Toward Understanding Fire Hazard Recognition in Construction: An immersive VR and Eye-Tracking Pilot Study

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Abstract –

Fire hazards on construction sites often involve complex visual and contextual cues that are difficult to detect and interpret. While immersive virtual reality (IVR) and eye-tracking technologies are increasingly adopted for construction hazard recognition, limited work has examined how fire hazard recognition failures arise. Situational awareness (SA) theory provides a structured framework for this purpose, yet SA-based analyses, particularly for fire scenarios, remain limited. This paper presents a pilot study investigating fire hazard recognition performance and SA failures using IVR and eye-tracking. Ten graduate students completed an inspection task involving six representative fire hazard scenarios. Hazard recognition outcomes were analyzed with eye-tracking metrics and post-task interviews. Results show substantial variability in hazard recognition performance across scenarios (10–100%). Some hazards failed at the perceptual level due to a lack of visual registration, while others were visually attended but not correctly interpreted. Multi-object fire hazards exhibited comprehension failures, where participants fixated on individual elements but failed to integrate their relationships into a coherent fire-risk interpretation. This study demonstrates the feasibility of applying an SA-based analytical framework, supported by IVR and eye-tracking, to diagnose how and where fire hazard recognition fails. These findings motivate larger-scale validation with more diverse participants and offer early insight into the mechanisms underlying construction fire hazard recognition.

Keywords –

Hazard recognition, situational awareness, eye-tracking, immersive virtual reality

1 Introduction

Construction sites are complex and dynamic systems in which fire hazards cannot be fully eliminated under current practices. Flammable materials, hot work, and temporary electrical installations are routinely present and often overlap in space and time as construction progresses. When a fire occurs on site, suppression is difficult, and consequences can escalate rapidly, posing serious risks to workers, property, and surrounding communities [1]. Effective fire prevention therefore depends not only on technological safeguards but also on workers' ability to recognize hazardous conditions before ignition occurs. Unlike post-ignition fire detection technologies, such as computer-vision-based flame or smoke detection systems [2], proactive fire prevention relies heavily on human situational awareness (SA). Workers need to perceive relevant cues in cluttered environments (Level 1), comprehend why certain conditions pose a fire hazard (Level 2), and anticipate how they could evolve into an accident (Level 3).

Despite its importance, fire hazard recognition remains one of the most challenging aspects of construction fire safety management [3]. Existing hazard-recognition research in construction has primarily focused on spatial and mechanical hazards such as falls and struck-by incidents [4,5]. However, these findings cannot be directly generalized to fire risks, which involve different objects, relational interpretation across multiple elements, and potentially different cognitive processes [6]. Although fire hazards have received increasing attention [1], limited evidence exists on how individuals identify fire hazards on construction sites, which types of fire hazards are most likely to be missed, and why these failures occur. In particular, the SA breakdowns underlying missed fire hazards, whether due to failures of perception, comprehension, or integration, remain poorly understood. Moreover, most prior studies rely on static construction site images. Among the limited studies using VR with eye tracking, some adopt desktop VR [7], while others use IVR but have participants observe the scene from a static point rather than navigate and determine their own search behavior [8]. These limit the examination of natural visual search and embodied exploration that are central to real-world site inspections.

To address these gaps, this paper presents an exploratory pilot study investigating construction fire hazard recognition and associated SA failures using IVR with integrated eye tracking. This approach enables an initial diagnostic examination of how different SA failures are associated with failures in fire hazard recognition, while providing a foundation for larger-scale studies and more targeted safety interventions.

2 Background

2.1 SA in Construction Hazard Recognition

SA provides a useful lens to explain why people miss hazards in dynamic construction settings. SA is typically described as a three-level process: perceiving task-relevant cues, comprehending their meaning in context, and projecting how the situation could develop [9]. Within this framework, hazard recognition failures can arise not only from a lack of visual attention, but also from difficulties in interpreting or integrating hazard-related cues. Existing construction safety research has applied SA from different perspectives. First, studies linking visual attention and SA show that gaze allocation and attentional patterns are associated with SA and hazard-recognition performance [4]. This work supports attention as a necessary condition for recognition, while also implying that attention alone does not guarantee understanding. Second, research on factors that influence SA demonstrates that task demands and worker state, such as task design, environmental complexity [5], and fatigue [10], can reduce attention and hazard recognition over time. Third, recent studies aim to operationalize SA levels and transitions using multimodal data, highlighting that different failures reflect distinct cognitive mechanisms rather than a single deficit [11,12].

