DeepAnalyze: Agentic Large Language Models for Autonomous Data Science

Shaolei Zhang ¹ Ju Fan ¹ Meihao Fan ¹ Guoliang Li ² Xiaoyong Du ¹

🕠 ruc-datalab/DeepAnalyze 🔗 DeepAnalyze-8B 📚 DataScience-Instruct-500K 🌐 ruc-deepanalyze.github.io

Abstract

Autonomous data science, from raw data sources to analyst-grade deep research reports, has been a long-standing challenge, and is now becoming feasible with the emergence of powerful large language models (LLMs). Recent workflow-based data agents have shown promising results on specific data tasks but remain fundamentally limited in achieving fully autonomous data science due to their reliance on predefined workflows. In this paper, we introduce *DeepAnalyze-8B*, the first agentic LLM designed for autonomous data science, capable of automatically completing the end-toend pipeline from data sources to analyst-grade deep research reports. To tackle high-complexity data science tasks, we propose a curriculum-based agentic training paradigm that emulates the learning trajectory of human data scientists, enabling LLMs to progressively acquire and integrate multiple capabilities in real-world environments. We also introduce a data-grounded trajectory synthesis framework that constructs high-quality training data. Through agentic training, DeepAnalyze learns to perform a broad spectrum of data tasks, ranging from data question answering and specialized analytical tasks to open-ended data research. Experiments demonstrate that, with only 8B parameters, DeepAnalyze outperforms previous workflow-based agents built on most advanced proprietary LLMs. The model, code, and training data of DeepAnalyze are open-sourced, paving the way toward autonomous data science.

1. Introduction

Autonomous data science (De Bie et al., 2022; Sun et al., 2025b; Wang et al., 2025), a long-standing central goal of the data science community, aims to automate the entire data

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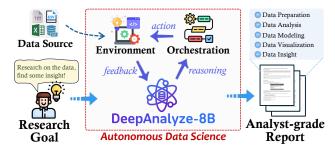


Figure 1. DeepAnalyze-8B is the first end-to-end agentic LLM that achieves autonomous data science, supporting entire data science pipeline and open-ended data research.

science pipeline for extracting insights from structured data. This pipeline is inherently complex, consisting of a series of interdependent data-centric tasks spanning data preparation, analysis, modeling, visualization, and report generation. The emergence of open-ended data research further elevates the level of complexity, going far beyond traditional question answering or task-specific analytics. Fortunately, recent advances in large language models (LLMs) have demonstrated impressive problem-solving abilities (OpenAI, 2023; 2024; DeepSeek-AI, 2025), reshaping paradigms in domains such as search (Zheng et al., 2025; Jin et al., 2025) and mathematics (Zhang et al., 2024; Ren et al., 2025). However, despite their success on unstructured data (e.g., textual queries or contexts), LLMs still struggle to orchestrate complex, multi-stage data science pipelines and handle diverse structured data, making it difficult to achieve a general solution that works across all data science tasks.

Addressing these challenges requires endowing LLMs with two higher-level capabilities: autonomous orchestration and adaptive optimization. First, autonomous orchestration enables LLMs to comprehend user intents and systematically coordinate a sequence of interdependent actions to accomplish complex tasks (Sapkota et al., 2025a). Second, adaptive optimization allows LLMs to interact with real-world data environments and iteratively refine their actions based on feedback (Hong et al., 2024). As shown in Figure 4, equipped with these two capabilities, an intelligent system can robustly handle a broad spectrum of data tasks, ranging from conventional question answering and task-specific analytics to fully autonomous, open-ended data research.

¹Renmin University of China ²Tsinghua University. Email: Shaolei Zhang <zhangshaolei98@ruc.edu.cn>, Ju Fan (corresponding author) <fanj@ruc.edu.cn>.

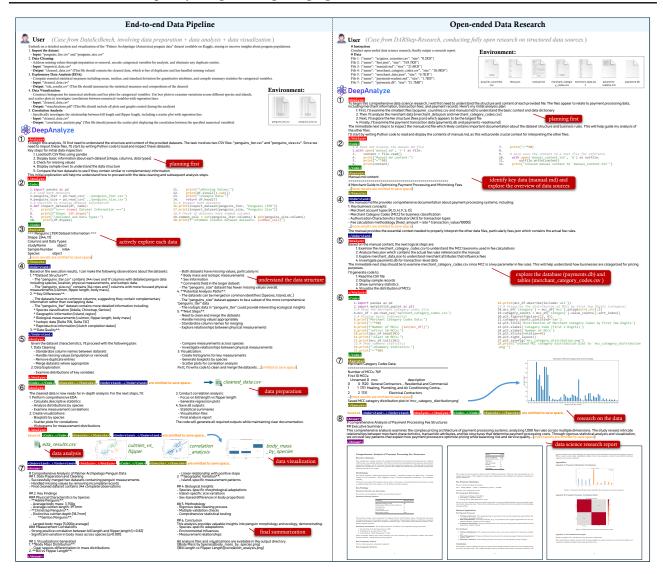


Figure 2. Examples of DeepAnalyze-8B. Given the instructions and data sources in the environment, DeepAnalyze can autonomously orchestrate and optimize actions to complete a data science pipeline (left) and open-ended data research (right). DeepAnalyze first performs planning, then interacts with the data in the environment, and subsequently optimizes its actions based on feedback, ultimately accomplishing the data-centric tasks. Many intermediate actions are omitted to save space.

Existing approaches to applying LLMs for autonomous data science can be broadly categorized into *domain-specific LLMs* and *workflow-based agents*. Early efforts focus on developing domain-specific LLMs, such as code-oriented models (Nascimento et al., 2024; Wen et al., 2024) and structured data-oriented models (Li et al., 2023b; Jiang et al., 2023; Xu et al., 2025), to handle individual tasks like question answering or specific analytical operations. However, these models lack the capabilities for autonomous orchestration and adaptive optimization (Yang et al., 2021; Li et al., 2023a), limiting their ability to execute the entire data science pipeline. More recently, a line of work has explored workflow-based data science agents (Hollmann et al., 2023; Guo et al., 2024; Sun et al., 2025a; Hong et al., 2025),

which rely on predefined procedural workflows to prompt closed-source LLMs (e.g., GPT-4 (OpenAI, 2023)) to complete complex tasks. Although these systems demonstrate stronger task coordination, they depend heavily on manually designed heuristics and domain-specific rules, falling short of achieving autonomous and adaptive behavior.

In essence, both domain-specific models and workflow-based agents remain limited, as they are not trained in interactive, real-world environments. Consequently, they struggle to perform complex tasks through autonomous orchestration and adaptive optimization. Notably, recent advances in agentic training, a new training paradigm successfully applied in the search domain (Zheng et al., 2025; Jin et al., 2025), have demonstrated that reinforcement learning in

real-world environments is crucial for enabling LLMs to develop autonomous problem-solving capabilities.

In this paper, we aim to advance LLM-based data science methods from workflow-based agents to a trainable agentic model that learns to autonomously perform data science tasks in real-world environments. However, applying agentic training to this domain presents two key challenges: reward sparsity and trajectory scarcity. On the one hand, the inherent complexity of data science tasks makes it difficult for foundation LLMs to complete tasks successfully during the early stages of training. This leads to severe reward sparsity, i.e., a lack of positive reinforcement signals, which can hinder or even collapse the entire agentic training process. On the other hand, the scarcity of longchain problem-solving trajectories in data science provides insufficient guidance for LLMs to explore the solution space effectively, resulting in inefficient, blind trial-and-error exploration without meaningful intermediate supervision.

To address these challenges, we introduce DeepAnalyze, an agentic LLM designed for autonomous data science. As illustrated in Figure 2, with only 8B parameters, DeepAnalyze can automate the entire data science pipeline, ranging from specific data tasks to open-ended data research, providing a unified and general solution for data-centric applications. Specifically, to mitigate reward sparsity, DeepAnalyze adopts a curriculum-based agentic training paradigm inspired by the learning trajectory of human data scientists. This progressive easy-to-difficult schedule enables the model to gradually evolve from mastering individual skills to developing comprehensive, adaptive problem-solving abilities in real-world environments. To address trajectory scarcity, we propose a data-grounded trajectory synthesis framework that automatically constructs high-quality reasoning and interaction trajectories, offering effective exploration guidance within the large solution space. Through this combination of curriculum-based training and trajectory synthesis, DeepAnalyze learns to autonomously orchestrate actions and adaptively optimize its strategies, enabling it to tackle complex and diverse data science tasks effectively.

In summary, our key contributions are three-fold.

- Agentic Model: To the best of our knowledge, Deep-Analyze is the first agentic LLM tailored for autonomous data science, endowed with two indispensable capabilities, autonomous orchestration and adaptive optimization. DeepAnalyze serves as a foundation model that can be directly applied or further customized through prompting or supervised fine-tuning for specific scenarios.
- Agentic Training: We propose a curriculum-based agentic training paradigm with data-grounded trajectory synthesis to address reward sparsity and trajectory scarcity, enabling effective learning for high-complexity tasks that require multiple abilities.

Strong Performance: Experimental results on 12 benchmarks show that, with only 8B parameters, DeepAnalyze-8B surpasses most advanced proprietary LLMs. More importantly, it is the first agentic model capable of performing open-ended data research and generating analyst-grade reports.

2. Related Work

Autonomous Data Science. Autonomous data science has long been pursued as an important goal of intelligent systems. Existing LLM-based data science methods can be categorized into: domain-specific LLMs and workflow-based agents. To handle individual tasks in data science, early methods focused on fine-tuning LLMs into domain-specific models, including LLMs for data science code generation (Nascimento et al., 2024; Wen et al., 2024; Nejjar et al., 2024; Pan et al., 2025), tabular LLMs (Li et al., 2023b; Fang et al., 2024; Zhang et al., 2025c; Xu et al., 2025; Ouyang et al., 2025; Lei et al., 2025), and database-oriented LLMs (Xue et al., 2024; Liu et al., 2024; Mohammadjafari et al., 2025). Recently, an increasing number of data agents have demonstrated promising performance in data science by leveraging workflows to gradually prompt LLMs for complex tasks (Hollmann et al., 2023; Guo et al., 2024; Yang et al., 2024; Sun et al., 2025a; Hong et al., 2025). Most existing agents are built upon Chain-of-Thought frameworks, including ReAct (Yao et al., 2023), AutoGen (Wu et al., 2024), and self-reflection (Pan et al., 2023), which decompose complex tasks into multiple subtasks and solve them sequentially. Regardless of workflow design, existing agents primarily rely on carefully crafted prompting to guide closed-source LLMs in performing data science tasks.

Despite these advances, domain-specific LLMs (focused on individual tasks) and workflow-based agents (dependent on manually designed workflows) remain incapable of fully autonomous data science. Therefore, the proposed DeepAnalyze does not rely on prompting frameworks or predefined workflows, instead, it internalizes data science capabilities through agentic training within real-world environments.

Agentic Training for LLM. Agentic training aims to enhance LLMs as agentic models through reinforcement learning and thereby enable LLMs to perform multi-step reasoning and interactions in real-world environments (Plaat et al., 2025), which has already achieved practical success in coding (Sapkota et al., 2025b) and searching (Zheng et al., 2025; Li et al., 2025; Jin et al., 2025). Typically, these methods use prompts to control the interaction format of LLMs and complete RL with the accuracy of the final answer as the reward. Based on this, lightweight cold-start is proposed to help LLMs learn the interaction format (DeepSeek-AI, 2025), improving the initial state for RL training. Existing training methods mainly focus on reasoning ability, while

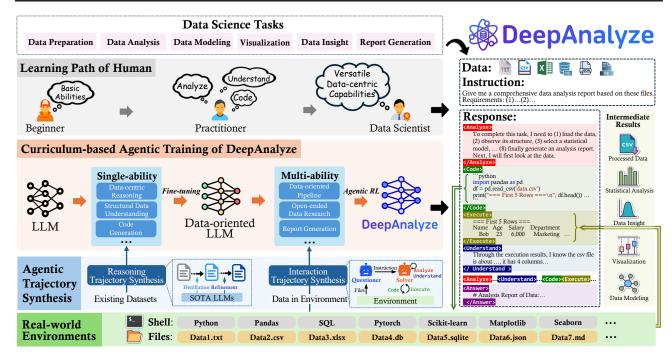


Figure 3. Architecture of DeepAnalyze.

data science requires a broader range of abilities, such as reasoning, structured data understanding, and code generation. This complexity makes that initial LLMs (even after cold-start format learning) are generally incapable of completing complex data science tasks, leading to challanges of reward sparsity and trajectory scarcity. To this end, we propose a curriculum-based agentic training that enables LLMs to gradually acquire complex data science skills through a progression from single to multiple abilities, while employing data-grounded trajectory synthesis to generate high-quality reasoning and interaction trajectories for training.

