SLP Project

AI-based Decision Support System for Process Risk Management

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Guide:
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AIM

- To develop an AI-based decision support system that uses LLMs and a historical incident database to assist operators during chemical process emergencies.

- To quantify process risk in real time by computing consequence and frequency scores and presenting the risk level based on the risk matrix.

- To generate incident-specific safety precautions by combining verified recommendations from past cases with LLM-generated guidance, ensuring rapid and contextual support for decision-making.

Why accident Happenes?

- Chemical Industry Risk: Bhopal (1984), Texas City (2005) – Catastrophic consequences
  (Equipment failures, system breakdowns, or procedural lapses can trigger chain reactions , human errors)
- Other issues like Cost-cutting decisions ,Weak safety culture

Issues

- Emergency Challenges: Rapid decisions needed under stress & uncertainty
- Information Bottleneck: Operators overwhelmed by complexity

Problems

- Missing Near-Miss Data

(The dataset contains only failures (accidents), not near-misses. Can't learn from successful barrier activation → Frequency calculations may be biased toward worst-case scenarios.)

- Data Incompleteness

(Many of the accident reports are missing "recommendations" sections → Dual-model solution: Model 1 extracts verified recommendations (when available), Model 2 generates contextual precautions via LLM (when missing).

Data Preparation

1. Data Collection & Extraction
2. Data Cleaning
3. Data vector embedding using Faiss Library

   Faiss - Facebook AI similarity Search

case_id	File Name	date	Country	Cause	recommendations	full_text	Direct Link
1	02-May-2024_GC	02-May-24	USA	Equipment failure Ã¢	BSEE Houma District h	UNITED STATES DEPARTMI	https://drive.gc
2	07-MAR-2024_KC	07-Mar-24	United States	Equipment Failure. In	The BSEE Lafayette Dis	UNITED STATES DEPARTMI	https://drive.gc
3	08-July-2024_ST_	08-Jul-24	United States	Human Performance	The BSEE Houma Distri	UNITED STATES DEPARTMI	https://drive.gc
4	10-Nov-2024_GC	10-Nov-24	USA	Human error perform	BSEE Houma District re	UNITED STATES DEPARTMI	https://drive.gc
5	11-JUL-2024_HIA	11-Jul-24	United States	Human Performance	BSEE Lake Jackson Dist	UNITED STATES DEPARTMI	https://drive.gc
6	13-MAR-2024_SS	13-Mar-24	United States	Human Performance	BSEE Houma District h	UNITED STATES DEPARTMI	https://drive.gc
7	16_20Feb_20202	16-Feb-24	USA	For Public Release Hu	BSEE Houma District h	UNITED STATES DEPARTMI	https://drive.gc

Model Working

USER INPUT (Gradio Interface)

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QUERY PROCESSING

• Normalise and validate text

• Extract key concepts (chemical, location, hazard level)

• Generate semantic embedding (384-dim vector)

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SEMANTIC SIMILARITY SEARCH

• Compute similarity between query and all incidents

• Rank incidents by relevance score

• Retrieve top-3 most similar incidents with full data

Query → Embed → FAISS.search(query_vector, k=3)

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RISK QUANTIFICATION

• Calculate Frequency score (IEF × PFD formula)

• Calculate Consequence score (keyword analysis)

• Determine Risk Category (LOW to CATASTROPHIC)

• Generate Risk Matrix visualization/heatmap

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Model Working

DUAL PRECAUTION GENERATION MODEL

1: Extract recommendations from dataset (proven, historically verified) MODEL

2: TinyLLaMA AI generation (adaptive to scenario specifics)

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PROMPT CONSTRUCTION

- System instruction (role & constraints)
- Retrieved incident context (similar cases)
- User query details

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LLM PROCESSING (TinyLLaMA via Ollama)

- Submit prompt to localhost:11434
- Process through TinyLLaMA model
- Generate contextually appropriate precautions

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```
prompt = f"""You are a safety expert. Situation: "{query}".
Review these similar past accidents: {context}.
List 5 critical, immediate safety precautions the operator must take."""
```

