

HealthFlow: A Self-Evolving AI Agent with Meta Planning for Autonomous Healthcare Research

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Abstract

The proliferation of scientific knowledge on the World Wide Web presents a grand challenge: transforming this passive repository into an active engine for discovery, especially in high-stakes domains like healthcare. Current AI agents, however, are constrained by static, predefined strategies, limiting their ability to navigate the complex, evolving information ecosystem of the Web. This paper introduces HealthFlow, a self-evolving AI agent that overcomes this limitation through a novel meta-level evolution mechanism. HealthFlow autonomously refines its high-level problem-solving policies by distilling procedural successes and failures into a durable, structured knowledge base. This enables it to learn not just how to use tools, but how to strategize. To anchor our research and provide a community resource, we introduce EHRFlowBench, a new benchmark featuring complex health data analysis tasks systematically derived from peer-reviewed research on the Web. Our experiments demonstrate that HealthFlow's self-evolving approach significantly outperforms state-of-the-art agent frameworks. This work contributes to the WWW community by offering a new paradigm for intelligent systems that can learn to operationalize the procedural knowledge embedded in Web-based scientific content, marking a critical step toward more autonomous and effective AI for healthcare scientific discovery. We have open-sourced all code and data on the anonymous project website: <https://healthflow-agent.netlify.app/>.

CCS Concepts

- Computing methodologies → Multi-agent systems; Planning with abstraction and generalization;
- Applied computing → Health informatics.

Keywords

large language model agent, multi-agent system, self-evolving, AI for healthcare

1 Introduction

The World Wide Web (WWW) has evolved into an indispensable infrastructure for scientific discovery, hosting a vast and rapidly expanding corpus of research articles, datasets, and knowledge bases [24, 34]. A central challenge for the WWW community is developing intelligent systems that can navigate this complex information ecosystem to accelerate research, particularly in high-stakes domains like healthcare. With the advent of Large Language Models (LLMs), a new paradigm of AI-driven scientific discovery has emerged, where autonomous agents are poised to revolutionize research workflows [4, 7, 9, 16, 41]. These agents promise to accelerate breakthroughs by automating complex data analysis, from hypothesis generation to navigating the vast, heterogeneous data landscapes of the Web and Electronic Health Records (EHRs) [11, 20, 37, 51]. By orchestrating sophisticated analytical pipelines, they offer the

potential to uncover novel clinical insights at an unprecedented scale and pace [13, 17].

However, the capabilities of current AI agents are often limited because their high-level strategic frameworks are static and pre-defined. This is particularly detrimental in healthcare research, a domain characterized by open-ended problems, noisy data, and the need to dynamically adapt plans based on intermediate findings [17]. Existing agents can learn to refine the usage of a specific tool [20, 30] or improve a reasoning template for a sub-problem [51], but they operate within a fixed cognitive architecture. The overarching strategy that dictates how to decompose a new problem, orchestrate a multi-step workflow, and revise a plan remains hard-coded by human engineers and is outside the agent's learning scope. This can impose a significant limit on their autonomy; an agent can become highly efficient at executing a brittle or suboptimal strategy, but it cannot learn to devise a better one. This reliance on hand-crafted priors is contrary to a core lesson from AI's history: the consistent superiority of learned, general mechanisms over fixed, engineered solutions [40].

To address this limitation, we propose HealthFlow, an AI agent framework driven by meta-level strategic planning, learning, and self-evolution. HealthFlow transcends component-level optimization by treating every task as an experience from which to refine its own high-level management policies. Its architecture features a reflective loop where the entire execution trace of a task, including successes, failures, and corrections, is analyzed to synthesize abstract, structured knowledge. This knowledge, encapsulated as effective procedural patterns or critical data-handling warnings, directly reshapes the agent's future strategic choices, such as how to triage tasks or structure an analytical plan. Consequently, HealthFlow learns not just to execute tasks more effectively but to strategically manage the problem-solving process itself.

Furthermore, evaluating such advanced agent capabilities reveals a critical gap in existing resources. General-purpose agent benchmarks [27] lack the necessary domain specificity, while prevalent medical datasets [18, 19] are dominated by closed-ended question-answering tasks, failing to assess the complex data analysis and modeling skills central to clinical research [32, 37]. To address this, we introduce EHRFlowBench, a new benchmark comprising realistic, evidence-grounded data analysis workflows. These workflows are systematically mined from established publications on Web-based academic repositories, effectively transforming unstructured Web content into a structured testbed for the WWW community.

Relevance to WWW and the Semantics and Knowledge Track.

The imperative to transform the Web from a passive repository of scientific knowledge into an active, operational engine for discovery is a grand challenge for the WWW community. This requires systems that can understand and act upon the complex, procedural knowledge embedded in scientific literature. While the WWW community has long focused on knowledge extraction and semantic representation, a gap remains in modeling the semantics

Table 1: Architectural and evolutionary comparison of representative AI agent frameworks.

Framework	Benchmarked Tasks	Evolutionary Mechanism	Key Characteristics & Limitations
Biomni [17] (<i>Stanford</i>)	Biomedical data analysis (gene, drug, etc.)	✗ No evolution	Dynamically composes workflows but relies on a fixed set of tools, limiting its adaptability to tasks that require newly developed tools.
AFlow [50] (<i>ICLR 2025 Oral</i>)	Code generation, Math, QA	✓ MCTS-based workflow refinement	Frames workflow generation as a search problem is computationally intensive. Rely on learning abstract strategic knowledge from outcomes.
Alita [30] (<i>Princeton</i>)	Agent (general), math, medical VQA	✓ MCP creation & reuse	Creating new MCP tools but lacks mechanism for refining its high-level strategic planning or workflow orchestration.
STELLA [20] (<i>Princeton</i>)	Biomedical QA	✓ Evolving template library & tool	Evolution is component-level, improving reasoning templates and the toolset. Core multi-agent coordination and strategy remain static.
Alpha-Evo [28] (<i>Google</i>)	Scientific computing, AI-algorithm optimization	✓ Evolutionary code mutation	Focus on optimizing a specific artifact (the code) based on a fixed evaluation metric, rather than evolving the agent's high-level strategic planning.
HealthFlow (Ours)	Agentic health data science, medical QA	✓ Synthesizing experience (reflection, feedback, etc.)	Meta-level learning, allowing agents to evolve its own strategic planning from experience, moving beyond component-level optimization.

of scientific procedures to support intelligent agent behavior. Our work directly answers this specific Web-related scientific research challenge. HealthFlow’s meta-level learning mechanism provides a novel framework for converting unstructured procedural experiences into an evolving, structured knowledge base of strategic plans. By creating and consuming a dynamic data model of scientific strategy, our work advances core themes of the Semantics and Knowledge track, including data modeling for human-machine intelligence, intelligent system behavior, and enabling LLM agents. By demonstrating this in the critical domain of healthcare and by creating EHRFlowBench from Web-based literature, we provide both a foundational method and a community resource to advance toward a more intelligent and scientifically potent Web.

In summary, our contributions are threefold:

- (1) We propose HealthFlow, an AI agent that introduces meta-level strategic learning. Its core innovation is an experience-driven evolution mechanism that refines the agent’s high-level orchestration policies, a stark contrast to prior work focused on operational-level components.
- (2) We introduce EHRFlowBench, a public benchmark for AI agent-driven analysis of electronic health records, featuring complex, realistic clinical research tasks derived from peer-reviewed literature to ground future research.
- (3) We conduct comprehensive experiments showing that HealthFlow’s self-evolving strategic approach yields significant improvements in task success, robustness, and efficiency compared to state-of-the-art agent frameworks.

2 Related Work

Predefined agentic workflows. Early and many contemporary agentic systems rely on human-designed workflows with fixed operational loops. Pioneering efforts like AutoGPT [39] and GPT4Tools [48] demonstrate autonomous task execution by chaining LLM calls, but their high-level strategy for task decomposition and execution is hard-coded. Subsequent systems such as HuggingGPT [36] and MetaGPT [15] introduce more sophisticated tool orchestration and multi-agent role-playing, yet their overarching operational sequences remain static. This paradigm extends to scientific domains. For instance, frameworks like SciToolAgent [8] provide more scientific tools, Robin [13] automates a predefined cycle of hypothesis generation and experimentation, and Biomni [17] executes complex biomedical tasks using a fixed “select-plan-execute” loop. While

powerful, these systems are fundamentally constrained by their inability to learn from or adapt their high-level strategy.

Towards self-evolving agents. A more advanced line of research enables agents to evolve, but this evolution is typically confined to the operational level, improving specific components or artifacts within a fixed strategic framework. One approach focuses on refining tools and reasoning templates. For example, STELLA [20] and OriGene [51] improve their performance by expanding a library of tools and refining thought-process templates based on feedback. Other methods focus on iterative self-improvement on a single output, such as self-reflection [38], Self-Refine [26], or optimizing a specific artifact, like the evolutionary code mutation in AlphaEvo [28]. Frameworks like TextGrad introduce optimization by backpropagating LLM-generated feedback, offering a different paradigm for refinement [49]. As summarized in Table 1, despite their advances, these approaches share a common limitation: the agent learns to be a better tool-user or solution-reuser, but not a better strategic manager. The overarching meta-strategy remains predefined and outside the agent’s learning scope.

3 Methodology

HealthFlow achieves autonomous healthcare research through a multi-agent architecture and a meta-level learning loop (Figure 1).

3.1 Formalism and System Overview

We formalize a research problem as a task T . The goal of HealthFlow is to produce a solution S that satisfies the requirements of T . This is achieved through a stateful, iterative process. At each turn i , the system generates a plan P_i , which is a sequence of actions $\{a_1, \dots, a_k\}$. An action a can be a tool call or code execution. The execution of plan P_i produces a trace τ_i , which logs all actions, intermediate outputs, and errors. The system’s strategic knowledge is stored in a dynamically growing experience memory, $\mathcal{M} = \{E_1, \dots, E_N\}$. The core of HealthFlow is a learning process that updates \mathcal{M} based on successful task completions, thereby improving its future planning capabilities.

3.2 A Collaborative Multi-Agent Architecture

To manage the cognitive complexity of research tasks, HealthFlow employs a team of four specialized agents, each responsible for a distinct phase of the problem-solving lifecycle: planning, execution, evaluation, and reflection.

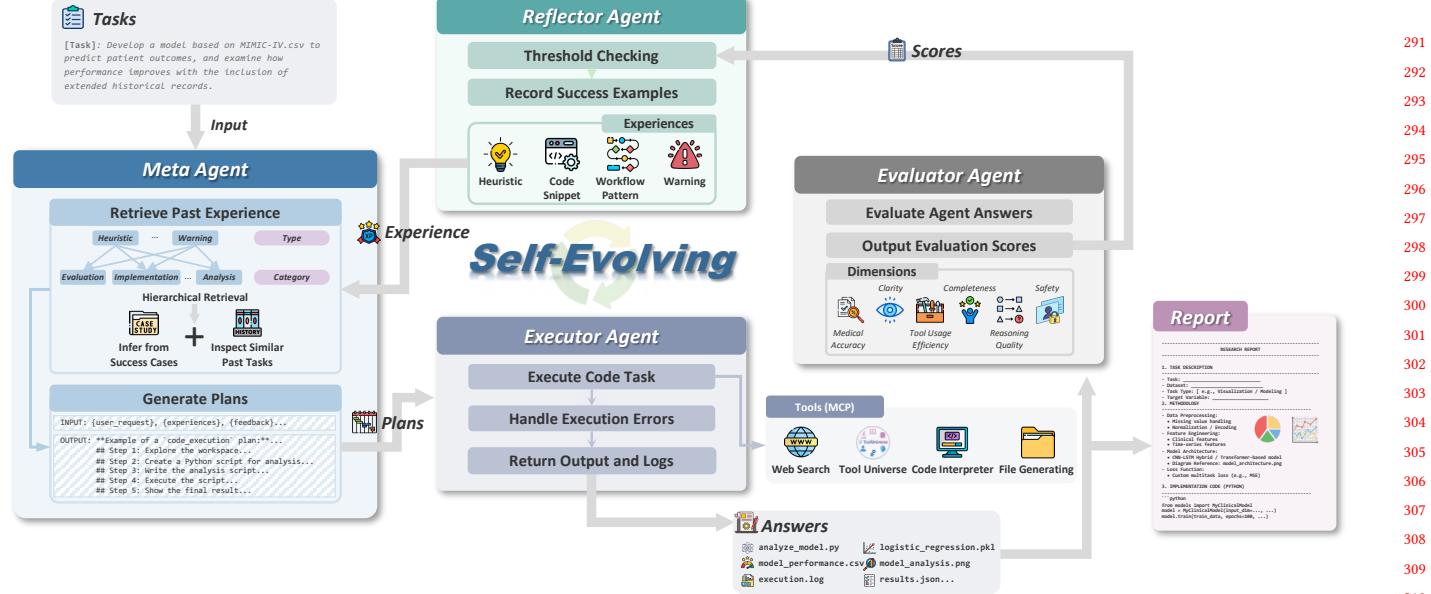


Figure 1: The self-evolving architecture of HealthFlow. The framework operates in a continuous learning loop. (1) A task is received by the meta agent, which generates a strategic plan by retrieving relevant past experiences. (2) The executor agent executes this plan using tools, producing results and detailed logs. (3) The evaluator agent assesses the execution, providing scores and feedback for immediate, short-term correction. (4) Upon successful completion, the reflector agent analyzes the entire process to synthesize abstract, structured experience (e.g., heuristics, workflow patterns). Experiences are stored in a persistent memory, augmenting the meta agent’s strategic capabilities for future tasks and enabling the system’s long-term, meta-level evolution.

