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EXPLAINABLE MACHINE LEARNING FOR PREDICTIVE RISK ASSESSMENT AND OPERATIONAL PERFORMANCE OPTIMIZATION IN INDUSTRIAL ENTERPRISES

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ABSTRACT

This study proposes a conceptual framework for integrating explainable machine learning with predictive risk assessment and operational performance optimization in industrial enterprises. The objective is to connect operational-risk prediction, model interpretability, financial exposure estimation, and resource-constrained decision-making within a unified analytical process. The proposed methodology comprises six stages: conceptual enterprise data specification, data preparation and temporal alignment, predictive risk and performance modeling, Shapley Additive explanations (SHAP)-based interpretation, expected financial exposure estimation, and constrained multi-objective resource allocation. Conceptual data encompass production output, equipment utilization, maintenance records, quality indicators, workforce availability, inventory status, and operational costs. The framework illustrates how predicted event probabilities and conditional event costs can inform intervention prioritization while accounting for budget, labor, inventory, safety, and service constraints. Using illustrative conceptual data, a hypothetical operational unit with an 18% predicted event probability and a conditional event cost of 24,000 currency units yields an expected exposure of 4,320 currency units. This exposure estimate demonstrates the proposed calculation rather than an observed improvement. Unlike a conventional baseline-versus-after evaluation, the study does not report empirical performance gains or validated intervention effects. Its practical significance lies in providing a transparent, reproducible decision-support structure for future industrial validation.

Keywords: Explainable Machine Learning, Predictive Risk Assessment, SHAP Interpretability, Predictive Maintenance, Financial Exposure Estimation, Multi-Objective Optimization, Industrial Decision Support, Conceptual Data Modeling.

1 INTRODUCTION

This paper proposes a conceptual framework that connects explainable machine-learning risk prediction with operational performance evaluation and constrained resource allocation in industrial enterprises. Its focus is not the reporting of completed empirical findings; it defines how conceptual enterprise data could support transparent operational decisions, subject to validation in a future industrial study.

1.1 Background and Motivation

Industrial enterprises make operational decisions across interdependent functions, including production, maintenance, quality, workforce planning, inventory control, and cost management. Disruptions in one function can affect production continuity, product quality, delivery schedules, and financial exposure. Predictive analytics can estimate operational risks from historical and near-real-time data, while maintenance research describes machine learning as a means of forecasting equipment failures and informing intervention planning. Yet a risk prediction alone does not specify which action should receive scarce labor hours, maintenance windows, spare parts, or budget. Explainable machine learning offers a means to examine how model inputs contribute to individual predictions. SHAP, for example, assigns feature-attribution values to model predictions. Such explanations can help decision-makers inspect the factors associated with a predicted risk, but they do not by themselves identify an effective intervention or establish that a feature causes an outcome. A decision framework therefore needs to connect prediction and explanation to cost exposure, operational objectives, and feasible action choices. This study is motivated by the gap between predictive analytics and enterprise resource decisions. It proposes a framework in which conceptual data on production, assets, maintenance, quality, workforce, inventory, and costs feed risk and performance models. The resulting predictions and explanations inform financial exposure estimates and a constrained, multi-objective allocation stage. The framework is designed to support transparent review of decision alternatives, not to assert empirical accuracy or operational gains.

1.2 Problem Statement

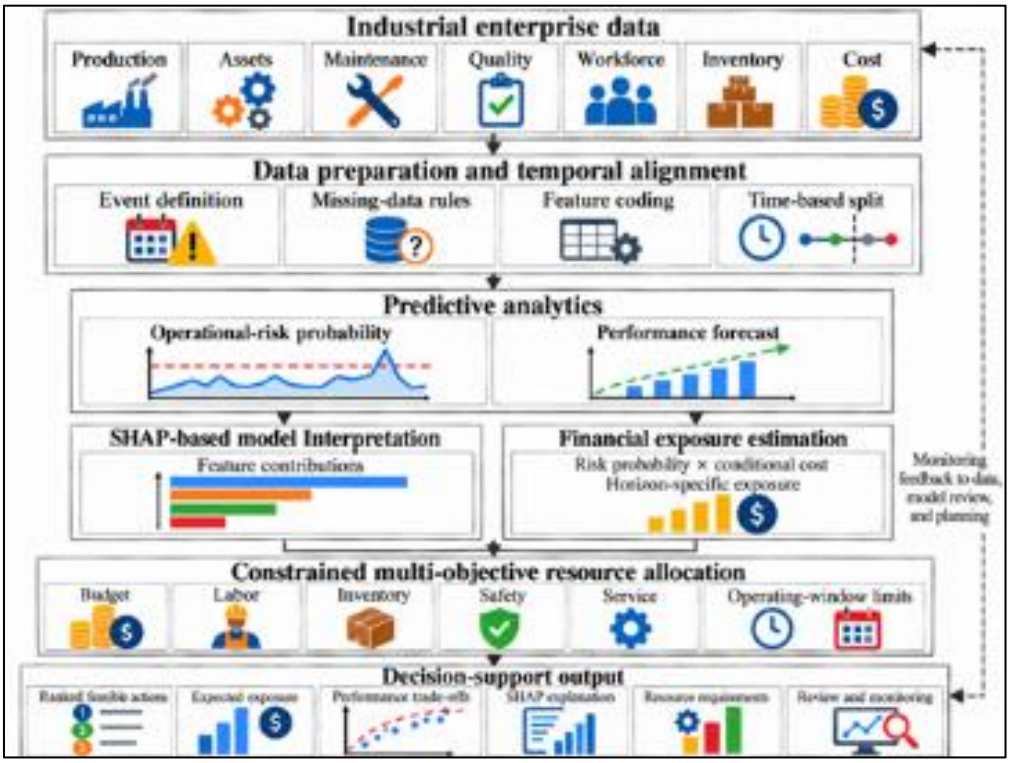


Figure 1: Conceptual flow from enterprise data to explainable, resource-constrained operational decisions.