```
def llm_call(prompt):
    try:
        # Deterministic generation (temperature=0)
        payload = {
            "model": "tinyllama",
            "prompt": prompt,
            "stream": False,
            "options": {"temperature": 0.0},
        }
        r = requests.post("http://localhost:11434/api/generate",
                          json=payload, timeout=30)
        if r.status_code == 200:
            return r.json().get("response", "").strip()
    except:
        return "AI Analysis Unavailable."
```

Model Working

OUTPUT ASSEMBLY

- Compile risk scores and category
- Create Risk Matrix heatmap visualisation
- displays case IDs and links
- Combine precautions

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USER OUTPUT (Gradio Interface)

- Display all results in organized layout
- Provide clickable links to original reports
- Enable follow-up queries
- Log query for system monitoring

Frequancy and Consequence

Method 1:

Using Faiss we get Simmilarity matrix For ex. S = [S1 S2 S3]

$$r = 0.5S_{\max} + 0.5S_{\text{mean}}$$

We interpolate in **$\log_{10}$ space** between 0.01 and 2:

$$\log_{10} f(r) = \log_{10} f_{\min} + r\left(\log_{10} f_{\max} - \log_{10} f_{\min}\right)$$

- $\log_{10} f_{\min} = \log_{10}(0.01) = -2$
- $\log_{10} f_{\max} = \log_{10}(2) \approx 0.3010$

So:

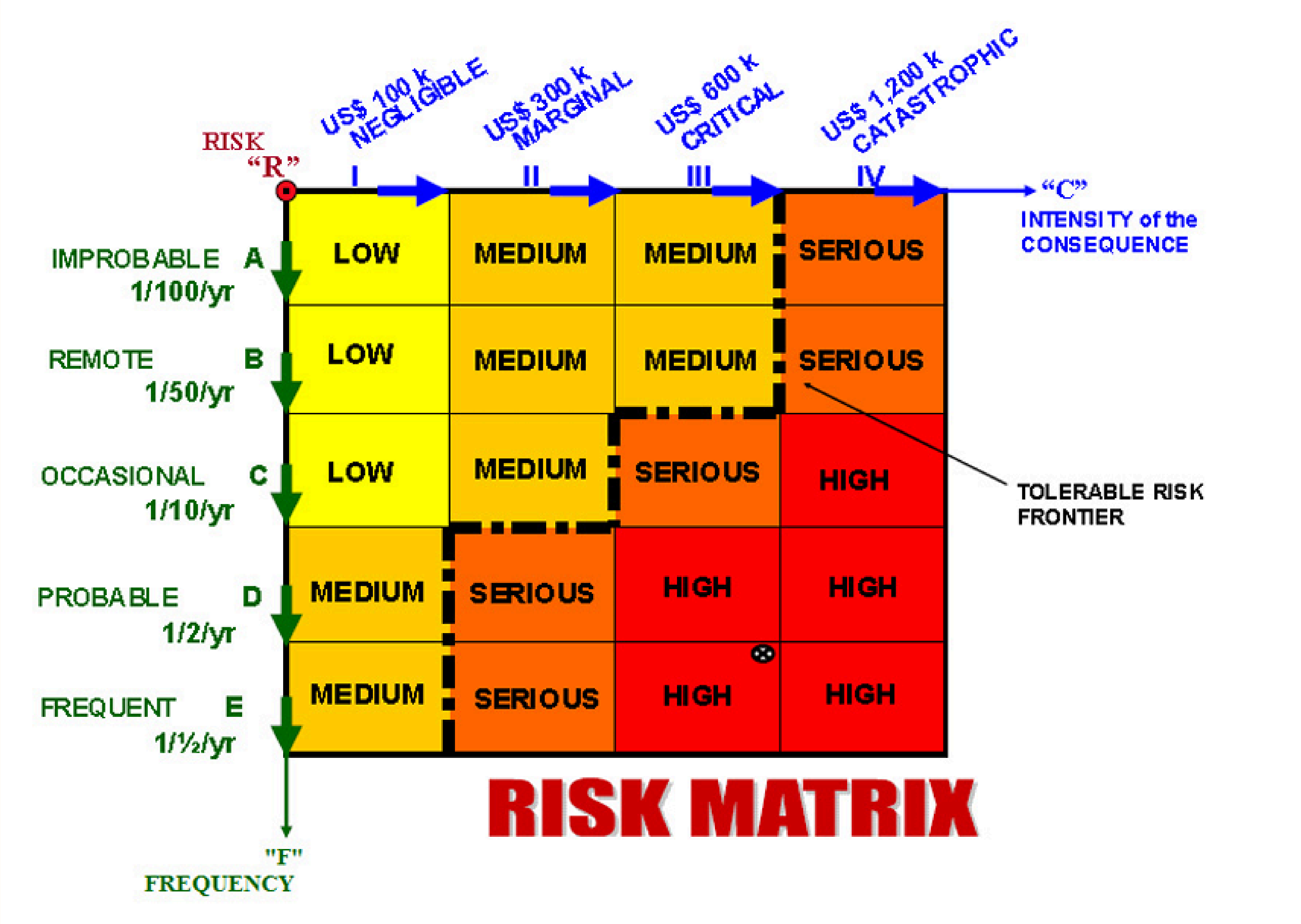
$$\log_{10} f(r) = -2 + r\,(0.3010 - (-2)) = -2 + 2.3010\,r$$

$$f(r) = 10^{-2+2.3010\,r}$$

- $r = 0 \Rightarrow f = 10^{-2} = 0.01$
- $r = 1 \Rightarrow f = 10^{0.3010} \approx 2.0$

Either version is valid; **log-scale** is closer to LOPA philosophy (orders of magnitude).

Risk Matrix



US$ 100 k NEGLIGIBLE
US$ 300 k MARGINAL
US$ 600 k CRITICAL
US$ 1,200 k CATASTROPHIC
RISK "R"
I
II
III
IV
"C"
INTENSITY of the CONSEQUENCE
IMPROBABLE A 1/100/yr
REMOTE B 1/50/yr
OCCASIONAL C 1/10/yr
PROBABLE D 1/2/yr
FREQUENT E 1/½/yr
LOW
MEDIUM
MEDIUM
SERIOUS
LOW
MEDIUM
MEDIUM
SERIOUS
LOW
MEDIUM
SERIOUS
HIGH
MEDIUM
SERIOUS
HIGH
HIGH
MEDIUM
SERIOUS
HIGH
HIGH
TOLERABLE RISK FRONTIER
RISK MATRIX
"F" FREQUENCY

Frequency and Consequence

Method 2

$$f_i^C = IEF_i \times PFD_{i1} \times PFD_{i2} \times \ldots \times PFD_{ij}$$

Consequence

