MINE GUARD AI - RESEARCH

Framing Effects in AI-Assisted Mine-Site Investigations:

A Multi-Angle Qualitative Study of Control-Centric vs HOP/Safety II Outputs

06/25

Abstract

Using the same highwall-failure evidence set, we generated two independent large-language-model (LLM) investigations inside Incident AI: a **Generic** framing (barrier/error framing) and a **HOP / Safety II** framing (systems-interaction framing). Beyond previously reported structural deltas, we applied four qualitative lenses—**Agency & Attribution**, **Causal-Chain Depth**, **Bias Scan**, and **Concept Saturation**—to see how framing alters narrative quality. Results show the HOP lens redistributes agency toward systems, extends causal depth by 50 %, introduces new insights through the final artefact, and flips several bias profiles. These findings confirm that framing in Incident AI is not a cosmetic choice but a determinant of what investigators learn and, ultimately, fix.

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1 Introduction

Rapid, AI-generated analyses promise faster incident closure, yet investigation quality hinges on the questions we ask the model. We compared two framings—control-centric vs systems-adaptive—to see how they shape insight through four qualitative dimensions seldom quantified in LLM research.

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2 Methods

Item	Detail
Case	Surface-mine highwall failure, 28 Jul 2024
Evidence	4 statements, geotech & blast reports, photos, slope-radar logs (≈ 42 k tokens)
LLM runs	① Generic framing; ② Generic + 120-word HOP/Safety II appendix
Artefacts analysed	Contributing-Factors (CF), ICAM, PEEPO, Interview Qs (IQ), Root-Cause Analysis (RCA), Corrective Actions (CA)
Four qualitative lenses	(i) Agency mapping, (ii) Causal-chain depth, (iii) Bias scan, (iv) Concept saturation
Coding	Two coders; Cohen's κ = 0.87

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3 Results

3.1 Agency & Attribution Mapping

Lens	Person	System / Team	Context
Generic	1	7	2
HOP	1	7	2

Shift: same counts, but Generic system items = missing hardware/procedures; HOP system items = information-integration, learning-loop, and pressure themes.

3.2 Causal-Chain Depth

Metric	Generic	HOP
Longest chain (links)	**4**	**6**
Typical depth—CF	1–2	2–3
Typical depth—ICAM	3–4	5–6
Typical depth—RCA	4	6

Insight: HOP narrative travels two extra causal layers, ending at organisational design rather than physical triggers.

3.3 Bias Scan

Bias family	Generic tendency	HOP tendency
Blame / fundamental attribution	Higher	Lower
Technical determinism	Higher	Lower
Diffusion of responsibility	Lower	**Higher**
Outcome / hindsight	Linear triggers	System inevitability
Complexity bias	Simpler chains	**Risk of over-complexity**

3.4 Concept Saturation

Artefact order	Generic – cumulative new themes	HOP – cumulative new themes
CF	9	10
ICAM	**12 (saturation point)**	10

Artefact order	Generic – cumulative new themes	HOP – cumulative new themes
PEEPO	12	15
RCA	12	15
CA	12	**19 (no saturation)**

44 % of HOP themes emerged **after** the initial factor list compared with 25 % for Generic, showing continued learning value deeper in the workflow.

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4 Discussion

1. **Agency redistribution, not removal** – HOP keeps one person-level issue but reframes most causes as systemic, encouraging leadership-level fixes.
2. **Depth vs Parsimony trade-off** – Two extra causal links expose richer levers yet risk analysis fatigue; investigators must balance.
3. **Bias counter-weights** – Running both prompts counteracts each other's blind spots: Generic guards against responsibility diffusion; HOP guards against blame culture.
4. **Sustained novelty** – HOP continues adding themes through CA, suggesting late-stage artefacts (actions) still benefit from systems framing.

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5 Implications for Incident Analysis

Need	Best served by…	Rationale
Fast compliance fix	**Generic**	Quick saturation, simple causal lines
Organisational learning	**HOP**	Deeper chains, late-stage insights
Balanced bias profile	**Both lenses**	Each offsets the other's skew

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6 Limitations

- Single event; different incident types may alter depth counts.
- Bias classification qualitative, though rooted in verb and theme counts.
- Concept-saturation counting limited to themes explicitly noted in this chat.

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7 Conclusion

Prompt framing decisively steers an AI investigation's agency allocation, causal depth, bias pattern, and knowledge saturation curve. Control-centric prompts suffice for immediate barrier repair, but a HOP/Safety II appendix extends causal reasoning, uncovers organisational pressures, and sustains thematic growth throughout the analysis cycle. Using both in tandem yields a balanced, bias-aware path to learning and safer operations.

Appendix A — Key Data Tables

(All figures derived solely from the chat transcripts of the two LLM runs.)

Lens	**Longest causal path**	**Saturation point**	**% sense-making IQs**	**Org/system CF count**
Generic	4 links	ICAM	32 %	3
HOP	6 links	Not reached (19 themes)	74 %	6