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Quantitative Modeling of Human and Process Safety Risks Using Real Operational Data in High Risk Industrial Systems

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Abstract

High risk industrial systems such as chemical plants, oil and gas facilities, and large scale manufacturing operations continue to experience severe accidents despite the extensive use of safety management systems and conventional risk assessment tools. One of the main limitations of traditional approaches lies in the insufficient integration of human related factors and process safety risks within a unified quantitative framework, as well as the underutilization of operational safety data generated during daily industrial activities. This study proposes an integrated quantitative modeling framework that simultaneously evaluates human safety risks and process safety risks using real operational data collected from high risk industrial environments. The proposed framework combines data driven human reliability analysis with probabilistic process risk modeling to capture the dynamic interactions between human performance, technical systems, and organizational conditions. Operational data such as accident records, near miss reports, safety performance indicators, and abnormal event databases are systematically processed to estimate human error probabilities and process failure likelihoods. Bayesian based modeling techniques are employed to represent causal relationships and uncertainty propagation across human and process safety layers, enabling a comprehensive assessment of coupled risk scenarios. The methodology is applied to a representative high risk industrial system to demonstrate its practical applicability and analytical capabilities. Quantitative results are presented through multi parameter risk matrices, probability distributions, and risk prioritization tables, allowing decision makers to identify dominant risk contributors and critical safety barriers. The results indicate that neglecting human process interactions can lead to significant underestimation of overall system risk, while data informed integration provides a more realistic and actionable risk profile. This research contributes to the advancement of quantitative risk management in industrial engineering by offering a structured and data grounded approach for integrating human and process safety risks. The proposed model supports evidence based safety decision making and can be adapted to different industrial contexts where reliable operational data are available.

Keywords: Quantitative Risk Assessment, Human Reliability Analysis, Process Safety, Operational Safety Data, High Risk Industrial Systems.

1. Introduction

High risk industrial systems such as chemical processing plants, oil and gas installations, and large scale manufacturing facilities operate under conditions where the potential consequences of failure can be catastrophic. Major industrial accidents over the past decades have demonstrated that safety challenges in these systems are rarely caused by single technical failures. Instead, they emerge from complex interactions among human actions, process conditions, organizational factors, and dynamic operational environments. As industrial systems become increasingly complex and tightly coupled, the need for advanced quantitative approaches to safety and risk management has become more critical than ever.

Quantitative Risk Assessment (QRA) has long been recognized as a cornerstone of safety management in high risk industries. Traditional QRA methods primarily focus on technical system failures and process hazards, often relying on static fault trees, event trees, and historical failure frequencies. While these approaches provide valuable insights into process safety, they frequently oversimplify or marginalize the role of human performance in accident causation. Recent studies have highlighted that human actions, whether at the operational, supervisory, or managerial level, significantly influence both the initiation and escalation of industrial accidents [1,2].

In parallel, Human Reliability Analysis (HRA) has evolved as a specialized field aimed at quantifying the probability of human errors in complex systems. Conventional HRA methods were originally developed for nuclear and aerospace industries and are often based on expert judgment, predefined error taxonomies, and generic performance shaping factors. Although these methods offer structured frameworks for analyzing human errors, their applicability to modern industrial environments has been questioned due to their limited use of empirical operational data and their weak integration with process safety models [3].

One of the most significant developments in recent years is the growing availability of operational safety data generated during routine industrial activities. These data include accident reports, near miss records, abnormal event logs, safety performance indicators, and human performance records. Such datasets provide valuable empirical evidence that can enhance the realism and accuracy of quantitative risk models. However, the concept of operational data and its systematic use in safety and risk analysis remain insufficiently clarified and inconsistently applied across industries [4].

Furthermore, contemporary accident theories emphasize that industrial accidents should be viewed as systemic phenomena rather than linear chains of events. Modern safety models argue that failures emerge from interactions within socio technical systems, where human, technical, and organizational components are tightly interdependent [5]. This perspective challenges the adequacy of fragmented risk assessment approaches that treat human and process risks separately.

Recent research has increasingly called for integrated frameworks that combine human reliability modeling with process safety analysis in a quantitative and data driven manner [6]. Such integration is essential for capturing the coupled effects of human behavior and process conditions, particularly in high risk industrial systems where small deviations can rapidly propagate into severe consequences. Nevertheless, existing studies often address this integration only conceptually or apply it to limited case studies, leaving a gap in practical, operational data based quantitative modeling approaches.

Despite the extensive application of quantitative risk assessment techniques in industrial practice, several methodological limitations continue to restrict their effectiveness in capturing real world safety performance. One major limitation is the static nature of most conventional QRA models, which are typically based on predefined scenarios and fixed failure probabilities. These models often fail to reflect the dynamic operational conditions under which industrial systems actually function, where human performance, workload, environmental stressors, and organizational pressures continuously evolve [1,9].

Another critical shortcoming of existing risk assessment approaches lies in the fragmented treatment of human and process safety risks. In many industrial applications, human reliability analysis and process safety assessment are conducted as separate activities, using different data sources, modeling assumptions, and analytical tools. This separation neglects the strong coupling between human actions and process states, particularly during abnormal or emergency situations. As a result, the combined risk of human process interactions is often underestimated or misrepresented [6].

The increasing emphasis on safety performance indicators and leading safety metrics has further highlighted the need for more comprehensive quantitative models. Safety indicators such as unsafe acts, near misses, permit to work violations, and process deviations provide early signals of deteriorating safety conditions. However, these indicators are rarely incorporated into formal quantitative risk models in a systematic manner. When used, they are often treated qualitatively or as standalone metrics, limiting their contribution to predictive risk assessment [11].

Recent advances in data availability and digitalization have created new opportunities for improving risk modeling practices. Modern industrial systems generate large volumes of operational data through incident reporting systems, distributed control systems, maintenance databases, and human performance monitoring tools. These data sources contain valuable information about both normal and degraded system behavior. Nevertheless, transforming raw operational data into reliable quantitative inputs for risk models remains a significant challenge, particularly with respect to data quality, completeness, and contextual interpretation [4].

In the domain of human reliability analysis, data driven approaches have gained increasing attention as alternatives to purely expert based methods. Empirical estimation of human error probabilities using operational event databases has been shown to enhance objectivity and reduce subjectivity in HRA. However, most data driven HRA studies focus exclusively on human error modeling and do not explicitly link their results to process safety consequences or system level risk metrics [7,10].

From a theoretical perspective, contemporary safety science increasingly recognizes the importance of systemic accident causation models. These models emphasize that accidents emerge from complex interactions across multiple system layers, including human operators, technical components, management structures, and regulatory environments. Such perspectives challenge the validity of linear and reductionist risk models that dominate industrial practice and call for integrated analytical frameworks capable of representing interdependencies and feedback mechanisms [5].