```
CONSEQ_KEYWORDS = {
    "fatal": 5, "death": 5, "explosion": 5, "rupture": 5, "catastrophic": 5,
    "fire": 4, "blast": 4, "release": 4, "vapor": 4, "cloud": 4,
    "leak": 3, "spill": 3, "injury": 3, "burn": 3, "damage": 3, "shutdown": 3,
    "failure": 2, "deviation": 2, "trip": 2, "stuck": 2, "corrosion": 2,
    "alarm": 1, "alert": 1, "warning": 1, "maintenance": 1, "noise": 1
}
```

Results

Component	Observed Strengths	Typical Limitations / Failure Modes
Retrieval (FAISS + embeddings)	Consistently retrieves semantically similar incidents when query mentions chemical, equipment and failure mode clearly	Struggles when query is vague, uses uncommon synonyms, or describes scenarios not well represented in database
Consequence scoring (keyword-based)	Quickly identifies high-severity scenarios (explosions, fatalities) with conservative scoring	Sensitive to wording; may under-score if severe terms absent, or over-score if strong words appear in non-critical context
Frequency scoring (IEF × PFD)	Transparent, formula-based calculation grounded in LOPA concepts	Dependent on small sample of similar incidents; results noisy for rare events or sparse data
Dataset-based precautions (Model 1)	When recommendations present in source reports, they are realistic and grounded in real incidents	Many incident files lack recommendation text; output can be empty or too brief
AI-generated precautions (Model 2)	Able to synthesize clear, structured precaution lists and adapt to current query	Quality depends on retrieved context; can become generic if relevant details missing
User interface and latency	Typical end-to-end response 2-5 seconds; clear presentation of scores, similar cases, precautions	Risk scores may appear more precise than justified; users may over-trust numerical outputs

Value Addition: Real-World Impact

- Rapid Response: Seconds vs. minutes to retrieve relevant incident information & recommendations
- Contextual Guidance: Operators get incident-specific precautions, not generic procedures
- Risk Quantification: Numerical risk score helps prioritize escalation & resource allocation
- Organizational Learning: System learns from historical mistakes → Prevents recurring failures
- Decision Support (not replacement): Augments human expertise → Human still makes final

Future Work

1 . User Experience: Trend Analysis and Safeguard Visualisation

2 . Importance of Recent Accidents

$$\text{Weighted Similarity} = \text{Base Similarity} \times \left(1 + \frac{\text{Years Since Incident}}{\text{Max Age in Database}}\right)$$

3. By determining Consequence severity based on the estimated damage cost in US dollars

Thank You