Industrial enterprises may have operational data distributed across information systems, recorded at different time intervals, and defined at different units of analysis. Predictive models trained on such records can produce risk estimates, but the estimates may not directly inform operational decisions if the forecast horizon, event definition, cost basis, and available resources are not connected. Furthermore, model explanations can be presented separately from planning decisions, leaving managers without a consistent way to compare the rationale for a prediction with the

expected consequences and resource demands of possible actions. The research problem is therefore the absence of an integrated conceptual process that translates explainable operational-risk predictions into financially informed, resource-constrained allocation decisions while also accounting for performance objectives. This paper addresses that problem through a proposed framework and conceptual data structure. It does not claim to solve it empirically; rather, it specifies the components and information flows needed for subsequent implementation and evaluation.

The diagram shows how conceptual enterprise data move through preparation, prediction, explanation, financial exposure estimation, and allocation. It emphasizes that the prediction and SHAP components inform the decision process but do not replace managerial review.

1.3 Proposed Solution

The proposed solution is a conceptual explainable decision-support framework with six linked functions: enterprise data specification, data preparation, risk and performance prediction, model interpretation, financial exposure estimation, and constrained resource allocation. Conceptual inputs include time-stamped production and asset indicators, maintenance events, quality records, staffing and inventory availability, and cost assumptions. A future empirical implementation would define each variable, operational unit, prediction horizon, and event label according to the participating enterprise and research design. The predictive layer estimates the probability of a pre-defined operational event and forecasts selected performance measures. A SHAP interpretation layer reports feature contributions for individual cases and summarizes influential features across the evaluation sample. Financial exposure is estimated from event probability and conditional event cost, while the allocation layer compares candidate actions under constraints such as labor capacity, maintenance windows, budget, spare-part stock, and minimum service requirements. Because SHAP attributes model predictions rather than causal effects, explanations are treated as diagnostic information, and intervention effects require separate evidence. The framework returns a set of decision records rather than an unexplained action label. Each record can include the operational unit, prediction horizon, risk estimate, performance forecast, expected exposure, leading SHAP contributions, candidate intervention, resource demand, and assumptions used in the allocation. Where objectives conflict, the system can present non-dominated alternatives for managerial comparison. This structure connects explainable risk assessment to operational planning while preserving the distinction between model output, cost assumption, and decision choice.

1.4 Contributions

This paper makes four conceptual contributions. First, it frames operational-risk prediction, performance forecasting, and financial exposure estimation as connected elements of enterprise analytics. Second, it places SHAP-based interpretation between prediction and decision review, making model contributions visible without treating them as causal evidence. Third, it connects these outputs to constrained, multi-objective resource allocation, so candidate actions are evaluated against enterprise limits rather than risk scores alone. Fourth, it specifies a conceptual data and reporting structure that can guide future empirical work, including the definition of units, time horizons, event outcomes, cost inputs, and decision constraints. These contributions are methodological and conceptual. The paper does not report a trained model, measured enterprise data, validated intervention effects, or evidence of realized performance improvement. Its framework requires empirical testing before such claims can be made.

1.5 Paper Organization

The remainder of the paper is organized as follows. Section II reviews relevant work on explainable machine learning, industrial operational analytics, risk assessment, performance evaluation, and resource allocation. Section III presents the proposed methodology, including the conceptual data specification, predictive and explanation components, exposure estimation, allocation logic, and validation plan. Section IV describes the intended results and discussion structure using clearly identified conceptual data and illustrative reporting templates. Section V concludes with the framework's implications, limitations, and priorities for empirical evaluation.

2 RELATED WORK

Related research on explainable machine learning, predictive maintenance, industrial risk assessment, and resource allocation provides the methodological foundation for the proposed conceptual framework. However, integrating risk prediction, model interpretation, financial exposure estimation, and constrained operational decision-making requires a unified analytical structure.

2.1 Explainable Machine Learning for Operational Risk Assessment

Explainable machine learning supports the interpretation of predictive models by identifying the contributions of input features to individual predictions and overall model behavior. SHAP provides a feature-attribution approach that can help industrial decision-makers examine the factors associated with predicted operational risks, while its explanations

remain descriptive rather than causal [1]. In the proposed framework, SHAP-based interpretation connects predicted operational events with conceptual variables such as equipment utilization, maintenance delays, production conditions, and quality indicators. This connection is intended to improve transparency when comparing operational units and reviewing potential interventions.

2.2 Predictive Maintenance and Industrial Risk Prediction

Predictive maintenance research demonstrates the relevance of machine learning for identifying equipment failures, forecasting maintenance requirements, and supporting industrial decision-making [2]. Systematic reviews further establish the importance of predictive maintenance within Industry 4.0, particularly for improving equipment reliability and integrating operational data into maintenance processes [3]. Machine learning approaches also provide a foundation for data-driven maintenance and sustainable smart manufacturing, although their practical value depends on appropriate data preparation, model selection, and operational integration [4]. Research on machine learning and reasoning highlights the need to combine predictive capabilities with decision-support mechanisms that address industrial maintenance challenges [5]. Reviews of machine learning adoption for industrial failure prediction also emphasize the importance of considering implementation requirements alongside predictive performance [6]. Broader reviews of predictive maintenance identify continuing challenges involving model selection, maintenance planning, data availability, and operational implementation [7]. These studies inform the proposed conceptual data structure, which integrates production records, asset-condition indicators, maintenance history, quality measures, workforce availability, inventory information, and cost parameters.