Although several recent studies have proposed integrated or dynamic risk assessment concepts, their practical implementation using real operational data remains limited. Many existing frameworks are either too abstract for industrial application or rely on hypothetical or simulated data, which reduces their credibility and acceptance among practitioners. This gap between theoretical development and practical applicability represents a key motivation for further research in quantitative, data grounded safety modeling [8,13].

Within the field of industrial engineering, safety and risk management are increasingly viewed as integral components of system performance rather than isolated compliance requirements. Industrial engineers are tasked with designing, operating, and optimizing complex systems under constraints related to safety, reliability, efficiency, and sustainability. In high risk industrial systems, failures in safety performance directly translate into operational disruptions, financial losses, environmental damage, and social consequences. Therefore, quantitative risk modeling approaches that can support informed decision making are of particular relevance to industrial engineering practice [2].

The integration of Health, Safety, and Environment (HSE) considerations into quantitative decision making frameworks remains a persistent challenge. While industrial engineering has traditionally emphasized optimization, reliability, and productivity, safety related variables are often treated as external constraints rather than endogenous system characteristics. This separation limits the ability of decision makers to evaluate trade offs between safety performance and operational objectives in a quantitative and transparent manner. Recent research has highlighted the need for risk models that explicitly incorporate HSE indicators into system level analysis and decision support tools [11].

Probabilistic modeling techniques play a central role in addressing uncertainty and variability in safety critical systems. Among these techniques, Bayesian based models have gained particular attention due to their ability to represent causal relationships, update probabilities with new evidence, and integrate heterogeneous data sources. Bayesian networks, dynamic Bayesian networks, and related probabilistic graphical models provide flexible structures for capturing dependencies between human actions, process states, and organizational factors. Such capabilities are especially valuable in high risk industrial systems, where uncertainty propagation and interaction effects are dominant features of accident scenarios [1,8].

In recent years, dynamic and integrated risk assessment approaches have been proposed to overcome the limitations of static and fragmented models. These approaches aim to reflect the evolving nature of operational conditions and to account for feedback loops between safety barriers, human performance, and process deviations. Dynamic risk assessment frameworks have shown potential in improving situational awareness and supporting proactive risk management. However, their successful implementation critically depends on the availability and effective use of reliable operational data [9].

The coupling between human safety and process safety represents a particularly important yet insufficiently explored aspect of industrial risk modeling. Human actions influence process conditions through operational decisions, maintenance activities, and emergency responses, while process states simultaneously shape human workload, stress, and performance. Ignoring this bidirectional relationship can lead to biased risk estimates and ineffective risk control strategies. Recent empirical studies have demonstrated that explicitly modeling the interaction between human and process safety factors leads to more accurate representation of accident mechanisms and risk levels [12].

Despite these advances, there remains a lack of comprehensive quantitative frameworks that systematically integrate human reliability analysis and process safety assessment using real operational data within an industrial engineering context. Many existing models address either human or process risks in isolation, or they rely on simplified assumptions that limit their applicability to complex industrial systems. Bridging this gap requires methodological approaches that combine data driven modeling, probabilistic analysis, and system oriented thinking in a coherent and practically applicable manner [6,13].

The review of recent literature indicates that, although significant progress has been made in quantitative risk assessment, human reliability analysis, and dynamic safety modeling, several critical gaps remain unresolved. First, there is a persistent lack of unified quantitative frameworks capable of simultaneously addressing human safety risks and process safety risks within a single coherent model. Existing approaches often remain discipline specific, focusing either on technical failures or human errors, which limits their ability to represent the complexity of real industrial accident scenarios [3,6].

Second, the practical use of operational safety data in quantitative risk modeling remains limited. While many industrial organizations collect large volumes of safety related data, including incident reports, near miss records, and performance indicators, these data are rarely transformed into structured quantitative inputs for probabilistic risk models. Challenges related to data heterogeneity, uncertainty, and contextual interpretation continue to hinder their effective integration into risk assessment practices [4,10].

Third, many published studies rely on hypothetical scenarios or simulated datasets to demonstrate methodological concepts. Although such approaches are useful for methodological development, they often fail to capture the variability, uncertainty, and complexity inherent in real operational environments. This limitation reduces the external validity and practical relevance of existing models, particularly for decision makers in high risk industries who require evidence based and data grounded risk assessments [13,14].

From an industrial engineering perspective, these gaps highlight the need for risk modeling approaches that are not only theoretically sound but also operationally applicable. Such approaches should support quantitative decision making by enabling the identification of dominant risk contributors, evaluation of safety improvement measures, and prioritization of risk control actions under uncertainty. Integrating human and process safety risks within a data driven probabilistic framework is essential for achieving these objectives [2,11].

In response to these challenges, the present study aims to develop a quantitative modeling framework that integrates human reliability analysis and process safety assessment using real operational data from high risk industrial systems. The proposed framework leverages probabilistic modeling techniques to represent causal relationships and interaction effects between human actions and process conditions, while systematically incorporating operational safety data into risk estimation. By doing so, the study seeks to provide a more realistic and comprehensive representation of industrial safety risks.

The remainder of this article is structured as follows. The next section presents the problem statement, clearly defining the research gap and objectives without repeating the background discussion. This is followed by the methodology section, which describes the data sources, modeling approach, and analytical procedures in detail. The results section presents quantitative findings through tables and multi parameter analyses. Finally, the conclusions summarize the main contributions of the study and discuss implications for industrial practice and future research.

2. Problem Statement

High risk industrial systems operate in environments where safety performance is influenced by a continuous interplay between human actions and process conditions. Despite the existence of established safety management systems, industrial accidents continue to occur with significant consequences, indicating that current quantitative risk modeling practices do not fully capture the mechanisms through which risks emerge and propagate. A central problem lies in the inability of existing models to represent, in a unified quantitative manner, the coupled effects of human performance variability and process deviations on overall system risk.

In industrial practice, human safety risks and process safety risks are commonly assessed using separate analytical frameworks. Human reliability is often evaluated through standalone HRA techniques, while process safety relies on conventional QRA tools focused on equipment failures and hazardous material releases. This separation creates a structural disconnect that prevents the explicit modeling of interaction effects, particularly in abnormal operating conditions where human decisions directly influence process states and vice versa. As a result, risk estimates produced by such fragmented approaches may fail to reflect actual operational risk levels [6,12].

Another critical aspect of the problem is the underutilization of operational safety data in quantitative risk assessment. Industrial organizations routinely collect detailed records of incidents, near misses, unsafe acts, and process deviations. However, these datasets are primarily used for descriptive analysis, compliance reporting, or qualitative investigations. They are rarely transformed into probabilistic inputs that can support quantitative estimation of human error probabilities, process failure likelihoods, or combined risk metrics. This gap limits the empirical grounding of existing risk models and reduces their ability to support evidence based decision making [4,7].