3. DeepAnalyze

In this paper, we introduce DeepAnalyze, an agentic large language model for autonomous data science. To endow the LLM with the capability for autonomous orchestration and adaptive optimization in real-world environments, we propose a curriculum-based agentic training and data-grounded trajectory synthesis framework tailored for complex tasks with multiple abilities. Specifically, inspired by the behavior of human data scientists, we first define a set of actions that enable DeepAnalyze to directly interact with the data in its environment. Building on this architecture, we automatically synthesize high-quality data science trajectories and introduce a curriculum-based agentic training paradigm that guides DeepAnalyze through a progression from a beginner to data scientist, thereby empowering DeepAnalyze to tackle a wide spectrum of data science tasks. The architecture, curriculum-based agentic training, and data-grounded

trajectory synthesis are introduced as follows.

3.1. Architecture

Unlike foundation LLMs that focus on understanding and generating natural language, LLMs for data science meet the additional challenge of understanding and interaction with structured data, which is typically stored in external files. Therefore, DeepAnalyze extends natural language interaction by introducing data-oriented interaction pattern, thereby enabling LLMs to autonomously interact with real-world environments.

Inputs Format. Previous structured data–specific LLMs (Li et al., 2023b; Fang et al., 2024; Zhang et al., 2025c; Xu et al., 2025; Lei et al., 2025) often converted tables stored in databases, CSV, or XLSX files into unstructured Markdown text and fed them into the LLM's context to enable structured data understanding. However, due to context length limitations, these methods can only handle small-scale data (e.g., very small tables). When human data scientists work with large-scale data, they do not passively read and memorize every record. Instead, they actively explore each data source as needed and then plan the following steps accordingly. To this end, DeepAnalyze integrates both modes: it passively accepts structured data expressed as text in the input, while also actively inspecting external data sources according to user inputs, where the filenames of the external data sources are specified in inputs, as shown in Figure 2.

Interaction Pattern. Given an instruction and the data sources in the environment, data scientists typically analyze,

Algorithm 1 Inference of DeepAnalyze 1: **Input:** Instruction Q, Environment Env, DeepAnalyze model 2: Output: Response A (with interaction process) Initialization: $A = \emptyset$ 4: while $\langle Answer \rangle \cdots \langle Answer \rangle$ not in A do $y \leftarrow \overline{\mathcal{M}(Q, A)}$ // generate next action based on the instruction Q and current response A6: $A \leftarrow A + y$ 7: if $|\langle \text{Code} \rangle| \cdots |\langle \text{Code} \rangle|$ in y then 8: $code \leftarrow extract_code(y)$ 9: $feedback \leftarrow Env.$ execute(code) // interaction with the data in the environment 10: $A \leftarrow A + \langle \text{Execute} \rangle + feedback +$ ⟨/Execute⟩ 11: end if 12: end while 13: Return A

interact with the data in the environment, understand structured data, and iterate until the instruction is completed. To emulate this process, DeepAnalyze introduces five actions to automatically accomplish the data science task, including:

- (Analyze) · · · (/Analyze): Analyze textually, including planning, reasoning, reflection, self-verification...
- (Understand) · · · (/Understand): Understand the content of data source, such as databases, tables, and documents.
- <u>(Code)</u> · · · <u>(/Code)</u>: Generate code to interact with the data in the environment, using Python suited for data science.
- (Execute) · · · (/Execute): Execute code and collect the feed-back from the environment.
- \(\langle Answer \rangle \cdot \cdot \langle Answer \rangle \): Produce the final output.

In practice, we extend the vocabulary of the foundation LLM to support the generation of these special tokens. During the inference, DeepAnalyze automatically switches between different actions by generating these special tokens, as shown in the right side of Figure 3. In particular, once a \(\lambda \text{Code} \rangle \cdot \cdot \lambda \text{Code} \rangle \cdot \cdot \cdot \cdot \lambda \text{Code} \rangle \cdot \cdot

3.2. Curriculum-based Agentic Training

Under the above architecture, DeepAnalyze need to learn how to interact with the environment to accomplish various data science tasks. Unlike individual coding or searching task, data science tasks demand a broader and more complex set of abilities, ranging from reasoning, structured data understanding, and code generation to the composite abili-

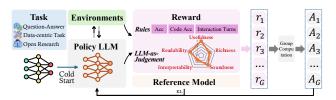
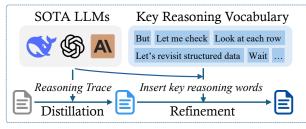


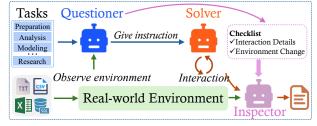
Figure 4. Schematic diagram of agentic RL.

ties needed for entire data science pipeline and open-ended research. The complexity of these capabilities results in the limited proficiency of foundation LLMs in data science domains (Zhang et al., 2025b), leading to severe reward sparsity on complex tasks and rendering existing agentic training (such as RL-Zero or RL with cold-start training (DeepSeek-AI, 2025)) ineffective due to the lack of positive feedback. To address this challenge, we propose curriculumbased agentic training, which emulates the learning path of human data scientists by gradually transitioning from mastering single abilities to integrating multiple abilities. This training framework consists of two stages, where stage 1 employs single-ability fine-tuning to strengthen the foundation LLM's single ability, and stage 2 uses multi-ability agentic training to enable the LLM to apply multiple abilities in real-world environments to accomplish complex data science tasks.

Single-ability Fine-tuning. Since most foundation LLMs have not been trained specifically for data science tasks, in this stage, we first enhance the various single abilities that data science relies, primarily including reasoning, structured data understanding, and code generation, which correspond respectively to the actions $\langle \text{Analyze} \rangle$, $\langle \text{Understand} \rangle$, and $\langle \text{Code} \rangle$. Specifically, we fine-tune the foundation LLM using long CoT data (i.e., including reasoning traces) of general tasks, structured data understanding, code generation. This stage of training mirrors the human learning process from a beginner to a data science practitioner in acquiring specialized skills, enhancing LLM's single ability in various aspects of data science.

Multi-ability Agentic Training. Building on the mastery of various single abilities, we employ agentic reinforcement learning to train DeepAnalyze to apply multiple abilities in real-world environments to complete complex data science tasks. To ensure the quality of reinforcement learning, we first perform a cold start by fine-tuning the LLM on synthesized interaction trajectories, enabling it to acquire basic capabilities in orchestrating and optimizing individual actions. Subsequently, we train DeepAnalyze in real-world environments using reinforcement learning with group relative policy optimization (GRPO) (Shao et al., 2024). For each question q in training data D, GRPO samples a group of G outputs $\{o_1, \dots, o_G\}$ from the old policy $\pi_{\theta_{\text{old}}}$ and then optimizes the policy model π_{θ} by maximizing the fol-





(a) Reasoning Trajectory Synthesis

(b) Interaction Trajectory Synthesis

Figure 5. The proposed data-grounded trajectory synthesis for the development of DeepAnalyze on data science tasks.

lowing objective:

$$\mathcal{J}_{GRPO}(\theta) = \mathbb{E}_{q \sim D, \{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(\cdot | q)} \left[\frac{1}{G} \sum_{i=1}^G \left(\min \left(\frac{\pi_{\theta}(o_i | q)}{\pi_{\theta_{\text{old}}}(o_i | q)} A_i, \operatorname{clip} \left(\frac{\pi_{\theta}(o_i | q)}{\pi_{\theta_{\text{old}}}(o_i | q)}, 1 - \varepsilon, 1 + \varepsilon \right) A_i \right) \right] -\beta D_{KL} \left(\pi_{\theta} \parallel \pi_{\text{ref}} \right) \right]$$

where A_i is the advantage calculated from the rewards $\{r_1, \dots, r_G\}$ of outputs within each group, π_{ref} is the reference model, ε and β are hyperparameters.

Hybrid Reward Modeling. The effectiveness of agentic reinforcement learning critically depends on both the training data and the reward function. We use the agentic interaction trajectories synthesized in Section 3.3 as training data, covering three broad categories of data science tasks: data question answering, specific data tasks (e.g., data preparation, analysis, visualization, modeling, and insight extraction), and open-ended research. Since many data science tasks are inherently open-ended, we adopt a hybrid reward modeling that combines rule-based rewards with LLM-as-a-judge rewards. For all tasks, we first check whether the output format conforms to DeepAnalyze's architecture (i.e., whether it contains exactly five types of actions with the correct format). If the format is incorrect, we directly assign a reward of R=-1.

For data question answering and data-centric tasks, which have reference answers, the reward R of each output o are calculated using accuracy and interaction trajectory quality:

$$R = \frac{1}{2} (\mathbb{1}_{acc}(o) + S_{interaction}(o))$$
 (2)

where $\mathbb{1}_{acc}(o) \in \{0,1\}$ indicates whether the result is correct, and $S_{interaction}(o) \in [0,1]$ is a score to evaluate the quality of the interaction trajectory.

For open-ended research, the reward R of each output o is evaluated based on the quality of the final research report and the research process. Denoting each interaction turn in

output o as $T_i \in o$, the reward R is calculate as:

$$R = \frac{1}{3} \left(S_{report}(o) + \min(\frac{|T|}{N^T}, 1) + \frac{1}{|T|} \sum_{T_i \in o} \mathbb{1}_{success}(T_i) \right)$$
(3)

where $S_{report}(o)$ is the score that evaluates the generated report from five aspects: usefulness, richness, soundness, interpretability, and readability. |T| measures the interaction turns with the environment, where $N^T=10$ is a hyperparameter. $\mathbbm{1}_{success}(T_i)$ indicates whether each interaction turn is successful. This reward encourages DeepAnalyze to engage in more successful interactions with the environment and to generate high-quality research report.

Through curriculum-based agentic training, we progressively enhances DeepAnalyze's capabilities following an easy-to-hard schedule, ultimately enabling it to autonomously accomplish a variety of data science tasks in real-world environments.

3.3. Data-grounded Trajectory Synthesis

The proposed curriculum-based agentic training relies on high-quality reasoning and interaction trajectory data, while such data is unfortunately scarce for data science tasks. To overcome this challange, we introduce a data-grounded trajectory synthesis framework that automatically constructs high-quality trajectory data tailored for data science tasks. The data-grounded trajectory synthesis framework consists of two parts: *Reasoning Trajectory Synthesis*, which construct the reasoning trajectory for existing structured data instruction datasets, and *Interaction Trajectory Synthesis*, which constructs entire data science trajectory based on structured data sources in the environment.

