

An Explainable Decision Intelligence Architecture for Secure Data Sharing and Risk-Aware Resource Governance

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Abstract: Healthcare providers, financial institutions, retailers, logistics operators, and workforce systems generate large amounts of information for planning and risk related decisions. Much of this information cannot be freely shared because it may contain sensitive organizational or consumer data. Resource decisions also become difficult when demand changes, fraud risks increase, capacity becomes limited, or operational disruptions occur. This study develops an explainable decision intelligence architecture for these conditions. The proposed framework combines hierarchical federated learning with multimodal data analysis, Self-Sovereign Identity, group signatures, differential privacy, SHAP based explanations, Siamese fine-tuning, and Pareto-based optimization. Data remain within participating organizations, while selected model information supports collaborative analysis. The decision model considers resource cost, unmet demand, risk exposure, privacy expenditure, and service vulnerability at the same time. Stochastic programming, fuzzy decision models, scenario analysis, and sensitivity analysis are used to represent uncertain operating conditions. Five scenarios are considered: normal operations, demand surges, fraud escalation, supplier disruption, and compound disruption. Public and synthetic datasets provide the basis for comparison with centralized learning, standard federated learning, and optimization approaches without integrated explainability and privacy governance. The study develops a common decision framework for resource planning across heterogeneous service networks.

Keywords: Explainable Decision Intelligence, Secure Data Sharing, Federated Learning, Risk-Aware Resource Governance, Differential Privacy, Multi-Objective Optimization, SHAP, Resource Allocation, Privacy-Preserving Analytics, Service-Network Resilience.

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I. INTRODUCTION

Organizations increasingly depend on data from multiple operational domains to support resource planning, risk assessment, service delivery, and strategic decisions. Healthcare providers, financial institutions, retailers, logistics operators, and workforce systems generate large volumes of sensitive and heterogeneous information. Effective decision systems must therefore address data-sharing restrictions, privacy requirements, uncertain demand, fraud exposure, capacity limitations, and operational disruptions at the same time. Federated learning provides a distributed approach for collaborative analytics without requiring direct centralization

of sensitive records [1], [2]. However, secure data sharing alone does not resolve the need for interpretable risk assessment or coordinated resource allocation. A decision intelligence architecture must connect these functions within a common governance structure.

➤ Background and Motivation

The growth of digital services has increased the dependence of organizations on interconnected analytical systems. Data from financial transactions, healthcare claims, inventory operations, workforce activities, supplier networks, and customer interactions can support resource decisions, yet these data often remain separated across organizational

boundaries. Privacy requirements and institutional policies restrict direct data exchange, while operational uncertainty creates additional difficulty for planning. Federated learning provides a mechanism for collaborative model development without transferring raw records to a central repository [1], [3]. At the same time, explainable artificial intelligence can provide information about the factors influencing analytical outputs. These capabilities create a foundation for decision systems that protect sensitive information while producing interpretable risk assessments and resource recommendations for complex service networks.

➤ *Problem Statement*

Current analytical approaches often address privacy, risk assessment, and resource optimization as separate problems. Federated learning can support decentralized analysis, but conventional implementations may provide limited connections between model outputs and resource-governance decisions. Enterprise dashboards and decision-support systems provide operational information, yet they may not account simultaneously for privacy constraints, fraud exposure, uncertain demand, capacity limitations, and service disruptions [7], [10], [13]. Resource optimization models also tend to focus on individual domains such as inventory, budgeting, workforce capacity, or infrastructure resources [8], [15], [16]. This separation creates a methodological gap. Organizations require a decision framework that can share analytical information securely, explain risk scores, and allocate limited resources across competing objectives under uncertain operating conditions.

➤ *Proposed Solution*

This study proposes an explainable decision-intelligence architecture that integrates secure data sharing, hierarchical federated learning, multimodal risk assessment, privacy protection, and multi-objective resource governance. Healthcare, financial, retail, logistics, and workforce environments are represented as independent data-owning nodes. Local data remain within organizational boundaries, while controlled model information participates in hierarchical federated learning. Self-Sovereign Identity, group signatures, consent policies, secure aggregation, and differential privacy provide the security and privacy mechanisms. SHAP-based analysis provides explanations for risk scores, while Siamese fine-tuning supports relationships across related data representations. A Pareto optimization model then evaluates cost, unmet demand, risk exposure, privacy expenditure, and service vulnerability across multiple operating scenarios. Existing privacy preserving approaches, including federated learning and secure multi-party computation, primarily focus on protected computation, while explainable resource-governance decisions remain less developed.

➤ *Contributions*

The study contributes an integrated architecture that connects privacy-preserving data collaboration with explainable risk assessment and resource governance. First, it defines a permissioned data-sharing structure that supports independent organizational nodes and controlled analytical participation. Second, it introduces multimodal risk

assessment across healthcare, financial, retail, logistics, and workforce variables. Third, SHAP-based explanations connect risk scores with identifiable decision factors. Fourth, the resource-governance model treats cost, unmet demand, risk, privacy expenditure, and service vulnerability as simultaneous optimization objectives. Fifth, stochastic scenarios and fuzzy decision mechanisms represent demand uncertainty, fraud escalation, supplier disruption, capacity limitations, and compound operational conditions. These components provide a unified methodological foundation for transparent and risk-sensitive resource decisions across heterogeneous service networks.