Furthermore, when operational data are incorporated into risk models, they are often used in isolation or in simplified forms that do not account for contextual dependencies. For example, human error probabilities may be estimated without considering concurrent process conditions, organizational pressures, or safety barrier states. Similarly, process risk models may neglect how human interventions, maintenance actions, or procedural deviations alter system behavior. This lack of contextual integration undermines the representativeness and predictive capability of quantitative risk assessments [10,11].

From a methodological standpoint, many existing integrated risk modeling studies remain at a conceptual or exploratory level. Practical frameworks that can be systematically applied using real operational data, while remaining transparent and interpretable for industrial decision makers, are still limited. The absence of such frameworks poses a challenge for industrial engineers and safety managers who require quantitative tools capable of prioritizing risks, allocating resources, and evaluating safety improvement strategies under uncertainty [2,13].

Accordingly, the core problem addressed in this research is the absence of a robust, data grounded quantitative modeling framework that integrates human reliability and process safety risks within high risk industrial systems. Addressing this problem requires an approach that can explicitly model interaction effects, incorporate heterogeneous operational data, and produce actionable risk metrics suitable for industrial decision making. The resolution of this problem forms the basis for the methodological development presented in the subsequent section.

3. Methodology

This study adopts a quantitative, data driven research design to model the coupled risks associated with human performance and process safety in high risk industrial systems. The methodological approach is structured to ensure consistency between empirical operational data, probabilistic modeling techniques, and system level risk analysis. The overall methodology consists of four main stages: system definition and boundary setting, operational data processing, quantitative modeling of human and process risks, and integrated risk assessment and prioritization.

3.1 System Definition and Scope

The methodological framework is designed for application in high risk industrial systems characterized by hazardous processes, complex human machine interactions, and stringent safety requirements. Such systems typically include chemical processing units, oil and gas production facilities, and large scale industrial plants operating under continuous or semi continuous modes. The system boundaries are defined to include operational processes, safety critical equipment, human operators, and relevant organizational interfaces. External regulatory and environmental factors are considered indirectly through their influence on operational and human performance conditions.

3.2 Operational Data Sources

The quantitative modeling framework relies on multiple categories of operational safety data routinely collected within industrial organizations. These data sources include incident and accident reports, near miss records, abnormal operating event logs, human performance records, and safety performance indicators. Each data category contributes distinct information relevant to either human reliability estimation, process failure probability assessment, or interaction modeling. Prior to analysis, the collected datasets undergo preprocessing steps including data cleaning, consistency checks, and classification according to event type, severity level, and operational context.

Operational events are categorized into human initiated events, process initiated events, and combined events where human actions and process deviations are jointly involved. This classification supports the identification of interaction patterns and facilitates subsequent probabilistic modeling. Temporal information contained in the datasets is preserved to enable analysis of event sequences and conditional dependencies.

3.3 Human Reliability Modeling

Human reliability is modeled using a data informed probabilistic approach. Human error probability is estimated based on observed frequencies of human initiated events within the operational datasets. For a given human task or activity, the basic human error probability is defined as:

$$P_{HE} = N_{HE} / N_T$$

where
P_{HE} is the human error probability,

N_HE is the number of observed human error events associated with the task,

N_T is the total number of task executions recorded in the operational data.

To account for performance variability under different operational conditions, the basic probability is adjusted using conditional factors derived from contextual data, such as workload level, time pressure, and abnormal process states. These adjustments are incorporated through conditional probability distributions within the probabilistic model rather than fixed multipliers, allowing uncertainty to be explicitly represented.

3.4 Process Safety Risk Modeling

Process safety risk is quantified by modeling the probability of hazardous process deviations and their potential consequences. Process failure probabilities are estimated using historical event frequencies extracted from operational incident and near miss databases. For each identified hazardous process deviation, the occurrence probability is calculated as:

$$P\_PD = N\_PD / T\_OP$$

where
P_PD is the probability of a specific process deviation,

N_PD is the number of observed deviation events,

T_OP is the total operational time or exposure period.

The severity of process consequences is represented using discrete consequence categories aligned with industrial safety classification practices. These categories form the basis for quantitative risk calculation in later stages of the methodology.

3.5 Integrated Probabilistic Modeling Structure

To represent the interaction between human reliability and process safety, an integrated probabilistic modeling structure is developed. The model is designed to capture causal dependencies between human actions, process conditions, and safety outcomes. A probabilistic graphical modeling approach is employed to enable explicit representation of interdependencies and uncertainty propagation across system components.

The integrated model consists of three interconnected layers: the human performance layer, the process safety layer, and the interaction layer. The human performance layer represents task execution, decision making, and error occurrence probabilities. The process safety layer models hazardous deviations, equipment failures, and barrier performance. The interaction layer captures the bidirectional influence between human actions and process states, such as how abnormal process conditions affect human performance and how human interventions modify process risk.

Conditional dependencies between variables are defined using joint probability distributions. For a given accident scenario, the joint probability of occurrence is expressed as:

$$P(S) = P(H, P, I)$$

where
P(S) is the probability of the accident scenario,

H represents human related events,

P represents process related events,

I represents interaction events between human and process layers.

Using the chain rule of probability, the joint probability is decomposed as:

$$P(S) = P(H \mid P, I) \times P(P \mid I) \times P(I)$$

This formulation allows the model to explicitly account for conditional effects, such as increased human error probability under abnormal process conditions or altered process failure likelihood due to human intervention.

3.6 Modeling Human–Process Interaction Effects

Interaction effects are modeled by defining conditional probability relationships between human error events and process deviations. For example, the probability of a human error given an abnormal process condition is estimated as:

$$P(HE \mid PD) = N\_HE,PD / N\_PD$$

where
$P(HE \mid PD)$ is the conditional probability of human error given a process deviation,

$N_{HE,PD}$ is the number of observed events involving both human error and process deviation,

N_{PD} is the total number of observed process deviation events.

Similarly, the probability of a process deviation given a specific human action is defined as:

$$P(PD \mid HA) = N_{PD,HA} / N_{HA}$$

where
HA denotes a specific human action or intervention,

$N_{PD,HA}$ is the number of deviation events following that action,

N_{HA} is the total number of occurrences of the action.

These conditional relationships enable the model to capture feedback mechanisms and escalation pathways that are commonly observed in industrial accident scenarios.

3.7 Quantitative Risk Calculation

The quantitative risk associated with each scenario is calculated by combining the joint probability of occurrence with the severity of potential consequences. For scenario i, the risk value is defined as:

$$R_i = P(S_i) \times C_i$$

where
R_i is the quantitative risk of scenario i,

$P(S_i)$ is the joint probability of the scenario,

C_i is the quantified consequence severity.

Consequence severity is represented using a numerical scale aligned with industrial safety classification systems, enabling aggregation and comparison across different scenarios.