Despite these advances, most SA-based construction studies focus on spatial or mechanical hazards, while fire hazards involving multiple interacting site elements remain underexplored. In addition, limited work has explicitly examined how and where SA breaks down during fire hazard recognition under realistic inspection conditions.

2.2 Eye Tracking Metrics in Construction Hazard Recognition

Eye-tracking metrics used for construction hazard recognition are often organized around different stages of processing [4,8,13]. Metrics related to initial visual detection are commonly used to distinguish hazards that enter visual awareness from those that are missed. In the study of construction site hazard recognition, the Area of Interest (AOI) is the area where the hazard is located [14,15]. AOI fixation occurrence indicates whether a hazard-related region receives at least one fixation and has been widely used as a basic indicator of visual registration [4]. First fixation duration reflects the temporal characteristics of the initial fixation on a hazard and has been interpreted as an indicator of early visual engagement once attention is directed to a relevant cue [8]. Metrics capturing sustained visual processing are frequently employed to characterize deeper engagement with hazards. For example, total dwell time and fixation count represent the amount and frequency of visual sampling within a hazard AOI and are frequently used to describe attention allocation and processing effort [4,5]. Measures reflecting iterative viewing further describe how hazards are revisited during interpretation. Revisit-based metrics capture returns to an AOI after attention shifts away and have been linked to rechecking and information updating during hazard assessment [16]. For multi-object hazards, component coverage indicates whether all required elements received visual sampling, supporting analysis of hazards that depend on integrating cues across multiple objects [8].

3 Research Method

3.1 Stimuli

A multi-story building construction site at the structure phase (after foundation completion and before interior finishing) was modeled in Unity 3D (unity3d.com) as the IVR environment. This phase is typically long in duration and involves dense inter-trade activity (e.g., welding, cutting, and forming), temporary electrical use, and substantial combustible materials. These conditions provide a realistic context in which fire hazards can arise from both individual items and interactions among multiple elements. To ensure ecological validity, the hazards embedded in the scene were designed to reflect realistic construction fire-risk conditions. Because systematic fire-incident datasets for construction are limited [1], hazard design was informed by multiple sources, including published case summaries [17], consultation with site professionals, and reports from major news outlets and other grey literature [1]. Two health and safety experts with a combined 35 years of construction experience reviewed the environment and hazard placements to confirm plausibility and practical relevance. Six fire-hazard scenarios were embedded in the scene (Table 1), with selected VR examples shown in Figure 1. The hazards were designed to range from single-object hazards to multi-object conditions requiring integration of multiple cues. This variation reflects the diversity of real site hazards and supports exploratory analysis of how participants allocate attention and recognize fire hazards when multiple cues must be integrated. The experience was presented in a first-person view, allowing participants to perform an inspection-like search through self-directed exploration.

Table 1 Fire hazard scenarios included in the IVR scene

ID	Fire hazard	Scenario on construction sites
H1	Oily rags on ground	Oil-contaminated rags commonly occur during equipment maintenance, cleaning, or painting and can self-heat or ignite if poorly managed.
H2	Gas cylinders in work area	Portable gas cylinders (e.g. oxygen, acetylene) used for welding and cutting can pose fire risks if improperly stored, handled, or exposed.
H3	Rebar grinding near plank stack	Hot work such as rebar grinding generates sparks that can easily ignite nearby wooden planks.
H4	Oil drums near scrap materials	Improper storage and mixed staging of materials commonly occur during site operations and cleanup.
H5	Running generator with nearby fuel container	Portable fuel containers are frequently used on construction sites to refuel generators and small equipment and may be left nearby after refueling.
H6	Coiled electrical cable under load near combustibles	Temporary power and extension cords are common on sites. If a cable is left coiled or overloaded while in use, heat can build up.

Figure 1. Examples of fire hazards in the IVR

3.2 Apparatus

The experiment was conducted using a wireless HTC VIVE Focus Vision head-mounted display (HMD) with integrated eye tracking (Figure 2). The headset provides a resolution of 2448 × 2448 pixels per eye, an up to 120° field of view, and 120 Hz eye-tracking sampling. Eye-tracking data were accessed and recorded via the VIVE OpenXR through custom C# scripts.

