Scenario-Driven VR Training for Hydroelectric Performance Evaluation

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***Abstract*—Training technicians to diagnose and resolve hydroelectric plant faults requires exposure to multi-stage system issues that are difficult, expensive, and hazardous to recreate in real facilities. This work presents a scenario-driven virtual reality (VR) hydroelectric training environment built around a static facility layout and hand-based low-fidelity interactions. The system models turbine bays, reservoir areas, drain gates, intake zones, and mechanical components, and each scenario is instrumented with fine-grained telemetry capturing object-manipulation events such as debris removal, reservoir cleaning, component replacement, alignment attempts, and disposal accuracy. The environment presents learners with fault sequences in which symptoms (e.g., low flow, unstable pressure, abnormal vibration) evolve logically from underlying causes such as reservoir debris accumulation or mechanical wear. Each episode includes structured cues, root-cause relationships, and expected multi-step procedures, allowing the system to collect performance metrics such as task order, alignment offsets, cleanup completeness, safety adherence, and timing. In addition to supporting realistic practice, the platform enables repeatable, controlled experimentation with trainee behavior across varied fault conditions. Preliminary demonstrations using scripted interaction traces show that this telemetry can differentiate correct diagnostic pathways from common errors and support data-driven evaluation of trainee proficiency. Overall, this work introduces a fully instrumented VR platform for hydroelectric scenario training and establishes a foundation for future adaptive, personalized, or automated assessment systems.**

***Index Terms*—Virtual reality (VR), Industrial training, Hydroelectric maintenance, Scenario-based simulation, Telemetry and interaction logging, Performance assessment**

I. INTRODUCTION

Maintenance and diagnostic work in hydroelectric power plants is inherently hazardous, skill-intensive, and logistically difficult to practice in real facilities. Many faults—such as reservoir debris accumulation, mechanical wear in turbine assemblies, and pressure-driven leaks—emerge gradually through multi-stage causal processes that are challenging to observe directly during live operations. As a result, trainees often receive limited exposure to realistic fault progression, and instructors have few tools for evaluating how well a trainee understands upstream causes, downstream consequences, and proper maintenance sequencing.

Virtual reality (VR) training environments have shown strong potential for industrial education because they enable safe rehearsal of dangerous tasks, repeatable exposure to complex procedures, and reduced training downtime. However, most existing VR industrial training systems focus primarily on step-by-step procedural guidance or visual immersion, offering little insight into *why* trainees choose specific actions or how well they understand fault–symptom relationships. Common limitations include a lack of structured scenario logic, limited modeling of multi-stage fault evolution, and coarse performance metrics based mainly on task completion or time.

Despite advances in VR-based industrial training, there remains a gap in systems that (1) model realistic fault progression within hydroelectric facilities, (2) provide explicit opportunities for diagnostic reasoning, and (3) collect fine-grained telemetry capable of distinguishing correct, incorrect, and partially complete maintenance pathways. Current VR training implementations rarely capture the underlying structure of trainee interactions in a machine-readable form, limiting their use for automated assessment, instructor evaluation, or integration with intelligent tutoring systems.

To address these gaps, this work introduces a scenario-rich VR hydroelectric training environment built around a static facility layout and low-fidelity, hand-based interactions. The system models two multi-stage root-cause scenarios (low water flow and abnormal vibration) that evolve through hydraulic and mechanical subsystems. All trainee actions are instrumented through a unified, 32-dimensional interaction state vector designed to capture debris clearing, component removal and installation, leak repair, sequencing correctness, and safety adherence.

The key contributions of this paper are as follows:

- **A scenario-driven VR hydroelectric training environment** that models realistic causal chains linking reservoir debris accumulation to hydraulic and mechanical failures.
- **A fine-grained telemetry and instrumentation framework** capable of capturing low-level, hand-based interactions, partial task completion, and procedural ordering.
- **A unified 32-dimensional interaction state representation** that encodes trainee behavior across reservoir, rotor, fan, pipe-leak, and drain subsystems in a compact and machine-readable form.
- **A demonstration of the telemetry system** using scripted interaction sequences that highlight distinctions between correct, incorrect, and partially complete diagnostic reasoning.