➤ *Paper Organization*

The remainder of the paper is organized as follows. Section II reviews related research. Section III presents the proposed methodology and experimental design. Section IV discusses the results across risk assessment, resource allocation, privacy, baseline comparison, and resilience scenarios. Section V concludes the study and outlines future research.

- **Objective of the Study:** The objective of this study is to develop an explainable decision-intelligence architecture that combines secure data sharing, risk assessment, privacy protection, and multi-objective resource governance.

II. RELATED WORK

Existing research has advanced privacy-preserving federated learning, healthcare collaboration, operational analytics, and resource optimization, but these areas remain largely fragmented. Prior studies address secure decentralized learning, cyber resilience, decision support, financial monitoring, inventory planning, and resource analytics separately. This section reviews these strands and identifies the methodological gap addressed by the proposed explainable, risk-aware decision intelligence architecture for multi-objective resource governance.

➤ *Privacy-Preserving Federated Learning and Secure Data Sharing*

Federated learning provides a foundation for collaborative analytics without requiring direct centralization of sensitive records. Zhang et al. [1] examine cross domain federated learning for privacy-preserving collaboration, while Madduri et al. [2] position privacy-preserving federated learning as an important component of healthcare learning systems. Ali et al. [3] further identify security, model misconduct, and implementation challenges. However, these studies primarily emphasize privacy and collaborative learning rather than explainable multi-objective resource allocation under operational uncertainty. This leaves an important gap for architectures that connect secure data sharing with transparent governance decisions across heterogeneous service networks and organizational trust boundaries across organizational settings.

➤ *Explainable Decision Intelligence and Enterprise Analytics*

Explainability and enterprise decision support are increasingly connected with operational analytics. Akter [7] presents an intelligent KPI-based decision support approach for data driven operations, while Dukkupati [14] addresses AI-driven feedback intelligence and enterprise decision support. Barua [10] focuses on business intelligence dashboards for operational performance monitoring, and Chokder [13] examines analytics and dashboard reporting for customer relationship and sales performance. These contributions demonstrate the value of analytical decision support, but they do not integrate explainability, privacy-preserving collaboration, and risk-aware resource optimization within one architecture. The proposed study therefore extends operational intelligence toward auditable decisions that explicitly connect model outputs with resource governance objectives while preserving data-sharing controls explicitly.

➤ *Resource Allocation, Capacity Planning, and Optimization*

Resource governance research provides several foundations for optimization under operational constraints. Adil [4] examines risk-resilient process safety design and operational optimization, while Bormon [12] demonstrates numerical modeling for assessing structural response under seismic loading and associated uncertainty. Al Sany [8] examines data analytics for budget allocation and financial efficiency, while Fareed [15] proposes a digital twin framework for safety-stock optimization in multi-stage manufacturing systems. Farooq [16] studies resource utilization analytics for cloud infrastructure management. Together, these studies show how analytical models can support allocation, inventory, and capacity-related decisions. Nevertheless, they largely address individual resource domains rather than a unified service-network problem involving demand uncertainty, fraud exposure, capacity limitations, and disruptions. A multi-objective formulation using Pareto optimization, stochastic scenarios, and fuzzy decision mechanisms can integrate these competing governance requirements within one framework for operational priorities.

➤ *Risk, Security, Compliance, and Governance Analytics*

Risk, security, and compliance are also central to trustworthy organizational decision systems. Afrin [5] investigates cyber resilient infrastructure using automated threat detection, while Akhter [6] examines algorithmic internal controls through MIS event logs. Alam [9] addresses regulatory reporting information systems for financial and institutional compliance, and Bhuiyan [11] studies customer complaint analytics for systemic risk reduction and consumer protection. These studies establish important foundations for risk monitoring and organizational accountability. However, they do not jointly model privacy preserving data sharing, explainable risk scoring, and resource allocation. The proposed architecture links these functions so risk information can directly influence transparent, multi objective governance decisions across service environments while retaining privacy constraints.

III. METHODOLOGY

The methodology develops an explainable decision architecture for secure data sharing and risk-aware resource governance. It integrates hierarchical federated learning, risk assessment, explainable machine learning, differential privacy, and multi-objective optimization. Synthetic datasets represent healthcare, financial, retail, logistics, workforce domains. Scenario analysis, stochastic programming, fuzzy models, Pareto optimization, and sensitivity analysis evaluate decisions under uncertainty, fraud, capacity limits, privacy, and disruptions.

