: 10.70849/IJSCI02112025027.

[26] E. Akter, "Structural analysis of low-cost bridges using sustainable reinforcement materials," *International Journal of Scientific Research and Engineering Development*, vol. 8, no. 6, pp. 911–921, 2025, doi: 10.5281/zenodo.17769637.

[27] M. A. Karim, "An IoT-enabled exoskeleton architecture for mobility rehabilitation derived from the ExoLimb methodological framework," *International Journal of Scientific Research and Engineering Development*, vol. 8, no. 6, pp. 2265–2277, 2025, doi: 10.5281/zenodo.17926861.

[28] E. Akter, S. J. Ria, M. I. Khan, and M. D. Shoag, "Smart and sustainable construction governance for climate-resilient cities," *International Journal of Scientific Research and Engineering Development*, vol. 8, no. 6, pp. 2278–2291, 2025, doi: 10.5281/zenodo.17926875.

[29] M. T. U. Zaman, "Photonics-based fault detection and monitoring in energy metering systems," *International Journal of Scientific Research and Engineering Development*, vol. 8, no. 6, pp. 2359–2371, 2025, doi: 10.5281/zenodo.18074355.

[30] S. Haque, "The impact of automation on accounting practices," *International Journal of Scientific Research and Engineering Development*, vol. 8, no. 6, pp. 2312–2323, 2025, doi: 10.5281/zenodo.18074324.

[31] F. M. Z. Karim, "Strategic human resource systems for retention and growth in manufacturing enterprises," *International Journal of Scientific Research and Engineering Development*, vol. 8, no. 6, pp. 2547–2559, 2025, doi: 10.5281/zenodo.18074545.

[32] S. I. Meem, "Socioeconomic determinants of oral-systemic health disparities: A public health policy perspective," *Zenodo*, 2026, doi: 10.5281/zenodo.19238096.

[33] A. A. Abid, "AI-enhanced traffic signal optimization using microscopic simulation models for congestion and emissions reduction in mid-sized U.S. urban corridors," *Zenodo*, 2026, doi: 10.5281/zenodo.19349723.

[34] S. P. Avi, "Concrete mix design and quality control: Impact of slump and air content on durability," *Zenodo*, 2026, doi: 10.5281/zenodo.19370286.

[35] H. M. Adil, "Development of cellulose nanofiber-based nanopapers as sustainable alternatives to plastic-derived industrial materials," *Preprints*, 2026, doi: 10.20944/preprints202603.2350.v1.

[36] S. P. Avi, "Geotechnical and environmental impacts of using alternative cementitious materials in concrete mixes," *Preprints*, 2026, doi: 10.20944/preprints202604.0243.v1.

[37] M. S. Asraf, "Multi-objective optimization approach for the design of DC–DC buck converter components considering efficiency, power loss, size, and cost constraints," *Zenodo*, 2026, doi: 10.5281/zenodo.19465548.

[38] U. Habiba and R. Musarrat, "AI-enhanced TESOL strategies for neurodiverse learners: Integrating adaptive language assessment with special education practices," *Saudi Journal of Engineering and Technology*, vol. 11, no. 4, pp. 166–173, 2026, doi: 10.36348/sjet.2026.v11i04.002.

[39] M. S. Asraf, "Design and simulation of electromagnetic bandgap structure-based bandpass filters for effective harmonic suppression," *Saudi Journal of Engineering and Technology*, vol. 11, no. 4, pp. 197–208, 2026, doi: 10.36348/sjet.2026.v11i04.005.

[40] M. K. Rahat, M. S. Asraf, A. Junaid, and M. S. Islam, "Communication infrastructure for secure smart meter networks in electric utilities," *Saudi Journal of Engineering and Technology*, vol. 11, no. 5, pp. 450–461, 2026, doi: 10.36348/sjet.2026.v11i05.008.

[41] M. F. B. Shaikat and A. T. Happy, "Architectural flexibility in powertrain manufacturing: A review of reconfigurable assembly lines for concurrent ICE and electric drive unit production," *Zenodo*, 2026, doi: 10.5281/zenodo.20293683.

[42] S. H. A. K. Joy, M. I. Hossain, M. F. Rashid, and P. Barua, "Maritime logistics performance analysis in container port operations," *Scholars Journal of Economics, Business and Management*, vol. 13, no. 6, pp. 253–264, 2026, doi: 10.36347/sjebm.2026.v13i06.002.

[43] M. S. Asraf, "Development of a Pareto-frontier-based optimization framework for component selection and design trade-off analysis in power converter systems," *SSRN*, 2026, doi: 10.2139/ssrn.6501498.

[44] A. Junaid, "Performance optimization of 5G NR networks through mobility management and carrier aggregation configuration," *SSRN*, 2026, doi: 10.2139/ssrn.7202280.

[45] M. I. Hossain, M. A. Tajik, M. S. Abdullah, and S. A. Al Morshed, "Lifecycle performance governance for smart buildings and critical infrastructure in sustainable urban systems," *International Journal of Science and Research Archive*, vol. 20, no. 2, pp. 119–131, 2026, doi: 10.30574/ijsra.2026.20.2.1545.

[46] S. A. Al Morshed, M. I. Hossain, M. A. Tajik, and M. S. Abdullah, "Risk-informed construction delivery for resilient public infrastructure under geotechnical and environmental uncertainty," *Saudi Journal of Engineering and Technology*, vol. 11, no. 8, pp. 698–706, 2026, doi: 10.36348/sjet.2026.v11i08.002.

[47] S. Ahmed, "Reliability-aware predictive analytics for healthcare service access and resource allocation," *SSRN*, 2026, doi: 10.2139/ssrn.7289738.