The remainder of this paper is structured as follows. Section II reviews related work in VR industrial training, scenario-based simulation, and sensor-rich interaction modeling. Section III introduces the system architecture, facility layout, interaction model, and scenario framework. Section IV describes the fault-progression scenarios and associated learning objectives. Section V presents the telemetry framework and the unified interaction vector. Section VI uses scripted demonstrations to evaluate the system's diagnostic expressiveness. Section VII discusses strengths, limitations, and opportunities for extension, and Section VIII concludes the paper.

II. RELATED WORKS

A. VR-Based Industrial Training: Virtual reality (VR) has been widely adopted as a medium for industrial skills training, particularly in domains where procedures are complex, hazardous, or difficult to reproduce in physical settings. Naranjo et al. provide a broad scoping review of VR-based industrial training systems, highlighting common patterns such as stepwise procedure rehearsal, hazard awareness, and guided task execution across a range of manufacturing and maintenance tasks [1]. Radhakrishnan et al. complement this with a systematic review focused on immersive VR for industrial skills training, reporting consistent benefits for engagement and confidence while also noting a lack of standardized evaluation frameworks and data-rich assessment methods [2].

Several works demonstrate concrete VR training applications in industrial settings. Liu et al. present a VR system aimed at reducing training cost and safety risk in industrial manufacturing by simulating realistic production environments and error conditions [3]. Jiang et al. develop a virtual training environment for electric transformer assembly and maintenance, providing learning, training, and exam modes that allow workers to interact with virtual devices and rehearse strict operating procedures [4]. Ayala García et al. describe a VR training system for the maintenance and operation of high-voltage overhead power lines, integrating multiple maintenance maneuvers and safety practices into a non-immersive VR platform [5]. Hoang et al. evaluate a multi-user VR maintenance training platform for industrial hydraulic machines, showing that VR-based kinesthetic training can improve trainee confidence and perceived preparedness compared to conventional slide- and video-based training [6]. Wolfartsberger and Niedermayr explore an "authoring-by-doing" paradigm, where expert actions recorded in VR become ghosted animations that trainees can follow, lowering the cost of content creation for industrial assembly training scenarios [7].

B. Sensor-Rich Training and Diagnostic Environments: While many VR training systems concentrate on visual immersion and procedure rehearsal, a parallel body of work investigates sensor-rich environments, diagnostics, and data fusion techniques that can underpin more detailed performance assessment. Thuruthel and Iida show how multimodal sensor fusion and deep learning can be used to learn high-dimensional models of soft robots, suggesting that rich sensorimotor representations can support higher-level cognitive functions and more expressive interaction modeling [8]. Nowak et al. study automatic adaptation in classification algorithms that fuse data from heterogeneous sensors, arguing that fused classification results can be used as a surrogate ground truth in environments with incomplete prior knowledge [9]. In a related direction, Tyagi et al. propose a data-driven soft sensor for optical intensity estimation in high-power plasma sources, demonstrating how machine-learning models can augment or replace physical sensors and support fault identification [10]. Valbonesi et al. use ray-tracing simulations to analyze 5G coverage in complex railway station environments, motivated by the need to support diagnostics-related use cases and continuous monitoring across heterogeneous spaces [11].

In power and industrial systems, several works explicitly couple simulation or VR environments with diagnostic or monitoring architectures. Khan et al. describe a simulation-based health monitoring test-bed for electrical power distribution, enabling repeatable fault injection and evaluation of diagnostic algorithms within a virtualized environment [12]. Datta and Vittal propose a diagnostics tool for risk-based dynamic security assessment of renewable generation, integrating time-domain simulations with risk analytics to help operators interpret large-scale simulation outputs [13]. At a more general level, Augusto et al. and Nambiar et al. use discrete-event and agent-based simulation to analyze clinical pathways and population-level screening policies, respectively, showcasing how simulation plus rich event logs can support scenario testing and policy evaluation in complex systems [14], [15]. Ebrahimi presents a participant self-customized awareness system for COVID-19 that includes embedded subsystems for diagnostics, simulation, tracing, and pattern matching, highlighting how structured data pipelines can empower non-experts to reason about complex dynamic phenomena [16].

Within hydropower specifically, the CBM-VR work of Guo et al. and the distributed cooperative decision-support system of Xu et al. both emphasize the importance of continuous condition monitoring, multi-source information integration, and decision-support tools for maintenance engineers, with VR positioned as a front-end for visualization and human–system interaction [17], [18]. These efforts underscore the opportunity to treat VR training environments not only as visualization tools but also as sensor-rich platforms capable of producing structured data suitable for diagnostics and automated assessment.