Meta agent: strategic planner. The meta agent, A_M , serves as the cognitive orchestrator. Given a task T , the experience memory \mathcal{M} , and feedback f_{i-1} from a previous attempt (where f_0 is null), it devises a high-level strategic plan P_i . This process begins by retrieving a set of relevant experiences $\{E_k\} \subset \mathcal{M}$. These experiences augment the agent’s context, guiding it to generate a more robust and efficient plan. Formally:

$$\{E_k\} = \text{Retrieve}(\mathcal{M}, T) \quad \text{and} \quad P_i = A_M(T, \{E_k\}, f_{i-1}) \quad (1)$$

Executor agent: transparent execution engine. The executor agent, A_E , is responsible for grounding the meta agent’s strategic plan into concrete actions. It operates within a secure, sandboxed environment and translates plan P_i into a sequence of tool calls and code executions, producing a detailed execution trace τ_i :

$$\tau_i = A_E(P_i) \quad (2)$$

Crucially, the executor is a transparent “CodeAct”-style engine [45], ensuring that every decision, tool interaction, and intermediate result is auditable and reproducible. The executor integrates a wide array of tools via the Model Context Protocol (MCP) [1], including web search and access to ToolUniverse [11, 12], an ecosystem of machine learning models, datasets, and scientific packages.

Evaluator agent: short-term corrector. The evaluator agent, A_V , provides immediate, task-specific critique to enable a tight self-correction loop. After an execution attempt, it assesses the trace τ_i and any generated artifacts against the task requirements T :

$$(s_i, f_i) = A_V(\tau_i, T) \quad (3)$$

It produces a quantitative score s_i and qualitative, actionable feedback f_i . If s_i is below a predefined success threshold θ_{succ} , the feedback f_i is routed back to the meta agent to guide the generation of a revised plan P_{i+1} , initiating a new cycle of execution and evaluation.

Reflector agent: long-term knowledge synthesizer. The reflector agent, A_R , is the engine of HealthFlow’s long-term, meta-level evolution. It is activated upon successful task completion (i.e., when $s_i \geq \theta_{succ}$). The reflector analyzes the entire history of the successful attempt, including initial failures and subsequent corrections documented in the traces $\{\tau_1, \dots, \tau_i\}$. Its goal is to distill this procedural history into abstract, generalizable knowledge. This is achieved by instructing an LLM to synthesize insights according to a predefined JSON schema:

$$E_{new} = A_R(\{\tau_1, \dots, \tau_i\}, T) \quad (4)$$

The output, a new set of experiences E_{new} , contains structured insights such as effective heuristics, reusable workflow patterns, or warnings about potential data pitfalls.

3.3 Meta-Level Evolution through Experience

HealthFlow adapts by transforming procedural execution into durable knowledge. We provide a formal proof for the efficacy of this evolutionary mechanism in Appendix D.

Synthesizing experience into structured knowledge. To ensure learned knowledge is actionable and retrievable, the reflector agent,

A_R, synthesizes experiences into a structured format. An experience E is a record with key attributes: a type E_{type} in {heuristic, code_snippet, workflow_pattern, warning}; a categorical label $E_{category}$ (e.g., pediatric_care, EHR_data_preprocessing), and a content body $E_{content}$ containing the specific knowledge. After a successful task, A_R analyzes the execution trace to generate a set of new experiences, E_{new} . These structured experiences are then added to the memory: $\mathcal{M} \leftarrow \mathcal{M} \cup E_{new}$.

Experience-augmented planning and learning. The framework learns by continuously populating its experience memory \mathcal{M} . When a new task T' is presented, the meta agent A_M retrieves relevant prior knowledge using an LLM-based re-ranking strategy. In this process, all experiences from \mathcal{M} are provided as context to an LLM, which then ranks them by semantic relevance to the task. The top- k ($k = 5$) experiences are incorporated into the prompt for A_M , providing a rich, contextual foundation for its initial plan. As \mathcal{M} grows, A_M gains access to a broader and more refined set of strategies. The full algorithm is detailed in Appendix C.

Handling conflicting and evolving knowledge. The experience memory may accumulate advice that appears contradictory when viewed in isolation. HealthFlow treats this not as a flaw, but as a feature of rich, context-dependent knowledge. Seemingly conflicting heuristics often reflect valid strategies for different scenarios (e.g., distinct patient cohorts or data types). Our framework leverages the meta agent’s contextual reasoning by retrieving a set of relevant, albeit potentially diverse, experiences. The LLM-based agent then dynamically synthesizes this advice, prioritizing or adapting strategies that are most applicable to the specific nuances of the current task, allowing for flexible, context-aware decision-making.

Knowledge bootstrapping in training mode. To address the cold-start problem, HealthFlow includes a training mode where it processes a curated set of problems with known reference solutions. In this mode, the evaluator uses the ground truth for critique, and crucially, the reflector is only permitted to synthesize experiences from tasks that are successfully validated against the reference. This supervised process populates the experience memory with verified, high-quality knowledge, bootstrapping the agent’s strategic capabilities before it encounters new, unseen tasks.

3.4 EHRFlowBench: A Benchmark for Agentic Healthcare Research

The development of increasingly sophisticated autonomous agents necessitates benchmarks that can rigorously assess their real-world problem-solving abilities. In the general domain, benchmarks like GAIA [27] have become a standard for evaluating agents on tasks requiring tool use, multi-step reasoning, and web navigation. However, a similar standard is conspicuously absent in healthcare research. We introduce EHRFlowBench, designed to mirror the complexity of real-world research challenges and facilitate the reproducible evaluation of advanced healthcare agents.

Our creation process is a two-stage, LLM-assisted and human-verified procedure. (1) *Candidate paper screening:* The process begins with the collection of 51,280 papers published between 2020 and 2025 from top-tier AI and data mining conferences (AAAI, ICLR,

ICML, NeurIPS, IJCAI, KDD, WWW). To identify EHR-related papers, we use a majority-voting ensemble of LLMs to classify titles based on their relevance to AI applications on EHR data, resulting in 162 candidate papers. This is followed by manual review, yielding 118 highly relevant papers. (2) *Task extraction:* We then prompt an LLM to extract evidence-grounded tasks from these papers. The LLM is instructed to generate a detailed task description, a category, and a reference answer for each, resulting in an initial pool of 585 tasks.

We manually consolidate semantically similar task types into a final taxonomy of 10 major categories that cover the research lifecycle (Figure 2). During the final manual selection phase, we apply stratified sampling to ensure category diversity. We retain all tasks from categories with fewer than 10 instances. For larger categories, we select a representative subset of 10 to 20 tasks, guided by criteria such as diversity of modeling techniques and clinical objectives. This process results in a final benchmark of 110 tasks, with 100 for evaluation and 10 (one from each of the 10 categories) for the training set used by HealthFlow.

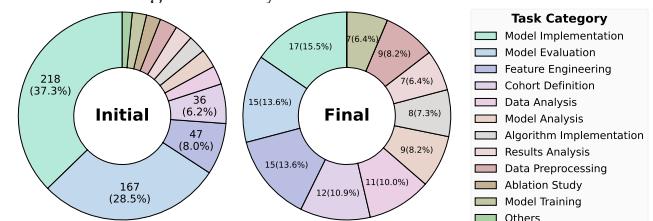


Figure 2: Task category distribution in EHRFlowBench. The initial distribution of 585 LLM-extracted tasks (left) is refined through manual curation and stratified sampling into a final set of 110 tasks across 10 core research categories (right), with irrelevant categories like “ablation study” being discarded.

4 Experimental Setups

4.1 Datasets, Tasks, and Evaluation

We define autonomous healthcare research as the ability to call tools, write code, and independently complete medical tasks for a given research question. To this end, we evaluate HealthFlow across five benchmarks assessing open-ended research capabilities (EHRFlowBench), complex EHR data analysis and modeling (MedAgentBoard [53]), medical knowledge reasoning (MedAgentsBench [42], HLE [29]), and tool-augmented clinical reasoning (CureBench [10]).

EHRFlowBench. Serving as the primary testbed for end-to-end, multi-step autonomous healthcare research, it consists of 110 complex tasks derived from peer-reviewed literature. Performance is assessed using an LLM-as-a-judge ensemble. For each task, the ensemble provides integer scores from 1 to 5 across three dimensions, which are then combined into a weighted final score for methodology soundness (70%), presentation (20%), and artifact quality (10%).

MedAgentBoard. MedAgentBoard [53] evaluates practical skills in handling structured EHR data. It includes 100 tasks on the MIMIC-IV [21, 22] and TJH [47] datasets, requiring a full analytical pipeline. Performance is primarily measured by task success rate, which is determined through manual human evaluation. A task is deemed successful if the agent’s final generated artifacts fully and correctly

465 **Table 2: Main evaluation results of HealthFlow and its variants on five medical agent benchmarks. We compare our framework**
 466 **against baselines and present an enhanced version, *HealthFlow + ToolUniverse*, which integrates a broader set of external**
 467 **tools. For fair comparison, all agent frameworks are powered by DeepSeek-V3 by default. The ablation study demonstrates**
 468 **the contribution of key components: *w/o Feedback* is a version without reflection or evaluation; *w/o Experience* disables the**
 469 **experience memory; and *w/o Training* omits initial knowledge bootstrapping on EHRFlowBench and CureBench (the two**
 470 **benchmarks with curated training samples). The best result in each column is in bold.**

Category	Methods	EHRFlowBench (LLM Score \uparrow)	MedAgentBoard (Success Rate % \uparrow)	MedAgentsBench (Accuracy % \uparrow)	HLE (Accuracy % \uparrow)	CureBench (Accuracy % \uparrow)
General LLM	DeepSeek-V3	2.65 \pm 0.03	3.70 \pm 2.28	8.42 \pm 2.29	2.33 \pm 2.45	86.20 \pm 3.57
	DeepSeek-R1	2.78 \pm 0.03	3.16 \pm 1.64	39.03 \pm 4.33	6.44 \pm 3.34	87.57 \pm 3.45
Medical LLM	HuatuoGPT-o1	1.83 \pm 0.06	0.00 \pm 0.00	19.10 \pm 3.58	6.91 \pm 3.97	78.31 \pm 4.26
	MedGemma	2.17 \pm 0.07	1.90 \pm 1.34	16.07 \pm 3.87	8.49 \pm 4.49	78.02 \pm 4.55
Multi-agent Collab.	MedAgents	1.76 \pm 0.06	0.00 \pm 0.00	20.00 \pm 3.64	2.33 \pm 2.45	86.15 \pm 3.80
	MDAgents	1.89 \pm 0.09	4.29 \pm 2.19	20.16 \pm 4.09	2.33 \pm 2.45	83.86 \pm 3.76
General Agent	ColaCare	2.04 \pm 0.07	1.16 \pm 1.04	21.58 \pm 3.54	0.00 \pm 0.00	85.95 \pm 3.62
	AFlow	3.31 \pm 0.06	4.90 \pm 2.11	30.30 \pm 4.46	0.00 \pm 0.00	81.95 \pm 3.80
Biomedical Agent	Alita	2.77 \pm 0.07	9.48 \pm 3.27	23.97 \pm 4.07	4.49 \pm 3.31	85.18 \pm 3.92
	Biomni	2.22 \pm 0.06	45.61 \pm 4.51	22.72 \pm 3.87	4.16 \pm 3.35	81.68 \pm 3.58
Ours	STELLA	2.39 \pm 0.07	38.46 \pm 4.61	26.97 \pm 4.60	7.11 \pm 3.72	85.98 \pm 3.78
	HealthFlow + ToolUniverse	3.98\pm0.06	81.89\pm3.87	30.68\pm4.28	9.13\pm4.52	90.29\pm3.17
Ours	HealthFlow	3.82 \pm 0.07	66.09 \pm 5.06	28.08 \pm 4.51	4.96 \pm 3.34	88.31 \pm 3.31
	w/o Feedback	2.78 \pm 0.07	42.63 \pm 4.48	21.52 \pm 3.70	2.33 \pm 2.45	87.20 \pm 3.66
	w/o Experience	3.63 \pm 0.08	57.59 \pm 5.46	25.59 \pm 4.25	6.44 \pm 3.34	87.83 \pm 2.91
Ours	w/o Training	3.80 \pm 0.07	—	—	—	88.01 \pm 3.59

491 satisfy all stated requirements. We also use an LLM to score so-
 492 lutions on a 1-to-5 scale across four key dimensions: (1) data ex-
 493 traction and statistical analysis, (2) predictive modeling, (3) data
 494 visualization, and (4) report generation.