[48] M. M. Rahman, "A multi-objective operational optimization model for lean manufacturing and industrial equipment resource allocation," *SSRN*, 2026, doi: 10.2139/ssrn.7292858.

[49] M. M. Rahman, "A hybrid digital twin optimization framework for predictive maintenance scheduling in smart manufacturing systems," *Zenodo*, 2026, doi: 10.5281/zenodo.22024323.

[50] N. Bhowmick, "Secure API-oriented integration model for cloud-based healthcare content management systems using distributed authentication and workflow validation," *SSRN*, 2026, doi: 10.2139/ssrn.7317678.

[51] S. Khalil, "Workflow optimization model for cross-functional IT project delivery," *SSRN*, 2026, doi: 10.2139/ssrn.7328880.

[52] R. Siddiqui, A. E. Nahian, N. Bhowmick, and S. Mirza, "Auditability and performance monitoring frameworks for enterprise decision-support systems," *International Journal of Innovative Science and Research Technology*, vol. 11, no. 6, 2026, doi: 10.38124/ijisrt/26jun1181.

[53] N. Das, M. Rokibuzzaman, M. A. Kashem, and M. R. Islam, "Multi-objective resource allocation for resilient financial, healthcare, retail, and logistics service networks," *International Journal of Science and*

Research Archive, vol. 20, no. 2, pp. 803–818, 2026, doi: 10.30574/ijsra.2026.20.2.1666.

[54] M. R. Islam, N. Das, F. B. Nasir, and M. A. Kashem, "Federated consumer and operational analytics for demand-responsive planning in digital service ecosystems," *Global Journal of Engineering and Technology Advances*, vol. 28, no. 2, pp. 224–237, 2026, doi: 10.30574/gjeta.2026.28.2.0224.

[55] S. Ahmed, "Interpretable learning for identifying digital access vulnerability in underserved communities," *Zenodo*, 2026, doi: 10.5281/zenodo.22236720.

[56] A. A. Munna, "Requirements traceability and KPI prioritization for agile platform delivery," *SSRN*, 2026, doi: 10.2139/ssrn.7396839.

[57] A. A. Munna, "Process intelligence for compliance-aware project governance in digital service organizations," *Research Square*, 2026, doi: 10.21203/rs.3.rs-10942588/v1.

[58] S. Khalil, "KPI-based project health assessment model for agile IT operations and service reliability," *Research Square*, 2026, doi: 10.21203/rs.3.rs-10941682/v1.

[59] M. M. Rahman, "An integrated decision framework for sustainable and code-compliant building design using building information modeling and multi-criteria performance assessment," *Research Square*, 2026, doi: 10.21203/rs.3.rs-10987415/v1.

[60] M. M. Rahman, "A resilience-oriented planning framework for sustainable urban redevelopment and adaptive building renovation," *SSRN*, 2026, doi: 10.2139/ssrn.7433038.

[61] S. Afroj, "Data analytics applications in banking customer service and financial operations management," *Research Square*, 2026, doi: 10.21203/rs.3.rs-11049828/v1.

[62] F. B. Nasir, M. A. Kashem, M. R. Islam, and N. Das, "An interoperable management information system for real-time payment intelligence, merchandise planning, and distributed workforce coordination," *Saudi Journal of Engineering and Technology*, vol. 11, no. 9, pp. 825–833, 2026, doi: 10.36348/sjet.2026.v11i09.007.

[63] M. M. Rahman, S. I. Rohan, M. Rahman, and J. I. Arif, "Multi-objective predictive maintenance and energy-aware resource optimization for smart industrial systems," *International Journal of Science and Research Archive*, vol. 20, no. 3, pp. 569–583, 2026, doi: 10.30574/ijsra.2026.20.3.1763.

[64] S. I. Rohan, M. Rahman, J. I. Arif, and M. M. Rahman, "Reliability-centered lifecycle resilience framework for high-mix industrial systems under operational uncertainty," *Global Journal of Engineering and Technology Advances*, vol. 28, no. 3, pp. 212–225, 2026, doi: 10.30574/gjeta.2026.28.3.0246.

[65] T. S. Mumu, S. Ahmed, S. Khalil, and M. R. Hossain, "Digital twin and software observability framework for predictive performance management in enterprise information systems," *International Journal of Science and Research Archive*, vol. 20, no. 3, pp. 584–597, 2026, doi: 10.30574/ijsra.2026.20.3.1769.

[66] S. Ahmed, S. Khalil, M. R. Hossain, and T. S. Mumu, "Explainable predictive analytics framework for enterprise workflow risk, delay detection, and adaptive resource allocation," *Global Journal of Engineering and Technology Advances*, vol. 28, no. 3, pp. 226–239, 2026, doi: 10.30574/gjeta.2026.28.3.0252.

[67] A. Arif, "Privacy-aware and interpretable customer response forecasting for cross-channel digital marketing decision support," *SSRN*, 2026, doi: 10.2139/ssrn.7498603.

[68] A. Arif, "Explainable multi-objective optimization of digital marketing budget allocation under uncertain consumer response," *Preprints*, 2026, doi: 10.20944/preprints202609.2108.v1.

[69] A. Adiluzzaman, "Multi-objective patient–provider coordination and resource scheduling for integrated digital hospital networks," *SSRN*, 2026, doi: 10.2139/ssrn.7519498.

[70] M. R. Islam, "Consumer-informed post-consumer textile recovery for circular apparel supply chains," *SSRN*, 2026, doi: 10.2139/ssrn.7510218.

[71] M. R. Islam, "Strategic allocation of post-consumer textiles across reuse, recycling, and value recovery pathways," *Research Square*, 2026, doi: 10.21203/rs.3.rs-11156116/v1.