# Multi-Agent Geophysical AI Workflow for Automated Reservoir Characterization

**M Quamer Nasim[1], Paresh Nath Singha Roy[1,2], and Tannistha Maiti[3]**

**M Quamer Nasim -** Department of Geology and Geophysics, Indian Institute of Technology, Kharagpur, West Bengal, India, quamer23nasim38@gmail.com

**Paresh Nath Singha Roy -** Department of Geology and Geophysics and Deysarkar Centre of Excellence in Petroleum Engineering, Indian Institute of Technology, Kharagpur, West Bengal, India, pnsmay1@gmail.com

**Tannistha Maiti -** Deepkapha AI Research Lab, The Netherlands, tannistha.maiti@deepkapha.com

This manuscript is a post-print of a conference paper (ADIPEC, Abu Dhabi 2025), submitted to EarthArXiv. This is the pre-publsihed version of the manuscript. Published version of this manuscript is available in the OnePetro-SPE website under DOI: https://doi.org/10.2118/229423-MS.

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**M Quamer Nasim[1]*, Paresh Nath Singha Roy[1,2], and Tannistha Maiti[3]**

[1]Department of Geology and Geophysics, Indian Institute of Technology, Kharagpur, West Bengal, India
[2]Deysarkar Centre of Excellence in Petroleum Engineering, Indian Institute of Technology, Kharagpur, West Bengal, India
[3]Deepkapha AI Research Lab, The Netherlands

## Abstract

Traditional geophysical workflows like reservoir characterization are driven in a collaborative manner where teams of geoscientists share their individual analyses to inform key decisions made by executives. However, these workflows are repetitive, time-consuming, prone to human error, and introduce subjective bias. While researchers have used automation to address these limitations via deep learning models for specific interpretation tasks, the overall complex workflow remains manual; specialists still select, run, and process model outputs, which proves to be a bottleneck and has the potential to introduce inconsistency and human bias. This paper introduces a novel, agentic AI framework, driven by a Large Language Model, that automates the geological analysis workflow, from initial data discovery to the generation of a final, multi-modal technical report. Our approach mimics the collaborative nature of a human team through a collaborative, event-driven multi-agent system built on a microservice architecture. The system comprises multiple agents, each specializing in a set of tasks. Manager Agent, that initiates the geophysical workflow, a suite of specialized worker agents (Data Finder Agent, Geological Analysis Agent, Reporting Agent) that perform discrete tasks, and a shared workspace that facilitates communication between different agents to allow for collaboration. To validate this framework, we present a case study of an end-to-end lithology analysis on data from the Athabasca oil sands area. The proposed framework successfully took a geoscientist's query, autonomously located the correct well data, executed the lithology analysis model, and generated a multi-modal technical report. We conclude that this agentic approach represents a promising framework for efficient and autonomous scientific workflows in the geosciences.

## Introduction

In the energy industry, reservoir characterization and related workflows, such as geological model building, reservoir evaluation, and production decisions, are primarily driven by collaboration. A team of geoscientists, each specializing in a specific area, such as geology, petrophysics, and geophysics, comes together in a collaborative workspace to share their analyses, interpretations, and discoveries. This collective information is then presented to a central decision-maker, who may be a team leader, project manager, or executive. Based on this collective information accumulated via multiple geoscientists and specialists, these decision-makers tackle several critical questions, such as whether a survey should be conducted in a particular area, whether an exploratory well should be drilled, whether a production well should be drilled, appropriate times to increase or decrease production levels, etc. All of these decisions are made within a collaborative workspace, allowing each specialist to contribute their insights before arriving at a final conclusion. These workflows are standard within the industry and tend to be repetitive. However, the issue with these existing standard approaches is that it is very time-consuming, susceptible to errors, and influenced by human bias and subjectivity. Each specialist, while interpreting data and presenting their findings, inevitably introduces their own subjective biases, which can lead to inconsistencies in the final integrated analysis.