Figure 2. VR headset with eye-tracking sensors

3.3 Participants

Hazard identification on construction sites can be affected by factors such as age [18], work experience [13], and individual differences [19]. To reduce variability related particularly to construction experience and participant background and to focus on evaluating the proposed SA measures in this pilot study, we recruited graduate students as participants, yielding a relatively homogeneous sample [23]. This also provides a baseline for future comparison with experienced construction workers. A total of 10 graduate students (7 male, 3 female) from the Construction Engineering and Management program participated. All reported very limited construction field experience (0–6 months, primarily through supervised site visits and short-term internships), consistent with novice-level participants in prior work [20]. All participants reported normal or corrected-to-normal vision and no color vision deficiencies. Participation was voluntary, and participants could withdraw at any time during the VR session. The study protocols were approved by the University of Alberta's Research Ethics Board (Ethics ID: Pro00156861).

3.4 Measurements

3.4.1 Hazard Recognition Performance

Hazard recognition performance (HRP) is a widely used metric for assessing participants' accuracy in identifying hazards presented in experimental stimuli. [7]. HRP was calculated as the proportion of hazards they successfully recognized (number of successful recognitions divided by the total number of hazards presented), expressed as a percentage. In this study, HRP was used as an overall performance indicator. A hazard was counted as successfully recognized only when the participant both identified the scenario as a fire hazard and provided a correct explanation of why it constituted a fire hazard [7]. Cases that did not meet both criteria were treated as unsuccessful and were further classified into SA failure types in the subsequent analysis.

3.4.2 SA Measurements

To capture different levels of SA during fire hazard recognition, the study integrated objective gaze behavior, explicit hazard-identification responses, and a post-task interview. This multi-method approach was adopted because no single measure can fully capture the multi-level nature of SA [21]. Eye-tracking metrics (Section 3.4.3) provide objective evidence of visual attention but cannot directly reveal understanding or reasoning [8], while identification outcomes alone do not indicate whether failures were perceptual or interpretive. Therefore, video-stimulated recall interviews were conducted after the IVR task. Participants reviewed their session recording and explained which scenarios they identified as fire hazards, why they considered them hazardous, and what could happen if the conditions were not addressed. They then watched a standardized replay of all hazard scenarios and were asked whether they had noticed each scene or object during the task; if they had, why did they not classify it as a fire hazard. While retrospective recall is subject to memory and hindsight bias, it provides hazard-specific insight into participants' understanding and reasoning that cannot be inferred from gaze data alone [22].

3.4.3 Eye Tracking Metrics

Eye-tracking data were used to quantify SA during the IVR task. In walkable IVR environments, AOIs can be defined by tagging 3D hazard-related objects and their invisible 3D regions (colliders) that Unity uses to detect hits [23]. Gaze rays are then logged through ray–object intersection, recording the attended object and 3D intersection point as participants moved and changed viewpoint. Fixation-based metrics were used because they are widely adopted in safety and training research and provide robust, interpretable indicators of visual processing [23]. A fixation is a period in which eye movements are relatively stable, allowing visual information to be acquired and processed at the attended location [24]. In natural viewing tasks, fixation durations are typically on the order of a few hundred milliseconds, with many fixations commonly falling within approximately 100–600 ms depending on task demands and scene complexity [23]. Because IVR involves additional head-motion dynamics compared to screen-based studies, which could introduce small gaze fluctuations that can cause very short stabilizations to be misclassified as fixations [23], we applied a minimum fixation duration threshold of 180 ms to reduce this risk and align with recent VR eye-tracking research [8]. The eye-tracking metrics used in this pilot study are summarized in Table 2. The definition of each metric is introduced in Section 2.2.