495 *MedAgentsBench*. This benchmark [42] is used to evaluate the
 496 agent’s foundational medical reasoning and knowledge retrieval
 497 capabilities, which are prerequisites for any meaningful healthcare
 498 research. We use a curated set of 100 challenging multiple-choice
 499 questions from its “hard set” to avoid ceiling effects. Performance
 500 is measured by accuracy.

502 *Humanity’s Last Exam (HLE)*. We use the medical subset of
 503 HLE [29] to assess reasoning on expert-level problems designed
 504 to be difficult for LLMs. Our test set includes 45 text-only ques-
 505 tions from the “Biology/Medicine” category. Following the official
 506 protocol [5], performance is measured by binary correctness.

508 *CureBench*. To evaluate agentic tool-augmented reasoning in a
 509 clinically relevant context, we include CureBench [10], a benchmark
 510 for therapeutic decision-making. CureBench tasks models with
 511 complex reasoning over patients, diseases, and drugs, requiring the
 512 use of external biomedical tools (e.g., FDA databases, PubMed). We
 513 use a randomly selected set of 100 multiple-choice questions from
 514 the validation set, as the official test set lacks ground-truth labels.
 515 An additional 10 samples are randomly selected for HealthFlow’s
 516 training. Performance is measured by accuracy.

518 4.2 Baseline Methods

519 We compare HealthFlow against a set of representative baselines:
 520 (1) general LLMs: DeepSeek-V3 [25], DeepSeek-R1 [14]; (2) medical
 521 LLMs: HuatuoGPT-o1 [6], MedGemma [35]; (3) multi-agent

523 collaboration frameworks: MedAgents [43], MDAgents [23], ColaCare [46]; (4) general agent frameworks: AFlow [50], Alita [30];
 524 and (5) biomedical agent frameworks: Biomni [17], STELLA [20].

525 4.3 Implementation Details

526 *EHRFlowBench curation and evaluation*. The LLM ensemble for
 527 paper filtering includes DeepSeek-V3, DeepSeek-R1, and Qwen3-
 528 235B (Qwen3-235B-A22B-Instruct-2507 [31]). Task extraction is
 529 performed by DeepSeek-V3. The EHRFlowBench’s LLM-as-a-judge
 530 evaluation ensemble consists of DeepSeek-V3, DeepSeek-R1, Claude-
 531 4-Sonnet [3], Kimi-K2 [44], and GLM-4.5 [52]. The MedAgent-
 532 Board’s LLM judge is DeepSeek-V3. We use bootstrapping on all
 533 test set samples 100 times to report the mean and standard deviations.
 534 Metrics of success rate and accuracy are multiplied by 100
 535 for readability purposes.

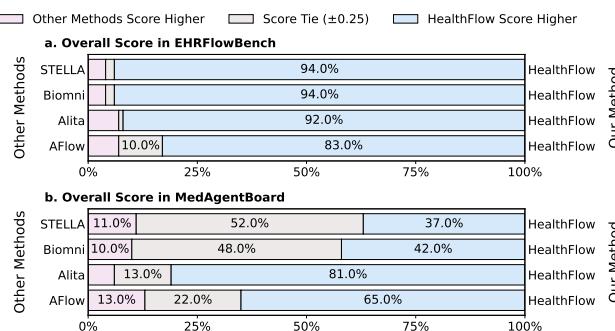
536 *Hardware and software configuration*. All experiments are con-
 537 ducted on a Mac Studio M3 Ultra with 512GB of RAM. HuatuoGPT-
 538 o1 and MedGemma are deployed locally using LMStudio. All agent-
 539 based baselines are powered by DeepSeek-V3 using their official
 540 implementations (except for Alita, for which we use the OpenAlita
 541 community implementation [33]). We configure external tools, in-
 542 cluding web search with the Serper search API and access to Tool-
 543 Universe, under MCP. HealthFlow is developed in Python 3.12. To
 544 ensure transparency and facilitate potential local deployment in
 545 healthcare settings, HealthFlow’s meta, evaluator, and reflector
 546 agents use DeepSeek-V3 by default. For our main experiments,
 547 HealthFlow’s executor backend integrates ToolUniverse and is also
 548 powered by DeepSeek-V3. To provide a robust and standardized
 549 execution environment for baselines, other HealthFlow variants de-
 550 fault to a Claude Code [2] backend powered by the Kimi-K2 model.

581 During a task, HealthFlow employs an internal self-correction loop;
 582 the evaluator agent assigns a score on a 10-point scale, and a score
 583 below 6.0 triggers a retry, with a maximum of 3 attempts per task.
 584

5 Experimental Results and Analysis

5.1 Main Results and Ablation Study

588 *Comparison against diverse baselines.* As shown in Table 2, Health-
 589 Flow substantially outperforms all baselines across tasks, especially
 590 on EHRFlowBench and MedAgentBoard, which test end-to-end
 591 data analysis and modeling. The integration of ToolUniverse pro-
 592 vides a substantial performance uplift, demonstrating the value of a
 593 rich, accessible scientific tool ecosystem. On knowledge-intensive,
 594 tool-light benchmarks like MedAgentsBench, HLE, and CureBench,
 595 HealthFlow’s performance is competitive. As expected, non-agentic
 596 LLMs and multi-agent frameworks that lack code execution capa-
 597 bilities struggle on these tasks; they are unable to complete the
 598 multi-step analytical pipelines. Biomedical agent frameworks like
 599 Biomni and STELLA outperform general agents on MedAgent-
 600 Board, likely benefiting from specialized, built-in tools that provide
 601 relevant priors for healthcare data analysis.



615 **Figure 3: Head-to-head performance of HealthFlow against**
 616 **leading agent frameworks on (a) EHRFlowBench and (b)**
 617 **MedAgentBoard. Each bar shows the distribution for all tasks**
 618 **in a direct comparison against a specific baseline. Outcomes**
 619 **are categorized as a tie if the score difference is ≤ 0.25 .**

620 Further illustrating this advantage, a head-to-head comparison in
 621 Figure 3 shows HealthFlow achieving a dominant win rate against
 622 other leading frameworks. On the highly complex and open-ended
 623 tasks of EHRFlowBench, HealthFlow’s superiority is clear. Its ro-
 624 bust performance is confirmed on MedAgentBoard, which focuses
 625 on structured EHR data analysis pipelines, where it maintains a
 626 significant lead even against strong, domain-specific baselines.

627 *Ablation on core components.* Our ablation study in Table 2 quan-
 628 tifies the contribution of HealthFlow’s core components. Removing
 629 the feedback loop entirely (*w/o Feedback*), which includes both the
 630 evaluator and reflector agents, leads to a significant performance
 631 drop on EHRFlowBench (from 3.82 to 2.78) and MedAgentBoard
 632 (from 66.09% to 42.63%). This result underscores a key finding: an
 633 initial plan is rarely perfect, and the ability to iteratively critique
 634 and refine the workflow is fundamental to success. Disabling only
 635 the long-term experience memory (*w/o Experience*) also degrades
 636 performance (from 3.82 to 3.63 on EHRFlowBench), demonstrating
 637 that while short-term correction is critical, the accumulation of

639 strategic knowledge provides a durable advantage. Finally, omit-
 640 ting the initial knowledge bootstrapping (*w/o Training*) results in a
 641 minor performance decrease on EHRFlowBench (from 3.82 to 3.80).
 642 This indicates that while pre-populating the memory with verified
 643 knowledge is beneficial, HealthFlow’s ability to learn on the fly
 644 from new tasks remains a powerful mechanism for adaptation.

5.2 Further Analysis

645 *Impact of LLM backbones and executors.* Table 3 reveals that the
 646 choice of underlying LLM is critical. The framework’s architecture
 647 separates frontend reasoning models (meta, reflector, evaluator)
 648 from the backend coding model (executor). Using a more powerful
 649 reasoning model like DeepSeek-R1 as the frontend significantly
 650 boosts performance, highlighting that better strategic planning
 651 directly translates to better outcomes. Conversely, a capable strategy
 652 is ineffective without a reliable backend. Substituting the executor
 653 with a less proficient Qwen3-Coder causes a near-total performance
 654 collapse on MedAgentBoard (from 66.09% to 6.04%). Failure analysis
 655 reveals that Qwen3-Coder frequently misinterpreted file system
 656 instructions, failing to locate input data and causing tasks to termi-
 657 nate prematurely. This starkly illustrates that a robust execution
 658 engine demands exceptional instruction-following fidelity, not just
 659 code generation. The best performance is achieved with our native
 660 backend powered by DeepSeek-V3 and integrated with ToolUni-
 661 verse due to pairing an execution backend that is not only a capable
 662 coder but also part of a rich, domain-aware tool ecosystem, confirm-
 663 ing that optimal performance requires synergy between high-level
 664 strategy and execution capability.

667 **Table 3: Impact of different LLM backbones on HealthFlow**
 668 **performance. We evaluate variants by changing the front-**
 669 **end (meta, reflector, evaluator agents) and backend (execu-**
 670 **tor agent).**

Frontend (Meta/Reflector)	Backend (Executor)	EHRFlowBench (LLM Score \uparrow)	MedAgentBoard (Success Rate % \uparrow)
DeepSeek-V3	Claude Code (Kimi)	3.82 ± 0.07	66.09 ± 5.06
DeepSeek-R1	Claude Code (Kimi)	3.84 ± 0.07	81.64 ± 3.77
Kimi-K2	Claude Code (Kimi)	2.41 ± 0.10	79.53 ± 4.54
Qwen3-235B	Claude Code (Kimi)	3.53 ± 0.09	79.03 ± 4.41
DeepSeek-V3	Qwen3-Coder (Qwen)	2.64 ± 0.07	6.04 ± 2.34
DeepSeek-V3	Ours (DeepSeek-V3)	3.98 ± 0.06	81.89 ± 3.87

681 *Fine-grained evaluation across task categories.* To better under-
 682 stand HealthFlow’s capabilities, we conduct a fine-grained analysis
 683 across key dimensions on EHRFlowBench and MedAgentBoard (Ta-
 684 ble 4). On EHRFlowBench, HealthFlow excels in method soundness
 685 (3.72) and artifact generation (3.96), demonstrating its ability to
 686 both devise sound research plans and produce high-quality outputs
 687 like statistical code, trained models, and visualizations. On MedA-
 688 gentBoard, HealthFlow shows superior performance on the most
 689 complex, integrative tasks: predictive modeling (4.21) and report
 690 generation (4.10). While a specialized baseline like STELLA per-
 691 forms competitively on routine sub-tasks such as data extraction
 692 and visualization, HealthFlow’s advantage in the end-to-end mod-
 693 eling process highlights the value of its adaptive meta-planning
 694 capabilities for holistic problem-solving.

Table 4: Fine-grained performance breakdown on EHRFlowBench and MedAgentBoard. Scores are the mean and standard deviation from multiple LLM judges on a 1-5 scale. This consolidated view shows HealthFlow’s strong performance across both high-level research methodology (EHRFlowBench) and practical health data science tasks (MedAgentBoard).

Methods	EHRFlowBench			MedAgentBoard			
	Method Soundness (70%)	Presentation Quality (20%)	Artifact Generation (10%)	Data Extraction & Stats	Predictive Modeling	Data Visualization	Report Generation
AFlow	3.22±0.95	3.99±0.58	2.60±1.12	3.67±1.20	3.84±0.73	3.64±1.63	3.79±0.97
Alita	2.64±1.04	3.49±0.81	2.19±1.01	3.24±1.40	2.70±1.13	3.00±1.34	2.79±1.06
Biomni	2.04±1.08	2.72±0.94	2.43±1.11	4.62±0.69	3.40±0.72	4.22±0.82	4.03±0.71
STELLA	2.17±1.03	2.92±0.93	2.80±1.09	4.68±0.65	3.28±1.13	4.75±0.43	3.15±1.13
HealthFlow	3.72±1.03	4.15±0.67	3.96±0.98	4.58±0.70	4.21±0.68	4.75±0.43	4.10±0.85

Dynamics of experience synthesis and retrieval. An analysis of HealthFlow’s learning loop reveals a dynamic adaptation to task structure (Figure 4). For the complex, open-ended tasks in EHRFlowBench, the agent prioritizes synthesizing abstract heuristics (31.1% of experiences) but most frequently retrieves concrete code_snippets (1.91 average per task). This indicates a strategy of grounding high-level plans with actionable code for novel problems. Conversely, for the structured pipelines in MedAgentBoard, the agent most often retrieves heuristics (1.91 average per task), suggesting a focus on refining existing workflows. Across both benchmarks, synthesized knowledge is overwhelmingly concentrated in the Clinical & Medical Analysis category (Figure 5), confirming that learning is sharply focused on core domain challenges. This interplay allows HealthFlow to build a contextually relevant knowledge base, optimizing for strategic guidance on routine tasks and reusable code for novel ones.