➤ *Overall Decision-Intelligence Architecture*

The proposed architecture connects secure data sharing, multimodal risk analytics, explainable machine learning, and multi-objective resource governance. Healthcare, financial, retail, logistics, and workforce environments operate as independent data-owning nodes. Sensitive records remain within local domains, while controlled model information moves through hierarchical federated learning. Self-Sovereign Identity, group signatures, consent policies, and secure aggregation define organizational trust boundaries. Differential privacy protects sensitive analytical outputs. At the decision layer, risk scores and operational indicators enter a Pareto-based optimization engine. This structure permits resource decisions that consider demand uncertainty, fraud risk, capacity limits, privacy requirements, and disruptions across participating service networks. Local ownership remains intact throughout the decision process and overall governance cycle.

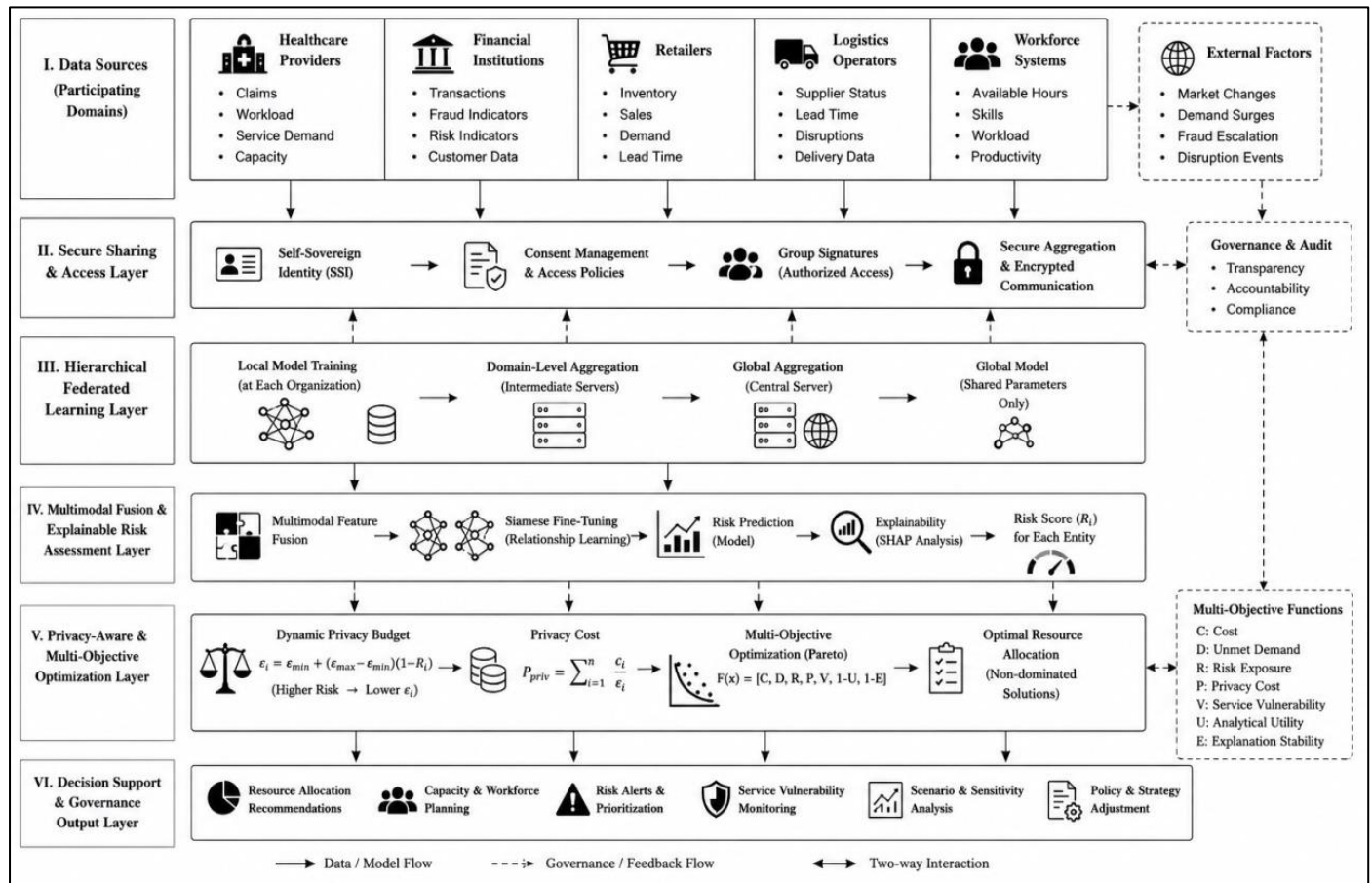


Fig 1 Proposed Explainable Decision Intelligence Architecture for Secure Data Sharing and Risk-Aware Resource Governance

➤ Multimodal Data Fusion and Explainable Risk Assessment

The data layer combines heterogeneous variables from participating domains. Healthcare inputs include claims indicators, service demand, and workload measures. Financial inputs include transaction characteristics and fraud-risk indicators. Retail and logistics inputs include inventory, supplier status, lead time, and demand variability. Workforce inputs include available hours, workload, and skill capacity. Data are normalized locally before federated participation, and direct identifiers are excluded. Multimodal representations are produced through domain-specific processing and feature fusion. Siamese fine-tuning supports relationship learning across related records without direct record exchange. Explainable models use SHAP contribution analysis to identify influential variables. The resulting multimodal risk assessments provide interpretable evidence for resource decisions under changing operational conditions and uncertainty.