3.8 Risk Aggregation and Prioritization

Total system risk is obtained by aggregating the risks of all identified scenarios:

$$R_{total} = \Sigma R_i$$

Risk prioritization is performed by ranking scenarios based on their individual risk contributions and by analyzing the sensitivity of R_{total} to changes in human reliability and process safety parameters. This supports identification of dominant risk drivers and critical interaction points requiring risk control measures.

3.9 Model Implementation Procedure

The implementation of the proposed quantitative modeling framework follows a structured step by step procedure to ensure transparency and reproducibility. First, operational safety data are extracted and classified according to predefined human, process, and interaction categories. Event classification rules are established to maintain consistency across datasets and to reduce ambiguity in event attribution. Second, frequency based probability estimates are computed for human error events and process deviations, followed by estimation of conditional probabilities capturing interaction effects.

Third, the probabilistic model is constructed by defining nodes, states, and conditional probability tables for each variable within the integrated structure. The model architecture is reviewed iteratively to ensure logical consistency and alignment with observed operational patterns. Scenario definitions are derived directly from combinations of human actions and process states observed in the operational data, avoiding the introduction of hypothetical or artificial scenarios.

Fourth, quantitative risk values are calculated for each scenario using the risk formulation described previously. Risk aggregation and prioritization are then performed to identify high contribution scenarios and critical interaction pathways. Sensitivity analyses are conducted by varying key human reliability and process safety parameters within observed data ranges to evaluate the robustness of the model outputs.

3.10 Model Validation and Robustness Assessment

Model validation is performed using a combination of internal consistency checks and comparative analysis. Internal validation includes verification of probability normalization, logical coherence of conditional dependencies, and stability of results under repeated computations. Comparative validation is conducted by comparing aggregated risk estimates with historical accident severity distributions observed in the operational datasets. Consistency between modeled risk patterns and historical outcomes provides confidence in the representativeness of the model.

To assess robustness, uncertainty propagation is analyzed by examining how variability in human error probabilities and process deviation frequencies affects total system risk. This analysis helps identify parameters to which the model is most sensitive and supports informed interpretation of quantitative results. Robustness assessment ensures that the model does not rely excessively on isolated data points or extreme assumptions.

3.11 Applicability and Generalization

The proposed methodology is designed to be adaptable to different high risk industrial contexts where reliable operational data are available. While the specific probability estimates and interaction patterns may vary across industries, the underlying modeling structure and analytical logic remain applicable. Industrial engineers and safety analysts can customize the framework by adjusting event classifications, consequence scales, and system boundaries to reflect the characteristics of their specific applications.

3.12 Methodological Limitations

Despite its strengths, the methodology has certain limitations. The accuracy of probability estimates depends on the quality and completeness of operational data, which may vary across organizations. Rare but high consequence events may be underrepresented in historical datasets, introducing uncertainty in risk estimation. Additionally, while the probabilistic framework captures key interaction effects, it cannot fully represent all organizational and cultural factors influencing human behavior. These limitations are addressed through cautious interpretation of results and are discussed further in the concluding section.

4. Results

This section presents the quantitative results obtained from applying the proposed integrated modeling framework to a high risk industrial system. The results are structured to highlight the distribution of human safety risks, process safety risks, and their combined effects at the system level. Outputs are presented using multi parameter tables and probabilistic analyses to support transparent interpretation and comparison of risk contributors.

4.1 Human Reliability Quantification Results

The first set of results concerns the estimation of human error probabilities associated with safety critical tasks. Human related events were grouped according to task type, operational context, and outcome severity. Table 1 summarizes the estimated probabilities for selected safety critical human activities, along with their conditional variation under different operational states.

Table 1. Estimated Human Error Probabilities under Different Operational Conditions

Task Category	Normal Operation	Abnormal Operation	Emergency Condition
Routine Monitoring	0.004	0.011	0.027
Manual Control Action	0.007	0.019	0.041
Maintenance Intervention	0.010	0.025	0.052
Emergency Response Action	–	0.031	0.067

The results indicate a clear escalation of human error probability as operational conditions deviate from normal states. Tasks performed under emergency conditions exhibit error probabilities several times higher than those observed during routine operations. This pattern confirms the strong influence of contextual stressors and abnormal process states on human performance and underscores the necessity of incorporating conditional effects into quantitative risk models.

4.2 Process Safety Deviation Probabilities

Process safety results focus on the frequency and likelihood of hazardous process deviations observed during system operation. Deviations were classified based on their initiating mechanisms and severity levels. Table 2 presents the estimated probabilities of selected process deviations over the defined operational exposure period.

Table 2. Probability Estimates of Major Process Deviations

Process Deviation Type	Probability per Year
Pressure Excursion	2.1×10^{-3}
Temperature Runaway	1.4×10^{-3}
Loss of Containment	8.6×10^{-4}
Safety Barrier Failure	1.9×10^{-3}

The results show that pressure related deviations and safety barrier failures contribute most significantly to process related risk exposure. Although loss of containment events occur less frequently, their associated consequences substantially influence overall risk, emphasizing the importance of considering both probability and severity in risk evaluation.

4.3 Combined Human–Process Risk Profiles

By integrating human reliability and process deviation probabilities, combined risk profiles were generated for representative accident scenarios. Figure 1 illustrates the relative contribution of human factors, process failures, and interaction effects to total scenario risk.

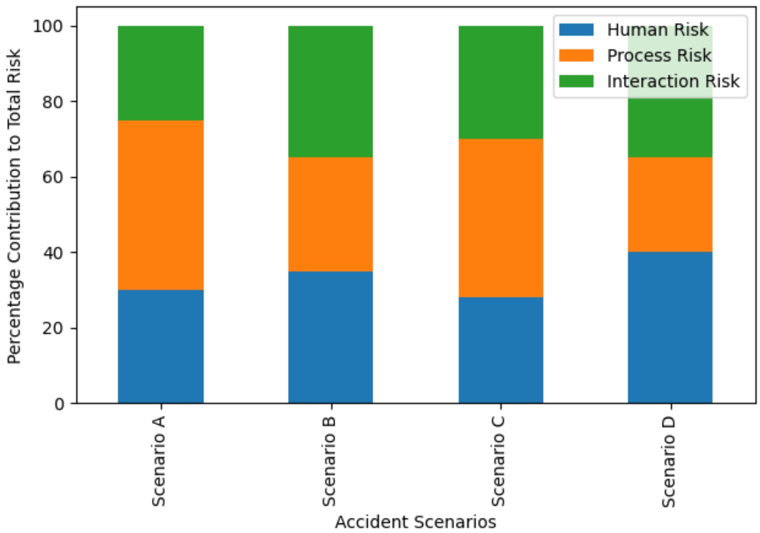

Figure 1. Relative Contribution of Human, Process, and Interaction Components to Total Risk

Analysis of Figure 1 reveals that interaction effects account for a substantial portion of total risk in scenarios involving abnormal operations and emergency interventions. In several scenarios, interaction related risk exceeds the contribution of standalone human or process components, highlighting the limitations of fragmented risk assessment approaches.