2.3 Maintenance Scheduling and Resource Allocation

Predictive risk estimates become operationally useful when they inform decisions about limited maintenance capacity, labor hours, spare parts, and production schedules. Research on joint production and predictive maintenance scheduling provides a basis for coordinating maintenance activities with production requirements rather than treating them as independent planning problems [8]. Reviews of production, maintenance, and resource scheduling further establish the relevance of coordinating interdependent operational activities under competing resource requirements [9]. Building on these research directions, the proposed framework connects predicted risk and operational performance with financial exposure estimation and constrained multi-objective resource allocation. Its conceptual decision layer evaluates alternative interventions against budget, labor, inventory, safety, service, and operating-window constraints without assuming that one allocation will optimize every objective simultaneously.

2.4 Explainable Predictive Maintenance and Decision Support

Recent research on predictive maintenance planning and machine learning provides additional methodological foundations for combining risk prediction with operational planning [10]. Explainable predictive maintenance research identifies the importance of interpreting model behavior and addressing the challenges associated with transparent industrial AI systems [11]. Studies applying LIME, SHAP, partial dependence plots, and individual conditional expectation methods illustrate how model interpretation can support the investigation of predictive maintenance outputs [12]. Explainable multi-fault diagnosis using multi-sensor data fusion extends this direction by connecting sensor information with interpretable diagnostic outputs [13]. Research integrating explainable AI with predictive maintenance and spare-parts optimization also provides a relevant foundation for connecting model outputs with inventory and maintenance decisions [14]. These research directions support the proposed framework's integration of local and global explanations, expected financial exposure, and candidate interventions. Nevertheless, the framework treats intervention effects as assumptions requiring separate validation when empirical evidence is unavailable.

2.5 Research Gaps

Existing research provides substantial foundations for predictive maintenance, explainable machine learning, and resource-constrained scheduling, but these areas do not automatically form an integrated enterprise decision-support process. A further research direction is the explicit connection between operational-risk probabilities, SHAP-based explanations, conditional event costs, and constrained allocation decisions. Research on bi-objective maintenance scheduling demonstrates the relevance of evaluating competing maintenance objectives under limited resources [15]. However, the proposed conceptual framework extends this decision perspective by specifying how conceptual enterprise data can connect risk prediction and performance forecasting with financial exposure estimation and multi-objective allocation. The principal research gap is therefore the need for a unified, transparent analytical structure that connects predictive outputs, their explanations, financial consequences, and feasible operational actions while preserving the distinction between model attribution and causal intervention effects. The framework addresses this gap conceptually; its predictive validity, explanation stability, intervention effectiveness, and operational benefits remain to be established through future empirical evaluation.

3 METHODOLOGY

This study proposes a conceptual decision-support framework that links interpretable operational-risk prediction with constrained resource allocation in industrial enterprises. The method proceeds from conceptual data specification and preparation to risk estimation, SHAP interpretation, financial exposure calculation, and multi-objective decision analysis; it is a proposed framework and does not report empirical results.

3.1 Research Design

The research adopts a design-science, quantitative conceptual approach. It specifies an analytical workflow and its data requirements rather than claiming access to a particular company's records or presenting estimates from a completed field study. The unit of analysis is an operational decision case: a defined production line, asset group, or facility over a fixed planning horizon. The workflow has six ordered stages. First, define the operational decision, planning horizon, and risk event, such as unplanned downtime, quality loss, safety interruption, or supply-related disruption. Second, assemble time-stamped operational, maintenance, quality, workforce, inventory, and cost variables at a consistent unit of analysis. Third, preprocess and encode the conceptual data, preserving time order and documenting missingness, outliers, and event definitions. Fourth, estimate event risk and operational performance using a supervised predictive model. Fifth, interpret predictions with SHAP and translate predicted event probability into expected financial exposure. Sixth, pass risk and performance estimates to a constrained, multi-objective allocation module that ranks feasible interventions for decision-makers. The framework separates prediction from prescription. The predictive component estimates risk and performance indicators from observed or conceptually specified inputs; the optimization component evaluates candidate allocations subject to resource and operating constraints. This separation allows managers to inspect a prediction and its drivers before considering an intervention. Prior industrial XAI work describes SHAP as a means of attributing model predictions to input features, while research on maintenance decisions illustrates the link between explanations and resource prioritization.