The core risk score is:

$$R_i = \sum_{j=1}^m w_j r_{ij}$$

Where R_i represents the risk score for decision entity i , r_{ij} represents the normalized value of risk factor j , and w_j represents the importance assigned to risk factor j .

➤ Multi-Objective Resource Allocation Model

Resource governance is formulated as a multi-objective optimization problem involving workforce assignments, inventory allocation, supplier selection, service capacity, and computing capacity. The model minimizes allocation cost, unmet demand, risk exposure, privacy-related computational cost, and service vulnerability while considering analytical utility and explanation stability. The objective vector is:

$$\min F(x) = [C(x), D(x), R(x), P(x), V(x), 1 - U(x), 1 - E(x)]$$

Where $U(x)$ represents normalized analytical utility and $E(x)$ represents normalized explanation stability. All objectives are normalized before Pareto evaluation. Lower values are preferred for cost, unmet demand, risk, privacy cost, and vulnerability, while higher values are preferred for utility and explanation stability. The terms $1 - U(x)$ and $1 - E(x)$ convert these criteria into minimization objectives. This formulation connects predictive usefulness and interpretability with governance decisions.

Where:

$C(x) \rightarrow$ Resource allocation cost
 $D(x) \rightarrow$ Unmet demand
 $R(x) \rightarrow$ Risk exposure
 $P(x) \rightarrow$ Privacy computational cost
 $V(x) \rightarrow$ Service vulnerability
 $U(x) \rightarrow$ Analytical utility

$E(x) \rightarrow$ Explanation stability

The formulation avoids a cost only decision rule. The formulation treats cost, demand, risk, privacy, service vulnerability, analytical utility, and explanation stability as simultaneous governance objectives.

➤ *Uncertainty, Scenario Analysis, and Risk-Aware Governance*

Scenario analysis evaluates the architecture under normal operations, demand surges, fraud escalation, supplier disruption, and compound disruption conditions. Each scenario changes relevant demand, capacity, risk, inventory, workforce, or supplier parameters while governance

constraints remain active. Stochastic evaluation compares outcomes across scenarios and identifies allocations that perform acceptably under uncertainty. Sensitivity analysis changes major parameters to determine their effects on risk scores and allocation priorities. Differential privacy is treated as a governance parameter rather than a fixed technical setting. The analysis examines trade-offs among privacy protection, analytical utility, explanation stability, and computational cost. These experiments support risk-sensitive resource decisions for healthcare, financial, retail, logistics, and workforce networks. Results support cross-scenario comparison.

Table 1 Principal Variables and Governance Functions

Variable category	Representative variables	Governance function
Demand	Forecast demand, demand variability	Capacity planning
Workforce	Available hours, workload, skill capacity	Workforce allocation
Financial risk	Transaction risk, fraud probability	Financial risk control
Healthcare	Claims indicators, service workload	Healthcare resource planning
Inventory	Stock level, safety stock, replenishment need	Inventory allocation
Supply chain	Supplier status, lead time, disruption level	Supplier governance
Privacy	Privacy budget, protection level	Privacy control
Capacity	Service capacity, infrastructure utilization	Capacity balancing
Resilience	Disruption severity, recovery requirement	Resilience planning

➤ *Privacy-Aware and Explainable Decision Optimization*

Privacy and explainability are treated as optimization considerations rather than separate security features. Differential privacy introduces controlled noise through a privacy budget, while the architecture records changes in utility and explanation quality. The assigned privacy budget is linked to the assessed risk of each resource:

$$\epsilon_i = \epsilon_{min} + (\epsilon_{max} - \epsilon_{min})(1 - Ri)$$

Where Ri denotes the normalized risk score and ϵ_i represents the assigned privacy budget. Higher-risk resources therefore receive stronger privacy protection. Privacy-related computational cost is represented as:

$$P_{priv} = \sum_{i=1}^n \frac{c_i}{\epsilon_i}$$

Where c_i denotes the computational cost coefficient. SHAP contribution patterns are then examined across privacy settings to assess explanation stability, analytical utility, and resource-governance performance.

➤ *Experimental Design, Baselines, and Validation*

Validation uses public and synthetic datasets because proprietary organizational records are unavailable. Healthcare experiments can use de-identified EHR or claims-oriented datasets, while financial, retail, logistics, and workforce conditions can use public benchmarks or controlled synthetic distributions. Data are partitioned into simulated organizations to reproduce heterogeneous local distributions. The proposed architecture is compared with centralized learning, standard federated learning, and resource optimization without explainable privacy-aware governance. Evaluation measures include allocation cost, unmet demand, risk-detection performance, Pareto-front quality, explanation stability, privacy expenditure, communication overhead, and computational cost. Repeated scenario experiments assess decisions under changes in demand, fraud risk, capacity limitations, and disruptions across participating service networks. Performance differences are reported across scenarios.