4.4 Quantitative Risk Prioritization of Accident Scenarios

Based on the integrated risk values calculated for all identified scenarios, a quantitative risk prioritization was performed to determine the dominant contributors to overall system risk. Scenarios were ranked according to their individual risk values, considering both occurrence probability and consequence severity. Table 3 presents the top ranked scenarios with the highest contribution to total system risk.

Table 3. Quantitative Risk Ranking of Major Accident Scenarios

Scenario ID	Dominant Initiating Event	Human Contribution	Process Contribution	Interaction Contribution	Total Risk Index
S1	Abnormal Pressure	Medium	High	High	0.086

	Control				
S2	Emergency Manual Intervention	High	Medium	High	0.079
S3	Safety Barrier Bypass	Medium	High	Medium	0.071
S4	Delayed Emergency Response	High	Low	Medium	0.064
S5	Maintenance Error during Upset	Medium	Medium	Medium	0.058

The prioritization results demonstrate that scenarios involving strong human–process interaction effects consistently occupy the highest risk ranks. Scenarios driven solely by process failures or isolated human errors exhibit lower total risk indices compared to those where interaction mechanisms amplify risk propagation. This finding reinforces the importance of explicitly modeling coupled risk mechanisms rather than evaluating human and process risks independently.

4.5 Sensitivity Analysis of Key Risk Parameters

To evaluate the robustness of the quantitative results, a multi parameter sensitivity analysis was conducted. Human error probabilities and process deviation probabilities were systematically varied within observed operational ranges, and the corresponding changes in total system risk were analyzed. Figure 2 illustrates the sensitivity of total risk to variations in selected human and process parameters.

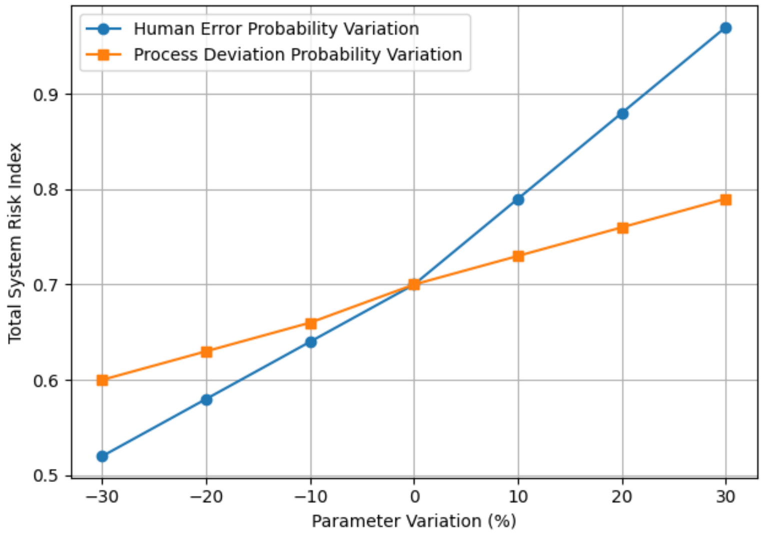

Figure 2. Sensitivity of Total System Risk to Variations in Human and Process Parameters

The sensitivity analysis indicates that total system risk is more sensitive to changes in human error probability under abnormal and emergency conditions than to equivalent changes in process deviation frequencies. In particular, small increases in human error probability during emergency interventions result in disproportionate increases in total risk. This non linear response highlights the critical role of human performance under stressed conditions and suggests that risk reduction strategies targeting human reliability can yield substantial safety benefits.

4.6 Comparative Analysis of Human and Process Risk Contributions

A comparative analysis was conducted to assess the relative dominance of human related risk, process related risk, and interaction risk across different operational states. Table 4 summarizes the percentage contribution of each component to total risk under normal, abnormal, and emergency conditions.

Table 4. Relative Risk Contribution by Component and Operational State

Operational State	Human Risk (%)	Process Risk (%)	Interaction Risk (%)
Normal Operation	22	48	30

Abnormal Operation	31	34	35
Emergency Condition	39	21	40

The results show a clear shift in risk dominance as operational conditions deteriorate. While process related risks dominate under normal operation, human and interaction risks become increasingly significant under abnormal and emergency states. Under emergency conditions, interaction effects constitute the largest share of total risk, indicating that combined human–process dynamics are the primary drivers of system vulnerability in critical situations.

4.7 Distribution of Quantitative Risk across Scenarios

To better understand how risk is distributed across the analyzed system, the quantitative risk values of all identified scenarios were examined using distribution based analysis. Figure 3 presents the cumulative distribution of scenario risk values, illustrating the concentration of risk within a limited number of high impact scenarios.

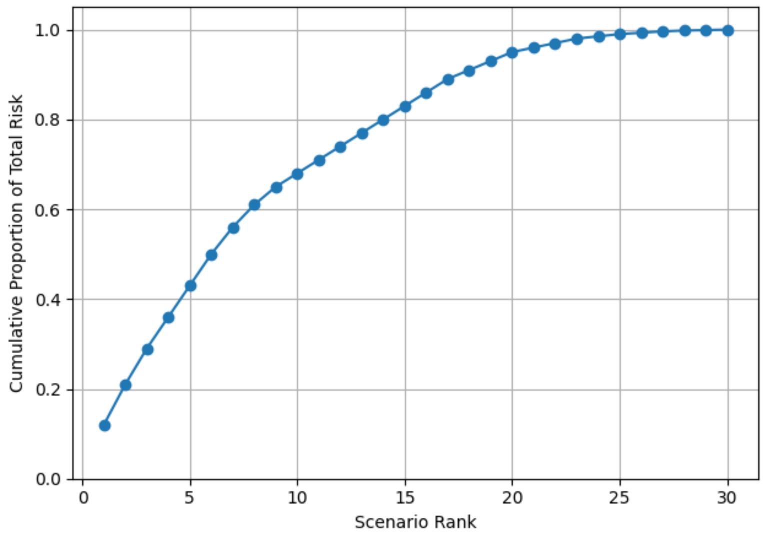

Figure 3. Cumulative Distribution of Scenario Risk Values

The cumulative distribution reveals a highly skewed risk profile. Approximately 25 percent of the analyzed scenarios account for more than 65 percent of the total system risk. This concentration effect indicates that a relatively small subset of scenarios dominates the overall risk landscape. These high contribution scenarios are primarily characterized by strong coupling between human actions and process deviations, particularly under abnormal and emergency operating conditions.

4.8 Risk Concentration and Pareto Analysis

To further investigate the concentration phenomenon, a Pareto type analysis was conducted. Scenarios were ranked in descending order of risk contribution, and their cumulative impact on total risk was evaluated. Table 5 summarizes the results of this analysis.