Table 2. Key eye-tracking metrics used in this paper

Metric	Purpose
AOI Fixation Occurrence First Fixation Duration (FFD)	SA Level 1
Fixation Count (FC) Total Dwell Time Component Coverage	SA Level 2

3.4.4 IVR User Experience Measurement

Perceived presence (PP) reflects the extent to which individuals experience a sense of "being there" in the virtual environment and may influence engagement and attention during the task. We chose the Independent Television Commission Sense of Presence Inventory (ITC-SOPI) [25] to evaluate PP, a validated and widely used self-report questionnaire for immersive media research [26]. We used the shortened 12-item version of ITC-SOPI, recommended by Busch et al. [27], to reduce participant burden while covering four subscales: spatial presence, engagement, ecological validity, and negative effects. Items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), and subscale scores were computed as the mean of their items; higher scores on the first three subscales indicate a stronger presence, whereas higher Negative Effects reflect greater discomfort.

3.5 Procedure

Participants were welcomed and briefed on the study procedure. They were informed to act as an inspector and intentionally search for fire hazards in an IVR scenario [28]. They then provided the consent form and completed a short demographic questionnaire. Participants were not informed of the total number of target fire hazards in the scenario. Controller use was briefly explained. Participants then put on the VR headset, adjusted it for comfort, and completed eye-tracking calibration, an automatic interpupillary distance (IPD) adjustment, followed by a five-point calibration. They then completed a shot tutorial in a neutral IVR environment. This tutorial trained locomotion and selection controls without including any fire hazard-related cues. The tutorial was untimed to allow participants to become familiar with the controller and lighting.

During the main task, participants were asked to follow a pre-designed path (Figure 3), while still having some freedom to navigate. At the start of the IVR trial, a visual cue showed the intended walking route, and the facilitator reminded participants to follow it. They used the right controller's grip button to start and stop forward motion and changed viewing direction by turning their head or body. This approach was intended to mimic real-world investigation behavior and is consistent with a real-world hazard recognition experiment [4]. They were also instructed to press the trigger button on the right-hand controller as soon as they believed they had identified a hazard to record the timestamp. Participants were instructed to complete the task as quickly as possible, with a maximum time limit of 2 minutes. This limit was set to discourage excessive wandering and to reduce unnatural inspection behavior [4]. Immediately after the VR session, they completed the ITC-SOPI questionnaires. The recorded session was then replayed, and participants were asked follow-up questions to evaluate SA. The experiment took place in a lab room that was not accessible to the public to minimize distractions.

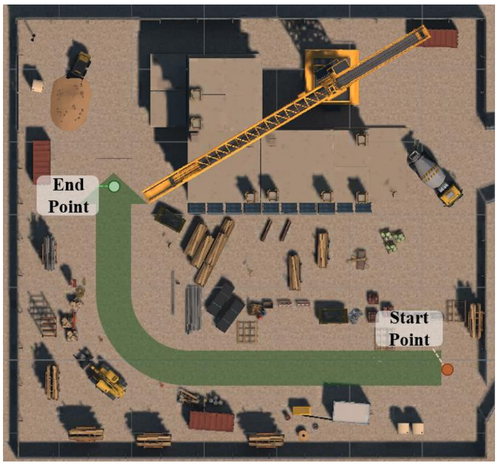

Figure 3. Predefined walking path used in the IVR hazard inspection task

3.6 Data Collection and Processing

Eye-tracking data were recorded for both eyes and stored in two comma-separated values (CSV) files through C# scripts in Unity. For each sample, one file recorded the gaze position for each eye, including a 3D gaze origin (position) and gaze orientation, along with pupil position and pupil diameter. Validity flags were also saved to indicate whether the gaze and pupil measurements were considered reliable. These validity signals are important because the data quality directly affects later analysis [29]. Each frame related to the head pose was recorded. Because visibility in walkable VR depends on head direction, these data were used to confirm when hazards entered the participant's field of view and to characterize head-based search behavior. A second file logged the same frame count, ray casting outputs used for object mapping, and trigger flag at the time stamps, indicating when participants pressed the button to report a detected hazard.

In eye-tracking research, samples are commonly considered invalid when the tracker cannot provide a reliable gaze estimate, such as during blinks, pupil loss, eyelid occlusion, or temporary tracking failure [23,24,30]. In this study, a gaze sample was treated as invalid when neither eye provided an invalid gaze signal, as indicated by the device's validity flags. Data screening was performed within the hazard exposure window, defined as the period from when the participant first viewed a hazard to when they last viewed a hazard. We set our data-quality rules in advance and used conservative cutoffs to avoid bias in fixation-based measures when a large portion of gaze data is missing. In line with prior eye-tracking work [31], we excluded a session if more than 30% of gaze samples within this window were invalid. This approach allows short tracking dropouts that are common in head-mounted eye tracking but removes cases where missing data is large enough to distort measures such as time to first fixation, fixation duration, and fixation count [23,24].