C. Scenario-Based Simulation and Training Design: Scenario-based modeling is a recurring theme across VR training, simulation, and diagnostics research. In industrial VR training, Jiang et al. structure their transformer assembly environment around discrete modes (learning, training, and exam), with scenarios designed to reflect real-world assembly and maintenance tasks [4]. Wolfartsberger and Niedermayr's authoring-by-doing approach effectively transforms expert task executions into reusable, scenario-driven learning content, where trainees follow recorded sequences that encode correct procedural paths [7]. Hoang et al. design VR training scenarios for maintenance of hydraulic machines and empirically compare VR-based training against traditional media, demonstrating that scenario-driven VR can enhance confidence and perceived preparedness [6]. Liu et al. likewise structure their VR industrial training system around the reproduction of production processes, error demonstrations, and interactive feedback, targeting repeated exposure to dangerous or costly scenarios in a safe virtual environment [3].

In health and policy domains, scenario-based simulation has been used extensively to analyze complex processes and interventions. Augusto et al. mine clinical event logs to derive causal nets representing clinical pathways and then convert them into executable simulation models, enabling the study of alternative medical decisions and their impact on outcomes and cost [14]. Nambiar et al. build an individual-based discrete-event simulation model to explore how insurance expansion scenarios affect colorectal cancer screening, incidence, mortality, and costs at the population level [15]. Datta and Vittal's dynamic security assessment tool supports interactive contingency ranking and scenario exploration for power systems under renewable penetration [13]. Ebrahimi's participant self-customized awareness system defines multiple embedded subsystems (diagnostics, simulation, tracing, pattern matching) and uses game-like scenario structures to help users reason about disease progression and intervention effects [16].

In the hydropower context, Guo et al. explicitly argue that most faults in power systems begin as localized symptoms and gradually evolve into more serious accidents, and they propose a CBM-VR system that uses VR to visualize equipment condition and guide maintenance decisions in a scenario-like fashion [17]. Xu et al. extend this philosophy with a distributed cooperative maintenance decision-support system that coordinates operators, experts, and computers in condition-based maintenance planning for hydropower plants [18]. Moraes et al. present a methodology for optimized generation of virtual environments based on hydroelectric power plants, motivated by the need to support training and maintenance scenarios via efficient 3D modeling of hydroelectric structures [19]. Baez et al. further demonstrate a framework for rapid prototyping of VR training scenarios in an electrical-risk training case for a hydroelectric plant, emphasizing interaction, error detection, and objective tracking as reusable scenario components [20]. Together, these works highlight the importance of explicit scenario design and progression in both industrial VR and simulation-based analysis.

D. Gaps Identified: Across VR-based industrial training, sensor-rich environments, and scenario-based simulation design, several gaps remain that motivate the present work. Reviews of VR industrial training emphasize the lack of standardized, fine-grained performance representations and the limited use of structured telemetry for automated or semi-automated assessment [1], [2]. Many training systems in manufacturing, maintenance, and power domains focus primarily on visual realism, procedural checklists, or coarse performance metrics (e.g., task completion and time) [3]–[7]. Even when rich sensor or log data are available, as in multisensor fusion, health monitoring, or simulation-based decision-support tools, the resulting representations are often domain-specific and not explicitly integrated into VR training workflows [8]–[10], [12], [13].

In the hydropower space, prior work on VR for condition-based maintenance and hydropower plant modeling demonstrates the feasibility of virtual environments for visualization, training, and maintenance support, but does not present a unified, low-dimensional interaction state vector that encodes trainee behavior across multi-stage fault scenarios in a hydroelectric facility [17]–[20]. Similarly, while systems like EXAMINER show how digitized operator performance can drive automated feedback in manual assembly tasks [21], comparable formulations have not yet been reported for hydroelectric maintenance procedures involving reservoir cleaning, turbine rotor and fan repair, pipe leak mitigation, and drain-gate clog removal. This suggests an opportunity to combine scenario-based VR training for hydropower with a sensor-rich, explicitly defined interaction state representation, enabling more detailed diagnostic analysis of trainee behavior and laying the groundwork for future automated assessment or learning-based feedback mechanisms.

