

AI Application in Risk Assessment and Resilience Management of Seveso Plants and Logistics within Industrial Port Environment

Evgeniia Taubert^{a*}, Tomaso Vairo^a, Andrea P. Reverberi^b, Margherita Pettinato^a, Bruno Fabiano^a

^a DICCA - Civil, Chemical and Environmental Engineering Dept., Genoa University, via Opera Pia 15, 16145, Genoa, Italy

^b DCCI - Department of Chemistry and Industrial Chemistry, Genoa University, via Dodecaneso 31, 16146, Genoa, Italy
 taueugen11@gmail.com

Assessing risks and resilience in safety management systems—especially in Seveso-classified industrial environments—requires a comprehensive evaluation of human factors, near-misses, and accidents, as well as the causal relationships between system components. A key challenge is incorporating human error into the analysis not just statistically, but in a way reflecting the actual operational conditions, similar to how technological risks are assessed. A resilient system should demonstrate four key capabilities: the ability to avoid, absorb, recover from, and learn from disruptions. Artificial Intelligence (AI), particularly through the use of Large Language Models (LLMs), Multimodal LLMs (MLLMs), and Vision-Language Models (VLMs), offers promising tools to embed these capabilities into safety and resilience frameworks. Introducing "living" qualities into resilience systems—an approach inspired by natural processes that also underpin models like LSTMs and attention-based neural networks—holds significant potential. This paper focuses on leveraging LLMs and Explainable AI (XAI) to improve communication and decision-making through transparent and interpretable methods. Specifically, it aims to define an Integrated Risk Assessment methodology to enhance the resilience of industrial port areas, involved in HazMat logistics, by developing tools and services that evaluate risks from a variety of threats, including those linked to human vulnerabilities.

1. Introduction

Open systems are structurally inseparable from their environment and evolve dynamically over time, undergoing both qualitative and quantitative transformations. Currently, research and industry attention is focused on improving multimodal models to effectively mediate between machines and humans, successfully handling tasks such as image-to-text, speech-to-text, text-to-image, omni-models. By leveraging these capabilities, a resilience system for an industrial plant could be endowed with the ability to understand human communication and predict behavioural and cognitive risks, as well as technological risks, in real-time, "seeing" some hazardous precursors. One of the main required features of a complex systems is its resilience, i.e., the ability to withstand and adapt to internal failures and unforeseen external disturbances, while maintaining core functionality and productivity (Vairo et al., 2023a). In this context, resilience implies a system's capacity to avoid, absorb, adapt to, and recover from disruptions, with rapid recovery being a key aspect. Traditional risk assessment approaches have shifted towards dynamic resilience modelling, emphasizing the temporal dimension of system performance under stress conditions, including unexpected disruptive events like pandemics (Fabiano et al., 2024). Generally, system resilience is expressed graphically as a performance curve before a disruption, during a disruption, and alongside the recovery phase. At the same time, recovery can be either full or partial. The curve consists of a survival state, when performance drops to a minimum, and a recovery state, which best expresses the core of resilience. A resilience system should possess four fundamental resilience attributes RAs whose joint efforts will influence the recovery degree: (1) Avoiding capacity: Ability to assess risks and develop strategies to mitigate and avoid hazards, expose protective and preventive barriers; (2) Absorption capacity: Ability to

maintain output through adaptability and reconfigurability of technological processes; (3) Recovery capacity: Ability to return to normal performance minimising the time interval; (4) Learning (adaptation) capacity: Ability of the system to exchange information between its components and learn from errors.

The approach here proposed to attain the above-mentioned target within an industrial site, is to organize RAs into hierarchical graphs, flows of various data types, such as textual information, images and video sequences, sensor data, as depicted in Figure 1. Artificial Intelligence (AI) is already massively applied in industry, especially in areas such as computer vision, intelligent decision support, predictive analytics and natural language processing. Among other things it didn't pass by the field of dynamic risk assessment, which is an essential part of resilience modelling. Text Mining and Natural Language Processing methods can help the resilience system to highlight its vulnerabilities in dynamic progression, especially with the active involvement of employees, providing data on current situations and emerging hazards (Pettinato et al., 2024). Construction industry risk management benefited from hybrid systems integrating Large Language Models with domain-specific knowledge graphs. Long-term infrastructure monitoring challenges led to the development of Kalman filter-enhanced Bayesian networks for concrete bridge safety assessment (Gong, 2025). Zheng et al. (2024) developed a contract review system where a construction risk knowledge graph containing 12,000 entity relationships provides contextual grounding for GPT-4 outputs. This tool reduced false negative rates by 37% compared to standalone LLMs by constraining generations within verified legal and technical boundaries. The graph structure explicitly models relationships between contractual clauses, regulatory requirements, and historical dispute patterns, enabling multi-hop reasoning about cascading risks. In this study, the emphasis is on the textual information handling capacity property; the relevant information source is the node 'complaints', that are observations from employees, third-party organisations and nearby residents, an unstructured source which may circulate as text messages, images, handwritten documents, audio files, etc.