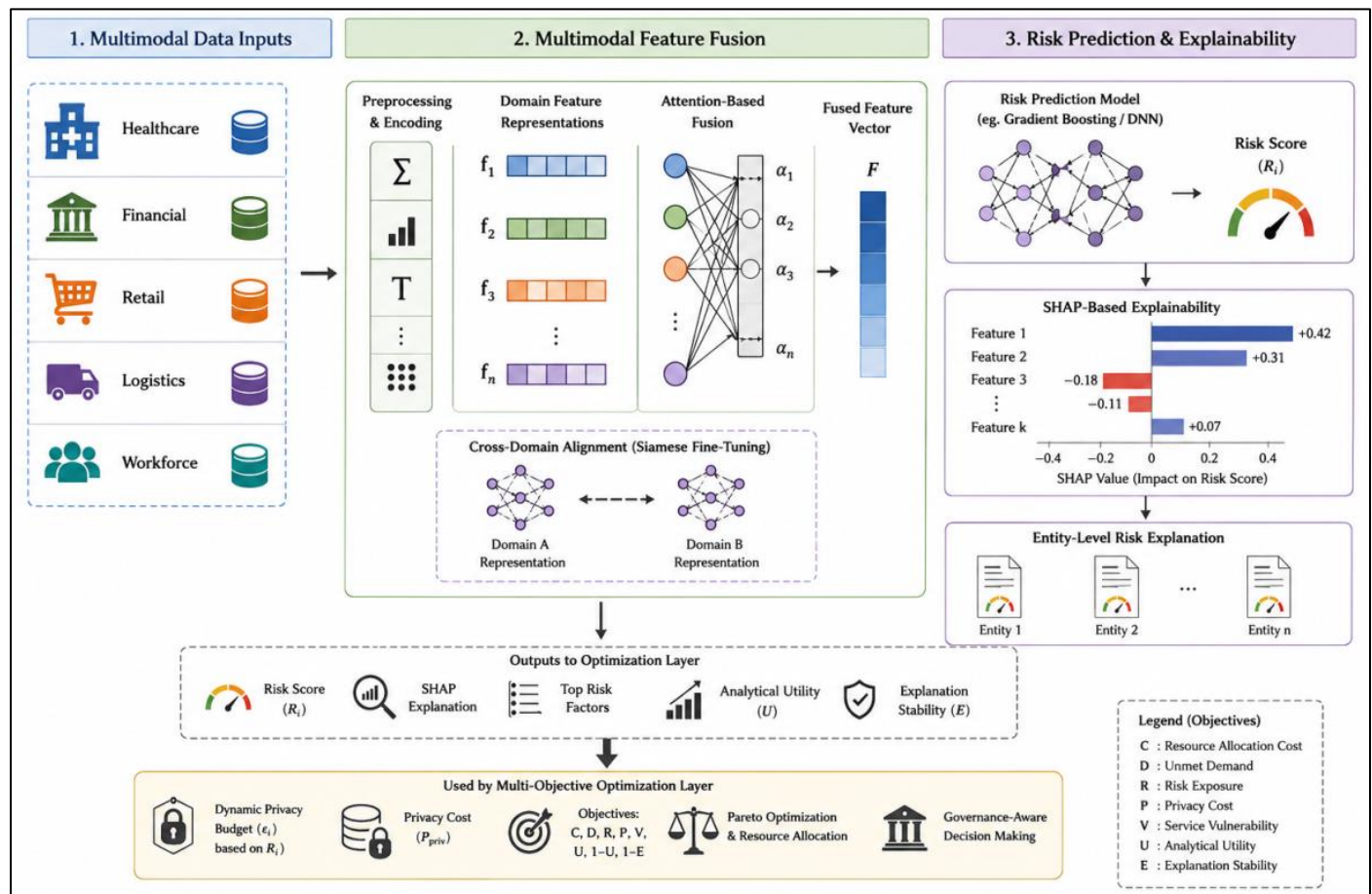


Fig 2 Multimodal Risk Assessment and SHAP-Based Explainability

IV. RESULTS AND DISCUSSION

The results assess the proposed architecture across multimodal risk assessment, resource allocation, privacy protection, explainability, and service-network resilience. Five scenarios represent normal operations, demand surges, fraud escalation, supplier disruption, and compound disruption. Comparative evaluation considers centralized learning, standard federated learning, and the proposed architecture. The analysis focuses on risk sensitivity, allocation quality, privacy cost, explanation stability, computational requirements, and resilience.

➤ Multimodal Risk Assessment and Explainability

The multimodal model produces risk scores from healthcare, financial, retail, logistics, and workforce variables while sensitive records remain within local organizational nodes. SHAP analysis identifies the contribution of factors to each decision. Demand variability, capacity availability, workload, inventory status, transaction risk, and supplier conditions are expected to produce different contribution patterns across scenarios. Higher risk scores should receive stronger resource priorities under capacity or disruption pressures. Explanation results provide decision makers with information about the factors that influence each allocation recommendation. Stability across privacy settings is also assessed to determine if important decision drivers remain interpretable. This analysis connects multimodal risk assessment with transparent resource governance across heterogeneous service networks.