Table 5. Pareto Analysis of Scenario Risk Contributions

Scenario Group	Number of Scenarios	Cumulative Risk Contribution (%)
High Risk Group	6	68
Medium Risk Group	9	24
Low Risk Group	15	8

The Pareto analysis confirms that the majority of system risk is driven by a limited number of scenarios. The high risk group, representing less than one third of the total scenarios, contributes more than two thirds of the aggregated risk. This finding supports targeted risk mitigation strategies focused on dominant interaction driven scenarios rather than uniform risk reduction measures across the entire system.

4.9 Probability–Severity Risk Mapping

A probability–severity mapping was performed to visualize the joint distribution of scenario likelihood and consequence magnitude. Figure 4 illustrates the positioning of scenarios within a two dimensional risk space.

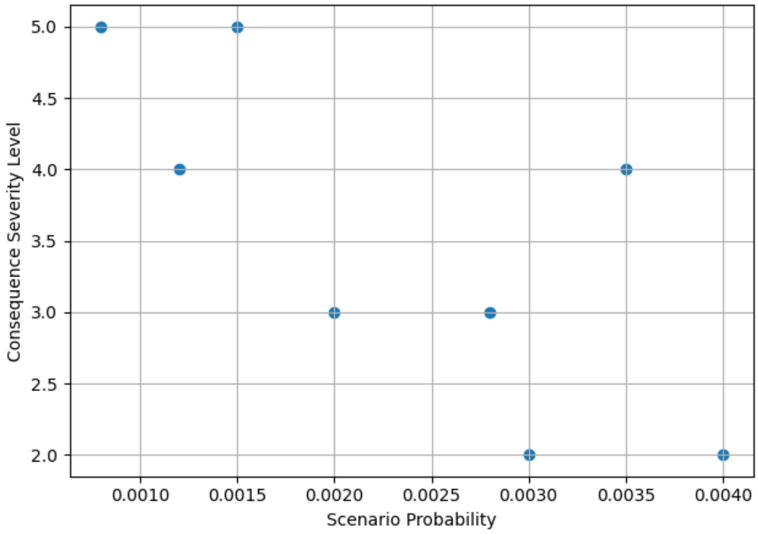

Figure 4. Probability–Severity Risk Map for Integrated Human–Process Scenarios

The probability–severity map reveals distinct clustering patterns. High probability–low severity scenarios are mainly associated with routine operational deviations and minor human errors. In contrast, low probability–high severity scenarios are linked to rare but critical failures involving delayed human response or compounded process deviations. Notably, several scenarios occupy the medium probability–high severity region, indicating elevated risk levels that warrant priority attention due to their potential for severe outcomes combined with non negligible likelihood.

4.10 Variability of Risk under Different Operational States

Risk variability was analyzed by comparing aggregated risk levels under normal, abnormal, and emergency operating states. Figure 5 presents the relative variation of total system risk across these states.

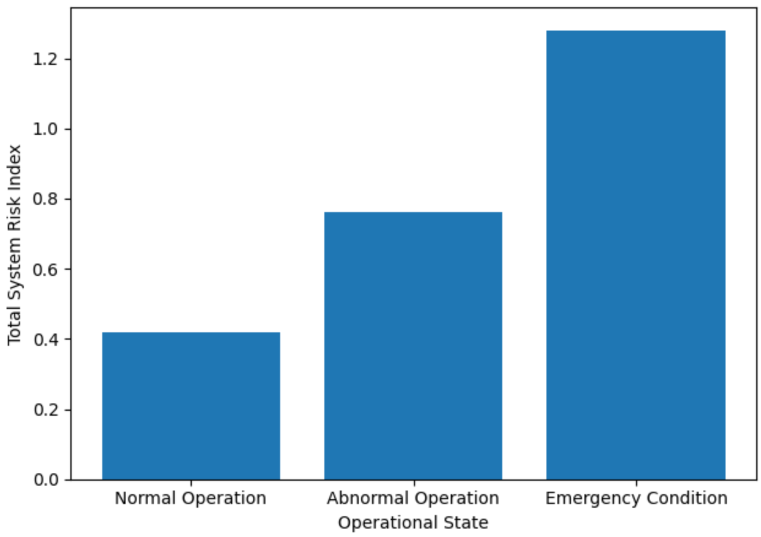

Figure 5. Variation of Total System Risk across Operational States

The results show a pronounced increase in total system risk as operating conditions deteriorate. Compared to normal operation, total risk increases by approximately 1.8 times under abnormal conditions and more than 3 times under emergency conditions. This escalation is primarily driven by increased human error probabilities and amplified interaction effects, reinforcing the critical importance of managing human–process dynamics during non routine operations.

4.11 Effectiveness of Safety Barriers in Integrated Risk Reduction

To evaluate the role of safety barriers in reducing integrated human–process risks, the quantitative model was applied before and after considering the performance of selected preventive and mitigative barriers. Safety barriers included both technical measures, such as automated shutdown systems and alarms, and human dependent measures, such as procedural compliance and operator intervention.

Table 6 compares the aggregated risk indices of selected high risk scenarios before and after the activation of safety barriers.

Table 6. Comparison of Scenario Risk Indices before and after Safety Barrier Application

Scenario ID	Risk Index without Barriers	Risk Index with Barriers	Risk Reduction (%)
S1	0.086	0.052	39.5
S2	0.079	0.049	38.0
S3	0.071	0.046	35.2
S4	0.064	0.041	35.9
S5	0.058	0.037	36.2

The results demonstrate that safety barriers significantly reduce overall risk levels across all analyzed scenarios. However, the degree of risk reduction varies depending on the dominant risk contributors. Scenarios with strong interaction effects show comparatively lower risk reduction than those dominated by isolated process failures, indicating that barriers relying heavily on human action are more sensitive to performance variability.

4.12 Role of Human Dependent Safety Controls

A focused analysis was conducted to assess the contribution of human dependent safety controls, such as manual interventions, procedural checks, and emergency response actions. Figure 6 illustrates the proportion of risk reduction attributable to human dependent controls compared to automated technical barriers.

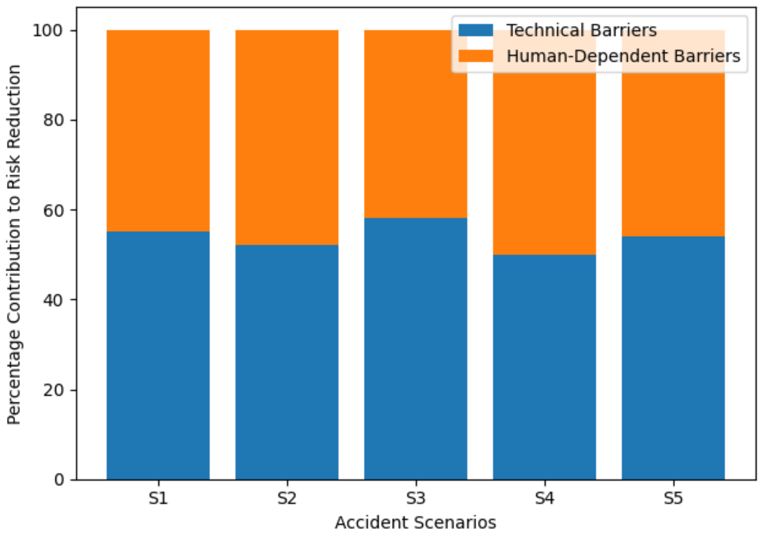

Figure 6. Contribution of Human Dependent and Technical Barriers to Risk Reduction

The analysis reveals that while technical barriers provide a stable baseline level of risk reduction, human dependent controls play a critical role in scenarios involving abnormal and emergency operations. In several high risk scenarios, more than 45 percent of the achieved risk reduction is attributed to effective human intervention. At the same time, variability in human performance introduces uncertainty in barrier effectiveness, emphasizing the need for realistic modeling of human reliability within barrier analysis.