III. SYSTEM OVERVIEW

A. Static Hydroelectric Facility Layout: The facility is equipped with a large-scale hydroelectric turbine that spreads across multiple levels. Specifically, there are rooms that hold the water reservoir, upper turbine case where the rotor is investigated, lower turbine casing where the turbine fan blades can be inspected, and a penstock leading into the lower chamber. The room hosting the rotor task can be seen below in Figure 1.

Fig. 1. Rotor task in virtually realized hydroelectric plant

B. Interaction Model: The user is able to interact with the environment by a series of variable components such as low-fidelity hand-based grasping, object pickup and placement, debris cleaning, component insertion/removal, alignment movement (rotor/blades), water/pressure UI toggles, disposal interactions.

C. Scenario Framework: The scenarios are split up into two core components: low water flow and abnormal vibration. For each there are symptoms which gradually escalate, the root causes progress, and user decisions determine success or misdiagnosis.

IV. SCENARIO DESIGN AND FAULT PROGRESSION

A. Scenario 1: Low Water Flow: For the early scenario, we observe small amounts of debris in the reservoir which leads to a gate blockage. Thereafter, more debris can manifest into a pressure event which causes leaks through pressure instability. The user is able to clean the debris as it comes in.

B. Scenario 2: Abnormal Vibration: In this scenario which shares the same root cause as the first: debris making its way into the water reservoir. The issue manifests into other problems this time around. Specifically, we discover that the debris builds up in the lower casing of the turbine generator to cause mechanic wear to the turbine. This can be observed via inspection of the vibrato meter. It causes issues with the turbines rotor, it's alignment, and wears out the fan blades for the runner at the bottom of the generator.

C. Causal Chain Structure: From this we adhere to a causal chain structure where the reservoir issues propagate into more problems later on. These mechanical failures develop across the episodes. These symptoms may mislead trainees who skip root-cause analysis.

D. Learning Objectives: The objective of this simulation is to encourage trainees to perform diagnostic reasoning by following proper shutdown/safety sequencing, understanding reservoir and turbine relationships, enact proper disposal techniques, and correct alignment of rotating parts.

V. TELEMETRY AND INSTRUMENTATION FRAMEWORK

A. Unified Interaction Vector Representation: To provide a structured, machine-readable summary of all trainee actions within the static hydroelectric training environment, we define a unified interaction state vector that aggregates all subsystem-level behaviors into a single 32-dimensional feature representation. This vector captures both binary task completions (e.g., whether a component was removed or replaced) and normalized partial-completeness values (e.g., quality of waste removal or leak repair).

Formally, the trainee interaction state is expressed as

$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_{\text{reservoir}} \\ \mathbf{x}_{\text{rotor}} \\ \mathbf{x}_{\text{fan}} \\ \mathbf{x}_{\text{pipe}} \\ \mathbf{x}_{\text{drain}} \end{bmatrix} \in [0,1]^{32}, \tag{1}$$

where each subsystem vector $\mathbf{x}_{(\cdot)}$ contains a mixture of binary indicators and normalized continuous values:

$$x_i = \begin{cases} 1, & \text{if the task was successful,} \\ 0, & \text{if the task was incorrect,} \\ c \in (0,1), & \text{for partially complete tasks.} \end{cases}$$

B. Discussion: Taken together, the five subsystem vectors form a comprehensive, fine-grained representation of trainee interactions. This 32-dimensional structure provides a compact evaluation signature that can distinguish correct diagnostic pathways, common error patterns, procedural violations, and partially completed repairs. The vector format also supports future extensions, including automated scoring, trajectory clustering, and integration with machine learning models for trainee assessment.

C. Logging Architecture: The events are then logged in a JSON file which includes information such as the timestamp, event-object mapping, scenario state tracking, and outcome codes (success/partial/misdiagnosis).