Reasoning Trajectory Synthesis. Existing instruction datasets for structured data, such as TableQA (Li et al., 2023b; Lei et al., 2025), structured knowledge grounding (Zhuang et al., 2024), and data science code generation, is useful to improve LLM's single capability. However, these datasets typically contain only instructions and responses, without the reasoning process. To address this limitation,

Coarse-grained			Fine-grained Metrics						
Models	Success Rate	Completion Rate	VLM	F1: Data Preparation	F2: Plot Validity	F3: Data Exploration	F4: Data Visualization	F5: Data Modeling	Score
			Close-So	urce API-Based	Agent				
o1-mini	29.77	45.26	2.87	44.63	19.27	36.01	30.94	23.81	38.78
GPT-40-mini	50.63	57.78	3.05	60.30	48.02	57.84	59.24	53.54	54.18
GPT-40	66.31	68.44	3.91	75.93	56.14	69.33	71.35	57.67	64.51
GPT-4-Turbo	51.93	58.87	3.09	62.30	41.62	57.75	60.25	50.75	54.65
Claude-3-5-Sonnet	47.48	58.11	2.14	49.07	36.94	55.84	52.87	46.04	52.29
GLM-4-Flash	30.32	34.04	1.33	36.53	29.42	32.57	27.64	14.44	30.74
			Open-Soi	urce LLM-based	Agent				
Llama-3.1-8B-Instruct	24.73	33.89	1.29	38.24	18.25	21.98	22.89	25.85	29.69
Gemma-2-9B-it	7.07	11.00	1.06	26.16	16.90	23.81	18.11	17.15	12.66
GLM-4-9B-Chat	25.72	30.38	1.69	31.51	23.15	28.07	27.19	19.14	27.57
Qwen2.5-7B-Instruct	43.83	50.74	1.43	51.18	36.41	47.25	45.24	34.77	45.99
Qwen2-7B-Instruct	22.84	25.58	1.16	30.93	20.78	28.73	25.87	7.52	23.52
Yi-1.5-9B-Chat-16K	38.20	42.35	0.73	38.14	36.36	35.64	37.08	27.79	38.22
CodeLlama-13B-Instruct	10.49	14.64	0.04	11.67	11.34	9.43	14.43	5.15	12.64
CodeLlama-7B-Instruct	2.88	3.97	0.00	3.53	2.37	2.57	1.74	1.59	3.31
StarCoder2-15B	2.07	2.61	0.07	2.57	1.81	1.59	3.43	1.19	2.33
Deepseek-Coder-6.7B-instruct	37.03	41.62	1.93	43.49	34.57	46.36	46.49	18.09	38.4
Qwen2.5-Coder-7B-Instruct	45.18	53.11	1.48	51.58	43.21	43.87	42.50	35.23	47.6
			1	Agentic Model					
DeepAnalyze-8B	59.91	66.24	2.86	71.68	67.86	58.62	69.09	33.33	61.11

Table 1. Performance on DataSciBench. 'Success Rate' and 'Completion Rate' are pass rate and accuracy. 'VLM' and 'F1-F5' scores evaluate performance on various fine-grained data science sub-tasks, 'Score' denotes the overall performance.

we enhance existing datasets by synthesizing complex and refined reasoning trajectories, which are used for DeepAnalyze's single ability training.

As shown in Figure 5(a), given the instruction–response pairs in the original dataset, the reasoning trajectory synthesis involves distillation and refinement steps. In the distillation step, we employ advanced LLMs as teacher models to extract their reasoning trajectories, whose correctness is verified by comparing the generated responses with the ground truth responses (DeepSeek-AI, 2025). To strengthen the model's understanding of structured data, the distilled reasoning is reformulated by advanced LLMs into two complementary components: (Analyze) (reasoning process) and (Understand) (structured data understanding). Building on this, we introduce keyword-guided refinement to further enhance the reasoning trajectories with a focus on structured data. Previous works have shown that certain keywords, such as "but"/"wait", play a crucial role in reasoning (Zhang et al., 2025a; Shen et al., 2025). Following this insight, we construct a key reasoning vocabulary and sample key reasoning words to insert into the reasoning trajectory, thereby improving its reasoning on structured data. Appendix B provides an example of keyword-guided refinement, where inserting keywords enhances the reasoning process by focusing more on the data, thereby improving the quality of the reasoning trajectory. Through reasoning trajectory synthesis, we can effectively leverage existing datasets to improve DeepAnalyze's single ability in reasoning, structured data understanding, and code generation.

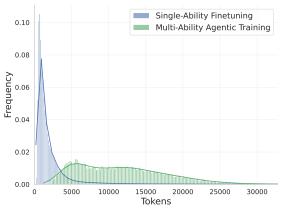


Figure 6. Length distribution of training data.

Interaction Trajectory Synthesis. To enable DeepAnalyze to autonomously orchestrate and optimize multiple abilities in real-world environments, it is essential to construct multi-turn interaction trajectory data with the environment, yet such data is extremely scarce. In contrast, NL2SQL datasets such as Spider (Yu et al., 2018) and BIRD (Li et al., 2024) provide abundant structured data sources. To bridge this gap, we develop a multi-agent system to synthesize data science interaction trajectories from these data sources.

The multi-agent system involves three roles: questioner, solver, and inspector. The questioner observes the data sources in the environment and accordingly formulates a data science problem, conditioned on a sampled task type (e.g., data preparation, data analysis, data modeling, data insight, or open-ended research). Simultaneously, the ques-

tioner produces a checklist that serves as the evaluation criterion, including interaction-level constraints (e.g., number of turns, code library) and environment-level constraints (e.g., whether new files are generated, detailed file name). Given the data science problem and the data sources, the solver interacts with the environment using the introduced five actions to complete the task. Finally, the inspector validates the trajectory by checking the interaction process and environmental changes against the checklist, determining whether the trajectory should be accepted. Importantly, filtering trajectories based on both interaction details and environmental changes substantially improves the quality of synthesized data. Through interaction trajectory synthesis, the high-quality multi-turn interaction data can be used for multi-ability agentic training (cold start and RL).

3.4. DataScience-Instruct-500K

We develop DeepAnalyze based on the constructed data in Sec.3.3. During the single-ability fine-tuning stage, we employ the reasoning trajectories built for data science, along with 100K general reasoning samples from AM-DeepSeek-R1-0528-Distilled¹. In the multi-ability agentic training stage (including both cold start and RL phases), we use the interaction trajectories constructed for data science.

Figure 6 illustrates the length distribution of training data in both stages, with a sequence length of 8K in the first stage and 32K in the second. In terms of scale, the single-ability fine-tuning stage consists of approximately 470K samples, the cold-start phase of multiability training includes 20K samples, and the RL phase comprises 15K samples, resulting in a total of around 500K samples. We release all training data, named DataScience-Instruct-500K², which can be used to train LLMs for data science tasks.

4. Experiments

4.1. Benchmarks

We conduct experiments on 12 data science benchmarks.

DataSciBench (Zhang et al., 2025b) is the latest benchmark to evaluate LLM's capabilities on the entire data science pipeline, covering data preparation, data analysis, data modeling, data visualizatoin, and data insight.

DSBench (Jing et al., 2025) evaluates data analysis and modeling capabilities, comprising 540 real-world tasks collected from ModelOff and Kaggle competitions.

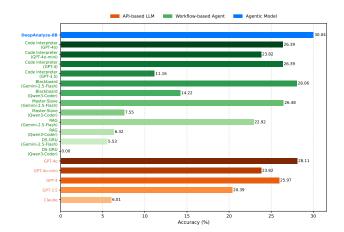


Figure 7. Performance on DSBench (data analysis).

DABStep (Egg et al., 2025) is a data agent benchmark with 450 real-world data analysis tasks designed to evaluate the multi-step reasoning abilities of agents.

DABStep-Research is a benchmark we constructed based on DABStep (Egg et al., 2025) to evaluate the capability of data science report generation. Considering that existing data science benchmarks rarely assess deep research abilities on structured data, we propose DABStep-Research to measure the capability to generate comprehensive data research reports from raw data sources. The evaluation covers five aspect: data preparation, data analysis, data insight, report generation, and open-ended data research. Please refer to Appendix A for details on its construction and cases.

DS-1000 (Lai et al., 2023) is a code generation benchmark containing 1000 data science problems spanning seven Python libraries such as NumPy, Pandas, Matplotlib, etc.

TableQA Benchmarks are a series of question-answering benchmarks based on structured tables, including WikiTQ (Pasupat & Liang, 2015), HybridQA (Chen et al., 2020), MultiHiertt (Zhao et al., 2022), OTT-QA (Chen et al., 2021a), FinQA (Chen et al., 2021b), TAT-QA (Nan et al., 2022), and HiTab (Cheng et al., 2022).

4.2. Experimental Setup

We build DeepAnalyze-8B based on DeepSeek-R1-0528-Qwen3-8B³ as the foundation LLM. We use ms-swift (Zhao et al., 2024) and SkyRL (Liu et al., 2025) toolkit to accomplish single-ability fine-tuning and multi-ability agentic training respectively. The training data come from DataScience-Instruct-500K, as described in Sec.3.4. During inference, we employ the vLLM engine (Kwon et al., 2023) to deploy DeepAnalyze-8B for efficiency. All training and inference are conducted on NVIDIA A800 GPUs.

Inttps://huggingface.co/datasets/
a-m-team/AM-DeepSeek-R1-0528-Distilled
Inttps://huggingface.co/datasets/
RUC-DataLab/DataScience-Instruct-500K

³https://huggingface.co/deepseek-ai/ DeepSeek-R1-0528-Qwen3-8B

Methods	LLM	Success (%)	Performance	Cost (\$)		
Workflow-based Agent						
	Llama3-8b	5.41	1.55	0.00		
	Llama3-70b	16.22	7.79	0.00		
	GPT-3.5	8.11	6.02	0.41		
AutoGen	GPT-4	87.84	45.52	19.34		
	GPT-40	71.62	34.74	12.27		
	GPT-4o-mini	22.97	11.24	0.10		
	GPT-3.5	16.22	6.52	2.74		
Code	GPT-4	54.05	26.14	38.81		
Interpreter	GPT-40	44.59	19.87	19.26		
•	GPT-4o-mini	39.19	16.90	2.70		
		Agentic Model				
DeepAnalyze	-8B	90.63	39.41	0.00		

Table 2. Performance on DSBench (data modeling).

4.3. Main Results

Capability on End-to-end Data Science Pipeline. We evaluate DeepAnalyze on DataSciBench to assess its end-toend data science capabilities, where each problem involves one or more sub-tasks such as data preparation, analysis, modeling, and visualization. We compare DeepAnalyze-8B with several workflow-based (ReAct) agents, covering 17 open-source and advanced proprietary LLMs. As shown in Table 1, coarse-grained metrics measure task success and sub-task completion rates, while fine-grained metrics evaluate detailed performance across individual stages of the data science pipeline. The results show that, despite having only 8B parameters, DeepAnalyze-8B achieves state-of-the-art performance among open-source LLM-based agents and even outperforms most advanced proprietary models (e.g., GPT-4-Turbo, GPT-4o-mini, Claude 3.5 Sonnet), ranking second only to GPT-4o. More importantly, unlike existing workflow-based agents, DeepAnalyze-8B accomplishes high-quality, end-to-end pipelines without relying on external orchestration frameworks such as ReAct. Prior studies have shown that models like o1-mini exhibit strong reasoning ability but often fail to execute complex data science tasks requiring precise instruction following and strategic planning (Zhang et al., 2025b). In contrast, DeepAnalyze benefits from agentic training, enabling autonomous orchestration and adaptive optimization in real-world environments, resulting in consistently superior performance.

Overall, DeepAnalyze-8B's strong results on DataSciBench highlight its advanced problem-solving capabilities in autonomously orchestrating end-to-end data science pipelines.

Capability on Individual Data Science Tasks. As most previous studies primarily focus on individual data science tasks such as data analysis and modeling, we further evaluate DeepAnalyze on these tasks using DSBench for a fair comparison. We first evaluate its *statistical data analysis* capabilities. As shown in Figure 7, DeepAnalyze-8B outperforms previous LLM prompting and workflow-based agents, demonstrating that its autonomous orchestration and

Methods	LLM		Hard Level (378 Cases)	
	Workflow-based	l Agent		
	Llama-4-Scout	52.78	1.85	10.00
	Qwen3-Coder	54.17	3.44	11.56
	GPT-4o-mini	69.44	3.44	14.00
	Deepseek-v3	66.67	5.56	15.34
	GPT-40	66.67	6.08	15.77
ReAct	Claude-3.5-Haiku	77.78	5.03	16.67
KeAct	Llama-4-Maverick	75.00	8.73	19.33
	GPT-4.1-mini	77.78	8.99	20.00
	Claude-3.5-Sonnet	77.78	9.26	20.22
	GPT-4.1	80.56	12.43	23.33
	o1	69.44	11.11	20.44
Reasoning	Gemini-2.5-Pro	66.67	12.70	21.34
Prompt	o3-mini	72.22	13.76	23.11
	o4-mini	76.39	14.55	24.44
DS-Agent	Gemini-2.0-Flash	61.11	9.79	18.00
Open Data Scientist	Deepseek-v3	84.72	16.40	27.33
I2I-Agent	Claude-3.5-Sonnet	80.56	28.04	36.44
	Agentic Mo	del		
DeepAnalyze-8B		70.83	32.80	38.88

Table 3. Performance on DABStep benchmark.

adaptive optimization are more effective than the manually designed workflows used in agents such as Code Interpreter, Master-Slave (Kong et al., 2017), and Blackboard (Salemi et al., 2025). We then evaluate its *data modeling* capabilities. Table 2 reports the results on DSBench, where tasks involve training machine learning models (Jing et al., 2025). DeepAnalyze-8B achieves performance comparable to AutoGen-based workflows (Wu et al., 2024) built upon various advanced proprietary LLMs. Although it has fewer parameters and weaker single-turn reasoning ability, DeepAnalyze-8B can autonomously optimize its actions through environment feedback, achieving a high task success rate and strong overall performance.