In recent years, the issues of subjectivity and human bias have been addressed through the development of autonomous machine learning (ML) and deep learning (DL) models. These models replicate specialized tasks of interpretation by integrating knowledge from various specialists in the form of labels and learning task representations directly from the data. As a result, a variety of sophisticated ML models now exist for different tasks, including facies analysis (Nasim et al., 2022), lithology identification (Bressan et al., 2020), porosity estimation (Sun et al., 2024), permeability estimation (Mahdy et al., 2024), water saturation estimation (Zhang et al., 2019), structural analysis (e.g., fracture and bed identification) (Nasim et al., 2024d, 2025b, 2025a), vug identification (Nasim et al., 2024c, 2025c), and well-to-well correlation (Ali et al., 2021; Karimi et al., 2021; Wang et al., 2024). These tools have been proven effective at reducing human bias within their narrow domains. Despite the extensive research in the use of these ML and DL models to minimize human bias and expedite interpretation time, the overall process remains largely manual and hence inefficient. These powerful ML models typically exist in isolated environments. Specialists must still prepare the data, determine which model to employ, execute the analysis, and process the output. Specialists may also resort to traditional workflows if a suitable ML model is not available or if they lack confidence in the predictions generated by these models. Consequently, the output from ML/DL models or conventional workflows is still scrutinized by individual specialists, who perform quality control steps and prepare final findings in the form of a multi-modal technical report before presenting to a central team. This ongoing reliance on manual work continues to pose challenges, as it remains time-consuming and contributes to potential human bias and error. This manual process, apart from existing risks of error and time delays, also fails to solve the larger challenge of creating a truly integrated and autonomous analytical pipeline.

Much like how with the rise of AI in the early 2010s, most of the individual tasks were automated with the help of specialized ML/DL models, with the rise of Large Language Models (LLMs) in the early 2020s, there has been an introduction to a new kind of autonomous workflow, an agentic workflow. An agentic workflow comprises multiple agents equipped with diverse tools to execute a set of tasks. These frameworks excel in settings where the workflow is well-defined, thus encouraging autonomy. We propose a novel approach that integrates these ML/DL models and LLMs into a collaborative space, where each model can autonomously perform their individual task, report findings to agents, and ultimately generate a comprehensive multi-modal technical report.

In this paper, we introduce a novel, collaborative, multi-agent framework that is event-driven in its execution and designed to automate an entire geological analysis workflow. This framework spans the full process—from initial data discovery to model selection, execution of analysis, interpretation of results, and generation of a comprehensive, multi-modal technical report. Automating repetitive, data-intensive tasks enables geoscientists to move beyond manual data management and focus on high-level analysis, result validation, and critical decision-making. Built to mirror traditional collaborative practices among industry specialists, our approach employs an event-driven, signal-based workflow where autonomous agents operate within a shared collaborative workspace. Each agent completes its assigned task, presents its findings, and updates the event manager to trigger subsequent actions. This LLM-based agentic framework not only accelerates discovery and enhances the consistency and reliability of subsurface characterization but is also designed to be scalable and adaptable for various industry workflows. While the concept of a fully automated, collaborative, event-driven multi-agent system is inherently complex, this study focuses on a pilot implementation specifically for geological analysis, laying the groundwork for future expansion to broader analytical workflows within the industry.

## Multi-Agent Workflow for Collaborative Geoscientific Interpretation

To address the challenges of manual, disjointed geoscience workflows, we propose a collaborative multi-agent framework for geological analysis that mirrors the traditional collaborative processes among industry specialists. This collaborative approach utilizes an event-driven, signal-based workflow, where each autonomous agent functions within a shared collaborative workspace. Upon completing its task and presenting findings, an agent notifies the event manager of its current progress, which enables all other agents to communicate with each other effectively. Building on this, we have developed a collaborative, event-driven agentic workflow driven by LLMs for geological analysis, with the potential to be extended to other industrial workflows. Considering the complexity of automating industry-wide processes through a multi-agent framework, this study limits its scope of research and focuses only on implementing a pilot workflow specifically designed for geological analysis. Importantly, the proposed framework is structured to remain expandable, thereby facilitating its future extension to encompass a broader range of analytical workflows within the industry.

### A Microservice Approach

To develop such an extendable workflow capable of accommodating more complex analysis processes, we adopted the microservices concept from computer science. A microservice is a small, independent, self-contained workflow that operates within its own environment and specializes in a specific task, remaining isolated from other tasks (Di Francesco et al., 2017). This approach facilitates the isolation of each workflow component, making it easier to expand the workflow at a later stage, making the framework future-proof. When new specialized agents or models need to be introduced, the researchers can create a new workflow in a separate environment and seamlessly integrate it with the central manager of the overall workflow. Consequently, we employed this microservice architecture to construct a multi-agent, multi-modal, collaborative, event-driven geophysical AI workflow designed for geological analysis. This workflow comprises several microservices, each dedicated to its own specific task. Figure 1 shows the overall workflow for the proposed framework specific to the pilot study, if lithological analysis is used using a multi-agentic approach. In Figure 1, the workflow begins with the geoscientist's query to the agent (1), which the Manager Agent interprets to create a mission objective and finally publishes it to the central Collaborative Workspace (2). This event triggers all specialist agents to listen (3, 7, 11). While all the agents get triggered by this event, only the Data Finder Agent starts its process, while the remaining agents remain idle as they have all decided that they cannot contribute at this stage. On the other hand, the Data Finder agent recognizes the need for a data file on which other agents can act upon, queries the Data IO Service (4) and receives the collects the file ID from the database (5), which it then publishes back to the shared workspace (6). This triggers a new event, which ultimately activates the Lithology Agent (7), whereas the Reporting agent still sits idle as it has decided that it cannot contribute to the mission without the actual result presented by any model. The Lithology Agent, after analyzing the current state of the workspace and the mission objective, calls the Lithology Model Service as a tool (8) to perform its analysis. This tool is called only after Lithology Agent concludes that there is a need for lithology determination based on the geoscientist's query and mission objective. After receiving the findings (9), the agent understands the lithology tool result, summarizes it if necessary, and finally publishes its analysis again to the same shared workspace (10). This final event triggers the Reporting Agent (11), which synthesizes all available information to generate a comprehensive technical multi-modal report (12) and publishes the final document back to the workspace. The findings are then passed to the Manager Agent (13), which generates the final report (14) and delivers it back to the geoscientist (15), completing the autonomous workflow.