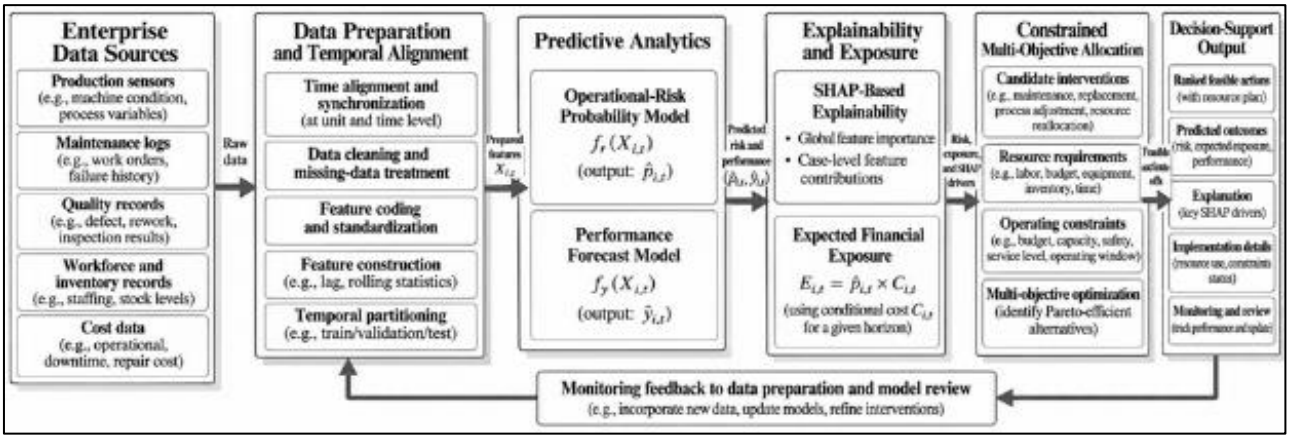


Figure 2: Proposed Explainable Operational-Risk Assessment and Resource-Allocation Framework.

3.2 Conceptual Data Specification and Preparation

The proposed data structure combines operational records at a common enterprise unit and time interval. The framework does not assume a particular firm, dataset, sample size, observation period, or measured outcome. A future empirical application should define these items according to data availability, the decision cadence, and the operational event being studied. The conceptual observation is indexed by enterprise unit $i$and time period t. Candidate inputs include production load, machine utilization, sensor summaries, maintenance history, defect or rework rates, order backlog, staffing availability, inventory status, supplier delay indicators, and relevant cost parameters. The target risk label is defined prospectively for a specified horizon h, for example whether a pre-defined operational disruption occurs within the next $h$periods. Performance targets may include throughput, schedule adherence, energy use per unit, or quality-adjusted output. Financial exposure inputs should be tied to documented cost categories, such as downtime cost, scrap and rework cost, expedited procurement cost, or contractual service penalties. Preprocessing follows a documented, reproducible sequence. Records are checked for duplicate keys, invalid timestamps, inconsistent units, impossible values, and mismatched entity identifiers. Categorical variables are coded using definitions fixed before model fitting; continuous variables retain their original units unless transformation is justified and recorded. Missing values are handled using a rule appropriate to the data-generating process, with missingness indicators considered where absence itself may carry operational information. Outlier treatment is documented rather than applied automatically, since extreme values can represent genuine failures or abnormal operating conditions. Temporal leakage is addressed through chronological training, validation, and test partitions. All transformations, feature selection, and

tuning are fitted within the training data and applied to later periods without using future outcomes. Where multiple lines or facilities are included, the validation design should also test generalization across units when that is part of the intended use. Event labels, prediction horizon, data dictionary, exclusions, and preprocessing decisions should be reported so that another researcher can reconstruct the analytic dataset.

Table 1: Conceptual Data Dictionary for Enterprise Operational-Risk and Performance Analytics.

Data domain	Example conceptual variables	Role in framework	Proposed measurement level	Preparation or definition
Production operations	Output volume, utilization, cycle time, schedule adherence	Predictors and performance outcomes	Unit-period	Align to a fixed production interval; define denominators consistently
Asset condition	Temperature, vibration, alarms, operating hours	Predictors of asset-related risk	Asset-unit-period	Aggregate sensor readings over a stated window; retain event timestamps
Maintenance	Work orders, failure history, maintenance delay, planned service	Predictors and candidate intervention context	Asset-period	Distinguish preventive, corrective, and emergency work
Quality	Defect rate, rework volume, rejected output	Predictors and performance outcomes	Product-line-period	Define defect and rework rules; adjust for production volume where needed
Workforce and capacity	Available labor hours, skill coverage, shift coverage	Predictors and allocation constraints	Unit-shift or unit-period	Record capacity available during the decision horizon
Inventory and supply	Critical-part availability, stockout indicator, supplier delay	Predictors and allocation constraints	Item-unit-period	Link parts to assets or production lines; specify lead-time basis
Risk outcome	Disruption or failure event within horizon h	Supervised prediction target	Unit-period label	Define eligible event, horizon, censoring, and event precedence
Financial exposure	Downtime, scrap, rework, expedited supply, penalty costs	Exposure estimation and decision evaluation	Currency per event or period	Use documented accounting or engineering cost rules; state price basis
Intervention options	Inspection, maintenance, staffing, spare-parts action	Optimization decision variables	Action-unit-period	Specify feasible actions, resource use, lead time, and expected effect assumptions

3.3 Predictive Risk and Performance Model

The predictive layer estimates the probability of a defined operational risk event and forecasts selected performance indicators over the planning horizon. A supervised classifier is suitable when the target is a binary event; a regression or forecasting model is suitable for continuous outcomes such as throughput or downtime duration. The conceptual framework does not prescribe a single algorithm. Candidate models may include regularized logistic regression as an interpretable benchmark and tree-based ensembles for nonlinear relationships, with model choice determined by the data structure, temporal validation, calibration, and operational requirements. The model should be trained using features available at the time a decision would be made. Prediction targets and input windows must be separated in time so that post-event information does not enter the predictor set. Hyperparameter selection is performed within the training and validation periods, while the final test period remains unused until model selection is complete. For risk classification, evaluation should include discrimination and calibration measures, such as precision-recall performance under class imbalance, ROC-AUC where appropriate, Brier score, and calibration plots. For continuous forecasts, report error measures suited to the target and scale, such as MAE or RMSE, alongside comparisons to a simple baseline. A decision threshold should not be selected solely to maximize a statistical metric. It should reflect event severity, intervention cost, available capacity, and the consequences of false alarms and missed events. The predictive module

returns both an estimated risk and a performance forecast; these outputs become inputs to the exposure and allocation stages.