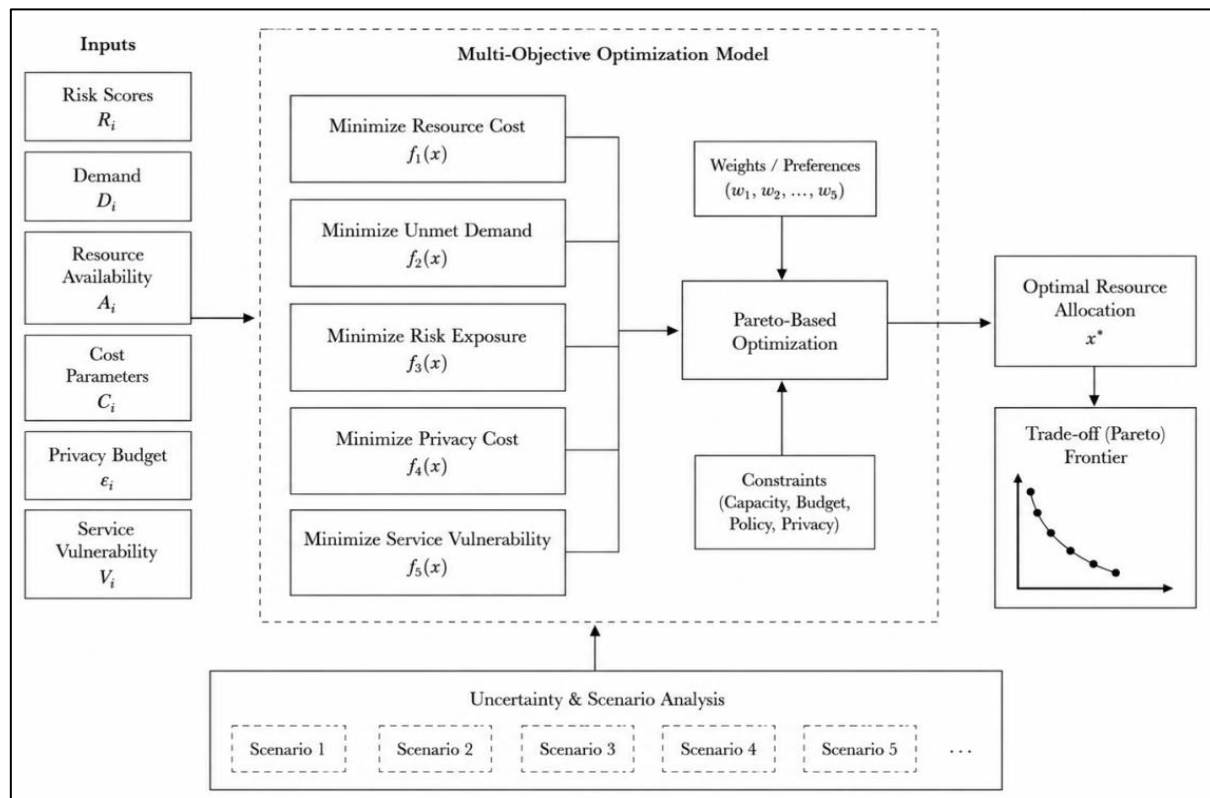


Fig 3 Multi-Objective Risk-Aware Resource Governance and Evaluation Workflow

➤ Multi-Objective Resource Allocation Evaluation

The multi objective model evaluates allocation cost, unmet demand, risk exposure, privacy expenditure, and service vulnerability as competing objectives. Pareto optimization generates non-dominated resource plans instead of one fixed solution. Normal operations are expected to produce balanced allocations across workforce, inventory, service capacity, and monitoring resources. Demand surges increase workforce and service-capacity requirements. Fraud

escalation shifts priority toward transaction monitoring and high-risk activities. Supplier disruption increases inventory and alternative-supplier requirements. Compound disruption creates stronger conflicts among cost, capacity, and risk objectives. Results allow comparison of resource plans according to priorities and risk tolerance. The analysis therefore connects risk scores with practical allocation decisions across healthcare, financial, retail, logistics, and workforce networks.

Table 2 Scenario-Based Resource Allocation Evaluation

Scenario	Primary resource priority	Main risk factor	Allocation response	Main evaluation measures
Normal operation	Balanced capacity	Moderate demand	Balanced allocation	Cost, demand fulfillment
Demand surge	Workforce and service capacity	Demand variability	Additional capacity	Unmet demand, utilization
Fraud escalation	Monitoring resources	Transaction risk	Higher-risk allocation	Risk detection, cost
Supplier disruption	Inventory and suppliers	Supply uncertainty	Alternative allocation	Inventory availability
Compound disruption	Multiple resources	Combined risk	Resilience-oriented allocation	Cost, risk, service level

➤ Privacy, Utility, and Explanation Trade-Off

The privacy experiment evaluates privacy protection, utility, explanation stability, and computational cost across different privacy-budget settings. Stronger privacy protection introduces greater perturbation and can reduce utility. Additional privacy processing can increase computational requirements. The proposed architecture treats this trade-off as part of resource governance rather than an isolated security setting. SHAP contribution patterns provide a second

evaluation dimension because decision factors should remain interpretable after privacy mechanisms are applied. High-risk healthcare and financial resources can receive stricter privacy settings, while lower-risk operational variables can use less restrictive controls. The resulting comparison shows how privacy choices affect decision quality, explanation stability, and computational requirements across participating organizations and service domains.