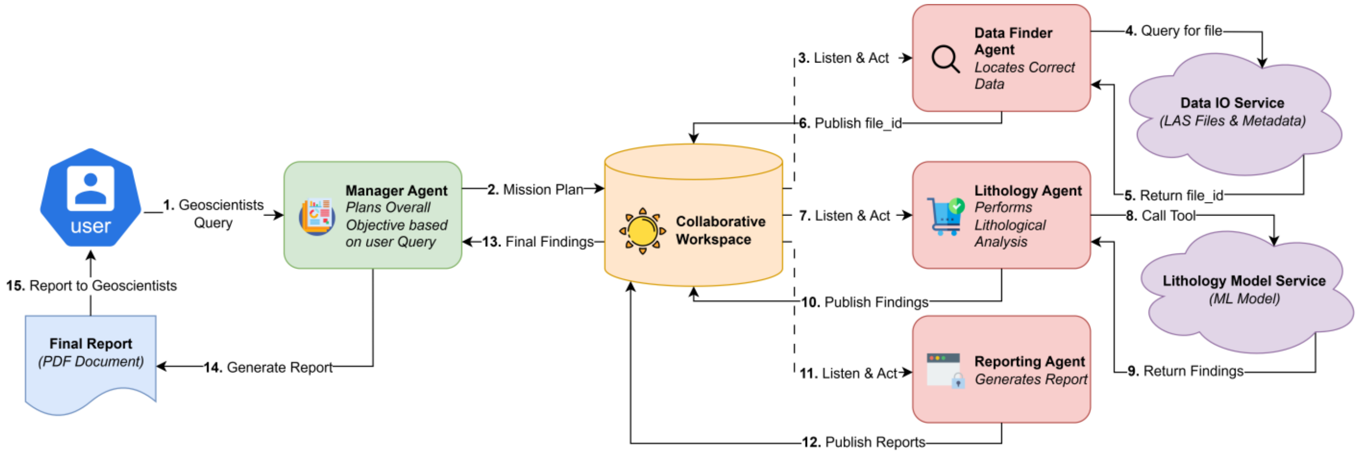


**Fig. 1—The overall architecture of the proposed collaborative event-driven multi-agent workflow for geophysical interpretation.**

The first microservice is the data-io service, designed for specialists to upload, download, and search for data that will be utilized in the agent-based workflow of this study. Currently, this service accepts only one type of data: LAS files, as we are focusing exclusively on geological analysis derived from wireline logs. The data-io service offers features such as data uploading, listing all available data, filtering data by metadata, and downloading data.

Another microservice within our framework is the model service. There can be as many model services as possible, depending on the workflow the researcher wants to automate. However, for the purposes of this study, we have selected a single model service, the Lithology model, developed by Nasim et al., 2024a in their ARViT paper, to serve as the focus of our pilot study on a multi-agent workflow.

The main task of the lithology model microservice includes getting the file ID from the user, downloading the relevant data through the data IO microservice, executing the lithology model, and ultimately generating the technical report for the predicted lithology. In the proposed multi-agent workflow, the integration of these two microservices will be instrumental in enhancing operational efficiency and facilitating inter-agent communication.