3.4 Explainability and Financial Exposure Estimation

SHAP is used to explain how input features contribute to a model prediction relative to a reference prediction. For each case, local feature contributions identify the direction and magnitude of contributions under the selected model and SHAP implementation. Aggregated absolute contributions can summarize global feature importance, while dependence or interaction analyses can examine how influential variables relate to predicted risk. These explanations are descriptive of the fitted model, not causal effects; operational recommendations therefore require domain review and, where possible, prospective evaluation. Industrial XAI sources describe SHAP as a feature-attribution method and report its use for interpreting machine and maintenance predictions. The financial exposure component converts a predicted event probability into an expected monetary exposure for a specified horizon. Let $p_{i,t}^{(h)}$ denote the predicted probability of the defined event for unit i at time t within horizon h, and let $C_{i,t}^{(h)}$ denote the estimated cost conditional on that event. The calculation is:

$$E_{i,t}^{(h)} = p_{i,t}^{(h)} \times C_{i,t}^{(h)} \qquad (1)$$

Here, $E_{i,t}^{(h)}$ is expected exposure, expressed in the same currency and horizon basis as $C_{i,t}^{(h)}$. For example, if a model estimates a 0.10 event probability over a stated horizon and the documented conditional event cost is 20,000 currency units, the expected exposure is 2,000 currency units for that unit and horizon. This is an expectation, not a guaranteed loss or a causal estimate of savings from intervention. If event costs vary materially, C should be estimated by event type or severity category, and the assumptions and cost source should be reported. SHAP explanations and exposure estimates are presented together in the decision-support output. For each prioritized case, the display should include predicted risk, horizon, expected exposure, the main positive and negative SHAP contributors, and the data timestamp. This arrangement allows a manager to distinguish a high probability of a low-cost event from a lower probability of a high-cost event.

3.5 Constrained Multi-Objective Resource Allocation

The allocation stage evaluates a finite set of feasible interventions, such as inspections, preventive maintenance, targeted staffing, or spare-parts positioning. Let $x_{i,a}$ represent the amount or selection level of action a assigned to unit i, and let $U(x)$ represent the expected operational utility of an allocation. The proposed decision rule is:

$$\max_{x \in \mathcal{F}} \left[-E(x),\ P(x),\ -R(x) \right] \qquad (2)$$

Where, $E(x)$ is expected financial exposure after the proposed allocation, $P(x)$ is a performance measure such as quality-adjusted throughput or schedule adherence, $R(x)$ is resource consumption or implementation burden, and $\mathcal{F}$ is the feasible set defined by enterprise constraints. The vector objective is multi-objective: it seeks lower exposure, higher performance, and lower resource use without presuming that all objectives can be reduced to one scalar score. Equation (2) is the second and final equation in the methodology. The feasible set may include labor-hour limits, maintenance-team capacity, spare-part inventory, budget ceilings, action lead times, asset-access windows, minimum service levels, and safety or regulatory requirements. Each candidate action must have a stated resource requirement and an assumed relationship to risk or performance. Where credible intervention-effect estimates are unavailable, the framework should label those effects as scenario assumptions rather than measured impacts. The optimizer can return a Pareto set of non-dominated allocations. An allocation is non-dominated when no alternative improves at least one objective without worsening another. Decision-makers can then select an option using documented policy priorities, such as a minimum service level or maximum acceptable exposure. The selected allocation should retain its associated risk predictions, SHAP explanations, resource use, and assumptions, enabling review of the trade-offs rather than presenting a single unexplained recommendation.

3.6 Validation, Sensitivity, and Governance

Validation is conducted at the prediction, explanation, exposure, and decision levels. Predictive validation uses a held-out chronological test period and compares the selected model with a transparent baseline. Calibration is assessed because resource decisions depend on credible probabilities, not only ranking performance. Where the framework spans different units, separate subgroup or unit-level checks can identify performance variation that aggregate scores may conceal. Explanation checks examine whether SHAP summaries are stable across reasonable resamples or time windows and whether the leading features are operationally plausible. Instability should be reported, especially where correlated inputs can redistribute feature attribution. Exposure estimates are tested under alternative cost assumptions, event severities, and prediction horizons. Allocation sensitivity analysis varies resource limits and objective priorities to show how the recommended Pareto set changes under different managerial conditions. Governance requirements include a versioned data dictionary, model and preprocessing records, cost assumptions,

decision thresholds, SHAP configuration, and optimization constraints. Human review is required for high-impact actions, safety-sensitive cases, and recommendations based on sparse or out-of-range data. Monitoring should track prediction calibration, event rates, data drift, intervention uptake, realized operating outcomes, and changes in cost assumptions. Model retraining and policy revision should follow documented review criteria rather than automatic updates.