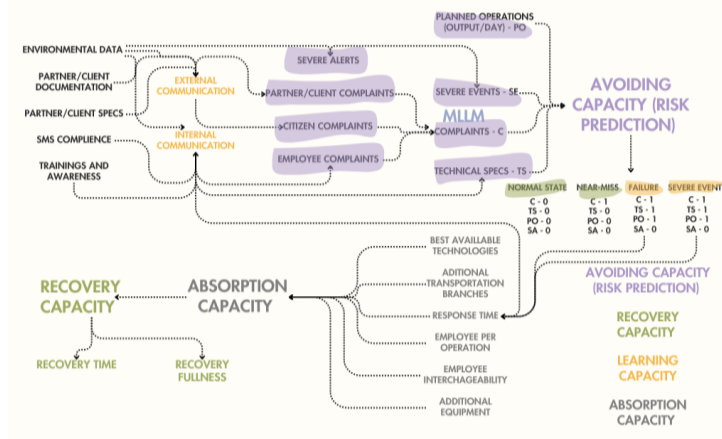


Figure 1: Layout of the conceived Hierarchical data flow for resilience assessment.

2. Materials and methods

2.1 Data

A case study to test the prediction capability and evaluate the performance of the proposed method was organised, within a liquid hydrocarbon transfer and storage company located in an urban port area. The site selection arises from the consideration that decarbonization and energy transition require many new technologies and scale-up of the amounts of stored and transported materials, which are known but never handled in large amounts and correspondingly new risk are possibly emerging in this context (Pasman et al., 2024). The field validation of the approach was performed with two types of corporate safety related data, i.e.;

1. A list of unexpected events descriptions and corrective actions in the form of textual reports (out of 250 reports) covering a 5 years-time span (2020-2024). The list included various types of events labelled as audits, process anomalies, safety training, near-misses, inspection visits, process deviations, complaints.
2. Safety planning meeting output, (2020-2024) providing an overview of current problems, proposals for activities, plans for replacement/maintenance of equipment etc.

In contrast to the former data source, the meeting outputs are not organised into a structured database, often lack paragraphs, lack some punctuation marks, or are presented just as one-line phrases. This type of data in its structure is close to digital communication traces within the organisation. Digital communication traces are data generated through networked sensors, control systems, and workforce interactions, which have emerged as critical precursors for quantifying and predicting risk fluctuations in real time. By integrating these traces with

advanced analytics allows enriching and fine-tuning the general predictive model of risk level changes and moving from reactive safety protocols to proactive hazard mitigation.

2.2 Methodology

Table 1 summarises the categorization approach developed for seven types of employee observations that, alongside with technical signals, weather alerts and planned output per day (hour), are considered suitable to provide a dynamic facet within a risk prediction system.

Table 1: Employee observations and complaints.