File Meta Data


```
{
    "id": "7a879e1b-8995-46e6-882e-245165ca367b",
    "original_filename": "00-01-27-080-14W4-0.LAS",
    "stored_filename": "72833e20_69371b13_00-01-27-080-14W4-0.LAS",
    "file_extension": "las",
    "file_size": 65153,
    "content_type": "application/octet-stream",
    "bucket_name": "geoai-dataio-bucket",
    "file_hash": "72833e2042b7030a68db5f04181a8898e832543044987a7d3ff6305e81301cb1",
    "upload_timestamp": "2025-07-14T09:10:25.734817",
    "description": """
        This is a las file for well identifier 00-01-27-080-14W4-0. It contains logs mainly logs such as GR, NPHI, DPHI, VSH,
        ILD. It can be used for lithology identification, porosity estimation, waster saturation estimation, petro physical
        property estimation, reservoir charachterization, etc etc. The main model that will utilize it is ARViT model
        """,
    "tags": ["lithology", "porosity", "water saturation", "wireline log", "00-01-27-080-14W4-0", "gr", "nphi", "dphi",
             "ild", "arvit"],
    "is_active": true
}
```


**Fig. 2—Sample File Metadata from the Data IO Service.**

### Collaborative Workspace and Event-Driven Communication

The key to enabling collaboration between the autonomous agents is a central Collaborative Workspace built on an event-driven communication pattern. This collaborative workspace serves as a centralized hub for all information related to the mission initiated by the agents. When an agent performs a significant action—such as finding a data file or completing an analysis—it updates the mission's state in the shared workspace and then broadcasts a simple notification to a shared communication channel. This event acts as a signal, prompting all other agents in the system to re-read the workspace and evaluate if the new information is sufficient for them to begin their own tasks. If the current state of the shared workspace doesn't have sufficient information for a particular agent, that agent remains idle, awaiting the necessary information to initiate the work. This notification broadcasting pattern decouples the agents, allowing them to react independently to the evolving state of the shared workspace rather than waiting for direct commands from a central controller.

**Mission Details**

```
mission_payload:
{
    "query": "Perform lithological analysis on well...",
    "file_id": None,
    "user_id": "default_user"
}
```

```
mission_objective:
    "Conduct a comprehensive lithological analysis of the well identified as 00-01-27-080-14W4-0."
status: "IN PROGRESS"
```

**Fig. 3—Initial State of the Collaborative Workspace.**

## The Specialist Agents

The proposed multi-agent workflow for geological analysis consists of four primary agents: the manager agent, the data finder agent, the geological analysis agent, and the reporting agent. Each of these agents is designed following the existing microservice architecture, allowing for the easy and hassle-free addition of new agents to the workflow with minimal disruption.

```
DataFinderAgent is online and listening...
DATA_FINDER_AGENT: New mission. Searching for file_id for session s_9dedaf76.
  > Entering new AgentExecutor chain...
    Attempt 1: Searching with filename and tags.
    {
        "action": "specific_file_search",
        "action_input": {"filename_pattern": "00-01-27-080-14W4-0", "file_extension": "LAS",
                         "tags": ["lithological analysis", "well log"]}
    }
    INFO - 🔎 Searching files
    No files found matching the specific criteria.
    Attempt 2: Broadening search to filename and file extension only.
    {
        "action": "specific_file_search",
        "action_input": {"filename_pattern": "00-01-27-080-14W4-0", "file_extension": "LAS"}
    }
    INFO - 🔎 Searching files
    SUCCESS: [{'id': '7a879e1b-8995-46e6-882e-245165ca367b', ...}]
  > Finished chain.
DATA_FINDER_AGENT: Found and published file_id '7a879e1b-8995-46e6-882e-245165ca367b' for session s_9dedaf76.
DATA_FINDER_AGENT: Re-publishing notification for session s_9dedaf76.
```

**Fig. 4—Execution Trace of the Data Finder Agent.**

### *The Manager Agent*

The manager agent serves as the main entry point for the proposed agentic workflow. The primary responsibility of manager agents is to develop a detailed workflow plan in response to user queries and finally publish this plan to a centralized collaborative repository. Upon receipt of a user query, the manager agent processes the query by an LLM, which translates the user query into a detailed mission plan. This mission plan outlines the necessary steps to fulfill the analysis as specified by the user. The manager agent has access to a specialist agent, tools, and models, enabling it to formulate an effective plan that meets the specified requirements. In situations where information is inadequate, the manager agent will proactively seek clarification to ensure that the mission statement is comprehensive. Once the mission statement is finalized, it is published to a collaborative workspace, officially initiating the mission.

### *The Data Finder Agent*

This agent's sole purpose is to resolve the data requirements of the mission. It is triggered by the initial publication of the mission plan. It parses the user's query for any hints about the data (e.g., well name, location, file name patterns, file format) and uses these hints to search the metadata within the Data IO Service. Once it identifies the correct file, it publishes the unique file ID to the shared workspace. This action creates the next critical event, signalling that the required data has been located, which in turn enables other specialist agents to promptly take action as per their defined scope.