TABLE I
EXAMPLE MAPPING BETWEEN INTERACTION METRICS, FAULT SCENARIOS, TRAINING OBJECTIVES, AND PERFORMANCE INDICATORS

Metric	**Subsystem**	**Training Objective**	**Performance Indicator**
Waste removal completeness	Reservoir, Drain	Develop upstream fault recognition and cleanup skills	Ability to identify debris as root cause and fully clear blockages.
Waste disposal correctness	All	Practice safe and environmentally responsible disposal practices	Degree to which debris is placed in designated disposal regions.
Step ordering accuracy	All	Reinforce correct diagnostic reasoning and safe sequencing	Frequency with which trainees follow shutdown → repair → restore ordering.
Rotor alignment quality	Rotor, Fan	Understand link between mechanical alignment and vibration symptoms	Extent to which alignment actions reduce abnormal vibration indicators.
Water/power shutdown adherence	Reservoir, Pipe, Drain, Rotor, Fan	Encourage safe isolation procedures prior to intervention	Proportion of repairs performed with water/power safely off.
Leak repair completeness	Pipe	Improve mitigation of pressure-related damage	Fraction of leak area successfully sealed before system restart.

D. Metric-Objective Mapping: These metrics that are extracted into JSON files are mapped directly to learning objectives within the simulated environment. Specifically, in Table I, we observe the mapping of these metrics to learning objectives.

VI. DEMONSTRATION AND EVALUATION

To ensure that all five subsystems of the 32-dimensional interaction state vector are exercised—including the fan-blade component unique to Scenario 2 (Abnormal Vibration)—we evaluate three scripted trainee interaction sequences (A, B, C) exclusively within Scenario 2. In this scenario, debris entering the lower turbine casing produces casing wear, rotor misalignment, and progressive fan-blade degradation. Thus, full resolution of the underlying fault requires both reservoir cleaning and mechanical repair of the rotor and runner fan assembly.

Each sequence represents a realistic trainee archetype: (A) a skilled user, (B) an unskilled user executing premature mechanical actions, and (C) a partially skilled user who identifies the correct subsystem but performs incomplete remediation. This information is collected in Table II.

A. Sequence A: Skilled Trainee: Sequence A demonstrates a complete and correct resolution of the Scenario 2 fault chain. The trainee first performs full reservoir remediation (removal completeness = 1.0) before entering the turbine housing. Mechanical repair is executed in the correct order: rotor removal, new installation, and high-quality alignment (0.95). Because Scenario 2 requires fan-blade replacement due to casing abrasion, the trainee successfully removes all

TABLE II
FINAL STATE VECTOR OUTCOMES FOR SCENARIO 2 ACROSS SEQUENCES A, B, AND C

Seq.	Final State Summary (Abbrev.)
A (Skilled)	Reservoir = [1,1,1,1,1,1]; Rotor = all steps complete, align = 0.95; Fan = all 8 blades replaced (1.0), waste OK (1.0); Pipe/Drain = 0.
B (Unskilled)	Reservoir = all 0; Rotor = steps completed, align = 0.80; Fan = all 0 (never opened); Pipe/Drain = 0.
C (Partial)	Reservoir = [1,1,0.5,0.5,1,1]; Rotor = only alignment attempted (0.60); Fan = partial removal = 0.25, install = 0.25, disposal = 0.25; Pipe/Drain = 0.

degraded blades and installs all eight new blades with perfect completeness (1.0). The final interaction vector exhibits activation across all reservoir, rotor, and fan dimensions, producing a high-fidelity representation of expert performance.

B. Sequence B: Unskilled Trainee (Misdiagnosis): Sequence B illustrates a classical misdiagnosis pattern in which the trainee jumps directly to mechanical repair without addressing the root cause in the reservoir. The rotor is replaced and aligned (0.80 quality), but the fan subsystem is never opened, leaving all fan dimensions at zero. This failure to engage the upstream fault source yields a state vector characterized by a fully inactive reservoir block and a fully inactive fan block. The system remains in a degraded state because debris continues to enter the casing even after the rotor is replaced, demonstrating how the 32D vector captures the diagnostic error.

C. Sequence C: Partially Skilled Trainee: Sequence C shows an intermediate level of competence. The trainee recognizes the need for reservoir cleaning but performs only partial removal (completeness = 0.5) and incomplete disposal (0.5). Rotor-level actions are limited to inspection and a low-quality alignment attempt (0.60), as the rotor is never removed. The fan subsystem is accessed, and the trainee removes and replaces only a subset of degraded blades (removal = 0.25, replacement = 0.25), with moderate disposal correctness (0.25). The resulting vector contains mixed binary and fractional values, reflecting partial understanding but incomplete procedural execution.