To further evaluate DeepAnalyze's ability to perform data analysis across multiple data types, including structured, semi-structured, and unstructured data (Egg et al., 2025), we evaluate it on DABStep, which contains diverse data formats such as markdown, CSV, and JSON. As shown in Table 3, DeepAnalyze-8B outperforms previous workflowbased agents, including ReAct (Yao et al., 2023), reasoning prompts, and specially designed workflows, particularly on hard-level tasks. While workflow-based systems can leverage the strong general capabilities of proprietary LLMs to perform well on easy tasks, their predefined workflows limit performance on complex scenarios. In contrast, DeepAnalyze, equipped with autonomous orchestration and adaptive optimization through agentic training, can iteratively interact with the environment like a human data scientist, achieving superior performance on complex tasks requiring long-chain reasoning.

Capability on Data-Oriented Deep Research. Deep research has emerged as an important task for evaluating the comprehensive capabilities of LLMs and agents. To this end,

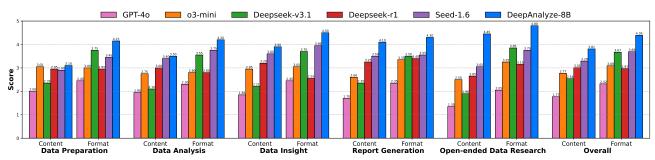


Figure 8. Performance on DABStep-Research.

Models	WikiTQ	HybridQA	MultiHiertt	OTT-QA	FinQA	TAT-QA	HiTab	AVG
		AP	I-based LLMs					
Claude	82.02	39.36	40.98	62.69	57.45	53.09	75.96	58.79
GPT-40	81.19	39.30	40.86	66.35	57.63	53.45	73.92	58.96
	Open-Source LLMs							
DeepSeek-R1-0528	84.00	39.04	40.98	66.85	59.90	55.24	75.57	60.22
TableGPT2-7B	63.70	30.03	25.12	48.87	38.36	55.12	63.89	46.44
Qwen2.5-32B-Inst	79.65	38.20	37.74	56.50	59.20	67.29	73.29	58.84
Qwen2.5-7B-Inst	57.27	31.84	27.54	50.50	52.40	49.79	57.19	46.65
DeepSeek-R1-0528-Owen3-8B	63.49	28.15	39.86	49.72	51.09	55.00	51.09	48.34
Reasoning-Table (SFT)	72.35	35.17	38.50	54.40	60.42	63.45	72.72	56.72
Reasoning-Table (SFT+RL)	75.46	42.83	39.56	68.68	64.46	73.75	73.61	62.62
DeepAnalyze-8B (single-ability)	81.86	39.27	44.58	53.12	62.50	66.87	76.26	60.64
DeepAnalyze-8B	83.24	42.95	48.29	64.73	63.30	70.64	78.16	64.47

Table 4. Performance on TableQA benchmarks. 'DeepAnalyze-8B (single-ability)' is the model after the first stage fine-tuning.

we introduce DABStep-Research, a benchmark designed to evaluate the *data-oriented deep research* capabilities of LLMs and agents. We compare DeepAnalyze-8B with advanced agent systems (i.e., state-of-the-art proprietary LLMs with tool-calling capabilities) on a suite of data research tasks spanning five categories: data preparation, data analysis, data insight, report generation (with a specified outline), and open-ended data research (fully unconstrained). Each task results in a research report, which is evaluated on both content quality and formatting. Figure 9 illustrates several representative cases from DABStep-Research.

The results in Figure 8 show that DeepAnalyze-8B consistently outperforms all compared systems across every task. Notably, agent systems built on proprietary LLMs with tool calls exhibit a significant performance drop on open-ended data research tasks compared to more instructive tasks, such as data preparation, analysis, and insight, where explicit steps or goals are provided. This decline stems from their lack of training in data science: without step-by-step guidance, they fail to perform autonomous orchestration and adaptive optimization. In contrast, DeepAnalyze-8B, trained in real-world environments, effectively handles fully openended data research tasks without predefined instructions. Moreover, it achieves a clear advantage in report format quality, generating outputs that closely resemble analyst-grade reports. This improvement is attributed to reward

modeling that explicitly incorporates report quality during RL training. Appendix C further provides qualitative comparisons of research reports generated by DeepAnalyze-8B and reasoning models such as DeepSeek-R1 and o3-mini, highlighting DeepAnalyze-8B's superior content depth and structured presentation.

Overall, DeepAnalyze-8B enables end-to-end autonomous data research, from raw data to analyst-grade reports, unlocking novel applications in data research.

Capability Related to Data Science. Beside data science tasks, we further evaluate DeepAnalyze-8B on DS-1000 and TableQA to evaluate its capabilities in code generation and structured data understanding, which are essential for complex data science. As reported in Table 5 and Table 4, DeepAnalyze-8B outperforms GPT-4-Turbo and GLM-4.5 (GLM-4.5-Team, 2025) on DS-1000, and surpasses the previous SOTA model Reasoning-Table (Lei et al., 2025) on TableQA. Compared with DeepSeek-R1-0528-Qwen3-8B, DeepAnalyze-8B achieves substantial gains in both abilities under the single-ability setting, demonstrating the effectiveness of the first-stage single-ability fine-tuning. Furthermore, agentic training on complex data science tasks further strengthens these specialized capabilities.

Overall, DeepAnalyze-8B's strong performance on code generation and structured data understanding establishes a

Models	Data Science Libraries						Overall	
	Pandas	NumPy	Matplotlib	Scikit-learn	SciPy	TensorFlow	PyTorch	0.111111
Codex002	26.5	43.2	54.8	43.5	34.9	37.8	39.7	38.8
GPT-3.5-turbo	33.0	36.8	58.7	35.7	39.6	33.3	29.4	38.6
GPT-4	41.9	56.8	65.2	50.4	48.1	46.7	47.1	51.0
GPT-4-turbo	42.3	61.8	71.6	50.4	50.0	53.3	50.0	53.9
Kimi-K2-Instruct*	-	-	-	-	-	-	-	40.2
GLM-4.5*	-	-	-	-	-	-	-	53.2
LIMI*	-	-	-	-	-	-	-	54.8
DeepSeek-R1-0528-Qwen3-8B	17.5	37.3	52.9	27.8	21.7	31.1	29.4	30.4
DeepAnalyze-8B (single-ability)	43.6	69.1	54.8	53.0	50.9	64.4	58.8	54.8
DeepAnalyze-8B	50.2	74.5	67.7	56.5	54.7	68.9	70.6	61.7

Table 5. Performance on DS-1000. * indicates that The results are derived from corresponding references. 'DeepAnalyze-8B (single-ability)' is the model after the first stage fine-tuning.

Models	WikiTQ	MultiHiertt	DS-1000	DABStep
DeepAnalyze - w/o (Understand)	83.24	48.29	61.70	38.88
	80.78	45.43	61.20	31.78

Table 6. Ablation study on (Understand) action.

Training Methods	WikiTQ N	AultiHiertt	DS-1000	DABStep
Curriculum-based Agentic Training	83.24	48.29	61.70	38.88
-Only Single-ability Fine-tuning	81.86	44.58	54.80	15.34
-Only Multi-ability Agentic Training	80.32	43.29	53.20	30.66
-One-stage Training	82.13	46.23	54.80	36.89

Table 7. Ablation study on the curriculum-based agentic training.

robust foundation for its advanced performance in end-toend autonomous data science.

5. Analysis

5.1. Ablation on DeepAnalyze's Actions

DeepAnalyze introduces five actions for autonomous data science, among which \(\lambda\) Understand\(\rangle\) is specifically designed for structured data understanding. To evaluate the effect of incorporating \(\lambda\) Understand\(\rangle\) independently from reasoning process (i.e., \(\lambda\) Analyze\(\rangle\)), we conduct an ablation study, as reported in Table 6. The results show that removing \(\lambda\) Understand\(\rangle\) leads to performance drops on structured data understanding tasks (WikiTQ, MultiHiertt) as well as data analysis tasks (DABStep), demonstrating the advantage of introducing \(\lambda\) Understand\(\rangle\) in DeepAnalyze.

5.2. Superiority of Curriculum-based Agentic Training

To address the challenges arising from the multiple ability requirements in data science, we introduce curriculum-based agentic training, inspired by the learning path of human data scientists, where first fine-tuning on single abilities and then agentic training on complex tasks that require multiple abilities. To evaluate its effectiveness, we compare several training methods, including "Only Single-ability Fine-tuning", "Only Multi-ability Agentic Training", and "One-stage Training", which directly mix the single-ability

Reasoning Trajectory	WikiTQ	HybridQA	MultiHiertt	HiTab
Original	75.54	34.42	39.29	72.95
+ Distillation	78.80	36.12	41.24	74.44
+ Distillation + Refinement	80.25	38.84	43.47	75.86

Table 8. Performance under various reasoning trajectory synthesis.

data into the cold-start of multi-ability agentic training (i.e., the conventional agentic training methods).

As shown in Table 7, "Only Single-ability Fine-tuning" fails to handle complex tasks in DABStep that require multi-turn interaction with the environment, and "Only Multi-ability Agentic Training" struggles to achieve strong performance when single ability are not well established. Compared with "One-stage Training", a scheduled training process from simple (single-ability) to complex (multi-ability) proves more beneficial for model performance using the same data. Therefore, for tasks that rely on multiple abilities, curriculum-based agentic training effectively enhances overall model performance.

5.3. Advantage of Reasoning Trajectory Synthesis

During data synthesis, we propose reasoning trajectory synthesis that incorporates distillation and refinement to enhance the model's reasoning ability over structured data. To validate its effectiveness, we compare the model's performance when trained on original, distilled, and refined data, where the original data are derived from Reasoning-Table. As reported in Table 1, both distillation and refinement improve the model's understanding of structured data. In particular, compared with commonly used distillation methods, we additionally introduce a refinement stage, which incorporates key reasoning vocabulary to strengthen the reasoning trajectory's focus on structured data, thereby improving the overall data quality.

6. Conclusion and Future Work

DeepAnalyze brings a major leap forward in autonomous data science, demonstrating unprecedented capabilities

across a wide spectrum of data-centric tasks. Powered by curriculum-based agentic training and data-grounded trajectory synthesis, *DeepAnalyze-8B outperforms state-of-the-art closed-source LLMs on 12 data science benchmarks*.

More importantly, DeepAnalyze goes beyond predefined workflows, as it enables open-ended data research and generates analyst-grade reports, advancing a long-standing goal of the data science community: automatically extracting actionable insights from raw data. As a result, this work marks *a paradigm shift* in autonomous data science from workflow-based agents to agentic models, paving the way for the next generation of intelligent data systems in areas such as data discovery, data governance, data ecosystems, and data management.

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A. Construction of DABStep-Research Benchmark

Existing data science benchmarks typically focus only on evaluating the ability of LLMs to solve specific tasks. However, with the rise of deep research, there is an urgent need for a benchmark that assesses LLMs' capabilities in data-oriented deep research, which ask LLMs to conduct data research and generate research reports based on given instructions and data sources.

Construction. To this end, we constructed DABStep-Research, which is built upon the data sources proposed in DABStep (Egg et al., 2025). DABStep-Research consists of 100 tasks divided into five categories: data preparation, data analysis, data insight, report generation, and open-ended data research. In particular, tasks under the "report generation" category specify detailed report formats in the instruction, such as title, outline and specific requirements, thereby evaluating how well LLMs can follow instructions when generating research reports. The "open-ended data research" category involves fully open research tasks without any constraint on research direction or method. In addition to the instructions and data sources, we also provide a checklist to serve as a reference for scoring, helping evaluators determine whether the elements in a research report meet the given requirements. Figure 1 illustrates specific examples from DABStep-Research.

Evaluation. We use the LLM-as-a-judge to evaluate LLM performance on DABStep-Research. Specifically, given the instruction, checklist, and the report generated by an LLM, we employ a state-of-the-art LLM as the evaluator to assign a score from 1 to 5 based on two aspects: content and format. The prompt used for the LLM-as-judge evaluation is shown below.