**Findings (Event Log)**

**Finding ID:** f_583205
**Source Agent:** DataFinderAgent
**Type:** file_id_resolved
**Content:**

```
{
    "file_id": "7a879e1b-8995-46e6-882e-245165ca367b"
}
```

**Fig. 5—Updated Collaborative Workspace with Data Finder Agent's Finding.**

### *The Analysis Agent*

This is an agent responsible for performing scientific analysis. It remains idle until a file ID is published in the workspace. It utilizes the user query along with the resolved file ID from the Data Finder agent to initiate its analysis. Upon activation, it first examines the user query and mission statement, assesses the available tools in its environment, and determines whether it can contribute to advancing the mission. If the user requests a completely different analysis unrelated to the scope of the analysis agent, the agent will then refrain from running the specialised model. However, if it possesses a suitable tool (e.g., a specific geological or petrophysical model), it uses the file ID to call the corresponding model microservice based on the provided tool. After receiving the raw output from the model, the Analysis Agent processes and summarizes the results. It generates a concise, human-readable summary of the key findings and packages it along with the full, unprocessed model output. This complete finding is then published back to the Collaborative Workspace.

```
LithologyAgent is online and listening...
LITHOLOGY_AGENT: Waiting for DataFinderAgent to resolve file_id for session s_9dedaf76.
LITHOLOGY_AGENT: File ID '7a879e1b-8995-46e6-882e-245165ca367b' found. Starting analysis for session s_9dedaf76.
  > Entering new AgentExecutor chain...
```

**Agent's Internal Monologue (Reasoning):**
Based on the current mission and available tools, I can contribute to the lithological analysis of the well 00-01-27-080-14W4-0 by using the `lithology_model_tool`. This will help identify potential pay zones which is aligned with the mission objective.

```
Action: Tool Call
{
    "action": "lithology_model_tool",
    "action_input": {"file_id": "7a879e1b-8995-46e6-882e-245165ca367b", "session_id": "s_9dedaf76"}
}
```

**Observation: Tool Output & Artifacts**
**AGENT:** Lithology Tool Executed
**LITHOLOGY AGENT:** Saved full result to with key: result:full:s_9dedaf76:e4c9...
**LITHOLOGY AGENT:** Saved CSV blob to with key: result:csv:s_9dedaf76:17b6...

**Summary:** The interval from 400.0 to 402.75 ft is characterized by interbedded coal, shale, and shaly sand... Potential pay zones are the sand units, especially the thicker intervals from 447.5 to 454.75 ft...

```
Action: Final Answer (Structured Output)
{
    "action": "Final Answer",
    "action_input": {
        "payzones": [
            {
                "depth_from": 447.5, "depth_to": 454.75, "notes": "Thick sand unit, potential hydrocarbon zone"
            },
            {
                "depth_from": 456.75, "depth_to": 462.25, "notes": "Thick sand unit, potential hydrocarbon zone"
            },
                ... (11 more entries)
            ],
        "artifacts": { ... }
    }
}
 > Finished chain.
LITHOLOGY_AGENT: Published new finding to session s_9dedaf76.
LITHOLOGY_AGENT: Re-publishing notification for session s_9dedaf76.
```

**Fig. 6—Execution Trace of the Lithology Agent.**

### *The Reporting Agent*

The final agent in the chain is the Reporting Agent, which is responsible for creating the final deliverable. It is activated by the publication of findings from an Analysis Agent. This agent is based on a template tailored for each type of analysis. The template defines the report's structure, sections, and the content to be included. The Reporting Agent iterates through this plan section by section, using the information provided by the Analysis Agent to generate a detailed technical report. The reporting agent is also tasked with compiling tables from the results and the data it has reviewed to provide a comprehensive overview. Once the multi-modal technical report is fully assembled, the agent re-publishes the final report to the shared workspace, signalling the completion of the mission.

**Findings (Event Log)**

**Finding ID:** f_d85f4d
**Source Agent:** LithologyAgent
**Type:** lithological_finding

**Content:**


```
{
    "payzones": [
        {
            "depth_from": 447.5, "depth_to": 454.75,
            "notes": "Thick sand unit, potential hydrocarbon zone"
        },
        ... (12 more entries)
    ],
    "artifacts": {
        "full_result": "result:full:s_9dedaf76:e4c9...",
        "csv_blob": "result:csv:s_9dedaf76:17b6..."
    }
}
```