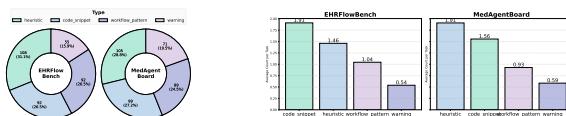


Figure 4: Distribution of experience synthesis and retrieval across EHRFlowBench and MedAgentBoard benchmarks.

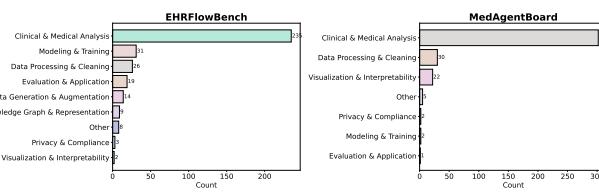


Figure 5: Distribution of synthesized experience categories.

Case studies. Two case studies illustrate HealthFlow’s capabilities. The first, a data visualization task from MedAgentBoard, demonstrates the practical impact of meta-level learning. As shown in Figure 6, when tasked with visualizing the correlation between systolic and diastolic blood pressure, HealthFlow’s meta agent retrieves relevant prior knowledge, including a critical heuristic about handling outliers in clinical data. This experience informs a robust plan that incorporates proactive data validation, such as setting

clinically plausible axis limits, a step that is not explicitly requested but is essential for meaningful analysis.

The outcome of this experience-driven approach is shown in Figure 7. HealthFlow produces a clean, interpretable visualization (b) that aligns closely with the reference answer (a). In stark contrast, competing agents like Biomni (c) and STELLA (d), which lack this adaptive planning mechanism, fail to perform the necessary validation. Their resulting plots are rendered uninterpretable by outliers that compress the primary data distribution, highlighting a critical failure mode for agents that operate without domain-aware, learned strategies.

A second case from EHRFlowBench demonstrates versatility on more complex research tasks. Without a provided dataset, HealthFlow autonomously simulates realistic data, implements a specified CNN-LSTM architecture, and executes a full training and evaluation workflow. It successfully produces all required artifacts, including a training loss plot, final accuracy metrics, and saved model checkpoints. These cases show that HealthFlow’s ability to learn and apply strategic knowledge enables it to conduct robust, multi-step research that adapts to domain-specific nuances.

Human evaluation. To complement our automated metrics, we conduct a rigorous human evaluation to assess the practical utility and quality of the generated solutions. We enlist 12 expert evaluators, comprising PhD and MD students from disciplines such as AI for healthcare, biostatistics, biomedical engineering, and clinical medicine. The evaluators are tasked with assessing a random subset of 20 tasks, with 10 drawn from EHRFlowBench and 10 from MedAgentBoard. In a blind review process, they perform a head-to-head comparison of the final solutions generated by HealthFlow, Alita, Biomni, and STELLA. For each task, evaluators select the single best solution, with the option to choose “None” if no output is satisfactory. To mitigate bias, the identities and presentation order of the agents are randomized for each task and evaluator. The average pairwise inter-rater agreement is 71.54%, indicating substantial consensus. The results, summarized in Figure 8, reveal a clear expert preference for HealthFlow’s solutions across tasks.

6 Discussion

Limitations. While HealthFlow represents a significant advance, its performance is fundamentally tethered to the capabilities of its underlying LLMs. Biases or knowledge gaps in the LLMs can

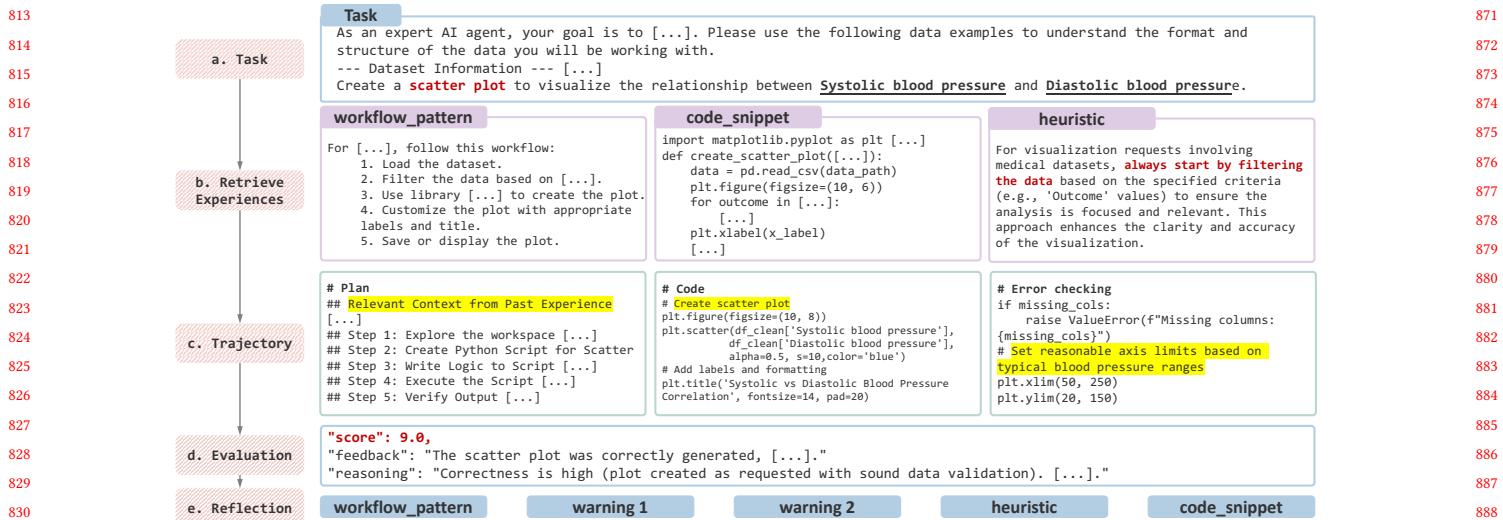


Figure 6: An illustration of HealthFlow’s workflow on a data visualization task from MedAgentBoard (#56). The agent retrieves past experiences (b) to inform its strategic plan (c), leading to a high-quality, domain-aware output. The entire trajectory is then analyzed to synthesize new, generalizable knowledge through reflection (e), completing the self-evolution loop.

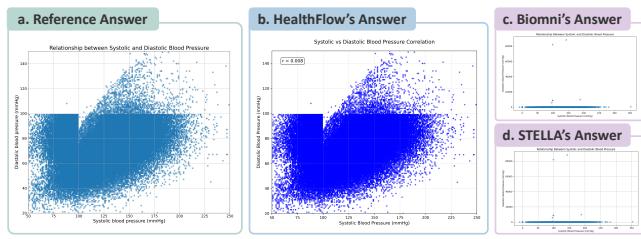


Figure 7: Comparison of outputs for a data visualization task on MedAgentBoard (#56). HealthFlow (b) performs essential, experience-driven data validation, producing a result comparable to the reference answer (a). In contrast, frameworks like Biomni (c) and STELLA (d) fail to handle outliers, rendering their visualizations uninterpretable. Alita failed to generate the required image.

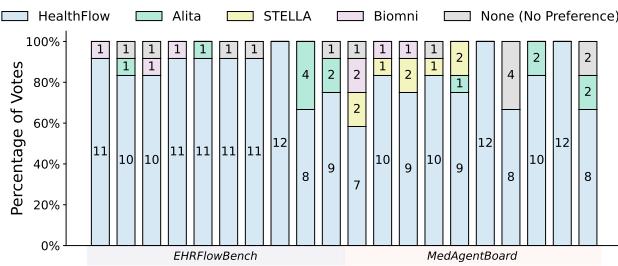


Figure 8: Human evaluation results. Distribution of votes from 12 domain experts comparing solutions from four agent frameworks across 20 tasks.

propagate into the agent’s strategic plans and synthesized experiences. Furthermore, the experience synthesis process itself carries an inherent risk: the agent might distill flawed or overly specific heuristics from idiosyncratic successes, which could degrade future performance if not properly generalized.

Future work. The HealthFlow framework could be adapted to other scientific fields, such as computational biology, by curating domain-specific tools and experiences. Extending the framework to handle multi-modal inputs, such as medical imaging alongside EHR data, would represent a major step towards a more comprehensive AI research assistant.

Broader impact. HealthFlow can significantly accelerate healthcare research by automating complex data analysis and operationalizing scientific knowledge from the Web. However, deploying autonomous agents in this high-stakes domain presents risks, including the potential for flawed scientific conclusions and data privacy concerns. We advocate for a human-in-the-loop approach, positioning the agent as a powerful tool to augment, not replace, expert oversight to ensure responsible and effective scientific discovery.

7 Conclusion

In this paper, we introduced HealthFlow, a self-evolving AI agent designed to address the challenge of creating autonomous systems that can effectively leverage Web-based scientific knowledge. By implementing a meta-level strategic planning and evolution mechanism, HealthFlow learns not only to execute tasks but to evolve its own high-level orchestration policies from experience. This ability to learn how to manage research, rather than just how to perform individual steps, directly tackles the bottleneck of static strategies in current agents. To validate our approach, we developed EHRFlowBench, a challenging new benchmark derived from Web-based scientific literature. Our experiments demonstrate that HealthFlow’s adaptive, experience-driven strategy leads to superior performance compared to state-of-the-art frameworks. This work contributes to the WWW community by offering a promising approach for intelligent systems that can operationalize the vast procedural knowledge on the Web, marking a significant step toward more autonomous and effective AI for healthcare scientific discovery.

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1161 A Ethical Statement

1162 The research presented in this paper adheres to high ethical standards for AI in healthcare. The development and evaluation of HealthFlow
 1163 and its accompanying benchmark, EHRFlowBench, are guided by the core principles of beneficence, non-maleficence, and fairness. All
 1164 datasets used in our experiments have been de-identified, ensuring that no protected health information (PHI) is exposed or used in our
 1165 research.

1166 HealthFlow is intended for use as a research tool to assist healthcare professionals and data scientists and is not designed to replace
 1167 human clinical judgment or provide medical advice. To promote transparency and enable independent verification of our results, we commit
 1168 to making our source code, including the HealthFlow framework and the EHRFlowBench benchmark, publicly available.
 1169

1170 B Reproducibility Statement

1171 We are committed to the reproducibility of our results. To ensure full transparency, all code and data are publicly available at the following
 1172 anonymous project website: <https://healthflow-agent.netlify.app/>.
 1173

1174 The website includes the EHRFlowBench benchmark, which contains the list of source papers and extracted tasks. For the HealthFlow
 1175 implementation, we also provide the complete source code, environment specifications, and the exact hyperparameters used in our
 1176 experiments.

1177 C HealthFlow Algorithm

1178 The core operational loop of HealthFlow is detailed in Algorithm 1. The process illustrates the collaboration between the specialized agents,
 1179 the short-term correction loop driven by the evaluator, and the long-term evolution driven by the reflector and the experience memory.
 1180

1183 **Algorithm 1** *The HealthFlow self-evolving workflow.*

1184 **Require:** Task T , Experience Memory \mathcal{M} , Max Retries N_{max} 1242
 1185 **Ensure:** Final Solution S or Failure 1243

```

1186   1: Initialize  $A_M, A_E, A_V, A_R$  1244
1187   2: Initialize retry count  $n \leftarrow 0$ , feedback  $f \leftarrow \text{null}$  1245
1188   3: while  $n < N_{max}$  do 1246
1189     4: ▷ Phase 1: Meta-Planning
1190       5: Retrieve relevant experiences  $\{E_k\} \subset \mathcal{M}$  for task  $T$  1247
1191       6: Augment context for  $A_M$  with  $\{E_k\}$  and feedback  $f$  1248
1192       7: Generate plan  $P \leftarrow A_M(T, \mathcal{M}, f)$  1249
1193       8: ▷ Phase 2: Execution
1194       9: Execute plan, get trace  $\tau \leftarrow A_E(P)$  1250
1195      10: ▷ Phase 3: Evaluation (Short-term Correction)
1196      11: Evaluate outcome  $(s, f) \leftarrow A_V(\tau, T)$  1251
1197      12: if  $s \geq \theta_{succ}$  then 1252
1198        13: ▷ Phase 4: Reflection (Long-term Evolution)
1199          14: Synthesize new experience  $E_{new} \leftarrow A_R(\tau, T)$  1253
1200          15: Update memory  $\mathcal{M} \leftarrow \mathcal{M} \cup \{E_{new}\}$  1254
1201          16: return Solution from trace  $\tau$  1255
1202        17: else 1256
1203          18: Increment retry count  $n \leftarrow n + 1$  1257
1204        19: end if 1258
1205      20: end while 1259
1206      21: return Failure 1260
  
```

1209 D Formal Proof of Evolving Efficacy

1210 We provide a formal argument for the efficacy of HealthFlow's self-evolution mechanism. Our goal is to show that as the agent completes
 1211 more tasks, its expected performance on future tasks monotonically improves.
 1212

1213 *Definitions.* Let \mathcal{D} be a stationary distribution of tasks T . Let $\pi(\mathcal{M})$ be the meta-agent's planning policy, which depends on the experience
 1214 memory \mathcal{M} . The policy maps a task T to a plan P . Let $S(T, P)$ be a stochastic binary outcome function, where $S = 1$ indicates task success
 1215 and $S = 0$ indicates failure. The quality of a policy is its expected success rate over the task distribution:
 1216

$$Q(\pi(\mathcal{M})) = \mathbb{E}_{T \sim \mathcal{D}} [S(T, \pi(\mathcal{M})(T))] \quad (5)$$

1277 *Assumptions.* Our proof relies on two idealized assumptions about the learning process to illustrate the mechanism's potential in a
 1278 theoretical model:

- 1279 (1) **Effective Reflection:** When a task T is solved successfully, the reflector agent A_R generates a new experience E_{new} . We assume this
 1280 experience captures a meaningful, generalizable aspect of the solution. Thus, for any future task T' that is "similar" to T (i.e., for which
 1281 E_{new} is relevant), using this experience will not decrease, and may increase, the probability of success. Formally, let $\mathcal{M}' = \mathcal{M} \cup \{E_{new}\}$.
 1282 Then for any T' ,

$$1283 \quad \mathbb{P}(S(T', \pi(\mathcal{M}')(T')) = 1) \geq \mathbb{P}(S(T', \pi(\mathcal{M})(T')) = 1) \quad (6)$$

- 1285 (2) **Effective Retrieval:** The meta-agent A_M can reliably retrieve relevant experiences. An irrelevant experience does not negatively impact
 1286 planning for a given task.