| Type | Description | Main precursors |
|---|--|--|
| Unsafe working conditions | Situations or factors in the workplace that pose a direct threat to the health or safety of employees. | Unintended presence in the danger zone; working in abnormal weather conditions; failure of protective equipment; ignoring protective equipment; lack of warning signs in high hazard areas; obstructed escape routes; major chemical or gas leaks; fires, explosions, smoke on site; exposed electrical wires or faulty cables; damaged or unstable structures; cracks in tanks or pipes; increased number and duration of absences from work due to illness or injury; complaints on atypical odours, density or colours of chemicals; complaints on headaches, blurred consciousness, localised itching of the skin. |
| Complaints on equipment or infrastructure | Employee feedback on equipment malfunctions, inadequate maintenance or deterioration of infrastructure, possibly impacting on production processes, or safety. | Reports on noise, vibration or temperature; minor leaks (equipment-related); sparks, ignition; unplanned equipment shutdown or slowdown; failure to maintain equipment in a timely manner; damaged protective coatings (e.g. corrosion); electrical power failures; improperly installed, or fixed devices; infrastructure damage (cracks, potholes) preventing safe site movement around; unsafe equipment placement; frequency and increase in downtime due to equipment failure; increased cost for temporary solutions; increased energy consumption; product quality decrease. |
| Lack of training | Lack of training of employees on job duties, including safety training, risk awareness, transparent (internally) incident analysis. | Employees inability to describe or demonstrate safety procedures; missing records of mandatory training; complaints about lack of training or instruction; improper HazMat storage or use; systematic errors in the use of equipment or tools; systematic violation of standard operating procedures (SOPs); refusal to perform tasks due to lack of knowledge; frequent request for assistance with standard operations; failure to recognise workplace risks; delays in completing tasks due to lack of skills. |
| Safety violations by external workers | Behaviour or actions non fully compliant with safety instructions or regulations. | Complaints on ignorance of the use of personal protective equipment (PPE); complaints on presence in restricted areas; complaints on using equipment without authorisation; complaints on working under the influence of alcohol, drugs or extreme fatigue; complaints on improper handling of chemicals/goods; complaints on ignoring alarms; complaints on smoking in prohibited areas; complaints on driving over the speed limit and changing the route of travel on the site. |
| Internal communication failures | Problems in transmitting information between employees or staffs possibly affecting HSE performances. | Information does not physically pass through the regular communication channels; deviations in daily incoming information flow; complaints on lack of awareness during workflow changes; information omissions during shift handovers; lack of feedback from management; low employee involvement in work processes decision making. |
| Load on work schedule | Excessive stress on employees due to overloaded work scheduling or understaffing. | Conflicts over the duty's distribution; non-compliance with regulations on the number of hours per week for a given work category; systematic complaints about stress, fatigue, complaints about the burnout; high staff turnover. |
| Team conflict | Employee relationship issues that may affect productivity and safety. | Disrespectful behaviour, pressure from management; disrespectful behaviour, pressure from employees. |

The textual data from both sources were extracted, cut into equal fragments (chunks) with overlap and organised into lists with metadata. In a process of chunking a long text, important contextual connections could be lost at their boundaries. Overlapping was employed to preserve important contextual connections that might otherwise

be lost at fragment boundaries during the chunking of lengthy passages. The chunks were passed through a Few-shot Chain-of-Thought (CoT) prompt to count mentions of precursors that could fall into seven categories of employee observations. The output is the quantity of identified categories per annual report. With each identified category comes a piece of text as the reason for the categorisation. After validation and identification of categories that are weak in terms of classification, there are several possible paths for development: to refine the prompt or to change the tactics to fine-tune the model, e.g., Parameter Efficient Fine Tuning (Wang et al., 2024). First path causes the work on quality of the examples for the few-shot part of the prompt or changing the prompt technique. The second one will bring much more effort to prepare the dataset for classification and partially retrain the weights of the model. A prompt is a key-request to a Large Language Model (LLM) and one of the most resource-saving iterative fine-tuning techniques. This method does not require any modifications to the weights of the original model (its partial or complete retraining). LLM is a type of deep neural network based on the transformer architecture, trained on vast textual datasets. At the same time, the largest and most advanced generative models (GPT, Claude, Llama, DeepSearch etc.) are built on the decoder part of the transformer and work in an autoregressive way: probabilistically generating text token by token. The main task of LLMs is to generate the most credible text, from which stems the problem of hallucinations. The result of the work depends on the language model itself (volume and quality of training data, language features, context window length, temperature of response generation, etc.) and on the complexity of the Prompt Engineering technique, which should help concretise the probabilities of response generation. The developed framework relies on the Few-shot Chain-of-Thought Prompt Engineering techniques with instruction, context information, and output indicator (Schulhoff et al., 2024). It combines Few-shot learning (providing the model with several examples of solving a task) and Chain of Thought (demonstrating intermediate steps of reasoning). During training, the model learns statistical patterns from huge arrays of text, including texts containing step-by-step reasoning (mathematical calculations, logical arguments, scientific justifications). During pre-training, an LLM learns statistical patterns from extensive text corpora, including texts containing step-by-step reasoning (such as mathematical derivations, logical arguments and scientific justifications). Prompts containing trigger phrases—such as “Let us consider the reasoning step by step” or “Reasoning:”—direct the model to compute the conditional probabilities of intermediate reasoning steps rather than to provide a direct answer based solely on the training data (Kojima et al., 2022). Moreover, by generating intermediate steps, the model establishes additional context for its subsequent tokens, thereby reducing the randomness of the generation.