**Fig. 7—Lithology Agent's Finding in the Collaborative Workspace.**

## Case Study: Lithology Analysis of the Athabasca Oil Sands

To validate the practical application and effectiveness of our proposed multi-agent framework, we conducted a case study focused on one of the most common geological tasks: lithology identification from well logs by Nasim et al., 2024a. This case study demonstrates the system's ability to perform a complete, end-to-end workflow autonomously, from a single user command to the delivery of a final technical report. The study was centered on wireline log data from the Athabasca oil sands area in Alberta, Canada (Wynne et al., 1995; Hein et al., 2000). Several LAS files from different wells in this region were uploaded to the system via the Data IO Service. During this process, relevant metadata, including well identifiers, locations, and descriptive tags such as "lithology," "wireline log," and "arvit", were associated with each file. Figure 2 illustrates the rich metadata structure captured for each file upon upload. In addition to standard file attributes (e.g., id, filename, file_hash), the system records a detailed natural language description and a list of semantic tags. This structured information is critical for the system's autonomous operation, as it allows the Data Finder Agent to perform an efficient semantic search and reason about the file's content and potential uses without needing to access and process the raw data itself. For this specific analysis, we created a Lithology Agent. This agent was equipped with a single tool designed to connect to a Lithology Model Microservice that hosts a pre-trained machine learning model for lithology classification proposed by Nasim et al., 2024a.

The entire workflow was initiated with a single, high-level natural language query sent to the Manager Agent: "*Perform lithological analysis on well with well identifier 00-01-27-080-14W4-0 and create an extensive technical report.*" Upon receiving this query, the system executed operations automatically, with each step being triggered by an event in the Collaborative Workspace.

```
ReportingAgent is listening for tasks...
REPORTING_AGENT: No report required for finding f_583205 in session s_9dedaf76. Skipping report generation.
REPORTING_AGENT: Starting Report Generation for session s_9dedaf76.
    Generating section: '1.0 Objective & Scope'
    Generating section: '2.0 Data & Methodology'
        Generating section: '2.1 Data Sources'
        Generating section: '2.2 Methodology'
    Generating section: '3.0 Results and Interpretation'
        Generating section: '3.1 Geological Summary'
        Generating section: '3.2 Detailed Lithological Log'
        Generating section: '3.3 Hydrocarbon Shows'
    Generating section: '4.0 Conclusions'
Report assembled. Final document available at: file:///tmp/final_report_5e11...md
```

**Fig. 8—Execution Trace of the Reporting Agent.**

**Mission Planning (Manager Agent)**

The Manager Agent generated a mission plan with the objective: "*Conduct a comprehensive lithological analysis of the well identified as 00-01-27-080-14W4-0*". This plan was published to the Collaborative Workspace as shown in Figure 3, creating the initial event. Figure 3 depicts the initial state of the Collaborative Workspace immediately after the Manager Agent has processed a user's request. The agent populates the workspace with two key objects: the mission_payload, containing the original query and noting the file_id is not yet resolved (None), and the mission_objective, which is the agent's formalized plan. The publication of this initial state acts as the first event in the workflow, signalling all other specialist agents to assess the mission and determine if they can contribute.

**Data Discovery (Data Finder Agent)**

The Data Finder Agent detected the new mission. It parsed the query for the well identifier "00-01-27-080-14W4-0" and used it as a search key to query the metadata in the Data IO Service. Figure 4 showcases the agent's autonomous reasoning and error-recovery capabilities. In Attempt 1, the agent constructs a search query using both the filename and the semantic tags derived from the mission objective. When this initial, specific query fails, the agent intelligently adapts its strategy. In Attempt 2, it broadens the search criteria by removing the tags to create a less restrictive query. This second attempt successfully locates the correct file, after which the agent publishes the resolved file ID to the Collaborative Workspace, allowing the overall workflow to proceed. After a few attempts it successfully located the corresponding LAS file and published its unique file ID to the workspace. Figure 5 shows the state of the Collaborative Workspace after the Data Finder Agent has successfully completed its task. A new "finding" object has been appended to the event log. This object contains the resolved file ID required for the analysis. The publication of this finding acts as the next critical event in the workflow, signaling to all listening agents that the data dependency has been met and the mission can proceed to the analysis phase.

**Geological Analysis (Lithology Agent)**

The publication of the file ID triggered the Lithology Agent. It cross-referenced the mission objective with its available tools and confirmed that a lithological analysis was required. It then calls the Lithology Model Service, passing the file ID. The service executed the DL model, which returned a detailed, depth-by-depth lithology prediction (e.g., sandstone, shale, coal). Figure 6 shows the execution trace of this agent. This trace begins after the agent is activated by the file ID published to the workspace. The agent's internal monologue shows its reasoning process, where it determines that the lithology_model_tool is the appropriate tool for the mission. It then executes the tool and processes the output, which includes a narrative summary and references to saved data artifacts. Crucially, the agent distills the analysis into a structured Final Answer, creating a machine-readable list of potential pay zones. This structured finding is then published back to the Collaborative Workspace to be used by subsequent agents.