1287 *Theorem.* Let \mathcal{M}_t be the experience memory after t successful task completions. Under the assumptions of Effective Reflection and
 1288 Effective Retrieval, the quality of the planning policy is monotonically non-decreasing.

$$1290 \quad Q(\pi(\mathcal{M}_{t+1})) \geq Q(\pi(\mathcal{M}_t)) \quad (7)$$

1292 *Proof.* At step t , the agent successfully completes a task T_t , generating a new experience E_{t+1} . The memory is updated to $\mathcal{M}_{t+1} =$
 1293 $\mathcal{M}_t \cup \{E_{t+1}\}$. We want to compare $Q(\pi(\mathcal{M}_{t+1}))$ with $Q(\pi(\mathcal{M}_t))$.

$$1294 \quad Q(\pi(\mathcal{M}_{t+1})) = \mathbb{E}_{T \sim \mathcal{D}} [S(T, \pi(\mathcal{M}_{t+1})(T))] \quad (8)$$

$$1296 \quad = \int_{T \in \mathcal{D}} \mathbb{P}(S(T, \pi(\mathcal{M}_{t+1})(T)) = 1) p(T) dT \quad (9)$$

1298 By the law of total expectation, we can condition on whether a task T is relevant to the new experience E_{t+1} or not. Let $\mathcal{D}_{rel} \subset \mathcal{D}$ be the
 1299 subset of tasks for which E_{t+1} is relevant, and $\mathcal{D}_{irrel} = \mathcal{D} \setminus \mathcal{D}_{rel}$.

1300 From our assumptions:

- For any $T' \in \mathcal{D}_{rel}$, by Effective Reflection (Assumption 1), the retrieval of E_{t+1} will lead to a plan that is at least as likely to succeed:

$$1303 \quad \mathbb{P}(S(T', \pi(\mathcal{M}_{t+1})(T')) = 1) \geq \mathbb{P}(S(T', \pi(\mathcal{M}_t)(T')) = 1) \quad (10)$$

- For any $T'' \in \mathcal{D}_{irrel}$, by Effective Retrieval (Assumption 2), the new experience E_{t+1} will not be retrieved or will be correctly identified as
 1305 irrelevant, so it does not affect the plan:

$$1307 \quad \pi(\mathcal{M}_{t+1})(T'') = \pi(\mathcal{M}_t)(T'') \quad (11)$$

1308 Therefore, the success probability remains unchanged:

$$1310 \quad \mathbb{P}(S(T'', \pi(\mathcal{M}_{t+1})(T'')) = 1) = \mathbb{P}(S(T'', \pi(\mathcal{M}_t)(T'')) = 1) \quad (12)$$

1312 Since the probability of success is greater than or equal to the previous probability for all tasks $T \in \mathcal{D}$, the expectation over the entire
 1313 distribution must also be greater than or equal.

$$1314 \quad \int_{T \in \mathcal{D}} \mathbb{P}(S(T, \pi(\mathcal{M}_{t+1})) = 1) p(T) dT \geq \int_{T \in \mathcal{D}} \mathbb{P}(S(T, \pi(\mathcal{M}_t)) = 1) p(T) dT \quad (13)$$

1317 Thus, $Q(\pi(\mathcal{M}_{t+1})) \geq Q(\pi(\mathcal{M}_t))$. The inequality becomes strict if the set of relevant future tasks \mathcal{D}_{rel} has a non-zero measure and the
 1318 experience E_{t+1} provides a strictly positive benefit for at least some of those tasks. This concludes the proof. We acknowledge that the
 1319 assumptions of perfect reflection and retrieval are strong simplifications. In practice, a poorly generalized experience could potentially
 1320 degrade performance, and irrelevant context might not be perfectly ignored.

1321 E Dataset and Benchmark Details

1322 E.1 EHRFlowBench Construction Details

1324 EHRFlowBench is designed to provide a rigorous and realistic testbed for evaluating AI agents on complex healthcare research tasks. Its
 1325 construction follows a systematic, two-stage procedure to ensure task relevance, diversity, and grounding in established scientific literature.

1327 *Stage 1: Candidate paper screening.* The process begins with a comprehensive collection of research papers from top-tier AI and data
 1328 mining conferences published between 2020 and 2025: AAAI, ICLR, ICML, NeurIPS, IJCAI, KDD, and WWW. This initial pool comprises
 1329 51,280 papers, with a breakdown by conference and year detailed in Table 5. To identify papers relevant to AI applications on EHR data, a
 1330 common focus in real-world healthcare research, we employ a majority-voting ensemble of three powerful LLMs (DeepSeek-V3, DeepSeek-R1,
 1331 and Qwen3-235B) to classify paper titles based on their relevance to the EHR field. The prompt used for this classification is detailed below.
 1332 This automated screening yields 162 candidate papers.

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1393 **Table 5: Number of papers collected from selected conferences (2020–2025) for the initial screening phase of EHRFlowBench**
 1394 **construction.**

Conference	2020	2021	2022	2023	2024	2025	Total
AAAI	1646	1654	1319	1578	2331	3028	11556
IJCAI	779	723	862	851	1048	–	4263
KDD	217	239	253	310	408	185	1612
WWW	219	355	367	402	428	440	2211
NeurIPS	1898	2334	2671	3218	4035	–	14156
ICML	1085	1183	1234	1828	2610	–	7940
ICLR	687	860	1094	1573	2260	3068	9542
Sum	6531	7348	7800	9760	13120	6721	51280

1408 *Prompt for LLM-based screening of paper titles.*

1410 You are an AI research assistant specializing in scientific literature. Your task is to identify research papers focused on applying AI to Electronic Health
 1411 Records (EHR).

1412 ****Classification Criteria:****
 1413 A paper is ****relevant (1)**** if its title indicates the use of AI, machine learning, or data science techniques on data explicitly from ****Electronic Health**
 1414 **Records (EHR)**.** This includes:
 1415 - Clinical notes (free-text)
 1415 - Structured data (diagnosis codes like ICD, procedure codes)
 1415 - Time-series data from EHR (lab results, vital signs)

1416
 1417 A paper is ****NOT relevant (0)**** if the title suggests a focus on:
 1417 - Medical Imaging (e.g., MRI, CT scans, X-rays, pathology slides)
 1418 - Genomics, proteomics, or any '-omics' data.
 1419 - Public health policy, hospital administration, or bioinformatics without direct patient-level EHR data analysis.
 1420 - Drug discovery or molecular modeling.
 1420 - Signal processing of physiological signals like ECG, EEG, unless contextually tied to an EHR system analysis.
 1421 - The term "administrative claims" or "billing data" alone, as this often lacks clinical depth.

1422 ****Your Task:****
 1422 Review the following list of paper titles.

1423 ---
 1424 {{numbered_titles}}
 1425 ---

1426 ****Output Format:****
 1427 Respond with a single, valid JSON object. This object must have one key: "selected_indices". The value must be an array of integers representing the 1-based
 1428 index of the titles you identified as relevant.

1429 ****Example:****
 1430 If you determine that papers 2, 5, and 19 are relevant, your response MUST be exactly:
 1431 ````json
 1431 {"selected_indices": [2, 5, 19]}
 1431 ````
 1432 Do not provide any explanations, apologies, or any text outside of the JSON object.

1434 Subsequently, these candidates undergo a manual review by human experts, who verify their relevance and methodology. This step
 1435 culminates in a final set of 118 high-quality seed papers for task extraction, which are enumerated below.

1437 *The complete list of 118 seed papers selected for EHRFlowBench task extraction.*

1. [AAAI, 2020] Generative Adversarial Regularized Mutual Information Policy Gradient Framework for Automatic Diagnosis
2. [AAAI, 2020] AdaCare: Explainable Clinical Health Status Representation Learning via Scale-Adaptive Feature Extraction and Recalibration
3. [AAAI, 2020] ConCare: Personalized Clinical Feature Embedding via Capturing the Healthcare Context
4. [AAAI, 2020] DeepAlerts: Deep Learning Based Multi-Horizon Alerts for Clinical Deterioration on Oncology Hospital Wards
5. [AAAI, 2020] Learning the Graphical Structure of Electronic Health Records with Graph Convolutional Transformer
6. [AAAI, 2020] Deep Mixed Effect Model Using Gaussian Processes: A Personalized and Reliable Prediction for Healthcare
7. [AAAI, 2020] Learning Conceptual-Contextual Embeddings for Medical Text
8. [AAAI, 2020] Understanding Medical Conversations with Scattered Keyword Attention and Weak Supervision from Responses
9. [AAAI, 2020] ICD Coding from Clinical Text Using Multi-Filter Residual Convolutional Neural Network
10. [AAAI, 2020] A System for Medical Information Extraction and Verification from Unstructured Text
11. [AAAI, 2021] GRASP: Generic Framework for Health Status Representation Learning Based on Incorporating Knowledge from Similar Patients
12. [AAAI, 2021] Clinical Risk Prediction with Temporal Probabilistic Asymmetric Multi-Task Learning
13. [AAAI, 2021] ESCAPED: Efficient Secure and Private Dot Product Framework for Kernel-based Machine Learning Algorithms with Applications in Healthcare
14. [AAAI, 2021] MUFASA: Multimodal Fusion Architecture Search for Electronic Health Records
15. [AAAI, 2021] MTAAL: Multi-Task Adversarial Active Learning for Medical Named Entity Recognition and Normalization