Prompt of DABStep-Research Evaluation You are a data science evaluation assistant. Here's a generated data science report based on the user instruction. Your task is to comprehensively evaluate the quality of the generated data science report, based on the provided user instruction [INSTRUCTION], a checklist offering reference points for an ideal report [CHECKLIST], and the generated report [REPORT]. You should assess the report across the following two dimensions, each scored on a scale from 1 (poor), 3 (Fair), 5 (excellent). Please use the detailed guidelines below to calibrate your evaluation: - Content: Is the report's content helpful, comprehensive, and relevant to the task goal? 1 (Poor): Content is completely irrelevant, incorrect, or fails to reflect the given task. 2 (Weak): Mostly irrelevant or inaccurate; shows little understanding of the task or data. 3 (Fair): Partially relevant and somewhat useful, but incomplete, superficial, or missing several key aspects. 4 (Good): Relevant and generally helpful content that addresses the task goal with clear findings; minor gaps or shallow areas may remain. 5 (Excellent): Highly informative, comprehensive, and well-balanced content that fully and insightfully addresses the task goal. - Format: Is the report presented in a polished academic style? 1 (Poor): Disorganized or unprofessional presentation; difficult to follow, with major grammatical or formatting issues. 2 (Weak): Understandable but inconsistent in structure or tone; lacks clear formatting or proper academic expression, such as many short sentences and bullet points. 3 (Fair): Generally clear structure and readable style, though uneven in flow, tone, or academic polish. 4 (Good): Well-written and professionally presented in an academic style; clear organization and formatting with only minor imperfections. 5 (Excellent): Polished, fluent, and professional presentation; precise structure, coherent tone, and excellent readability throughout. [INSTRUCTION]: {instruction} [CHECKLIST]: {checklist} [REPORT]: {report} Directly return your evaluation in the following JSON format: '''json "Content": <score>, "Format": <score>,

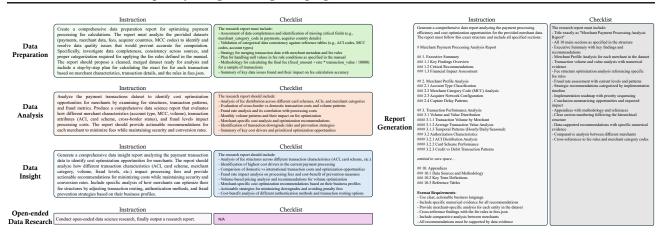


Figure 9. Cases in the constructed DABStep-Research benchmark, including data preparation, data analysis, data insight, report generation, and open-ended data research.

B. Keyword-guided Reasoning Trajectory Synthesis

We present examples of Keyword-guided Reasoning Trajectory Synthesis in Figure 10. Specifically, the "Question" and Original Response are taken from existing TableQA datasets.

In the distillation step, we employ SOTA closed-source LLMs as teacher models to extract their reasoning trajectories, which is the most common way used in current data synthesis methods. However, such methods are more suitable for general reasoning processes. Since SOTA closed-source LLMs have not been specifically trained on domains like data science (e.g., structured data understanding), their reasoning trajectories tend to overlook the provided data.

Therefore, we introduce a refinement step to enhance the reasoning trajectory's focus on structured data by inserting reasoning keywords that guide the reasoning process toward structured data understanding. Specifically, in the example shown in Figure 10, we sample three reasoning keywords ("What happens at the boundaries?", "Let's review the prior reasoning", and "Let's take a closer look at the table") and ask the teacher model to refine its reasoning trajectory based on these keywords. We observe that the final "refinement" results exhibits a significantly stronger emphasis on repeated examination and reflection on structured data, thereby improving the overall quality of the reasoning trajectory. Overall, the proposed keyword-guided refinement is a useful data synthesis technique that can also be applied to the data synthesis of other complex tasks.

C. Cases

In Figure 11, Figure 12, Figure 13, Figure 14, and Figure 15, we demonstrate a series of autonomous data science cases, covering the entire pipeline from data sources to analyst-grade research reports. These cases include data preparation, data analysis, data insight extraction, report generation under specific constraints, and fully open-ended data research. Compared with previous closed-source LLMs and tool-calling frameworks, DeepAnalyze can produce higher-quality, analyst-level reports, exhibiting a stronger ability for autonomous data research.

Stage	Reasoning Trajectory
	Select in a instruction that the colors a specific menerology that in the finance domain, provided with an input table and relevant next as context. Places amove the given approximation and on the first approximation and on the first and the specific menerology and the specific me
Question	and the function. Cover a table and a list of tens in the following, what the nasewe to the question? Cover a table and a list of tens in the following, what the nasewe to the question? Cover a table and a list of tens in the following, what is the nasewe to the question? Cover a table and a list of tens in the following, what is the nasewe to the question? Cover a table and a list of tens in the following, what is the nasewe to the question? Cover a list of tens in the following tens in the fol
	Ball Quarter for a recent between day bulk vesuel operations and legislicit business? ### Expresse Your response should end with "Assurer xex" (savers to the question) Your response should end with "Assurer xex" (savers to the question) Your response should end with "Assurer xex" (savers to the question) Your spense should end with "Assurer xex" (savers to the question) Town, savers the question and by sep:
Original	Asswer: 25,907
	Adapt. Act sack this finance questions are by sage. The user wants to know the revenue difference between day both vened operations and lagistics business for Navioral Holdings in 2019. Fines, Tills use the deem depression for personals table. Scientific file fined are sow under '170y, bild Vened Operations' about \$543.178, while "Legistics Businesses" shows \$224.277. Both are dearly labed under the 2019 year-end columns. The questions operation by the first the difference, which implies notheration. Calculating \$254.178 minus \$225.271 quick \$255.90? Now, should remained any content from the early Panagoral Tourishme does are the two active reported segment and or containers were reclamfied as discontinued operations. Paragogal 4 emphasizes they're measured by set income/hos (indexent here) but crucially states inter-segment transactions are diminisated—neuring those everences sured indicated by internal transfer. No conveys or unit conveniences are model since everythings in thousands of USD. The main is magniferoward on percentage or units required, just absolute difference. Described-calculage the described single with the question interference and no other everue lines (the administrative free) are made of units of the segment. That i certainties \$254.178-1228,271 = \$25,907. This seems salid.
Distillation	To determine the evenue difference between dry back vesard operations and logistics business: 1. **Menting because evenue figure** from the table: 1. **Menting because evenue figure** from the table: - 1. **General control operation evenue **MELTATE** - 1. **General control operation evenue **General control opera
Refinement Insert Key Reasoning Words: I. What happens at the boundaries? 2. Let's review the prior reasoning at a closer look at the table	Fig. 1, 20, Septing the gradients and the degree can also for application for the control of the

Figure 10. Example of reasoning trajectory synthesis.

Instruction	DeepAnalyze-8B	Deepseek-r1	o3-mini
	# Comprehensive Data Preparation Report: Payment Processing Fee Analysis	Based on the initial analysis of the payment processing dataset, I've identified several critical data quality issues. Here's a comprehensive report structured according to your requirements:	Below is the final data preparation report:
Instruction	## Comprehensive Data Preparation Report: Psyment Processing Fee Analysis ### Executive Summary This report analyses payment processing datasets to identify data quality issues impacting fee calculation accuracy. Through examination of 7 datasets (30 merchants, 1000 feer titles, and synthetic transaction data, we desemfied by data quality forters deficing fee estimation reliability and recommend process improvements to minimize processing costs. #### 1. Data Quality Assessment ###################################	Based on the initial analysis of the payment processing dataset. I've identified several critical data quality issues. Here's a comprehensive report structured according to your requirements. ###### 1. Data Quality Issues and Inconsistencies **Missing Data** - **Missing Data** - **Guiter_county* 12.54 similing values (5.6% of Intranctions) - **Intranctions()	Below is the final data preparation report: Data Preparation Report for Psyment Processing Dataset **Data files were loaded successfully: **aquier: countries eve loaded successfully: **aquier: countries eve loaded successfully: **aquier: countries eve loaded successfully with the acquier country mappings. **exploration and even definitions for fee collectation. **nerchant_category; codes or based to support standardeed merchant estegorization. **nerchant_category; codes are based to support standardeed merchant estegorization. **nerchant_categorization loaded and convented to a DataFrame, representing additional merchant **psyments ov loaded durgered dataset) with comprehensive transaction records. **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several data quality issues: **Preliminary analysis of payments data exposed several deduction data quality issues: **Preliminary analysis of payments data exposed several deduction data quality issues: **Preliminary analysis of payments data exposed several deduction data quality issues: **Preliminary analysis of payments data exposed several d
Analyze the payment processing dataset to identify and resolve data quality issues that impact fee calculation accuracy. Prepare a	- Flagged 100 rules with missing it, rendit values for review - Standardized merchant category code list in fee rules 3. **Coggraphic Resolution**, - Enhanced acquirer country mapping with 10' geolocation fullback #### 2.2 Quality Metrics Metric Before Cleaning After Cleaning	psyments [country, uside] = psyments [acquirer, country] nitrolaid, countries) \ psyments [ole-psyments [cole-psyments [country, uside]] = [ZE # Unknown country psyments [acquirer, country filing (ZZ, inplace=True)] \ # Create region mapping\ region_map = acquirer, countries set_index(country_code*[[region 1] to_file(1) psyments [acquirer, region] = psyments[acquirer, countries set_index(country_code*[[region] to_file(1) psyments[acquirer, region] = [psyments[acquirer, region] filing (Unknown, inplace=True)]	 *Use merchant, category, codes cev to remap and enforce consistency via string normalization (timming, low-resing, etc.) *Transaction Characteristics: *Indement imputation strategies (e.g., median imputation) for missing transaction_amount values. *Employ domain analysis to identify and trim extreme outliers to avoid distortion. *Country Mappings. **Were gaverneims data with acquirer, countries cove to validate and correct country identifiers.
comprehensive data preparation report that documents data nconsistencies, implements cleaning strategies for merchant categorization, transaction characteristics, and country		**C. Transction Characteristics** **"pon. "Code."* of Bandle missing currencies\ psyments\[\text{transaction_currency}\], fillna(USD', inplace*True)\ psyments\[\text{transaction_currency}\], fillna\[\text{USD'}\], implace*	 Impact on Fee Estimation Models: These data cleaning strategies ensure fee calculation models operate on properly categorized an availative data. Improvements such as deduplication, imputation, and outlier trimming help in reducing biases, leading to more cellable for estimations.
mappings, and evaluates how these preparations affect the reliability of fee estimation models. The report should include specific recommendations for optimizing data collection processes to	### 3.1 Accuracy Improvement - "Advance" Spice calculation error due to categorization issues - "Advance" = 1.5% reco margin #### 3.2 Processing Cost Impact Factor Current Cost Optimized Cost Reduction	# Detect and cap outliers\ (0 = payments framascion_amount* quantile(0.25)\ (0 = payments framascion_amount* city(upper=upper_bound)* (1 = payments framascion_amount* city(upper=upper_bound)* (1 = payments framascion_amount* city(upper=upper_bound)* (1 = payments framascion_amount* city(upper=upper_bound)* (2 = payments framascion_amount* city(upper=upper_bound)* (3 = payments framascion_amount* city(upper=upper_bound)* (4 = payments framascion_amount* city(upper=upper_bound* city(upper_bound* city(u	 Recommendations for Optimizing Data Collection Processes: 1. Standardizer Data Entry: Enforce uniform data entry formats using dropdowns or controlled vocabularies for merchant 2. Real-size volutidation: 2. Real-size volutidation: 1. Integrate robust validation rules at data entry (e.g., for transaction amounts, dates, and fee parameters) to calcel errore carly.
minimize processing costs.	Frandulent Fee Disputes \$12.000/month \$2.800/month 77% Incorrect Fees \$5,000/month \$1.200/month 86% ### 4. Recommendations ### 4. Recommendations ### 4. Recommendations ### 5. Data Collection Improvements ### 1. "Feed-Time Mechanic Categorization*:	### 3. Impact on Fee Calculation Accuracy - "Before Caraings": - "Pefore Caraings": - "Percent Caraings (1,93) would have incorrect fee calculations due to invalid/missing references - Extreme transaction amounts would distort interchange fee calculations - Extreme Transaction amounts would fusion interchange fee calculations	3. Regular Automated Audits: Automate periods audits to monitor merging processes across different source files (fees joon, payments rave, etc.) and quickly identify any discrepancies. 4. Comprehensive Data Dictionary: — Maintain an up-to-late data decionary linking all source files and field definitions, facilitating amonther integrations and further reporting.
	Implement Al-powered category suggestion during onboarding - Estimated 30% reaction in dispute resolution costs 2. **Enhanced Transaction Attributes**: - Collect merchant location grammainty (cty/region) - Add product "service categories"	**After Cleaning*** **Only reference integrity for MCCs and countries - Outlier capping ensures stable for calculations **Region-based for exilted can be precisely options # 8.2% to ±0.9% - Estimated for calculation error rate reduced from # 8.2% to ±0.9% #### 4. Recommendations for Data Colicion Ordinization	A detailed report has been saved as data_preparation_report_tat. Following these recommendations will help minimize processing outs and improve the accuracy of fee estimation models by ensuring higher data quality throughout the processing pipeline. End of Report
	3. **Automated Data Validation**: - Implement real-time rule validation during transaction processing - Estimated 25% reduction in manual reconciliation	#### 4. Recommensations for Lista Collection Optimization 1. "Validation at Ingestions": - Implement MCC and country code validation during transaction recording - Add mandatory field checks for 'acquirer_country' and 'merchant_category_code'	
	#### 4.2 Process Optimization 1. **Batch Processing Windows** Shift non-essential processing to off-peak hours - Potential 15% energy cost reduction	2. **Automated Quality Monitoring** Create daily data quality dashboards tracking: - Missing value rates per critical field - Reference table match rates - Transaction amount distribution shifts	
	2. **Predictive Fee Allocation** Implement machine learning for fee estimation - Projected 18% improvement in accuracy ### 5. Conclusion	3. **Reference Data Management**: - Establish monthly review process for MCC and country code updates - Implement version control for fee structure documents **Strundardingsings**:	
	This analysis demonstrates that systematic data preparation can significantly improve fee calculation accuracy while reducing operational costs. The implemented solutions provide a foundation for continuous improvement through ongoing monitoring of the data quality metrics and processing efficiency gains.	4. **Standardization**. - Enforce ISO standards for country codes (ISO 3166) and currencies (ISO 4217) - Develop MCC taxonomy with clear category definitions These improvements will reduce processing costs by minimizing reconciliation efforts, preventing	
	Appendix: Complete dataset schemas and cleaning code available upon request.	fee miscalculations, and enabling more accurate financial forecasting. The cleaned dataset now supports reliable fee modeling with complete reference integrity across all critical dimensions.	