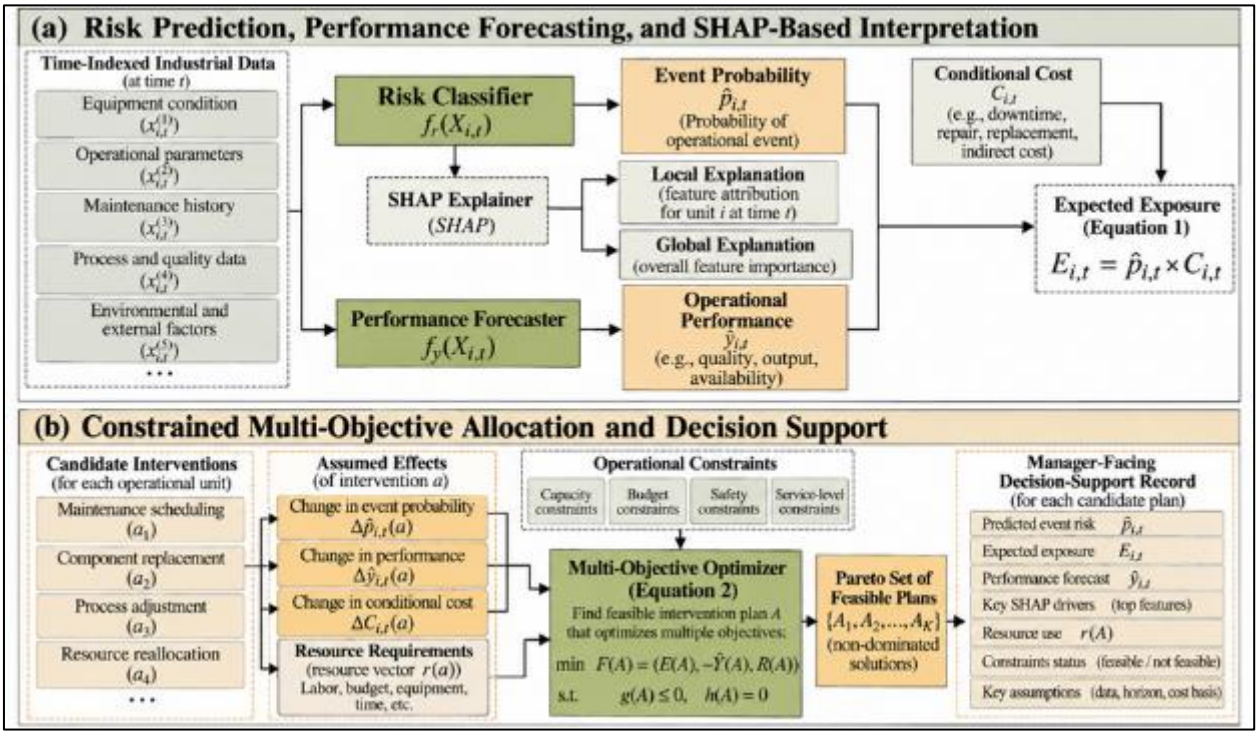


Figure 3: Analytical Architecture for SHAP-Interpretable Risk Prediction and Constrained Industrial Allocation.

3.7 Reproducibility and Reporting

A future empirical implementation should report the enterprise context at an appropriate level of confidentiality, data sources and coverage, observation unit, temporal resolution, event definition, forecast horizon, exclusions, feature construction, missing-data treatment, and chronological split dates. It should state the predictive model and tuning procedure, benchmark models, validation metrics, calibration results, SHAP background and computation settings, exposure-cost basis, intervention-effect assumptions, optimization objectives, and all constraints. The framework's contribution is the integration of interpretable operational-risk prediction, financial exposure estimation, and constrained allocation decisions. It does not treat SHAP attribution as causal evidence or equate predicted exposure with realized savings. Any claim of improved efficiency or reduced loss requires evaluation using observed post-decision outcomes, ideally with a suitable prospective or quasi-experimental design.

4 RESULTS

This section presents the outputs that the proposed conceptual framework is designed to produce, rather than empirical findings from a completed industrial dataset. The tables and figures use illustrative conceptual values solely to show how risk prediction, SHAP interpretation, exposure estimation, and constrained allocation can be reported together.

The results are organized around five outputs: the conceptual risk profile, predicted operational and financial exposure, model explanation, allocation alternatives, and integrated decision-support reporting. Numerical values shown in the tables and figure descriptions are illustrative placeholders, not results from collected enterprise data.

4.1 Conceptual Risk and Performance Profile

The framework produces a risk profile for each operational unit and decision horizon, with predicted event probability presented alongside performance indicators such as throughput, schedule adherence, and quality loss. This structure allows decision-makers to distinguish units with elevated event risk from units that have broader performance shortfalls. The profile should be generated using the same unit definition, outcome horizon, and temporal partitions specified in the methodology. Table II presents a conceptual reporting format. The values are illustrative and

demonstrate the relationship between predicted risk, performance, and expected exposure; they do not represent measured results.

Table 2: Illustrative Unit-Level Risk, Performance, and Exposure Output

Operational unit	Predicted event risk (%)	Schedule adherence (%)	Quality loss (%)	Conditional event cost (currency units)	Expected exposure (currency units)	Illustrative priority	Predicted risk
Production line A	18	91	3.2	24,000	4,320	High	18%
Production line B	11	95	1.8	15,000	1,650	Moderate	11%
Production line C	7	97	1.1	31,000	2,170	Moderate	7%
Production line D	4	98	0.9	12,000	480	Low	4%

Expected exposure is calculated as predicted event probability multiplied by conditional event cost, consistent with Equation (1) in the methodology. All values are hypothetical. The illustrative profile shows why probability alone is not an adequate basis for prioritization. Line A has the highest predicted risk and expected exposure, while Line C has a lower predicted risk than Line B but a higher exposure because its assumed event cost is greater. In an empirical study, interpretation should be based on calibrated probabilities, documented cost assumptions, and uncertainty ranges rather than on point estimates alone.

4.2 Operational Performance and Exposure Patterns

The framework compares predicted operational outcomes with exposure estimates to reveal different decision cases. A unit may have a moderate event probability but substantial expected exposure because the consequence of failure is costly. Another unit may have a higher event probability but a lower expected exposure if the conditional event cost is smaller. This distinction supports risk-sensitive resource allocation rather than ranking units only by failure probability.