1509	16. [AAAI, 2021] Clinical Temporal Relation Extraction with Probabilistic Soft Logic Regularization and Global Inference	1567
1510	17. [AAAI, 2022] Diaformer: Automatic Diagnosis via Symptoms Sequence Generation	1568
1511	18. [AAAI, 2022] Context-Aware Health Event Prediction via Transition Functions on Dynamic Disease Graphs	1569
1512	19. [AAAI, 2022] Clustering Interval-Censored Time-Series for Disease Phenotyping	1570
1513	20. [AAAI, 2023] Heterogeneous Graph Learning for Multi-Modal Medical Data Analysis	1571
1514	21. [AAAI, 2023] KerPrint: Local-Global Knowledge Graph Enhanced Diagnosis Prediction for Retrospective and Prospective Interpretations	1572
1515	22. [AAAI, 2023] Multi-Label Few-Shot ICD Coding as Autoregressive Generation with Prompt	1573
1516	23. [AAAI, 2023] Estimating Treatment Effects from Irregular Time Series Observations with Hidden Confounders	1574
1517	24. [AAAI, 2023] Estimating Average Causal Effects from Patient Trajectories	1575
1518	25. [AAAI, 2023] Causal Recurrent Variational Autoencoder for Medical Time Series Generation	1576
1519	26. [AAAI, 2023] MHCL: Masked Hierarchical Cluster-Wise Contrastive Learning for Multivariate Time Series	1577
1520	27. [AAAI, 2023] Forecasting with Sparse but Informative Variables: A Case Study in Predicting Blood Glucose	1578
1521	28. [AAAI, 2024] PromptMRG: Diagnosis-Driven Prompts for Medical Report Generation	1579
1522	29. [AAAI, 2024] Automatic Radiology Reports Generation via Memory Alignment Network	1580
1523	30. [AAAI, 2024] KG-TREAT: Pre-training for Treatment Effect Estimation by Synergizing Patient Data with Knowledge Graphs	1581
1524	31. [AAAI, 2024] Inducing Clusters Deep Kernel Gaussian Process for Longitudinal Data	1582
1525	32. [AAAI, 2024] ConSequence: Synthesizing Logically Constrained Sequences for Electronic Health Record Generation	1583
1526	33. [AAAI, 2024] IGAMT: Privacy-Preserving Electronic Health Record Synthesization with Heterogeneity and Irregularity	1584
1527	34. [AAAI, 2024] IVP-VAE: Modeling EHR Time Series with Initial Value Problem Solvers	1585
1528	35. [AAAI, 2024] DRfuse: Learning Disentangled Representation for Clinical Multi-Modal Fusion with Missing Modality and Modal Inconsistency	1586
1529	36. [AAAI, 2024] Large Language Models Are Clinical Reasoners: Reasoning-Aware Diagnosis Framework with Prompt-Generated Rationales	1587
1530	37. [AAAI, 2024] Collaborative Synthesis of Patient Records through Multi-Visit Health State Inference	1588
1531	38. [AAAI, 2025] DAMPER: A Dual-Stage Medical Report Generation Framework with Coarse-Grained MeSH Alignment and Fine-Grained Hypergraph Matching	1589
1532	39. [AAAI, 2025] Memorize and Rank: Elevating Large Language Models for Clinical Diagnosis Prediction	1590
1533	40. [AAAI, 2025] DECT: Harnessing LLM-assisted Fine-Grained Linguistic Knowledge and Label-Switched and Label-Preserved Data Generation for Diagnosis of Alzheimer's Disease	1591
1534	41. [AAAI, 2025] Medical Manifestation-Aware De-Identification	1592
1535	42. [ICLR, 2024] GraphCare: Enhancing Healthcare Predictions with Personalized Knowledge Graphs.	1593
1536	43. [ICLR, 2024] Diagnosing Transformers: Illuminating Feature Spaces for Clinical Decision-Making.	1594
1537	44. [ICLR, 2024] A Flexible Generative Model for Heterogeneous Tabular EHR with Missing Modality.	1595
1538	45. [ICLR, 2024] Graph Transformers: Better Representation Improves Downstream Performance.	1596
1539	46. [ICLR, 2025] Small Models are LLM Knowledge Triggers for Medical Tabular Prediction.	1597
1540	47. [ICLR, 2025] Efficiently Democratizing Medical LLMs for 50 Languages via a Mixture of Language Family Experts.	1598
1541	48. [ICML, 2020] BoXHED: Boosted eXact Hazard Estimator with Dynamic covariates.	1599
1542	49. [ICML, 2020] Temporal Phenotyping using Deep Predictive Clustering of Disease Progression.	1600
1543	50. [ICML, 2020] DeepCoDA: personalized interpretability for compositional health data.	1601
1544	51. [ICML, 2021] Neighborhood Contrastive Learning Applied to Online Patient Monitoring.	1602
1545	52. [ICML, 2022] Locally Sparse Neural Networks for Tabular Biomedical Data.	1603
1546	53. [ICML, 2022] Learning of Cluster-based Feature Importance for Electronic Health Record Time-series.	1604
1547	54. [ICML, 2023] Improving Medical Predictions by Irregular Multimodal Electronic Health Records Modeling.	1605
1548	55. [ICML, 2023] Sequential Multi-Dimensional Self-Supervised Learning for Clinical Time Series.	1606
1549	56. [ICML, 2024] Contrastive Learning for Clinical Outcome Prediction with Partial Data Sources.	1607
1550	57. [ICML, 2024] Reservoir Computing for Short High-Dimensional Time Series: an Application to SARS-CoV-2 Hospitalization Forecast.	1608
1551	58. [ICML, 2024] Exploiting Negative Samples: A Catalyst for Cohort Discovery in Healthcare Analytics.	1609
1552	59. [ICML, 2024] ED-Copilot: Reduce Emergency Department Wait Time with Language Model Diagnostic Assistance.	1610
1553	60. [ICML, 2024] ProtoGate: Prototype-based Neural Networks with Global-to-local Feature Selection for Tabular Biomedical Data.	1611
1554	61. [IJCAI, 2020] A Label Attention Model for ICD Coding from Clinical Text	1612
1555	62. [IJCAI, 2020] The Graph-based Mutual Attentive Network for Automatic Diagnosis	1613
1556	63. [IJCAI, 2020] Automatic Emergency Diagnosis with Knowledge-Based Tree Decoding	1614
1557	64. [IJCAI, 2020] Learning Latent Forests for Medical Relation Extraction	1615
1558	65. [IJCAI, 2020] Generalized Zero-Shot Text Classification for ICD Coding	1616
1559	66. [IJCAI, 2021] Cooperative Joint Attentive Network for Patient Outcome Prediction on Irregular Multi-Rate Multivariate Health Data	1617
1560	67. [IJCAI, 2021] AMA-GCN: Adaptive Multi-layer Aggregation Graph Convolutional Network for Disease Prediction	1618
1561	68. [IJCAI, 2021] Collaborative Graph Learning with Auxiliary Text for Temporal Event Prediction in Healthcare	1619
1562	69. [IJCAI, 2021] Multi-series Time-aware Sequence Partitioning for Disease Progression Modeling	1620
1563	70. [IJCAI, 2021] A Novel Sequence-to-Subgraph Framework for Diagnosis Classification	1621
1564	71. [IJCAI, 2022] Cumulative Stay-time Representation for Electronic Health Records in Medical Event Time Prediction	1622
1565	72. [IJCAI, 2022] "My nose is running." "Are you also coughing?": Building A Medical Diagnosis Agent with Interpretable Inquiry Logics	1623
1566	73. [IJCAI, 2022] Chronic Disease Management with Personalized Lab Test Response Prediction	1624
1567	74. [IJCAI, 2022] Data-Efficient Algorithms and Neural Natural Language Processing: Applications in the Healthcare Domain	1625
1568	75. [IJCAI, 2023] Hierarchical Apprenticeship Learning for Disease Progression Modeling	1626
1569	76. [IJCAI, 2023] A Diffusion Model with Contrastive Learning for ICU False Arrhythmia Alarm Reduction	1627
1570	77. [IJCAI, 2023] VecoCare: Visit Sequences-Clinical Notes Joint Learning for Diagnosis Prediction in Healthcare Data	1628
1571	78. [IJCAI, 2024] Predictive Modeling with Temporal Graphical Representation on Electronic Health Records	1629
1572	79. [IJCAI, 2024] Multi-TA: Multilevel Temporal Augmentation for Robust Septic Shock Early Prediction	1630
1573	80. [IJCAI, 2024] Meditab: Scaling Medical Tabular Data Predictors via Data Consolidation, Enrichment, and Refinement	1631
1574	81. [KDD, 2020] Hierarchical Attention Propagation for Healthcare Representation Learning	1632
1575	82. [KDD, 2020] INPREM: An Interpretable and Trustworthy Predictive Model for Healthcare	1633
1576	83. [KDD, 2020] DETERRENT: Knowledge Guided Graph Attention Network for Detecting Healthcare Misinformation	1634
1577	84. [KDD, 2020] HITANet: Hierarchical Time-Aware Attention Networks for Risk Prediction on Electronic Health Records	1635
1578	85. [KDD, 2020] Identifying Sepsis Subphenotypes via Time-Aware Multi-Modal Auto-Encoder	1636
1579	86. [KDD, 2020] HOLMES: Health Online Model Ensemble Serving for Deep Learning Models in Intensive Care Units	1637
1580	87. [KDD, 2022] M3Care: Learning with Missing Modalities in Multimodal Healthcare Data	1638
1581	88. [KDD, 2023] Granger Causal Chain Discovery for Sepsis-Associated Derangements via Continuous-Time Hawkes Processes	1639
1582	89. [KDD, 2023] MediLink: De-Identified Patient Health Record Linkage	1640
1583	90. [KDD, 2023] Warfperformer: A Multi-scale Modeling Approach for Irregular Clinical Time Series	1641
1584	91. [KDD, 2024] FlexCare: Leveraging Cross-Task Synergy for Flexible Multimodal Healthcare Prediction	1642
1585	92. [KDD, 2024] ProtoMix: Augmenting Health Status Representation Learning via Prototype-based Mixup	1643
1586	93. [KDD, 2024] Synthesizing Multimodal Electronic Health Records via Predictive Diffusion Models	1644
1587	94. [NeurIPS, 2020] Learning to Select Best Forecast Tasks for Clinical Outcome Prediction	1645
1588	95. [NeurIPS, 2021] Medical Dead-ends and Learning to Identify High-Risk States and Treatments	1646
1589	96. [NeurIPS, 2021] Auto-Encoding Knowledge Graph for Unsupervised Medical Report Generation	1647
1590	97. [NeurIPS, 2021] Closing the loop in medical decision support by understanding clinical decision-making: A case study on organ transplantation	1648
1591	98. [NeurIPS, 2023] Contrast Everything: A Hierarchical Contrastive Framework for Medical Time-Series	1649
1592	99. [NeurIPS, 2023] Temporal Causal Mediation through a Point Process: Direct and Indirect Effects of Healthcare Interventions	1650
1593	100. [NeurIPS, 2023] Towards Semi-Structured Automatic ICD Coding via Tree-based Contrastive Learning	1651

1625	101. [NeurIPS, 2024] Medformer: A Multi-Granularity Patching Transformer for Medical Time-Series Classification	1683
1626	102. [NeurIPS, 2024] SMART: Towards Pre-trained Missing-Aware Model for Patient Health Status Prediction	1684
1627	103. [NeurIPS, 2024] Knowledge-Empowered Dynamic Graph Network for Irregularly Sampled Medical Time Series	1685
1628	104. [NeurIPS, 2024] Trajectory Flow Matching with Applications to Clinical Time Series Modelling	1686
1629	105. [NeurIPS, 2024] A teacher-teacher framework for clinical language representation learning	1687
1630	106. [NeurIPS, 2024] Automated Multi-Task Learning for Joint Disease Prediction on Electronic Health Records	1688
1631	107. [WWW, 2020] Text-to-SQL Generation for Question Answering on Electronic Medical Records	1689
1632	108. [WWW, 2020] StageNet: Stage-Aware Neural Networks for Health Risk Prediction	1690
1633	109. [WWW, 2020] CLARA: Clinical Report Auto-completion	1691
1634	110. [WWW, 2020] Learning Contextualized Document Representations for Healthcare Answer Retrieval	1692
1635	111. [WWW, 2020] DyCRS: Dynamic Interpretable Postoperative Complication Risk Scoring	1693
1636	112. [WWW, 2021] Online Disease Diagnosis with Inductive Heterogeneous Graph Convolutional Networks	1694
1637	113. [WWW, 2021] Distilling Knowledge from Publicly Available Online EMR Data to Emerging Epidemic for Prognosis	1695
1638	114. [WWW, 2023] SeqCare: Sequential Training with External Medical Knowledge Graph for Diagnosis Prediction in Healthcare Data	1696
1639	115. [WWW, 2023] Cross-center Early Sepsis Recognition by Medical Knowledge Guided Collaborative Learning for Data-scarce Hospitals	1697
1640	116. [WWW, 2025] ColaCare: Enhancing Electronic Health Record Modeling through Large Language Model-Driven Multi-Agent Collaboration	1698
1641	117. [WWW, 2025] MedRAG: Enhancing Retrieval-augmented Generation with Knowledge Graph-Elicited Reasoning for Healthcare Copilot	1699
1642	118. [WWW, 2025] Towards Multi-resolution Spatiotemporal Graph Learning for Medical Time Series Classification	1700

1639 *Stage 2: Task extraction and curation.* We then utilize an LLM (DeepSeek-V3) to extract evidence-grounded tasks from the full text of these
 1640 118 papers. For each paper, the LLM is prompted to generate a detailed task description, a primary research category (e.g., “Data Analysis”,
 1641 “Algorithm Implementation”), and a reference answer or expected outcome based on the paper’s findings. The prompt for this process is
 1642 provided below. This semi-automated process yields an initial pool of 585 tasks. To create a well-balanced and non-redundant benchmark,
 1643 these 585 tasks undergo a final manual curation phase. Our team of researchers consolidates semantically similar task types, discards
 1644 irrelevant or hard-to-evaluate categories (e.g., “Ablation Study”), and refines task descriptions for clarity. We apply stratified sampling to
 1645 ensure diversity across research domains, retaining all tasks from smaller categories and selecting a representative subset from larger ones.
 1646 This meticulous process results in the final EHRFlowBench, which contains 110 high-quality tasks: 100 for evaluation and 10 (one from each
 1647 of the 10 final categories) reserved for the training set used to bootstrap HealthFlow’s experience memory.