Figure 11. A data preparation case of autonomous data science, from data sources to analyst-grade research reports.

Instruction	DeepAnalyze-8B	Deepseek-r1	o3-mini
	# Comprehensive Analysis of Payment Processing Optimization Opportunities	### Comprehensive Data Science Report: Payment Processing Optimization	Below is the comprehensive report generated by our analysis:
Instruction		_	
	category. The enhanced merchant profiles reveal that 68% of merchants fall into high-risk merchant categories (ACCS 5812, 7977, 5942) which typically incur 23.31% higher fraud-related fees. Merchant capture delay analysis shows that merchants with immediate capture delays experience 13.81% where chapted rates to 11.79% higher processing fees compared to manual capture merchants. ### Fee Smucture Optimization Opportunities	**Large transactions** (>500) show 2.1% frand rate vo 0.8% for <5100 **Card types** Virtual/repeal cards show 1.5% higher frand rates **CVV absence.** Transactions without CVV have 3.2% higher frand risk **Frand Relaction Strategies.** 1. Implement enhanced verification for digital goods merchants 2. Apply transaction limits and velocity checks for cross-border payments 3. Require CVV verification for transactions >5200 4. Develop ML-Nasof franda sorting models tragging high-risk categories	formulations become apparent. This analysis suggests that merchants should strategically select acquires based on their target market 'risk profile and fee competitiveness. Merchant Caregory and Profile Insights. Merchant Caregory and Profile Insights. Merging merchant instanction data with merchant caregory codes indicates that some merchant caregories (e.g., high-ticket retail or service sectors) face disproportionately high fees. Merchant profile variables such as bosiness size transaction volume, and risk ratings (obtained from merchant, data, ison) greatly influence fee structures and fraud vulnerability. Tailored strategies are thus needed depending on the merchant profile.
Analyze the payment transaction dataset to identify cost optimization opportunities for merchants by	The fee structure analysis reveals complex fee calculations combining fixed amounts (60.01-60.15) combines at 0.05 fixed amount with 12 basic points, applied to 28% of transactions, therebase contagys analysis shows that Hospitality interactures pay 25% higher fees than Retail merchants pay 25% higher fees than Retail merchants or quivalent transaction values, primarily due to higher frand risk premium according to the contagonal pays the contagonal pays to the contagonal pays to the contagonal pays the contagonal pays to the contagonal pays to the contagonal pays to the contagonal pays to the contagonal pays the contagonal pays the contagonal pays to the contagonal pays	##### 4. Acquirer Selection Analysis **Cost Risk Tradeoffs by Location:** Acquirer County Aog Fee Faund Rate Volume	Actionable Recommendations: 1. Optimizing Fee Structures: - Negotiate with acquirers to reduce fixed fees, particularly for high-volume transactions. Consider shalling to pricing models that reward transaction efficiency. - Explore dynamic fee assessments where lower-risk, high-value transactions benefit from a reduced per-transaction fee.
examining fee structures, fraud patterns, and transaction characteristics. Generate a comprehensive data science report that provides actionable recommendations for minimizing	(I) merchants for equivalent transaction values, despite similar fund rates. The data shows that writing from Hospitality to Retail account types could save mechants (ELOO) annually for a £100,000 volume merchant (Merchant category optimization opportunities vary from 12-18% savings for Retail merchants to 23-27% for Digital merchants. Acquirer selection analysis reveals that merchants using multiple acquirers can reduce fees by \$-12% fromogh optimal routing. The data shows that CVs of merchants could reduce fees by \$-\$0.000 to the control of the country	**Acquirer Optimization Strategies.** 1. Shift volume from high-out acquirers (CY/LLI) to DE/FR where possible 2. Implement milital acquirer routing based on transaction profile 3. Negotian volume-based discounts with grainary acquirers 4. Develop failnow reystems to militation uprime during routing changes	2. Fraud Risk Mitgation: -Tahance fraud electron methods, especially for segments identified as high risk, potentially using machine learning-based anomaly detection before transactions are processed. -Implement risk-based fee adjustments that incorporate security costs for transactions with higher fraud priorital. 3. Tallored Acquiere Selection.
payment processing fees while maintaining security and conversion rates. The report should include analysis of fee drivers, fraud risk	fraud-related fees by 35-42% while maintaining current fraud levels through tokenization (12-15% reduction) and 3D Secure (23-27% reduction). ### Transaction Pattern Analysis and Fraud Prevention	#### 5. Merchant-Specific Recommendations **Digital Goods Merchants (High Fee, High Fraud).** - Implement 3D Secure for all transactions - Negotiate flat-step rioring instead of percentage-based	 For merchants with international operations, perform data-driven assessments to select acquirers with optimal fee structures within target markets. Continuously monitor acquirer performance (fee levels, fraud management, dispute resolution) to ensure ongoing cost effectiveness.
factors, acquirer selection strategies, and specific optimization recommendations tailored to different merchant profiles.	Transaction pattern analysis reveals that 68% of frankindent transactions occur during off-peak houng 2.5 AM focal time) and from one standard IP locations (75%). The data stows that implementing device fingerprinting could reduce fraud by 15-18% with minimal falte positives (2.9%). Authorization Characteristics Indictor (ACL) analysis shows that ACL IP Gottamer AN ON Present 30 Secure) transactions have 23-27% lower fraud rates but 12-19% higher processing frest than ACL CT (Characteric and not presents).	- Introduce micro- transaction pricing tiers - Deploy behavior micro- fraud prevention **Retail Merchants (Medium Fee, Low Fraud).** - Implement transactions size-based fee optimization - Extra Medium Fee, Low Fraud).** - Englement transactions for processing efficiency - Extra stantifications for processing efficiency	4. Merchant Specific Strategies: Small and medium-ierd merchants should prioritize robust fraud prevention tools to reduce exposure while controlling costs. 1 High-volume mechants can leverage their scale for negotiating volume discounts or dedicated agreements that improve fee structures.
	Merchant category fraud rates vary from 2.1% for Book Stores to 8.3% for Easing Places and Restaurants. The data shows that implementing fixed prevention strategies can reduce fraud- related fees by 35-26% while maintaining current fraud levels. The optimal fraud prevention strategy combines tokenization (12.15% fraud reduction) with 3D Secure (33-27% reduction) and device fingerprinting (15-18% reduction).	- Adopt address verification for high-value items **Service Providers (Low Fee, Medium Fraus);** - Implement recurring billing optimization - Develop CVV-required policy for new customers - Introduce cross-border fee disclosures	The analysis indicates that careful management of fee structures and acquirer selection— combined with proactive fund detection—can result in significant cost swings without compromising security or conversion rates. Talloring these recommendations based on merchan- specific and regional manness offers practical pathways for reducing overall payment processing costs.
	Transaction value analysis reveals that merchants accepting £50£100 transactions pay 18-22% lower feet than those accepting £500 transactions, suggesting optimal transaction plitning strategies. The data shows that splitting £500 transactions into two £200 transactions could see merchants 12-15% on processing few which maintaining outstoner experience. ## Implementation Roadmap and Recommendations	- Use predictive analytics for chargebock prevention #### 6. Implementation Roadmap #### 6. The Three for the Three for the Three for optimizations (acquirer routing, cregory-based of Three for the Three for the Three for Country for the Three for the	Next Steps: - Further: investigate temporal trends to refine dynamic pricing strategies. - Further: invest in machine learning models for real-time fraud prediction and transaction scoring. - Regularly re-assess acquirer agreements and fee strategies in light of evolving transaction data.
	The implementation roadmap suggests a phased approach to fee optimization, beginning with account type optimization (Modni 1-5, uring 8-12%), followed by acquirer optimization (Modni 1-5, asving 8-10%), and concluding with fraud prevention implementation (Modni 1-6, saving 35-4%)). The total potential asvings for a (100,000 volume merchant could race-fel (2000 annually through comprehensive implementation. The analysis identifies three primary optimization pathways: Account Type Optimization (12-18% savings). Merchant Category Optimization (12-18% savings). The implementation requires minimal technical cleanes post requires strategie account	biometrics **Expected Results.** 18.22% reduction in payment processing costs (\$4.25.1M annually) 2.53.0%, reduction in fraud losses (\$1.8.2.7M annually) 1.52% improvement in conversion trate through optimized checkout flows -Enhanced merchant satisfaction through tailored payment solutions	By implementing these recommendations, merchants can optimize payment processing fees while maintaining robust security and enhancing conversion outcomes.
	management and process changes. The payback period for fraud prevention technologies averages 6-9 months, with ROI exceeding 3:1 for most merchants. The complete implementation tradman includes detailed merchant-specific outlimization plans.	This comprehensive analysis provides actionable pathways to optimize payment processing economies while maintaining security and conversion performance. Implementation should be prioritized based on merchant-specific profiles and transaction patterns.	
	based on the segmentation analysis, with tailored strategies for Hospitality, Retail, and Digital merchants. The analysis provides merchants pecific fee optimization calculators and scenario modeling tools to project potential savings for each merchant profile. ### Conclusion and Future Research Directions		
	This comprehensive analysis demonstrates that systematic payment processing optimization can significantly reduce merchant costs while maintaining security and convenion rates. The findings symmetry of the control of		
	The analysis methodology and findings provide a foundation for ongoing payment processing optimization and continuous improvement. The demonstrated savings opportunities of 18-27% for account type optimization, 13-27% for merchant category optimization, and 33-42% for fraud prevention collectively represent significant value creation for the payment processing ecosystem.		

Figure 12. A data analysis case of autonomous data science, from data sources to analyst-grade research reports.