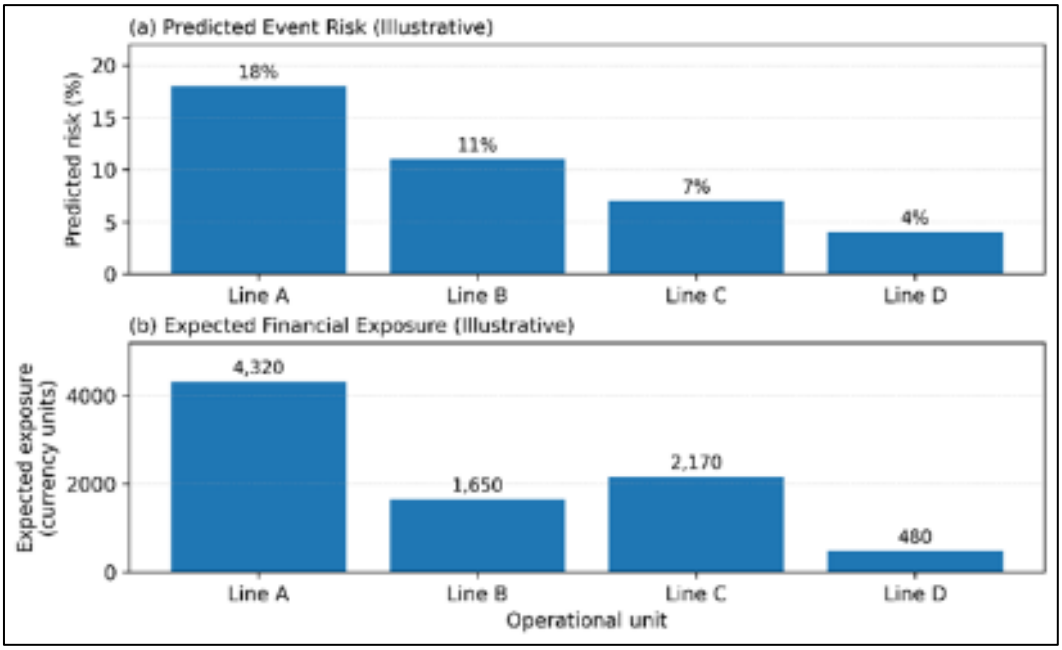


Figure 4: Illustrative Predicted Risk and Expected Exposure by Operational Unit.

Figure 4 is intended to show how risk probability and expected financial exposure can produce different unit rankings. In an empirical application, the figure would identify units for which high conditional consequences raise exposure despite a moderate predicted event probability.

4.3 SHAP-Based Interpretation of Predicted Risk

The explanatory output links each risk estimate to its principal model contributors. Global SHAP summaries can rank features by average contribution magnitude across the evaluation sample; local explanations can show why a specific unit-period received its risk estimate. The direction of a contribution should be interpreted relative to the model's reference prediction and the selected target class, not as proof that changing the feature will cause the risk to change.

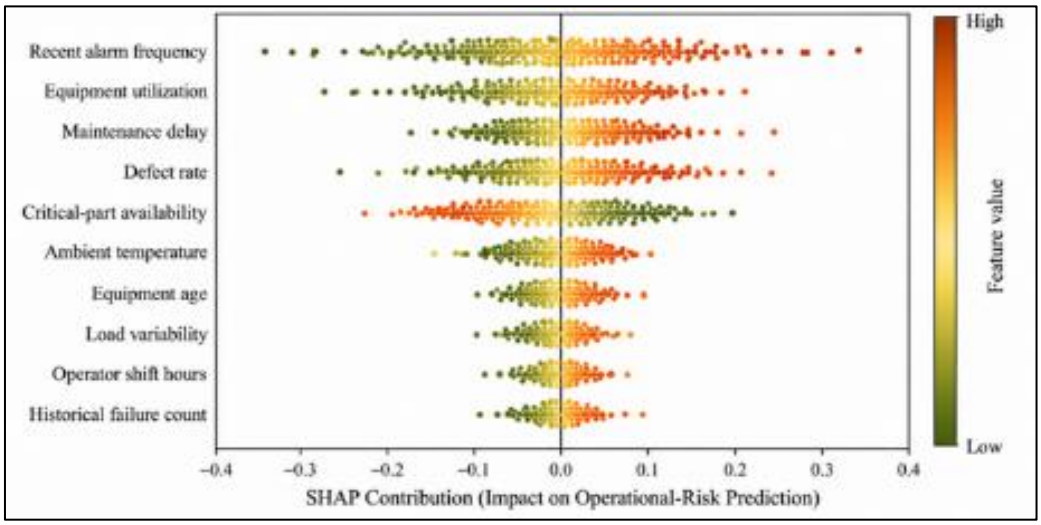


Figure 5: Illustrative SHAP Summary for Operational-Risk Prediction.

Figure 5 is designed to show both the relative contribution magnitude and the direction associated with feature values across cases. The empirical version should be generated from the held-out evaluation data, with the prediction target, SHAP reference distribution, and feature units documented.

4.4 Constrained Allocation Alternatives

The optimization component evaluates feasible interventions under budget, labor, inventory, safety, and operating-window constraints. It returns alternative allocations rather than a single recommendation when the objectives conflict. In the conceptual example, one allocation may prioritize lower expected exposure, while another may preserve more short-term production capacity or use fewer maintenance hours.