3. Results and Discussion

Categories 'unsafe working conditions', 'complaints on equipment and infrastructure', 'lack of training', 'safety violations by other workers', 'internal communication failures', 'load on work schedule', 'team conflicts' both in the case of processing planned meetings (Figure 2) and list of incidents (Figure 3) were normalized by the total number of extracted categories per year.

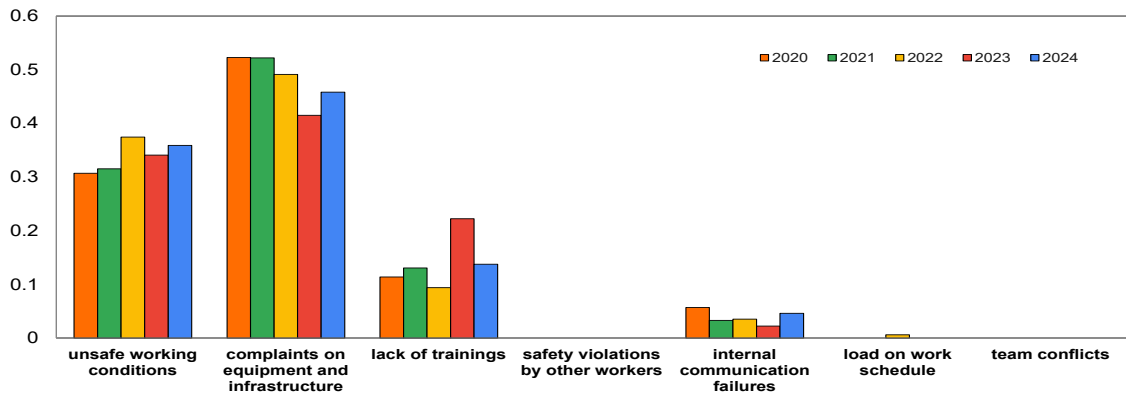


Figure 2: Category counting obtained from planned safety meetings.

In the case of routine safety meetings, both the number of pages in the annual report and the number of meetings themselves are spread. The categories “unsafe working conditions” and “complaints on equipment and infrastructure” resulted the most frequent in both data sources. The obtained statistical figures are consistent with the prevalent types of records (audits, process anomalies, safety training, near-misses, inspection visits, unexpected events, complaints, environmental accidents). The preliminary analysis of records was used to validate the results from the LLM, evidencing a notable correlation between incidents related to external factors and complaints. At the same time, all complaints, both from partners and customers, are related to non-

compliance with product specifications and documentary non-compliance. To ensure transparency regarding event categorisation, the system prompt included instructions for extracting a reference text fragment (Description column in Tables 2 and 3).

Table 2: Examples of category description of planned safety meetings.

| ID | Category | Description |
|----|---|---|
| 1 | Unsafe working conditions | Fire protection system break. |
| 2 | Unsafe working conditions | Pneumatic valve in tunnel opened manually without compressed air. |
| 3 | Unsafe working conditions | No sound alarm in the control room. |
| 4 | Unsafe working conditions | Nitrogen leak in tunnel. |
| 5 | Extreme environmental conditions | Presence of high temperature during operations |
| 6 | Complaints on equipment or infrastructure | Pneumatic valve open for 30 minutes. |
| 7 | Complaints on equipment or infrastructure | Valve not suitable, to be replaced |

According to safety report records processed by the LLM, it is evident that all major events are connected to product spills due to human error rather than to technical failure. Near-misses were also the result of human error: non-compliance with the rules for loading products into the tanker truck, distorted communication with the outsourced/external workers, due to language barriers, manoeuvring the truck in an area not intended for this purpose. The most common reasons for categorisation into 'process anomalies' was the relevant role of pumps, valves and tanks. Here it should be emphasized the importance of an enhanced interaction between the reporting system and the organizational capacity of the system to learn from what is reported. In this regard, the proposed approach allows paying close attention to "weak signals" of failure or malfunctioning, which possibly may be considered as precursor of larger problems in the site, analogously to ML approaches recently applied in the process sector (Vairo et al., 2023b).