4 Pilot Study Results and Discussions

Ten participants completed the study, and no samples were excluded by the predefined validity criteria.

4.1 Hazard Recognition Performance

Figure 4 summarizes the HRP for each of the six fire hazard scenarios, which varied substantially across hazards (10% - 100%). The following sections examine the mechanisms underlying these differences by mapping observed failures to different SA levels.

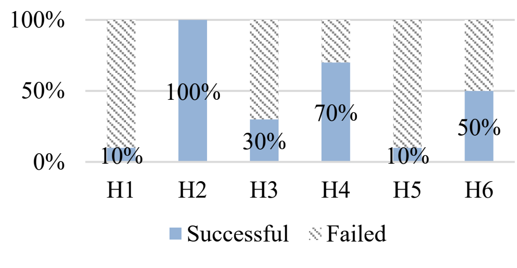

Figure 4. Hazard recognition performance (n=10)

4.2 Analysis of SA Failure

Based on the eye-tracking results and post-task interview, we summarized the SA failure type, as shown in Table 3. The classification was conducted by a single coder using a structured decision framework. Given the small sample size (N = 10) and the exploratory nature of this pilot study, inter-rater reliability was not assessed at this stage. The following sections detail failures at each

SA level with corresponding eye-tracking metrics. Given the page limitation, only part of the hazards are detailed.

Table 3. Classification of situational awareness failure types in construction fire hazard recognition

Type		Situation	Quote from post-VR interview
SA L1 failure	S1	The hazard was not visually detected.	"I never noticed the oily rag"; "I did not see this fuel container"
SA L2/L3 failure	S2/3a	The hazard was seen, but the object was not recognized or understood	"I see this yellow box, but I do not know it is a generator"
	S2/3b	The hazard elements were seen, but the relationship between them was not understood	"I see the generator and the fuel container, but I didn't know they could lead to a fire"
	S2/3c	The hazard was noticed and judged as a hazard, but the participant could not explain the reason	"Something feels off about the electrical panel, but I cannot explain the exact reason"

4.2.1 SA Level 1 Failure

SA Level 1 failures were defined as cases where a hazard was not visually registered, operationalized as no fixation on the hazard AOI. Figure 5 summarizes the performance using the AOI fixation occurrence rate and average FFD. One hazard showed the strongest evidence of SA Level 1 failure. H1(oily rag) had the lowest fixation occurrence (30%), indicating that 70% of participants never fixated on it, consistent with interview reports that *"they didn't see it"*. Only 10% of participants successfully identified H1; the other 20% reported they saw the oily rag, but they were not sure what it was and did not consider it a fire hazard. This could be because the oily rag is relatively small and on the ground.

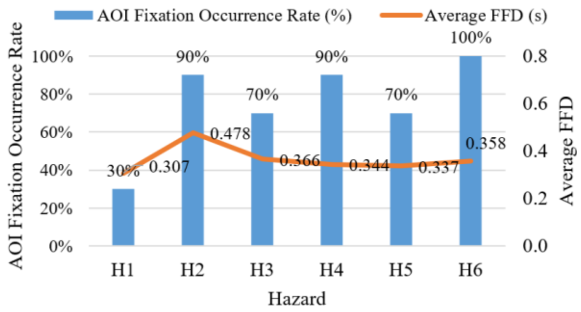

Figure 5. AOI fixation occurrence and first fixation duration (FFD) across six hazards

4.2.2 SA Level 2 and Level 3 Failure

Because SA Level 2 and Level 3 are closely related and difficult to distinguish reliably in practice, this section discusses them together as higher-level SA failures [8,9]. For hazards with fixation occurrence, identification failures are less likely to be explained by SA Level 1 alone and instead require SA Level 2 and Level 3 analysis. As shown in Figure 6, component coverage and recognition performance diverged substantially across hazards, highlighting different SA Level 2 failure mechanisms. H5 exhibited the lowest recognition rate (10%) despite no widespread perceptual failure. While some participants achieved partial component coverage, full coverage was rare, and most participants failed to integrate the generator and fuel container as a combined fire hazard. This pattern corresponds to S2/3b failures (Table 3), in which hazard elements are seen, but their relationship is not understood.