Prompt for LLM-based extraction of research tasks from papers.

```

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1651     ### CORE MISSION ###
1652     Please dissect the provided research paper and generate a series of self-contained, complex "mini-projects." These projects will be used to evaluate an
1653     advanced AI agent's ability to implement algorithms and reproduce scientific findings. You will generate approximately 5 such projects.
1654
1655     ### ABSOLUTE RULES FOR TASK GENERATION (NON-NEGOTIABLE) ###
1656
1657     1. **ZERO-REFERENCE MANDATE:** The task description MUST be entirely self-contained. It must NOT reference the source paper in any way (e.g., "as described in
1658     Section 3," "using Equation (5)," "from Table 2"). The AI agent performing the task will NOT have access to the paper. All necessary information, formulas,
1659     parameters, and constants must be explicitly defined within the `<task>`.
1660
1661         * **FAILURE EXAMPLE (DO NOT DO THIS):** "Implement the time-aware graph attention mechanism from equations (1)-(4)."
1662         * **SUCCESS EXAMPLE (DO THIS):** "Implement a time-aware graph attention mechanism. Given a head entity \(\mathbf{c}_h\), its neighbors \(\mathbf{N}_h\), and a time
1663             interval \(\mathbf{t}\), compute the aggregated neighbor representation \(\mathbf{e}_{\mathbf{N}_h}\). First, compute the time embedding \(\mathbf{f}_t = \mathbf{t} \cdot \mathbf{W}_f + \mathbf{b}_f\). Then,
1664             for each neighbor \(\mathbf{c}_u \in \mathbf{N}_h\), calculate the attention score \(\mathbf{a}_{\mathbf{c}_h, \mathbf{c}_u, \mathbf{t}} = \mathbf{c}_h^\top \mathbf{W}_a \mathbf{f}_t + \mathbf{b}_a\). Finally, compute \(\mathbf{e}_{\mathbf{N}_h} = \sum_{\mathbf{c}_u \in \mathbf{N}_h} \tilde{\mathbf{a}}_{\mathbf{c}_h, \mathbf{c}_u, \mathbf{t}} \mathbf{c}_u\). Use parameter dimensions: \(\mathbf{c}_h \in \mathbb{R}^{100}\), \(\mathbf{N}_h \in \mathbb{R}^{100 \times 100}\), \(\mathbf{W}_f \in \mathbb{R}^{100 \times 64}\),
1665             \(\mathbf{b}_f \in \mathbb{R}^{64}\), \(\mathbf{W}_a \in \mathbb{R}^{100 \times 100}\), \(\mathbf{b}_a \in \mathbb{R}^{100}\)."
1666
1667     2. **MANDATORY LATEX:** All mathematical variables, formulas, and expressions MUST be formatted using LaTeX syntax.
1668         * For inline math, use `\\( ... \\)`. Example: The loss is calculated for each sample `\\(y_i)`.
1669         * For block/display math, use `\\[ ... \\]`. Example: `\\[ L_{\\text{total}} = \\sum_{i=1}^N (y_i - \\hat{y}_i)^2 \\]`
1670
1671     3. **DIVERSE & SUBSTANTIAL TASKS:** Generate a variety of tasks covering different research stages (e.g., Cohort Definition, Feature Engineering, Model
1672     Implementation, etc.). Each task should be a meaningful unit of work, not a trivial query.
1673
1674     4. **VERIFIABLE ANSWER:** The `<answer>` field must contain the specific, verifiable result from the paper that directly corresponds to the completion of the
1675     task. The answer must also include a brief interpretation of the result's significance within the context of the study. Use LaTeX for any math in the answer.
1676
1677     ### XML OUTPUT SPECIFICATION (STRICTLY ENFORCED) ###
1678     Your entire output must be a single, valid XML block. Do not include any text, explanations, or markdown fences before or after the XML. The root element must
1679     be `<response>`. Each task must be enclosed in an `<item>` tag with exactly these three child tags: `<category>`, `<task>`, and `<answer>`:
1680
1681         1. `<category>`: A descriptive category for the task.
1682         2. `<task>`: The detailed, self-contained, imperative instructions for the AI agent, following all rules above. **All math must be in LaTeX.**
1683         3. `<answer>`: The verifiable result from the paper. This should contain the specific value/outcome and a brief sentence explaining its context. **Any math
1684         must be in LaTeX.**
1685
1686     --- BEGIN RESEARCH PAPER TEXT ---
1687     {{paper_text}}
1688     --- END RESEARCH PAPER TEXT ---
  
```

1679 An example of a task extracted and curated for EHRFlowBench is provided below.

1741 Example task from the EHRFlowBench benchmark.

1742

1743 <item>

1744 <category>Cohort Definition</category>

1745 <task>

1746 You are given the patient statistics for three distinct disease cohorts used in a risk prediction study. Your task is to perform a calculation for the "Heart Failure" cohort.

1747

1748 **Cohort Data:**

1749 1. **COPD Cohort:**

1750 * Case (Positive) Patients: 7,314

1751 * Control (Negative) Patients: 21,942

1752 2. **Heart Failure Cohort:**

1753 * Case (Positive) Patients: 3,080

1754 * Control (Negative) Patients: 9,240

1755 3. **Kidney Disease Cohort:**

1756 * Case (Positive) Patients: 2,810

1757 * Control (Negative) Patients: 8,430

1758

1759 **Instructions:**

1760 1. Identify the data for the "Heart Failure" cohort.

1761 2. Calculate the total number of patients in this cohort.

1762 3. Calculate the control-to-case ratio for this cohort. Express the ratio as a single number (e.g., if there are 100 controls and 50 cases, the ratio is 2.0).

1763 4. Report the average number of visits per patient for this cohort, which is given as 38.74.

1764

1765 </task>

1766 <answer>

1767 For the Heart Failure cohort:

1768 - Total Patients: 3,080 (Case) + 9,240 (Control) = 12,320

1769 - Control-to-Case Ratio: 9,240 / 3,080 = 3.0

1770 - Average Visits Per Patient: 38.74

1771

1772 **Interpretation:** The dataset for Heart Failure is imbalanced with a 3:1 ratio of control to case patients. This is a common characteristic in medical datasets and must be accounted for during model training and evaluation.

1773

1774 </answer>

1775 </item>

1768 E.2 External Datasets and Benchmarks Used

1769 To ensure a comprehensive evaluation of HealthFlow's capabilities, we utilize several publicly available datasets and benchmarks, each
 1770 targeting distinct aspects of medical reasoning and data analysis.
 1771

1772 *Motivation for dataset selection.* Our selection of benchmarks is driven by the need to assess the multifaceted capabilities required for
 1773 autonomous healthcare research. EHRFlowBench serves as our primary benchmark for evaluating end-to-end, complex research workflows.
 1774 MedAgentBoard is chosen to test practical skills in structured EHR data processing and modeling. MedAgentsBench and the medical subset
 1775 of Humanity's Last Exam (HLE) are included to measure foundational medical knowledge and expert-level reasoning, which are prerequisites
 1776 for high-quality analysis. Finally, CureBench is incorporated to specifically evaluate tool-augmented reasoning in the context of clinical
 1777 therapeutic decision-making. This combination allows for a holistic assessment of our agent, from core knowledge to practical application
 1778 and complex research execution.
 1779

1780 *Dataset descriptions and availability.* All datasets employed in this paper are publicly available or accessible upon request and are used
 1781 under their respective data use agreements.

- 1782 • **EHRFlowBench:** This benchmark is introduced in this work. Details are provided in Section E.1. The complete dataset is available in the
 1783 GitHub repository.
- 1784 • **MedAgentBoard** [53]: A benchmark designed to evaluate AI agents on practical, multi-step data science tasks using real-world EHR data
 1785 (MIMIC-IV [21, 22] and TJH [47]). It assesses the entire pipeline from data extraction and cohort definition to predictive modeling and
 1786 report generation. The benchmark is publicly available on GitHub.
- 1787 • **MedAgentsBench** [42]: A benchmark consisting of challenging multiple-choice questions designed to test the medical knowledge and
 1788 clinical reasoning abilities of AI agents across various medical specialties. We randomly select 100 questions from its "hard set" using a
 1789 random seed of 42.
- 1790 • **Humanity's Last Exam (HLE)** [29]: A collection of expert-level problems designed to be exceptionally challenging for current AI
 1791 systems. We use 45 text-only questions from the "Medicine" and "Health Science" subcategories within its "Biology/Medicine" category to
 1792 assess specialized domain reasoning under difficult conditions.
- 1793 • **CureBench** [10]: A benchmark for therapeutic decision-making that tasks agents with complex reasoning over patients, diseases, and
 1794 drugs, requiring the use of external biomedical tools like FDA databases and PubMed. The data can be downloaded from the Data section
 1795 of the associated Kaggle competition, accessible via the official website: <https://curebench.ai/>.

1857 F Experimental Setup Details

1858 F.1 Computing Infrastructure

1860 All experiments are conducted on a consistent hardware and software platform to ensure reproducibility.

1861 • **Hardware:** Apple Mac Studio with an M3 Ultra chip and 512 GB of unified memory.

1862 • **Software:** We develop HealthFlow using Python 3.12. The environment is managed using uv, with all dependencies specified in a pyproject.toml file for reproducibility.

1863 • **Locally deployed models:** The HuatuoGPT-o1 (QuantFactory/HuatuoGPT-o1-7B-GGUF (8-bit quantized version)) and MedGemma (google/medgemma-27b-text-it (8-bit quantized version)) models are deployed and run locally using LMStudio on the Mac Studio.

1864 • **Online LLM APIs:** Calls to online LLM APIs (e.g., DeepSeek, Qwen, Claude, Kimi, and GLM) utilize their respective official platforms. For 1865 models that support it, we leverage an OpenAI-compatible API interface for standardized communication.

1866 F.2 Hyperparameter Details

1867 The hyperparameters for our framework are selected to balance performance, computational cost, and stability, based on preliminary 1868 experiments on an internal validation set.

1869 Key hyperparameters for HealthFlow are tuned as follows:

1870 • **Maximum retries:** We test values of 1, 2, and 3. A value of 1 corresponds to a single attempt with no self-correction. Our experiments 1871 indicate that a maximum of 3 trials provides a good balance between performance and cost, allowing the agent sufficient opportunity to 1872 correct initial failures without excessive computational overhead.

1873 • **Success threshold:** The evaluator agent as an LLM judge to assigns the evaluation score, where this parameter determines the minimum 1874 evaluation score (on a 1.0–10.0 scale) required to consider a task successful and halt the retry loop. We evaluate thresholds of 6.0 and 1875 8.0. We select a threshold of 6.0, as a value of 8.0 leads to an unnecessarily high number of retries for tasks that are already functionally 1876 complete, thereby reducing overall efficiency.

1877 For all external LLM API calls within our framework and all baselines, we use the default parameters provided by the respective services 1878 (e.g., for temperature, top_p, and max_tokens). This approach ensures that our evaluation focuses on the performance of the agentic 1879 architecture rather than on the effects of hyperparameter tuning for the backbone models.

1880 F.3 Implementation of Baseline Methods

1881 For a fair and rigorous comparison, all baseline methods are configured to the best of our ability according to their original papers and public 1882 implementations. Unless otherwise specified, all agent frameworks are powered by the DeepSeek-V3 model to normalize for the effect of the 1883 backbone LLM and isolate the performance of the agentic architecture itself.

1884 *General and medical LLMs.* DeepSeek-V3 [25] and DeepSeek-R1 [14] are accessed via their official APIs. HuatuoGPT-o1 [6] and 1885 MedGemma [35] are run locally using LMStudio. These models are prompted with the raw task description and are evaluated based 1886 on their direct, single-turn responses without any agentic scaffolding.

1887 *Multi-agent collaboration frameworks.* We use the official open-source implementations for MedAgents [43], MDAgents [23], and Co- 1888 laCare [46]. As these frameworks are designed primarily for conversational QA or summarization and often lack robust, sandboxed code 1889 execution environments, we adapt their inputs to be the research tasks from our benchmarks and evaluate their final textual outputs.

1890 *General and biomedical agent frameworks.* All general and medical LLMs, as well as multi-agent collaboration frameworks, lack the 1891 capability to read and execute code. Therefore, for open-ended tasks such as those in EHRFlowBench and MedAgentBoard, we evaluate only 1892 their generated code and answers.

1893 We use the official repositories for AFlow [50], Biomni [17], and STELLA [20], reproducing results according to the instructions provided 1894 in their README files. For Alita [30], whose official implementation is not public, we adopt the widely used open-source community 1895 version, OpenAlita [33]. All frameworks are configured to use DeepSeek-V3 as their primary reasoning and execution model to ensure a fair 1896 comparison with HealthFlow.

1897 F.4 Evaluation Metrics Details

1898 We employ a combination of automated metrics and LLM-based evaluation to assess agent performance across different benchmarks.

1899 *Standard metrics.* For benchmarks with ground-truth answers, we use standard metrics.

1900 • **Accuracy:** This is used for MedAgentsBench and HLE, where tasks are multiple-choice or have a binary correct/incorrect answer. It is the 1901 percentage of correctly answered questions. We first use LLM-based extraction to obtain the predicted answer and then apply the official 1902 evaluation prompt to determine correctness.

1903 • **Success rate:** The primary metric for MedAgentBoard. A task is considered successful if the agent produces the correct final numerical 1904 answer or a functionally correct artifact (e.g., a plot), as verified against the ground-truth solution through manual human evaluation.

1973 *LLM-as-a-judge evaluation.*

2031

- 1974 • For **EHRFlowBench**, we use an ensemble of five diverse LLMs (DeepSeek-V3, DeepSeek-R1, Claude-4-Sonnet, Kimi-K2, GLM-4.5) to
 1975 mitigate single-model bias. Each judge scores a solution on a 1–5 scale across three dimensions: methodology soundness (70% weight),
 1976 presentation quality (20%), and artifact generation (10%). The final score is the weighted average of the mean scores from the five judges.
 1977 The evaluation prompt is detailed below.