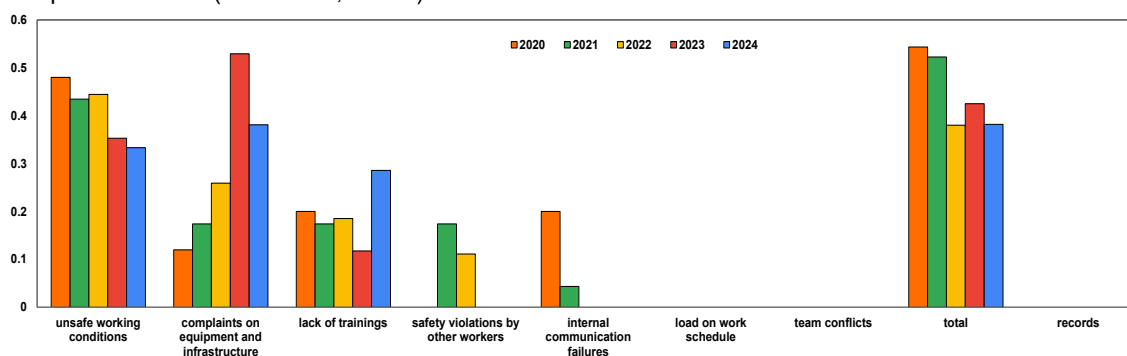


Figure 3: Category counting of unexpected events records over one-year time span - 2024.

Table 3: Examples of category descriptions of unexpected events records.

| Category | Description |
|---|--|
| Unsafe working conditions | Presence of liquid in the pipeline, which could cause significant leaks of chemicals. |
| Unsafe working conditions | Storage of flammable products samples may not comply with fire prevention regulations. |
| Unsafe working conditions | Leakage of diesel fuel from the underground tank due to overfilling. |
| Unsafe working conditions | Possible risk of overloading the underground tank due to the recirculation of diesel fuel. |
| Unsafe working conditions | Leakage of diesel fuel due to vehicle accident. |
| Complaints on equipment or infrastructure | Suction problems due to the presence of liquid in the line, requiring corrective action. |
| Complaints on equipment or infrastructure | Lack of periodic maintenance of the fire-fighting motor pumps. |
| Complaints on equipment or infrastructure | Vehicle damage and breakage of the regasification circuit. |
| Lack of safety training | Need to update safety information and verify the effectiveness of worker training. |
| Lack of operative training | The driver made a connection error during loading. |

4. Conclusions

This study presented a novel Integrated risk analysis methodology designed to enhance the resilience of Seveso-classified industrial port areas, particularly those involved in HazMat logistics. At its core, the methodology leverages the capabilities of LLMs and Explainable AI to extract actionable insights from unstructured textual data such as reports and internal communications. By applying Few-shot Chain-of-Thought prompting techniques, the system categorizes risk-relevant information into seven classes of human-centred vulnerabilities-ranging from unsafe working conditions and equipment complaints- to communication failures and training deficiencies. The most frequent risk precursors are related to human factors rather than technical faults, such as operational errors, training gaps, and breakdowns in communication, especially with external workers. The framework also highlights the value of integrating employee complaints, meeting notes, and near-miss data to detect weak signals of emerging risk. Normalizing incident category data across different reporting structures enabled consistent insight extraction, with high correspondence between LLM-extracted patterns and real-world incident causes. The results support the feasibility of using advanced prompt engineering techniques to transform fragmented textual data into structured risk intelligence without the need for full retraining. Looking forward, the study outlines a roadmap for expanding the model by incorporating visual information via Multimodal and Vision-Language Models (MLLMs and VLMs), allowing the system to analyze diagrams, images, and sensor-based video feeds. This facet would enrich the detection of visual precursors - such as leaks, corrosion, or unsafe layout - and support more holistic safety assessments strengthening safety management. The broader technological context indicates three key converging trends: (1) LLMs increasingly serving as core reasoning engines grounded in structured knowledge graphs; (2) Bayesian models evolving into dynamic, multi-layered representations of complex system behaviors; (3) hybrid approaches combining high-performance prediction with transparent, explainable outputs to meet regulatory and operational demands. The methodology offers challenges related to real-time deployment, computational efficiency, and the standardization of cross-domain risk ontologies. The methodology still faces challenges related to real-time deployment, computational efficiency, and the standardization of cross-domain risk ontologies. Addressing these limitations is essential to transition from experimental prototypes to robust tools for managing safety in critical, high-risk environments.

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