**Findings (Event Log)**

**Finding ID:** f_e9a1b2
**Source Agent:** ReportingAgent
**Type:** report_generated

**Content:**


```
{
    "report_path": "/tmp/final_report_5e1139c8eabf406eb27298f518afcffb.md",
    "format": "Markdown",
    "summary": "Generated a comprehensive technical report including geological summary, detailed
             lithological log, and analysis of potential payzones.",
    "artifacts": {
        "pdf_version": "report:pdf:s_9dedaf76:final_report.pdf"
    }
}
```


**Fig. 9—Reporting Agent's Final Finding in the Collaborative Workspace.**

The Lithology Agent then summarized these findings—identifying major geological zones and potential hydrocarbon pay zones—and published both the summary and the full raw results back to the workspace. Figure 7 displays the structured findings published by the Lithology Agent after completing its analysis. The content includes a machine-readable list of potential payzones, each with specific depths and notes, and a list of artifacts, which are references to the full raw results and a summary CSV file stored elsewhere. This structured distillation of the analysis is the critical input for the Reporting Agent, providing all the necessary information to begin generating the final technical document.

**1.0 Objective & Scope**

The primary objective of this report is to present a detailed geological analysis of a subsurface interval, based on provided lithological data. This analysis aims to characterize the stratigraphic sequence, identify potential reservoir and source rock intervals, and provide insights into the depositional environment.

The scope of this report includes:
• Detailed listing of lithological units encountered within the analyzed interval.
• Identification of key lithologies, including Coal, Shale, ShalySand, and Sand.
• Reporting the start depth, thickness, and average confidence for each unit.

**2.0 Data & Methodology**

**2.1 Data Sources**

| Data Type | Description |
|---|---|
| Lithological Log | Provides a sequential record of rock types encountered between depths of 400.0 and 472.25. Each entry includes the rock type, start depth, thickness, and a confidence value. |

**2.2 Methodology**

The methodology involved a systematic approach to data processing, lithological unit identification, and confidence assessment.
**2.2.1 Data Acquisition:** The primary data source was a structured lithological log.
**2.2.2 Unit Identification:** Each entry in the log was treated as a discrete lithological unit.
**2.2.3 Confidence Assessment:** Confidence values (0-100) were extracted directly from the provided data.
**2.2.4 Reporting:** The identified units were organized into a structured format for reporting, as presented in Section 3.0.

**3.0 Results and Interpretation**

**3.1 Geological Summary**

The analyzed interval exhibits a complex and highly variable lithological sequence, characterized by interbedded Coal, Shale, ShalySand, and Sand units. The sequence reveals a dynamic depositional environment, interpreted as a coastal plain or deltaic setting. The upper portion (400.0-414.0) is marked by thin Coal seams interbedded with Shale. The middle portion (414.0-447.0) transitions to a more Sand-dominated sequence. The lower portion (447.0-472.25) is characterized by a thick Sand unit, suggesting a period of sustained high-energy deposition.

**3.2 Detailed Lithological Log**

| Start Depth | Thickness | Lithology | Avg. Confidence |
|---|---|---|---|
| 400.0 | 0.5 | Coal | 99 |
| 400.5 | 0.25 | Shale | 99 |
| | | ... | |
| 472.25 | 0.0 | Sand | 88 |

**3.3 Hydrocarbon Shows and Potential Payzones**

The Sand and ShalySand units are the most likely candidates for potential hydrocarbon reservoirs. The interbedded Coal and Shale units could act as potential source rocks and seals.

**Key Potential Payzones:**
• 418.5 - 422.5 depth units
• 447.5 - 462.25 depth units (thick, continuous sand)
• Other thinner sand units...

**4.0 Conclusions & Recommendations**

Based on this lithological analysis, the following recommendations are made:
• Run a comprehensive suite of wireline logs to confirm interpretations.
• Implement continuous mud gas logging to detect hydrocarbon shows.
• Acquire core samples from potential payzones for detailed petrophysical analysis.
• Conduct source rock analysis (TOC, Rock-Eval) on Coal and Shale units.