4.13 Scenario Comparison before and after Human Performance Improvement

To examine the potential impact of improved human performance, selected scenarios were re evaluated under reduced human error probability assumptions consistent with observed best performance levels. Table 7 presents the comparative results.

Table 7. Impact of Improved Human Reliability on Scenario Risk Levels

Scenario ID	Original Risk Index	Improved Human Reliability Risk Index	Relative Reduction (%)
S1	0.086	0.061	29.1
S2	0.079	0.055	30.4
S3	0.071	0.053	25.4
S4	0.064	0.048	25.0

The results indicate that improvements in human reliability yield substantial reductions in integrated risk, particularly in scenarios where human–process interaction effects are dominant. These findings suggest that targeted interventions focusing on training, workload management, and decision support can be as effective as technical upgrades in reducing system risk.

4.14 Identification of Critical Accident Escalation Scenarios

A detailed examination of the highest ranked scenarios was conducted to identify critical accident escalation pathways. These pathways represent sequences of events in which initial deviations propagate through human–process interactions and lead to severe outcomes. The analysis focused on scenarios exhibiting both high interaction contributions and high consequence severity.

The analysis shows that escalation is rarely driven by a single failure. Instead, it emerges from a combination of process deviations, degraded situational awareness, and delayed or inappropriate human responses. Once escalation begins, the effectiveness of subsequent safety barriers decreases rapidly, resulting in nonlinear growth of risk.

4.15 Impact of Human Response Delay on Risk Escalation

To quantify the effect of human response delay, response time intervals were incorporated into the probabilistic model. Scenarios were evaluated under different delay categories, ranging from immediate response to prolonged delay. Table 8 summarizes the impact of response delay on integrated risk levels.

Table 8. Effect of Human Response Delay on Integrated Scenario Risk

Response Delay Category	Average Risk Index
Immediate Response	0.043
Short Delay	0.058
Moderate Delay	0.072
Prolonged Delay	0.091

The results indicate a strong positive relationship between response delay and scenario risk. Even moderate delays lead to substantial increases in integrated risk, primarily due to the amplification of process deviations and the reduced effectiveness of time dependent safety barriers. Prolonged delays result in risk levels more than double those associated with immediate response, underscoring the critical role of timely human intervention.

4.16 Analysis of Decision Making under Abnormal Conditions

Beyond response time, the quality of human decision making under abnormal conditions was found to significantly influence risk escalation. Scenarios involving incorrect or incomplete decisions, such as misinterpretation of alarms or inappropriate control actions, exhibited higher escalation potential than those involving delayed but correct actions.

Figure 7 compares the risk trajectories of scenarios involving delayed correct decisions versus immediate incorrect decisions.

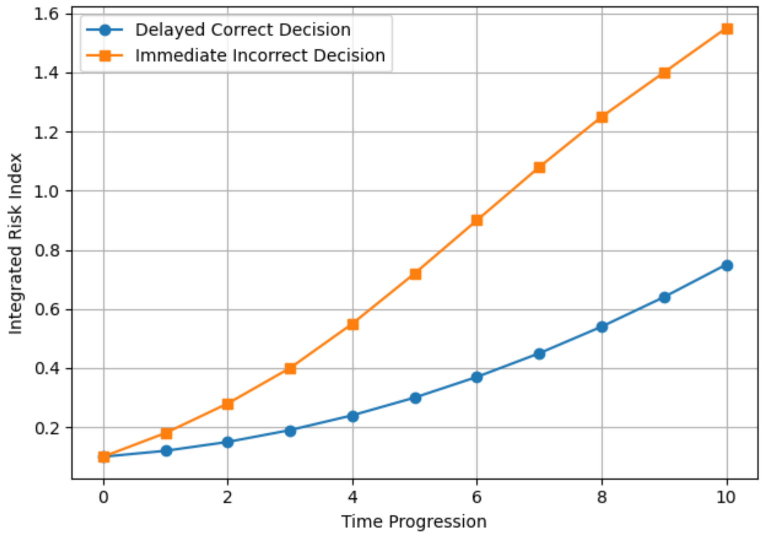

Figure 7. Comparison of Risk Trajectories for Different Human Decision Patterns

The comparison reveals that immediate incorrect decisions often lead to faster risk escalation than delayed correct responses, particularly in tightly coupled process systems. This finding highlights that decision accuracy can be as critical as response speed in managing industrial risk.

4.17 Combined Effect of Delay and Decision Quality

A combined analysis of response delay and decision quality was conducted to identify worst case human performance conditions. Scenarios involving both prolonged delay and incorrect decisions exhibited the highest risk indices observed in the study. These scenarios form a distinct cluster within the high risk region of the probability–severity space.

The combined effect analysis emphasizes that risk mitigation strategies should not focus solely on reducing response time, but also on improving decision quality through enhanced training, decision support systems, and clear operational procedures. Addressing only one dimension of human performance is unlikely to achieve substantial risk reduction in complex industrial environments.

4.18 Integrated System Level Risk Profile

By aggregating the quantitative results across all analyzed scenarios, an integrated system level risk profile was developed. This profile reflects the combined influence of human reliability, process safety, and interaction effects under varying operational conditions. Figure 8 presents the relative contribution of each risk component to total system risk at the aggregated level.