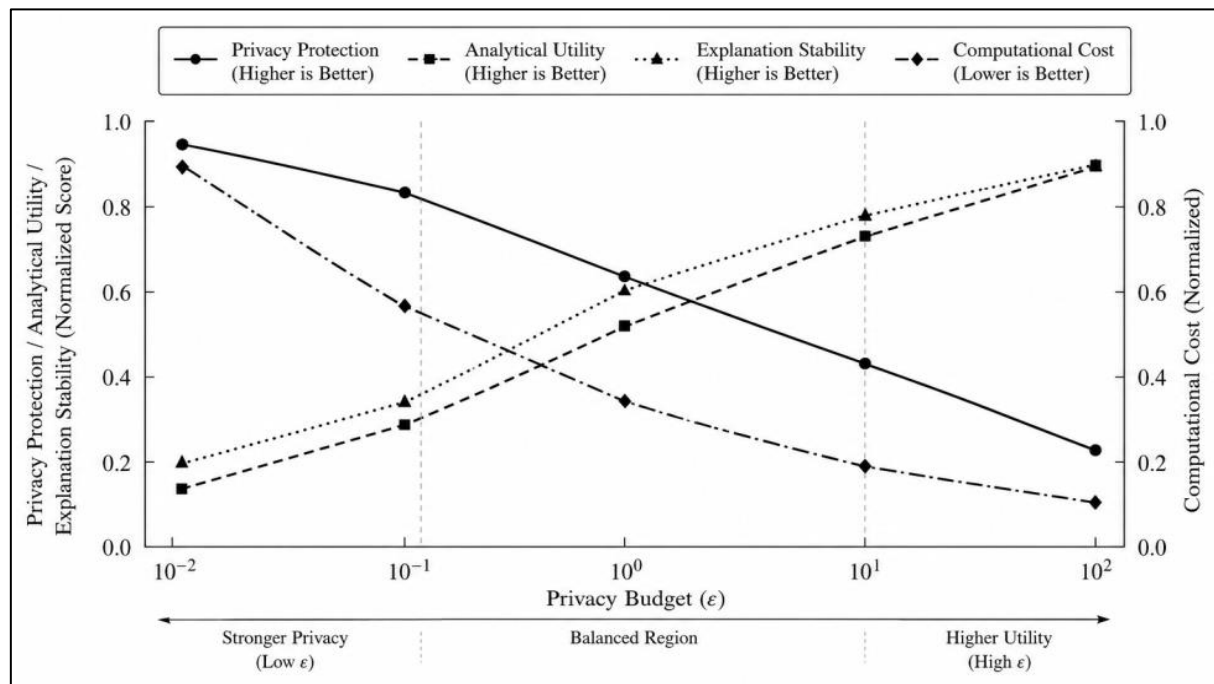


Fig 4 Privacy–Utility–Explainability Trade-Off

➤ Comparative Performance Across Baselines

The proposed architecture is compared with centralized learning, standard federated learning, and resource optimization without explainable privacy-aware governance. Centralized learning provides a common environment but requires sensitive information within a shared repository. Standard federated learning limits direct data exchange, yet it does not integrate multi-objective resource governance, dynamic privacy control, explanation within one decision process. The proposed architecture combines decentralized

learning, multimodal risk assessment, SHAP explanations, privacy controls, and Pareto optimization. Comparative evaluation considers risk-detection performance, allocation cost, unmet demand, privacy expenditure, explanation stability, communication overhead, and computational cost. The comparison identifies contributions of integrated governance components under changing demand, fraud exposure, capacity limitations, supplier disruption, and compound conditions.

Table 3 Comparative Evaluation of Decision-Intelligence Approaches

Evaluation dimension	Centralized learning	Standard federated learning	Proposed architecture
Sensitive data centralization	Required	Not required	Not required
Multimodal fusion	Available	Partial	Integrated
Explainable risk scoring	Limited	Limited	Integrated
Privacy control	Limited	Available	Dynamic
Multi-objective allocation	Separate	Limited	Integrated
Scenario analysis	Available	Available	Integrated
Dynamic privacy budget	Not included	Limited	Included
Pareto decision alternatives	Not included	Limited	Included
Governance feedback	Limited	Limited	Included

➤ Scenario-Based Service-Network Resilience

Scenario analysis examines model behavior under normal operation, demand surge, fraud escalation, supplier disruption, and compound disruption. Normal operation provides the reference condition for allocation and risk. Demand surge tests workforce pressure, while fraud escalation tests risk-sensitive financial allocation. Supplier disruption examines inventory availability and alternative sourcing. Compound disruption combines multiple pressures

and creates strong resource conflicts. The proposed model is expected to modify allocation priorities as scenario conditions change rather than applying fixed resource rules. Scenario comparison also identifies which objectives become dominant under specific disruptions. These results indicate service-network resilience and decision flexibility in diverse healthcare, financial, retail, logistics, and workforce service environments with uncertain demand and operational constraints.