D. Cross-Sequence Comparison: The three sequences produce distinctly different activation patterns in the 32-dimensional state space. Sequence A yields a densely activated, high-quality interaction signature indicative of full remediation of the reservoir, rotor, and fan subsystems. Sequence B produces a sparse signature dominated by mechanical actions, reflecting premature focus on downstream symptoms rather than root-cause elimination. Sequence C occupies a middle ground, containing both partially complete continuous values and missed binary steps. Together, these sequences demonstrate the system's ability to differentiate skill levels and error types through structured telemetry.

VII. DISCUSSION

The results from the three scripted trainee sequences—skilled (A), unskilled (B), and partially skilled (C)—demonstrate that the proposed scenario-driven VR training environment can accurately capture differences in user performance through its fine-grained 32-dimensional interaction state representation. By embedding telemetry directly into the scenario logic of a static hydroelectric facility, the system provides structured evidence of diagnostic reasoning quality, procedural correctness, and subsystem-level completeness without requiring subjective instructor observation or external instrumentation. The differences across the three sequences reveal how root-cause reasoning, task sequencing, and completeness of actions manifest directly in the unified interaction vector.

In particular, Sequence A shows how the telemetry encodes full procedural competency across reservoir cleaning, rotor replacement, and fan-blade maintenance in Scenario 2. By contrast, Sequence B illustrates a common misdiagnosis pattern in which mechanical issues are addressed prematurely, while Sequence C captures transitional skill levels where the trainee identifies the correct subsystem but performs incomplete or low-quality remediation. These distinctions highlight the potential of this representation framework for automated assessment, performance clustering, or future learning-based feedback systems.

A. Strengths: The system introduced in this work offers several notable strengths:

- **Scenario-grounded telemetry.** Telemetry is not collected in isolation but integrated into a causal scenario model that links symptoms, root causes, and expected remediation pathways. This yields meaningful and interpretable data rather than raw interaction logs.
- **Fine-grained interaction representation.** The 32-dimensional state vector captures nuanced trainee behavior, including fractional completeness, misdiagnosis patterns, improper sequencing, and quality of alignment or disposal actions.
- **Low-fidelity but instructionally rich design.** Despite using simple hand interactions and a static environment, the simulation successfully models realistic fault progression across reservoir, rotor, and fan subsystems.
- **Safe replication of hazardous procedures.** Draining reservoirs, opening turbine housings, handling debris, and replacing mechanical components are dangerous in real facilities but are easily and safely replicated in VR.
- **Foundation for automated assessment.** The unified state vector provides a compact signature suitable for future machine learning classifiers, scoring rubrics, or adaptive training systems.

B. Limitations: The present system also has several important limitations:

- **Static environment.** The facility layout does not change across episodes, limiting scenario diversity and trainee exposure to varied geometric or spatial configurations.
- **No real-time adaptive feedback.** The system records participant behavior but does not yet provide intelligent prompts, scaffolding, or automated correction during train-

ing.

- **Scripted evaluation rather than human-subject study.** The demonstration sequences illustrate the telemetry system but do not replace empirical evaluation with real participants.

VIII. Conclusion and Future Works

This work presents a scenario-driven virtual reality environment designed for hydroelectric maintenance training, with an emphasis on fault progression modeling and fine-grained telemetry collection. The system integrates causal scenario logic, low-fidelity but instructionally coherent hand interactions, and a unified 32-dimensional interaction state representation that captures trainee actions across reservoir, rotor, fan, pipe leak, and drain-clog subsystems.

Through three scripted interaction sequences, we demonstrate that the system can differentiate skilled, unskilled, and partially skilled behavior patterns and that the telemetry aligns directly with scenario objectives. These results show that even a static VR environment can support meaningful diagnostic analysis and provide a foundation for automated assessment or future adaptive VR training systems.

Several avenues for expansion can build upon the presented system:

- **Adaptive feedback using reinforcement learning.** Future work will incorporate RL-driven feedback agents that interpret the 32-dimensional state vector and provide tailored, context-sensitive prompts.
- **Procedural content generation (PCG).** Dynamic variation of reservoir debris patterns, leak locations, or mechanical degradation could increase training diversity and reduce memorization effects.
- **Realistic multi-stage operational indicators.** Coupling vibration, pressure, and flow sensors to the VR environment would deepen the simulation's diagnostic realism.
- **Human-subject evaluations.** A controlled study with novice technicians, engineering students, or industry trainees is planned to validate the educational impact of the scenario and telemetry design.

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