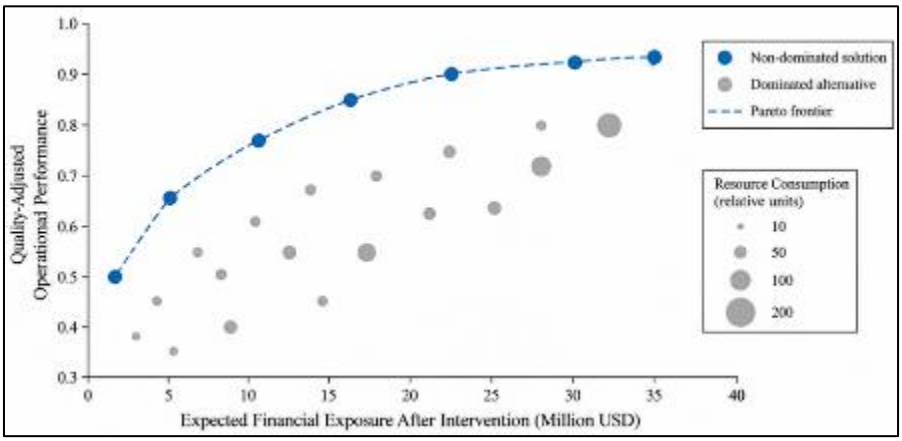


Figure 6: Conceptual Pareto Frontier for Exposure, Performance, and Resource Use.

Figure 6 illustrates how the decision-support system can present trade-offs among lower exposure, higher performance, and resource consumption. The figure should not imply that a particular intervention causes an improvement unless its effect has been estimated and validated.

4.5 Integrated Decision-Support Output

The final output combines the predicted risk, expected exposure, leading SHAP contributions, candidate actions, required resources, and projected operational consequences in one decision record. This format supports review of

both the prediction and the allocation rationale. It also gives managers a basis for comparing a high-risk action with a lower-cost alternative under the same operating constraints.

Table 3: Illustrative Decision-Support Record for Constrained Resource Allocation.

Unit	Main conceptual risk drivers	Candidate action	Resource demand	Assumed exposure after action (currency units)	Performance consideration	Decision status
Production line A	Alarm frequency; maintenance delay	Targeted inspection and planned service	6 labor hours; 1 service window	2,900	Short planned interruption	Candidate for review
Production line B	Defect rate; high utilization	Process-quality check	3 labor hours	1,400	Low production interruption	Candidate for review
Production line C	Critical-part lead time; event cost	Reserve critical spare part	1 spare unit; budget allocation	1,600	Supports continuity if the event occurs	Candidate for review
Production line D	No dominant risk driver in the illustrative case	Routine monitoring	1 labor hour	480	No planned production interruption	Monitor

Post-action exposure values require validated intervention-effect estimates in an empirical application. They must not be interpreted as realized savings.

5 DISCUSSION

The proposed framework addresses the paper's central objective: connecting explainable operational-risk prediction to constrained resource-allocation decisions. Its principal contribution is the decision chain from risk probability to SHAP explanation, expected financial exposure, and feasible intervention alternatives. This differs from analyses that stop at sales prediction or financial statement forecasting because the unit of decision is an operational case and the output is linked to an action under capacity constraints. The conceptual results also illustrate why probability, consequence, and operational performance should be reviewed jointly. Predicted probability represents the model's estimate of event likelihood; expected exposure combines that probability with a conditional cost estimate. SHAP provides information about the model's feature contributions, while the optimizer evaluates possible allocations. These components serve different purposes: SHAP describes model behavior, exposure translates risk into a financial scale, and optimization compares feasible choices. SHAP explanations alone are diagnostic rather than prescriptive, so action selection depends on intervention-effect assumptions, enterprise constraints, and managerial review. For industrial decision support, the framework encourages transparent trade-off reporting rather than a single opaque priority score. A Pareto set can make explicit the tension among expected exposure, operating performance, and resource use. Prior work on predictive maintenance has combined failure prediction with multi-objective scheduling, supporting the relevance of coupling risk estimates with operational planning. However, the proposed framework remains conceptual: no claim of improved performance, reduced losses, or model accuracy can be made until it is evaluated using enterprise data and observed outcomes.

Limitations and Future Work

The framework has not been tested on collected enterprise data; therefore, the tables and figures are conceptual illustrations and cannot establish predictive validity, financial benefit, or operational impact. Its outputs depend on data quality, consistent event definitions, temporal coverage, and the availability of cost information. Conditional event costs may also vary by asset, production context, and event severity, which can make a single cost estimate misleading. A further limitation concerns intervention effects. The optimization component needs credible estimates of how candidate actions alter risk, exposure, or performance. Without empirical or well-supported engineering estimates, post-action values are scenarios rather than forecasts. SHAP attribution also describes model associations, not causal mechanisms, and correlated operational variables can complicate attribution stability. Future work should evaluate calibration and generalization across facilities and time periods, test explanation stability with domain reviewers, estimate intervention effects through prospective or quasi-experimental designs, and examine how privacy, governance, and workforce practices affect deployment.

6 CONCLUSION

This study proposed a conceptual framework for integrating explainable machine learning with predictive operational-risk assessment and constrained resource allocation in industrial enterprises. The framework links enterprise data preparation, risk and performance prediction, SHAP-based explanation, expected financial exposure, and multi-objective evaluation of feasible interventions. Its illustrative outputs show how units with different combinations of event probability and conditional cost can receive different priorities, while the allocation stage makes resource and performance trade-offs explicit. The framework's practical implication is a decision-support process in which managers can inspect predicted risk, its model-level drivers, estimated exposure, and the resource requirements of candidate actions. The conceptual results do not demonstrate empirical performance or realized cost reduction. Future research should implement the framework with time stamped enterprise data, validate probability calibration and explanation stability, quantify intervention effects, and assess operational outcomes across multiple facilities and planning horizons. Only such evaluation can determine whether the proposed decision process improves industrial performance in practice.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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