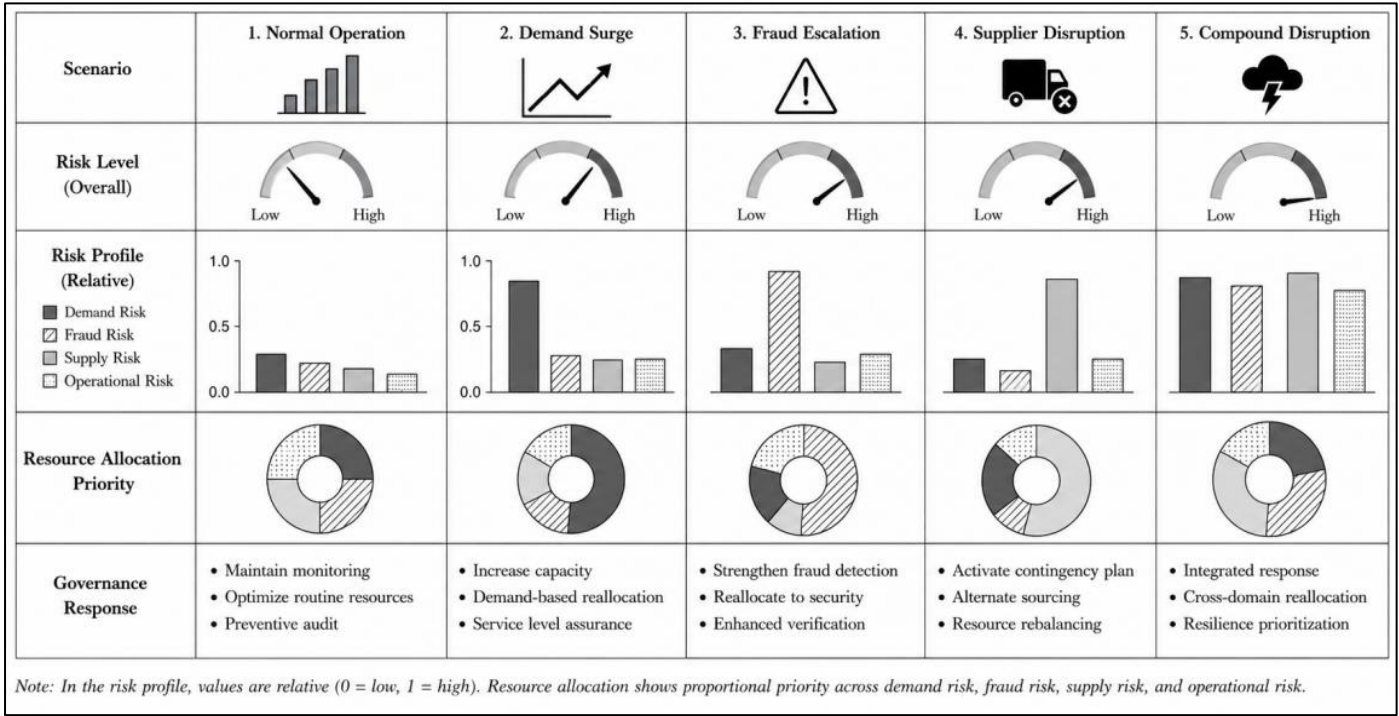


Fig 5 Scenario-Wise Risk and Resource Governance Response

V. LIMITATIONS OF THE STUDY

The study relies on public and synthetic datasets rather than proprietary organizational records. Large scale real time validation across healthcare, financial, retail, logistics, and workforce environments remains limited, particularly for communication overhead, computational cost, and long term governance performance.

VI. CONCLUSION

This study proposes a decision intelligence architecture for secure data sharing and risk-aware resource governance across healthcare, finance, retail, logistics, and workforce services. Local organizations retain control of sensitive information, while hierarchical federated learning supports collaborative analysis. The framework combines multimodal risk assessment, SHAP-based explanations, differential privacy, and Pareto optimization. Resource decisions account for cost, unmet demand, risk exposure, privacy expenditure, capacity limits, and service vulnerability. Scenario analysis further examines how allocation priorities change under demand variation, fraud risk, supplier disruption, and operational constraints. These components provide an integrated basis for transparent resource decisions across heterogeneous service networks.

Future studies should test the framework with larger public datasets and, where permitted, domain-specific operational data. Additional work can examine dynamic privacy budgets, adaptive federated aggregation, multimodal fusion, and real-time allocation. Evaluation of explanation stability, communication overhead, computational requirements, and scalability would also provide useful evidence. Further experiments across healthcare claims, financial transactions, retail inventory, logistics operations,

and workforce planning could show how the framework performs under different risk and capacity conditions.

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