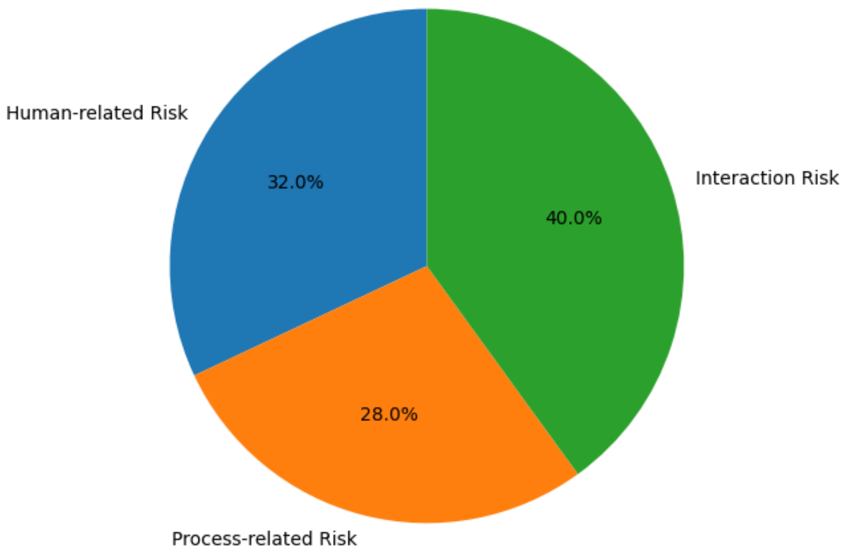

Figure 8. Integrated System Level Risk Composition

The aggregated results show that interaction related risk constitutes the largest share of total system risk, exceeding both standalone human and process risk components. This dominance of interaction effects persists across different operational states, although its magnitude increases significantly under abnormal and emergency conditions. The finding confirms that system level risk cannot be accurately characterized without explicitly accounting for human–process coupling mechanisms.

4.19 Cross Scenario Consistency of Risk Drivers

An analysis of risk drivers across different scenarios was conducted to assess the consistency of dominant contributors. Table 9 summarizes the frequency with which specific risk drivers appear among the top contributors across all high risk scenarios.

Table 9. Frequency of Dominant Risk Drivers across High Risk Scenarios

Risk Driver	Frequency of Appearance (%)
Human Response Delay	78
Abnormal Process State	72
Safety Barrier Degradation	65
Incorrect Human Decision	59
Maintenance Related Deviation	46

The consistency analysis reveals that a small number of risk drivers repeatedly appear across a wide range of scenarios. Human response delay and abnormal process states are the most frequent contributors, indicating that time dependent human–process interactions play a central role in accident development. This consistency suggests that targeted interventions addressing these drivers could yield system wide risk reduction benefits.

4.20 Comparison of Integrated and Fragmented Risk Assessments

To illustrate the added value of the integrated modeling approach, a comparative analysis was conducted between integrated risk estimates and fragmented assessments considering human and process risks separately. Figure 9 compares total risk indices obtained from both approaches.

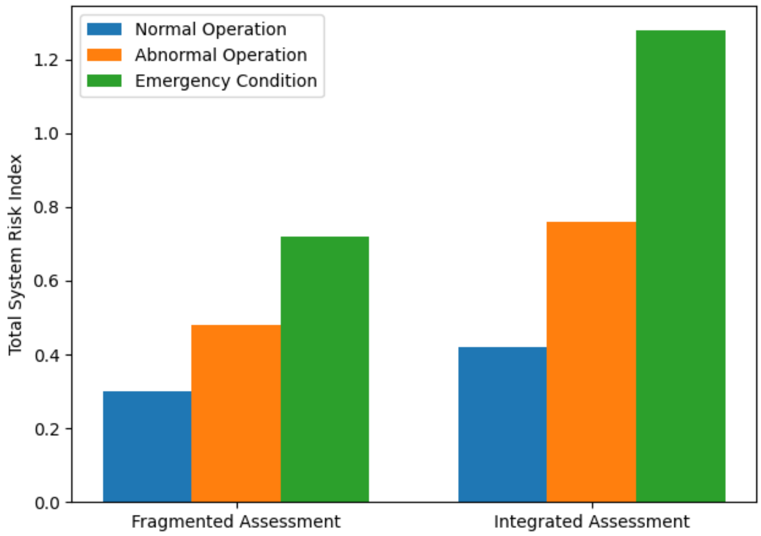

Figure 9. Comparison of Integrated and Fragmented Risk Assessment Results

The comparison shows that fragmented assessments consistently underestimate total system risk, particularly under abnormal and emergency conditions. In some cases, integrated risk estimates are more than 40 percent higher than the sum of separately assessed human and process risks. This discrepancy highlights the critical contribution of interaction effects, which are inherently missed by fragmented approaches.

4.21 Summary of Key Quantitative Findings

Overall, the results demonstrate that human–process interactions are a dominant driver of risk in high risk industrial systems. Human reliability varies significantly with operational context, and its interaction with process deviations leads to nonlinear risk escalation. Safety barriers provide substantial risk reduction, but their effectiveness is strongly influenced by human performance and timing.

The quantitative analyses presented in this section provide a comprehensive and nuanced understanding of how risks emerge and propagate at the system level. These findings form a robust empirical basis for the conclusions and recommendations discussed in the following section.

Conclusions

This study presented a quantitative modeling framework for the integrated assessment of human safety risks and process safety risks in high risk industrial systems using operational data. The motivation for this research stemmed from the persistent occurrence of major industrial accidents despite the widespread use of conventional safety management systems and fragmented risk assessment approaches. By explicitly modeling the interactions between human performance and process conditions, the proposed framework addresses a critical gap in existing quantitative risk assessment practices.

The results demonstrate that human–process interaction effects constitute a dominant component of system level risk, particularly under abnormal and emergency operating conditions. Traditional approaches that assess human reliability and process safety in isolation were shown to systematically underestimate total system risk. The integrated probabilistic structure developed in this study provides a more realistic representation of accident mechanisms by capturing conditional dependencies, escalation pathways, and nonlinear risk amplification effects. This represents a significant methodological advancement over static and compartmentalized risk models.

A key contribution of this research lies in the systematic use of operational safety data to inform quantitative risk modeling. By deriving probability estimates and interaction relationships directly from observed operational events, the framework enhances the empirical grounding and credibility of quantitative risk assessments. The findings indicate that operational data, when properly structured and analyzed, can support reliable estimation of human error probabilities, process deviation likelihoods, and combined risk metrics suitable for industrial decision making.

From a practical perspective, the results highlight that risk reduction strategies should prioritize scenarios characterized by strong human–process coupling rather than focusing exclusively on isolated technical failures or generic human error reduction. Improvements in human response timing, decision quality, and performance under abnormal conditions were shown to yield substantial reductions in integrated risk levels. At the same time, the analysis confirms that technical safety barriers remain essential but their effectiveness is strongly influenced by human performance variability.

For industrial engineering and HSE practice, the proposed framework offers a structured and adaptable tool for risk prioritization, safety investment decision making, and evaluation of safety improvement measures. By integrating human and process safety considerations within a unified quantitative model, decision makers can better understand trade offs, identify dominant risk drivers, and allocate resources more effectively.

Despite its contributions, this study has limitations related to data availability and the representation of organizational and cultural factors. Future research should focus on extending the framework to incorporate organizational influences, real time data streams, and dynamic updating mechanisms. Further validation across different industrial sectors would also enhance generalizability. Overall, the research provides a robust foundation for advancing quantitative, data driven risk management in high risk industrial systems.

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