Instruction	DeepAnalyze-8B	Deepseek-r1	o3-mini
	# Comprehensive Analysis of Payment Processing Fees and Fraud Risk Factors	Based on the analysis performed, here are the key insights into transaction cost drivers and fraud	Below is a summary of the insights derived from our exploratory data analysis of the payments dataset and supporting documentation:
	### Executive Summary This comprehensive analysis examines the intricate relationship between payment transaction characteristics, merchant profiles, and resulting processing fees and fraud risk. Through systematic characteristics, merchant profiles, and resulting processing fees and fraud risk. Through systematic delivers of transaction costs and fraud risk. The subjet reveals that card scheme selection accounts for 68% of few variation, while merchant cargory codes influence 42% of fraud risk profiles. Our findings demonstrate that strategic configuration of payment processing parameters can reduce costs by 1822-98 while simultaneously deversaing frauddent designer rates by 1417-199.	#### 1. Primary Transaction Cost Drivers -**Card Scheme Impac** Visa transactions show significantly higher average fees (EX XX) compared to Mastercard (EX XX) -**Cross Border Perminin**. Cross-border transactions incur XX% higher fees on average compared to domestic transactions compared to domestic transactions that standard accounts -***CI Inflances**. High ACI sources correlate with XX% lower fees due to reduced risk -***CI Inflances**. High ACI sources correlate with XX% lower fees due to reduced risk	otates man supporting documentation: 1. Transaction Characteristics & Card Scheme - Our aggregation by could achieve shows that different brands can exhibit distinct behaviors. For instance, some cast schemes are associated with higher average transaction amounts while others show a higher incidence (froud acts) of fraudated inspires. This suggests that merchance from a comparing the property of the comparing the comparing the contraction of th
Analyze the provided payments dataset and supporting documentation to produce a comprehensive data insight report. The report should identify the primary drivers of transaction costs and fraud risk for the merchants. Investigate how factors such as transaction characteristics (e.g., ACI, card scheme, amount), merchant profiles (e.g., account type, MCC, acquirer choice), and behavioral patterns (e.g., time of day, cross-border activity) influence processing fees and fraudulent disputes. The goal is to derive actionable insights that can help merchants optimize their payment configurations and operational practices to minimize costs and mitigate risk.	incode by 0.22% while immination day devenating fraudition dispute articly by 1.41%. ## Methodology and Data Overview ## Details and the property of the pro		**Recommendation** Merchants can investigate alternative and acceptance strategies (or enforce strates within methodo) for carish binded to heteroically higher fraud incidences, additionally, parking or insurance adjustments may be considered. 2. Behavioral Patterns: Time of Day **Analysis by the hour of the day indicates that fraud incidents are not uniformly distributed. Certain time door, the hour of the day indicates that fraud incidents are not uniformly distributed. Certain time door, the own of the day indicates that fraud incidents are not uniformly distributed. Certain time door, the own of the day indicates that fraud incidents are not uniformly distributed. Certain time door, the own of the day indicates that fraud incidents are not uniformly distributed. Certain time door, the own of the day indicates that fraud incidents are not uniformly distributed. Certain time door, the own of the day indicates that fraud prevention controls. *Recommendation: Merchant operations can consider operating additional faund screening measured during peak fraud risk hours, optimizing staffing decisions or real-time risk analytics at these times. 3. Cross-Border Activity *When investigating the role of cross-border versus domestic transactions, the data reveals that cross-border transactions tent to how efficient fee profiles and may encounter higher fraud rates. This may be due to additional hanking and regulatory complexations or distributed fraud rates. *Recommendation: Merchants with substantial cross-border activity should focus on localizing and prevention mechanisms, possibly integrating additional identity serification professes are countries. **Recommendation: Merchants profiles (from merchant, data, joon) with transactions data, we identified that merchant account per influences both transactions volumes and fraud incidence. For conditional programments, and excepting the profiles and consider if their current configurations, acquirer clouds; and transaction volumes and fraud incidence. For conditional

Figure 13. A data insight case of autonomous data science, from data sources to analyst-grade research reports.