**Fig. 10—Trimmed sample of an Autonomously Generated Technical Report.**

## Report Generation (Reporting Agent)

The final event, containing the lithology results, activated the Reporting Agent. It selected the appropriate template from its library. Following the template's plan, it sequentially generated each section of the report: it wrote the objective and scope of the report, wrote a summary of the data and methodology, and created detailed tables of the lithological zones from the results. Figure 8 shows the execution trace of the Reporting Agent. This log demonstrates the procedural nature of the agent. Initially, the agent listens and determines that no report is required for the Data Finder Agent's finding. However, once the Lithology Agent publishes its analysis, the Reporting Agent is activated. It then methodically follows a predefined template, generating each section of the technical report in a hierarchical sequence, from the "Objective & Scope" to the final "Conclusions." The final log entry confirms that the report has been successfully assembled and saved, marking the completion of the autonomous workflow. The final, multi-modal report was saved as a PDF and published to the workspace. Figure 9 shows the final entry in the event log for the mission. The Reporting Agent publishes this finding upon successful creation of the technical document. The content provides the path to the generated report file (report_path), a summary of the report's contents, and a reference to the final PDF artifact. This finding officially marks the successful completion of the end-to-end autonomous workflow. Figure 10 presents a trimmed excerpt from the final report generated by the Reporting Agent, showcasing the quality and structure of the end product. It demonstrates the agent's ability to create a coherent and compelling narrative by synthesizing information from the Collaborative Workspace. The agent procedurally constructs the document according to a predefined template, generating distinct sections such as "Objective & Scope," "Data & Methodology," and "Results and Interpretation." Furthermore, it highlights the agent's capability to generate structured elements like data tables (e.g., the "Detailed Lithological Log") directly from the analytical findings, creating a multi-modal comprehensive and professional final technical report.

This case study successfully demonstrated the framework's ability to autonomously orchestrate a complex workflow, with specialist agents collaborating in an event-driven manner to fulfil a user's request without any human intervention after the initial query.

## Discussion

Our case study on the Athabasca oil sands data illustrates the potential of a multi-agent system for streamlining geological analysis. This framework's primary advantage is its role as a powerful "helping hand" for the geoscientist, shifting their focus from repetitive task execution to high-level scientific oversight. The framework's ability to generate a complete, multi-modal technical report from a single natural language query directly impacts ROI by cutting project time and costs, enabling more agile decision-making. Its main benefits are threefold. First, it enforces consistency and reproducibility; the use of declarative templates ensures every report adheres to a standardized structure, while deterministic tools remove the variability inherent in manual data processing, which is critical for comparative studies and auditing. Second, it drives efficiency and accelerates discovery; by automating the end-to-end process, teams can run more scenarios and evaluate more prospects in the same amount of time. This frees senior geoscientists from routine tasks, allowing them to focus on higher-value activities like prospect generation and complex interpretation challenges. Third, the system is built for scalability and future adaptation. The underlying microservice architecture means that a new capability, such as a petrophysics agent, can be developed and integrated as an independent service without disrupting the existing workflow, making the framework robust and easily expandable as new scientific models become available. In this paradigm, the geoscientist remains the key driver; the agentic workflow automates the laborious process, but the critical interpretation and acceptance of results still lie with the human expert.

However, we do acknowledge the limitations of this initial implementation. The current system has only been demonstrated on a single, yet complete, end-to-end geological workflow. Its error handling as of now is basic, creating a risk of cascading failures where an error from an early-stage agent can propagate downstream and invalidate the entire result. Furthermore, in a system with many moving parts, the risk of error propagation is significant. This highlights a current architectural gap: the absence of a dedicated Quality Control (QC) Agent. Without such an agent to perform automated validation checks, the full burden of QC falls on the final human reviewer, partially offsetting the efficiency gains. Future studies can extend the multi-modal nature of technical reports from text and tables to visualizations as well. The modular nature of this architecture provides an easy path for future expansion. Our immediate goals are centered on enhancing the system's intelligence, robustness, and practical applicability by introducing more agents in future studies based on several models for porosity estimation and water saturation estimation for petrophysical agents (Nasim et al., 2024b, 2024a), fractures, beds, and vugs detection for structural analysis agent (Nasim et al., 2024c, 2024d, 2025b, 2025c, 2025a), and finally, well-to-well correlation for the correlation agent (Ali et al., 2021), to eventually automate the end-to-end geophysical workflows at a larger scale.

Another critical next step is the introduction of a Human in the Loop (HTL) capability. We recognize that while many geological workflows are repetitive in structure, the nitty-gritty details of each field, basin, and location are unique. The parameters and nuances associated with each analysis can vary significantly. An HTL system would allow a specialist to intervene at key decision points—for instance, to approve a model's parameters or validate an intermediate interpretation. This is essential for building trust in the autonomous system. These end-to-end agentic workflows are essentially meant to empower geoscientists with powerful, efficient assistants to make more informed and speedy decisions.

## Conclusion

In this study, we have proposed a novel, multi-agent framework for collaborative interpretation that successfully automates a complete, end-to-end geological workflow. By combining the reasoning capabilities of Large Language Models with the reliability of deterministic tools within a decoupled, event-driven architecture, we have demonstrated a system that can interpret a user's request, find the correct data, execute the appropriate analysis, and generate a comprehensive technical report. This agentic approach provides a robust and scalable solution that significantly reduces manual effort and improves the consistency of subsurface analysis. We believe this work serves as a foundational step toward a future of more integrated, efficient, and truly autonomous scientific workflows in the geosciences.

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