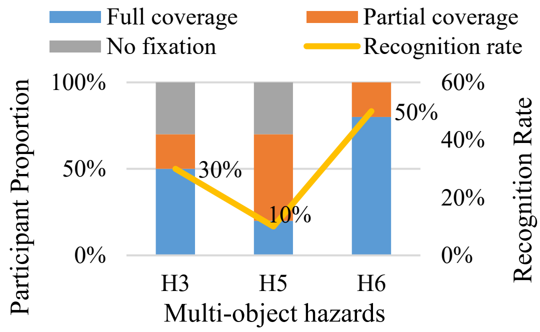

Figure 6. Component coverage and recognition rate for multi-object hazards (H3, H5, and H6)

In contrast, H6 showed a distinct SA Level 2 pattern. All participants fixated on at least one hazard component, and many achieved full component coverage (electric panel with power cable). However, recognition remained limited to 50%. Eye-tracking metrics revealed moderate to high visual engagement for H6, including higher dwell times (2.59s), fixation count (6.4) compared to H5 (0.39s and 1.2, respectively). In addition, 80% of participants revisited H6, with an average revisit count of 2.5. Despite this sustained attention, many participants were unable to articulate the specific fire-risk mechanism during post-VR interviews. These cases align most closely with S2/3c failures (Table 3), in which a hazard is noticed and judged as potentially risky, but the underlying causal explanation remains unclear. Although prior work has explored pupil diameter as a potential indicator of higher-level processing [8], and pupil data were collected in this study, these data were not analyzed due to the limited scope of the pilot case's results and the page limit in this paper.

In this pilot study, all participants who demonstrated SA Level 2 success also correctly described what could happen next, indicating SA Level 3 success. It is worth noting that two participants showed evidence of full SA success for H3 yet did not report the hazard. In interviews, both explained that they noticed and understood the hazard but did not consider it serious enough to report. These cases were therefore interpreted as failures in risk perception rather than SA failure [15].

4.2.3 Success Case

H2 (Gas cylinders) showed consistently strong performance, with a high AOI fixation occurrence rate (90%) alongside a 100% recognition rate. In post-VR interviews, participants frequently reported that the red gas bottle and visible hazard label drew their attention immediately. One participant reported H2 despite no recorded AOI fixation. During recall, this participant described noticing the bottles instantly and moving on quickly. This case suggests that very rapid or peripheral visual sampling may not always be registered as a fixation, highlighting a limitation of fixation-based measures for capturing extremely brief perceptual events.

4.3 IVR Experience

ITC-SOPI results are reported descriptively to characterize VR user experience in this pilot study. Participants reported high presence, with strong Spatial Presence (M = 4.15, SD = 0.50) and Engagement (M = 4.04, SD = 0.68), and moderate-to-high Ecological Validity (M = 3.81, SD = 0.56). Negative Effects were low overall (M = 2.07, SD = 0.76), although two participants reported high dizziness (score = 4) without stopping the session. Overall, the IVR environment provided an immersive and acceptable experience, with limited disruption from discomfort.

5 Conclusion

This pilot study examined construction fire-hazard recognition in a walkable IVR environment with integrated eye tracking and a post-task interview. Results show that the recognition performance varied widely across scenarios, and recognition failure could not be attributed to a single limitation. By mapping these patterns onto the three-level SA model, the study offers preliminary insight into the mechanisms underlying fire-hazard recognition and provides a basis for more targeted training design and safety interventions. The results also demonstrate the feasibility of using IVR with eye tracking to study proactive hazard identification under inspection-like viewing conditions.

This study has several limitations. SA failure classifications were completed by a single coder using a structured decision framework, without formal assessment of inter-rater reliability. In the larger follow-up study, two independent coders will be used, and Cohen's kappa will be calculated. In addition, the study recruited only a small sample of novice workers, intending to guide larger-scale studies rather than support broad generalization. The follow-up study will recruit experienced construction workers to compare SA failure patterns and visual search behaviors across experience levels. Viewing distance and hazard-level characteristics, such as visual saliency and AOI size, may also influence fixation behavior and missed hazards and should be examined in future analyses.

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