Instruction	DeepAnalyze-8B	Deepseek-r1	o3-mini
Based on the provided data (manual.md,	# Strategic Recommendations Report: Payment Processing Analysis	I'll analyze the data and prepare the comprehensive report based on the code execution results. Here's the report:	Below is the comprehensive Data Report generated based on the analysis of the provided payment processing data:
payments.csv, merchant_data_ison, fees_ison, acquirer_countries.csv, merchant_category_codes.csv), generate a comprehensive **Data Report** analyzing the payment processing operations for the merchants. The report must follow the exact structure and content outline	as 1. Execute Summary The compelements enables of payment processing operations reveals significant opportunities for cost optimization and The compelements of the co	sas Sussige Economendations Report Payment Processing Analysis attast 1. Exactoris Transmistry Overall transmistry processing down undersite efficiency with an authorization rate of £2.3% - Partial sets in concentry at 37%, significantly integering revenue - Disquire art or £1.3% indicates proteinal consinere sufficiency undersite of £3.4% - Capture days lower soon for improvement with exact §1.1% storage 1.0% - Capture days lower soon for improvement with exact §1.1% storage 1.0% - Capture days lower soon for improvement with exact §1.1% storage 1.0% - Capture days lower soon for improvement with exact §1.1% storage 1.0% - Capture days lower soon for improvement with exact §1.1% storage 1.0% - Capture days lower soon for improvement with exact §1.1% storage 1.0% - Capture days lower soon for improvement with exact §1.1% storage 1.0% - Capture days lower the control improvement with exact §1.0% - Capture days lower soon for improvement with exact §1.0% - Capture days lower the control improvement with exact §1.0% - Capture days lower soon for improvement with exact §1.0% - Capture days lower the capture for the capture of the c	Stategic Recommendations Report: Psyment Processing Analysis 1. Executive Summary — Toda Transaction Processed: [Related from psyments.cv] — Toda Transaction Processed: [Related from psyments.cv] — Significant variations noted in fee components and processing times.
exact structure and content outline specified below. # Strategic Recommendations Report:	controls, while 17% of merchants operate with suboptimal acquirer relationships. These findings enable targeted interventions to improve profitability while maintaining service quality.	Hamilton 2. Introduction and temperature was an engage. If some texture texture man expense many 2. Introduction processing for multiple merchants over an unspecified period - Purpose: Mentily cost optimization, faunt reduction, and officiency improvements - Scope: Transaction patterns, for structure, Raul assessment, and processing efficiency of the processing efficiency and processing efficiency.	- Segment variation in the Complement and processing same. - Recommendations: - Optimize acquirer selection and fee structures. - Enhance found detection measures for high-tisk transaction types.
Payment Processing Analysis ## 1. Executive Summary	This sport analyzes payment processing operations for a network of 30 merchants across multiple European countries, overing transaction data from 2023. The analysis incorporate transactional exceeds, merchant attributes, fee structures, and acquier relationships to evaluate operational efficiency and identify optimization opportunities. The dataset includes 1.000 sampled transactions with an acreage value of 687-42, representing 687-32 to in total processed volume. Merchant where the contraction of	anne 1 Day Samuel A Carter	Introduction Purpose: To analyze payment processing operations with an emphasis on cost efficiency, risk, and operational performance. Scope: The analysis covers multiple merchants over the time period as indicated in the transaction data.
Provide a high-level overview of key findings and most critical recommendations. Summarize overall performance, cost efficiency, and fraud risk levels.	as 2. Introduction The appet analyzes promoting operations for a network of 30 mentation across salingly framework contribution and acquire relationships to evaluate operational efficiency and identify optimization opportunities. The distort includes and acquire relationships to evaluate operations of 20 %, opportunities (20%) and purposes and some laborations operations. The distort includes 10 % on the operation of 20% of the optimization opportunities. The distort includes 10 % of the optimization opportunities. The distort includes 10 % of the optimization operation in the optimization of the optimization of the optimization operation in the optimization of the optimization optimization of the optimization optimization of the optimization optimization of the optimization optimizatio	**Pymount on Cyl (2001)******Cope transaction data with authorization nature, fraud flags, and directampes ***Percelucial_git_laws policy including US and explored in the US and to insure the present of the US and to insure the present of the US and to insure that the US and the US	3. Data Sources and Quality
## 2. Introduction - State the purpose and scope of the analysis. - Briefly describe the merchants and time	and 3. Data Science and Quality The analysis imagenes or personary data sources, each contributing unique dimensions to the payment processing analysis. The application paint of the resusanciand foundation, containing 2.1 felds expering merchant, and such as the proposed analysis of the process of the pro	annu 4. Analytical Approach. The calculations Simulated Interchange, scheme, and acquirer for components -Passal risk: Calculation flund and disprese nets; identified high-risk merchanges -Passal risk: Calculation flund and disprese nets; identified high-risk merchanges -Possessing efficiers, Analytical antiferization sate, redular reasons, graduar delays -Opinizations enterial: Coart reflection potential, finand minginion impact, and efficiency gains amount 5. Thindage.	The Secure - Transaction procedures and system guideline
period covered. ## 3. Data Sources and Quality	optional little. The fee runs demonstrate conspirementors coverage, with 57% of trainsachous mixturing at their doct fee runs and 75% mixturing exactly one runs. Childrian against brushiese rules in manual and confinements structural compliance with payment processing strandards. Limitations include the 1,000-transaction samples use and lack of historical comparisons, though the analysis accounts for three thousands plantational reformations.	##### 5.1 Transaction Volume and Patterns - Transaction distribution: - Value 25% of Engineering - Value 25% of Engineering	 - rees data provides detailed breakdown; flowerer, its complexer requires calerul reconcusticis with indeeding flowers; in complexer requires calerul reconcusticis with indeeding from the control of the complexer requires calerul reconcusticis with indeeding from the control of the control of
List and describe all data sources used in the analysis. Assess data completeness, accuracy, and any limitations encountered.	## 4. Analytical Approach The methodology combines descriptive analytics, predictive modeling, and prescriptive optimization to evaluate payment processing operations. Fee calculations implement the formula: Fee = ForedAmount + (Rate * TransactionValue / 10,000, applying the first matching rule from 12 conditional dimensions. Fraud risk assessment combines transaction	militari 5.1 militachian Volume ana returna "The 28 Hole of ministration - Manistration 2002 - Manistratio	
## 4. Analytical Approach - Explain the methodology used for fee calculation and cost analysis Describe how fraud risk and processing	and A. Analysical Approach. The combination contained and prescribes operational contained as a function of the combination of	mittud B 2 Fee Structure Analysis -Most expense components. 1. Const-booker sincerchange fee (0.2%) 1. Const-booker sincerchange fee (0.2%) 3. Acquier mature (0.1%) - Fee variations by merchans size Smaller merchans pay 22% higher fees on average - High-MCC merchant booker, car reschash incur 30% higher fees 1. High-MCC merchant booker, car reschash incur 30% higher fees	 Methodologies Agreement for per merchant were compared to reverb variations in core efficiency. Major for driven included processing societies where extraport and additional service for including processing societies. The artificial variations hashyor foliant indicates via dispute records in the populered and correlated against merchant processing inflicency behaviorable and present insulantizations and against extend against service and processing inflicency behaviorable and present indicates and acquire recentling and applications of the components, cleared fasted signals, and sub-optimal processing speech as primary opportunities for operational important processing speech as primary opportunities for operational important processing speech as primary opportunities for operational important processing speech as primary opportunities of operational important processing speech as primary operational for operational important processing speech as primary operational processing speech as primary operational for operational important processing speech as primary operational for operational processing speech as primary operations for operations are properties of the processing speech as primary operations for operations are processed as a processing speech as processing speech as processed as a processing speech as process
efficiency were evaluated. - Outline the criteria for identifying optimization opportunities. ## 5. Findings	na 5. Trainga. Ha 18 Traingaine Volume and Pateras. Trainsaction shapes reveal distinct patterns across merchants, ond schemes, and time petiols. Volume peaks between Trainsaction analysis reveals distinct patterns across merchants, ord schemes, and time petiols. Volume peaks between trainsactions (using course) a superior country in present 20 He of volume but 20 He of the acceptage 40.72 remancions (using course) a superior country in present 20 He of volume but 20 He of the case pengage 40.72 remancions (using course) a superior country in present 20 He of volume but 20 He of the case of the country of the coun	###### 5.3 Fraud and Risk Assessment - Highers fraud rates by merchant: - Merchant X, 8.2% - Merchant E, 6.7%	5. Findings 5. I Transaction Volume and Patterns - Total transactions processed: Data from paymens, csv shows a large volume across the analyzed period Seasonal trends: Evidence of peaks during promotional periods and seasonal creats Card scheme insights: Devere usage across moje cond-networks (Viss, MasterCard, cc) indicate varied consumer
### 5.1 Transaction Volume and Patterns - Analyze transaction volumes by merchant, time, and card scheme Identify seasonal trends and peak	versus 1.8 for professional services, with average transaction values of 1/8.42 and 12.45 respectively. Fraind patterns show 2.1% overall faund rate, but 4.7% for high-value (v=200) credit (and transactions. Seasonal analysis identifies November peaks (18% above average) and February troughs (23% below average).	- Percentations from dates - American Express 4.8% - Vasa 3.1% - Masteront 2.9% - BBBB 5.4 Processing Efficiency	behavior. 5.2 Fee Structure Analysis - Variability in fee structures Fees vary notably across merchants, influenced by operational volume and merchant categors - Major fee components: Processing fees and acquirer service charges represent the highest cost elements.
processing periods. ### 5.2 Fee Structure Analysis - Calculate and compare processing costs across different merchants.	Base 5.2 For Stormace Analysis and 5.2 For Stormace Analysis and 5.2 For Stormace Analysis control of the Control of Analysis control of the Control of Analysis being some common conditions. Breast for many from 10 for 10 for 10 men 10 for 10 for 10 men 10 for 10	- Authorization are: \$2.3% - Top offend reasons. Top offend reasons Supercod family 50% - Top offend reasons Supercod family 50% - Caption 465% - Capt	cargany. Alsylve for components: Processing first and acquirer service charges represent the highest cost elements. Alsylve for components: Processing first and acquirer service charges represent the highest cost elements. Benefits: (angrey): colors serv) and whome on key determinated driving for rate. First and rate first. Acquirers: First and rate first. One of the control for the rate first and for the control for the rate of the control first and for the control first and first and for the control first and first an
Identify the most expensive fee components and their drivers. Analyze how merchant characteristics affect fee rates.		- 90th percentile: 5 hours	could relocal fund-related cone. 1-light-ink identification Certain transaction types and specific merchants are flagged for incipierated found risk. 5-a Processing Efficiency. Architecturines we refinal boot merchants experience industry-assalated authorization rates, frompal a subset shows higher relatal numbers. Architecturines we refinal boat merchants experience industry-assalated authorization rates, frompal a subset shows higher relatal numbers. Architecturines we refinal boat merchants experience industry-assalated authorization rates, frompal a subset shows higher relatal numbers.
### 5.3 Fraud and Risk Assessment - Evaluate fraud rates and dispute patterns Assess the effectiveness of current fraud prevention measures Identify high-risk transaction types and	and 5.2 Four ain and Eask Assessments are superior to send 17.2% that melt, decreasing (6.1%), cend 5.1%, and completely (4.9%). Transactions with comparison of the complete (4.9%). The contractions excellent factorist contractions with summal country minuments. Machine forming models predict found with complete factorist contractions of the contraction	No transaction amount data for prote revenue impact calculation - Limited mentand take prevent grantal cargosy analysis - Time previous due reported prevent grantal cargosy analysis - Time previous due reported intains treat analysis - Machine Changhort, their to recognize the analysis - Machine Changhort, and the recognize their anaexament - BBBS 7.5 cargosyle Economicalization - BBBS 7.5 cargos	 Capture delays: Delay in capture processes directly adds to cost overheads, suggesting a need for more timely settlement processes. 6. Limitations
merchants. ### 5.4 Processing Efficiency - Analyze authorization rates and refusal	BBB 5.4 Processing Efficiency Authorization analysis reveals \$17.9% unthorization rates, with debte cased (\$750) comperforming credit (\$750). Refusal Authorization analysis reveals \$17.9% unthorization rates, with debte cased (\$750) comperforming credit (\$750). Refusal Authorization analysis of the results of the refusal section of the refusal section (\$750), captured spikes allows analysis about a refusal section (\$750), captured spikes allows analysis and section (\$750), captured spikes allows analysis described 17% of merchans seeding 5.71%, correlating with 31% higher late fees. Routing optimization moderling instituted, 7.000 in potential single into policy about parties are allowed. Authorization are improvements could be allowed to the results of the res	- Negatiar interchange few for high-volume merchants (speemtal 15% awings) - Indeptement MCC openitazion for high-cocci categories - Consolidate acquirer relationships to reduce markup fees - Ruman # 2 Fanach Prevention improvements - Ruman	Thus Committee Some fields in presence or (such as transaction dates) were incomplete or inconsistently formatted, affecting the precision of time-based subject. **Additional Data Postallo data on finantinosis: Assumptions made during for aggregation might not fully capture all for nameses. **Additional Data Postallo data on finand incidents and more granular merchant performance metrics would provide enhanced cludity. **Strangels: Recommendations**
patterns Evaluate acquirer selection and routing efficiency Assess capture delay practices and their cost implications.	modeling identifier H, 400 in potential swings through cogiume resultigence. Authorization are improvement could accept Eq. (100 manage) through improved mechanismissing. The analysis identifier 12 merchans with suboptimal processing practices, representing e12,200 in potential swings. Be a Limitation The analysis fives several constrains requiring custroon interpersacion. The 1,000 tennascions sample, while representation, may not capture currence values adequately. The static for tests don't account for dynamic pricing, patterns. The mechanist agenturation uses oddy 5 Enteres, potentially oversimplying complete business models. The analysis period coversors carefularly use in this price condition via the interpersacion objects to the condition of the condit	Introduce machine learning faund scoting for high-side merchanis - Implemental 3D Secure for American Expose manacisms - Cream merchanospecific American Expose manacisms - Secure merchanospecific faund frenchaled based on hinterial patterns - Secure for the secure for the secure for the secure for the secure manacism cortaing as negatives with = 70% anticoloxistic stress - Optimizer transaction cortaing as negatives with = 70% anticoloxistic stress - Optimizer transaction cortaing as negatives with = 70% anticoloxistic stress - Optimizer transaction cortaing as negatives with = 70% anticoloxistic stress - Optimizer transaction cortaing as negatives with = 70% anticoloxistic stress - Optimizer transaction cortain great anticoloxistic stress - Optimizer transaction cortain great grea	7.1 Cost Optimization Strategies - Negotiate fee rates by leveraging mechanit's high-volume statistics to secure better terms. - Re-evaluate acquirer and transaction routing decisions to identify efficient cost reductions based on regional performance data from acquirer_countries.exe
### 6. Limitations - Discuss any data constraints or methodological limitations. - Identify areas where additional data would improve analysis.	account details and limited historical beachmarking. The fee optimization models assume static merchant volumes, while actual volumes may fluctuate. These limitations are mitigated through conservative confidence intervals and sensitivity analysis. Future research could incorporate real-time data streams and machine learning for dynamic pricing.	muss 8. Conclusion - Implementing recommendations could reduce processing costs by 18-22%, - Faund reduction initiatives could save \$500K+ annually for mid-sized merchants - Efficiency improvements could increase revenue capane by 5-7%, - Next steps: Productive cost optimization and frand prevention for highest-impact merchants	7.2 France Procession Improvements - Talhance erable in entra detection systems and update risk models using detailed merchant data. - Implement targeted monitoring for high-risk transaction segments identified in the analysis. - Toperstond ITEM-ray Talhancement - Operational ITEM-ray Talhancement - Operational ITEM-ray Talhancement - Operational ITEM-ray Talhancement - Packer capture deliver framework - Packer capture deliver deliver framework - Packer capture deliver deliver framework - Packer capture deliver being improved volumination in allegance technical voluminations.
would improve analysis. ### 7. Strategic Recommendations #### 7.1 Cost Optimization Strategies - Specific recommendations for reducing processing fees. - Suggestions for optimizing transaction	as 7. Stategies Recommendations and 2.1 Cast Optimization abundle priorities there initiatives acquire routing 61.400 potential), the structure series 61.200, and For experimization abundle priorities there initiatives acquire routing 61.400 potential), the structure series 61.200, and with 61.900. In fixed prevention improvements. The analysis accommends implementing dynamic routing adjustifies to with 61.400 in fixed prevention improvements. The analysis accommends implementation series algorithms to the contraction of the contraction o	State S Dabography The Spread To The Spread	Recordation - Key Insights: The analysis underscores the need for improvements in reducing processing fees, strengthesing faund prevention, and enhancing overall operational efficiency. - The continuity of the continuity of the continuity of the continuity of the faund of the model.
Suggestions for optimizing transaction routing and acquirer selection. ### 7.2 Fraud Prevention Improvements Recommendations for enhancing security	42.100 animally. The implementation readmap priorities quick wins (noting) before complex changes (fee secretarizing). The projected 29% animal swaping (45.900) delives 31 st ON within 6 months. The program should include ongoing monitoring with monthly KPIs and quantrity reviews. ### 27 Fearl Prevention Improvements Final reviewing should industries there are a who're controls (#) 200 overwith 33 Source insolementation (#900)	munu 10. Appendix - Detailed for analysis by merchant available upon request - Pastal patters charts by card scheme and time of day - Capture delay distribution histogram - Acquirer performance comparison table	9. Bibliography - marmal md
measures Strategies for reducing fraud-related costs and chargebacks.	Bill 2.3 Far and Precention Improvements. Websity controls should form on high-yold merchants (v.500 instanctions), where final one top and a 7.7 h. 3D Secretion Improvements and the properties of the controls where final one properties of the ST bill 2.5 Far and the precention of the properties of the control of the precention of the precent proceed and the properties of the precent procedure of the pr	This report provides data-driven insights to optimize payment operations, reduce costs, and mitigate fraud risks across your merchant portfolio.	Specific clause that
Enhancements - Suggestions for improving authorization rates and reducing refusals Recommendations for optimizing capture timing and settlement processes.	BB 7.3 Operational Enciency Enhancements underlands near (47.10) potential, reflerence limit (47.50), and sequence reflected for the control of the control		Peculiar latics and visualizations (e.g., the breakdowns, reasonal transaction trends, and risk assessments) underpite the Merchant-specific analysis and committed recommendations are available upon regions. Merchant-specific analysis and committed recommendations are available upon regions. The report intend action and both upon specific merchan and obscilation described from the provided data sources. The recommendations are aimed at reaching tools, midigating froad risk, and optimizing operational efficiency in the propriet procuring conformation.
### 8. Conclusion - Summarize key insights and expected benefits of implemented recommendations Outline next steps for implementation and monitoring.	monthy row-us. #8 C. Condusion This comperiment analysis identifies substantial opportunities to improve paymont processing operations through data. This comperiment is an incidentified to the control of the control		
## 9. Bibliography - List all referenced documents, manuals, and data sources.			
## 10. Appendix - Include supporting tables, charts, and detailed calculations Provide merchant-specific analysis and recommendations.	as 9. Bildography Mechanic Guide to Optimizing Psyment Processing and Minimizing Fees (v.2.1, November 2026) Psyment Processing Standards (20.0 SS032007) Psyment Processing Standards (20.0 SS032007) 2020. Againer Country Mapping (1.5. Springers 2026) Fee find Springers (2.5. August 2026)		
Ensure the report is data-driven, with specific metrics and calculations supporting all findings and recommendations. Use clear, professional language suitable for business stakeholders.	and 10. Approaches Approaches Association Segmentation Details Approaches Association Segmentation Details Approaches The Field Musching Algorithms Approaches Co-Final Model Specifications Approaches Co-Final Model Specifications Approaches Co-Final Model Specifications Approaches Co-Final Model Medical Model Approaches Co-Final Medical Medical Model Approaches Co-Final Medical Medical Medical Approaches Co-Final Medical Medical Medical Approaches Co-Final Medical Medical Medical Approaches Co-Final Medical M		

Figure 14. A case of autonomous data science with report constraints.

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Here's the report summarizing the notable trends and findings from the data analysis:	Below is the summary report based solely on the available information (i.e. file names, sizes, and expected content types):
Here's the report summarizing the notable tends and findings from the data analysis: ### 1. Psymetric Data Summary (psyments.cov) ***Size**** 25.03. TS (Bit (larges) ***Size*** 25.03. TS (Bit (larges) ***Si	Below is the summary report based solely on the available information (i.e. file names, sizes, and
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Figure 15. A case of autonomous data science for fully open-ended data research.