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1979 *Evaluation prompt for EHRFlowBench.*

1980 ****1. method_soundness****

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1981 Evaluate the overall quality of the solution path. Assess the chosen method's soundness and correctness. More importantly, ****this score heavily weights the quality and completeness of the agent's justification for its approach****. A well-reasoned, comprehensive report that discusses problem framing, results, and limitations should score highly, even if its method intelligently deviates from the reference answer. The reference serves as a benchmark, not a strict mandate.

2040

1982 * ****5 (Exemplary):**** **MUST** meet all criteria for a score of 4. In addition, the **Methodology Justification** is exceptionally insightful, comparing the approach to viable alternatives and providing a profound analysis of the **generated results** and limitations.
 1983 * ****4 (Strong):**** A score of 4 is IMPOSSIBLE without clear evidence of successful execution (explicit statements OR output files like `*.png`/`*.csv` in `{'file_structure_info'}`). The response must also contain a true **Methodology Justification** (as defined above), not just a code explanation.
 1984 * ****3 (Acceptable):**** This is the ABSOLUTE MAXIMUM score for any solution that LACKS execution evidence. To achieve this score, the response **MUST** provide a strong **Methodology Justification** (the "Why"). It presents a well-reasoned strategic plan, even if it's not proven with results.
 1985 * ****2 (Weak):**** Assign this score if a response's justification consists ONLY of code and a Code Explanation (the "What" and "How"), like the provided example. This score is the correct rating for a submission that presents a function or script but fails to provide the strategic "Why" behind it. This score also applies if the method is flawed or execution failed.
 1986 * ****1 (Poor):**** The method is fundamentally flawed or irrelevant, and there is no meaningful justification of any kind.

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1987 ****2. presentation_quality****

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1988 Clarity, structure, and completeness of the final answer's explanation and formatting. Is it easy to read and understand?

2045

1989 * ****5 (Exemplary):**** The presentation is exceptionally clear, professional, and well-structured. It uses formatting, language, and structure to make complex information easy to digest.
 1990 * ****4 (Strong):**** The presentation is clear, well-structured, and complete. It is easy to read and understand with only minor room for refinement.
 1991 * ****3 (Acceptable):**** The core message is communicated clearly and the structure is adequate. A reader can understand the answer, though it may have minor issues with clarity, organization, or formatting.
 1992 * ****2 (Weak):**** The presentation is disorganized, unclear, or incomplete, making it difficult for the reader to follow.
 1993 * ****1 (Poor):**** The presentation is confusing, unstructured, or poorly formatted, failing to communicate the information effectively.

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1994 ****3. artifact_generation****

2049

1995 Functionality, correctness, and completeness of generated files (e.g., code, plots, data). Are they usable and aligned with the task?

2050

1996 * ****5 (Exemplary):**** Artifacts are not only correct and well-organized into files but also demonstrate exemplary software engineering practices. The code architecture is robust and clean (e.g., using functions/classes), well-commented, and easily understandable or reusable.
 1997 * ****4 (Strong):**** Generates correct and functional artifacts. The code is well-organized, logically structured, and is appropriately saved into distinct files (e.g., `code.py` for code, `data.csv` for data).
 1998 * ****3 (Acceptable):**** Artifacts are generated and are largely functional. The code may require minor corrections to run, ript), but it successfully implements the core logic.
 1999 * ****2 (Weak):**** Artifacts are generated but contain significant errors or are incomplete. This score recognizes the attempt to generate code but notes its flaws.
 2000 * ****1 (Poor):**** Fails to generate the required artifacts.

2051

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2053

2001 ****4. overall_score****

2054

2002 Your holistic assessment, ****not a simple average****. A critical failure (score of 0 or 1) in one key area should heavily penalize the overall score. Conversely, exceptional performance (4 or 5) in key areas should elevate it.

2055

2056

2003 * ****5 (Exemplary):**** An exemplary performance (score of 5) on `solution_approach_justification` with at least strong performance (4) on other dimensions. A model answer.
 2004 * ****4 (Strong):**** Strong performance (4 or higher) across all key dimensions, or an exemplary performance in one key area balanced by acceptable performance elsewhere. A high-quality submission.
 2005 * ****3 (Acceptable):**** Meets expectations (score of 3) on all dimensions. A solid, complete solution with no major flaws.
 2006 * ****2 (Weak):**** Weak performance (score of 2) in one or more dimensions, especially `solution_approach_justification` or `artifact_generation`, but is not a complete failure.
 2007 * ****1 (Poor):**** Contains a fundamental flaw or critical error (score of 1) in a key dimension, severely compromising the value of the submission.

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2020 *Evaluation prompt for data extraction and statistical analysis in MedAgentBoard.*

2021 ### 1. Correctness of Data Selection (1-5 points)

2022 - ****5 (Perfect):**** The selected data subset (rows and columns) is **exactly** what is required by the task and perfectly matches the standard answer.

```

2089
2090 - **4 (Minor Deviation):** The core data is correct, but there are minor discrepancies, such as an extra non-essential column or a slightly different but
2091 still valid filter condition.
2092 - **3 (Partial Match):** The selected data has some correct elements but misses significant portions of required data or includes a large amount of
2093 incorrect data. E.g., correct rows but wrong columns.
2094 - **2 (Incorrect):** The data selection logic is fundamentally flawed. The resulting dataset is largely irrelevant to the task.
2095 - **1 (Critically Flawed):** No data is selected, or the selected data is completely wrong.
2096
2097     ### 2. Transformation Logic (1-5 points)
2098 - **5 (Perfect):** All data transformations (e.g., calculations, aggregations, reshaping) are implemented correctly and efficiently, yielding results
2099 identical to the standard answer.
2100 - **4 (Mostly Correct):** The logic is sound and achieves the correct outcome, but with minor inefficiencies or stylistic differences from the ideal
2101 implementation. The final numbers are correct.
2102 - **3 (Partially Correct):** The transformation logic contains errors that lead to partially incorrect results. For example, a calculation is wrong, or
2103 an aggregation is performed on the wrong group.
2104 - **2 (Incorrect):** The transformation logic is fundamentally incorrect and does not produce the required output format or values.
2105 - **1 (Critically Flawed):** The code for transformation is non-functional, absent, or completely irrelevant.
2106
2107     ### 3. Handling of Missing Values (1-5 points)
2108 - **5 (Perfect):** Missing values are handled appropriately as dictated by the task or best practices (e.g., imputation, removal) and aligns perfectly
2109 with the standard answer's approach.
2110 - **4 (Acceptable Alternative):** An alternative, valid method for handling missing values was used that still leads to a correct or very similar outcome.
2111 - **3 (Suboptimal Handling):** Missing values were handled, but in a way that negatively impacts the final result or is not appropriate for the data type
2112 (e.g., filling categorical data with 0).
2113 - **2 (Incorrect Handling):** The method for handling missing values is wrong or leads to significant errors in the analysis.
2114 - **1 (Critically Flawed):** Missing values were completely ignored when they should have been handled, or the handling method caused the process to fail.
2115
2116     ### 4. Appropriateness of Statistical Methods (1-5 points)
2117 - **5 (Perfect):** The statistical methods used (e.g., mean, median, standard deviation, t-test) are perfectly appropriate for the data and the question,
2118 matching the standard answer.
2119 - **4 (Mostly Appropriate):** The chosen statistical method is valid and yields a correct conclusion, though a slightly more optimal method might exist.
2120 - **3 (Partially Appropriate):** A statistical method was used, but it was not the right choice for the data distribution or task, leading to potentially
2121 misleading results.
2122 - **2 (Inappropriate):** The statistical method is clearly wrong (e.g., using mean on ordinal data, correlation on non-linear data).
2123 - **1 (Critically Flawed):** No statistical analysis was performed, or a completely nonsensical method was applied.
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- **Predictive modeling:** Suitability of model choice, soundness of training procedures, inclusion of relevant evaluation metrics, and proper validation practices.

Evaluation prompt for predictive modeling in MedAgentBoard.

```

2116
2117
2118     ### 1. Appropriateness of Model Selection (1-5 points)
2119 - **5 (Perfect):** The chosen model is highly appropriate for the data type, task (e.g., classification, regression), and complexity, aligning with the
2120 standard answer.
2121 - **4 (Acceptable):** The model is a reasonable choice and works, but a more standard or higher-performing model is available and used in the standard
2122 answer.
2123 - **3 (Suboptimal):** The chosen model is unconventional or ill-suited for the task, leading to poor performance or unnecessarily complex implementation.
2124 - **2 (Incorrect):** The model type is wrong for the task (e.g., using a regression model for a classification task).
2125 - **1 (Critically Flawed):** No model was selected, or a completely nonsensical choice was made.
2126
2127     ### 2. Implementation of Training Procedures (1-5 points)
2128 - **5 (Perfect):** The model training code is bug-free, efficient, and correctly implemented, including data splitting, feature preparation, and fitting.
2129 It matches the standard answer's implementation.
2130 - **4 (Mostly Correct):** The training procedure is correct, but with minor issues like suboptimal hyperparameter defaults or inefficient data handling.
2131 The model trains successfully.
2132 - **3 (Partially Correct):** The training code has errors that allow it to run but produce a poorly trained model (e.g., data leakage, wrong feature
2133 scaling).
2134 - **2 (Incorrect):** The training code has significant bugs that prevent the model from training correctly or at all.
2135 - **1 (Critically Flawed):** The training code is completely non-functional or absent.
2136
2137     ### 3. Inclusion of Necessary Evaluation Metrics (1-5 points)
2138 - **5 (Perfect):** All relevant evaluation metrics for the task (e.g., AUC, F1-score for classification; R-squared, MSE for regression) are correctly
2139 calculated and reported, matching the standard answer.
2140 - **4 (Mostly Complete):** The primary metrics are reported, but some useful secondary metrics are missing.
2141 - **3 (Partially Complete):** Some key metrics are missing, or the reported metrics are not the most appropriate for the task.
2142 - **2 (Incorrect):** The wrong metrics are calculated (e.g., accuracy on a highly imbalanced dataset without other metrics), or they are calculated
2143 incorrectly.
2144 - **1 (Critically Flawed):** No evaluation metrics are provided.
2145
2146     ### 4. Adherence to Proper Validation Practices (1-5 points)
2147 - **5 (Perfect):** A proper validation strategy (e.g., train-test split, cross-validation) is used correctly, ensuring no data leakage and providing an
2148 unbiased estimate of performance.
2149 - **4 (Acceptable):** A simple train-test split is used correctly, where cross-validation might have been more robust. The validation is still sound.
2150 - **3 (Flawed):** The validation practice has flaws, such as not stratifying a split on an imbalanced dataset or testing on data that was used in
2151 training (leakage).
2152 - **2 (Incorrect):** The concept of validation is misunderstood. For example, the model is evaluated on the training set.
2153 - **1 (Critically Flawed):** There is no validation procedure at all.
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- **Data visualization:** Correct application of visualization techniques, alignment with analytical goals, aesthetic clarity, and overall readability.

2205 *Evaluation prompt for data visualization in MedAgentBoard.*

2206

2207 ### 1. Correctness of Visualization Techniques (Code-based) (1-5 points)

2208 - **5 (Perfect):** The agent's plotting code is logically identical to the standard answer's code. It selects the correct data, uses the right plot type (e.g., bar, scatter), and correctly maps variables to axes.

2209 - **4 (Mostly Correct):** The plotting code produces the same type of plot with the correct data, but may have minor differences in implementation (e.g., using a different library but achieving the same result).

2210 - **3 (Partially Correct):** The code attempts to create the right kind of plot but makes significant errors, such as plotting the wrong variables, using incorrect data aggregations, or choosing a plot type that obscures the insight.

2211 - **2 (Incorrect):** The plotting code is fundamentally flawed and would produce a visualization that is misleading or completely different from the required one.

2212 - **1 (Critically Flawed):** The plotting code is non-functional, absent, or completely irrelevant.

2213

2214 ### 2. Alignment with Analytical Objectives (1-5 points)

2215 - **5 (Perfect):** The visualization (as inferred from the code) directly and clearly answers the question posed in the task brief.

2216 - **4 (Mostly Aligned):** The visualization is relevant but might not be the most effective way to show the specific insight required.

2217 - **3 (Partially Aligned):** The visualization shows related data but does not directly address the core analytical objective of the task.

2218 - **2 (Poorly Aligned):** The visualization is only tangentially related to the task.

2219 - **1 (Critically Flawed):** The visualization is completely irrelevant to the analytical objective.

2220

2221 ### 3. Aesthetic Quality and Readability (Inferred) (1-5 points)

2222 - **5 (Perfect):** The code includes clear labels for the title, x-axis, and y-axis, and a legend if necessary. The implementation suggests a clean, professional, and easy-to-read plot.

2223 - **4 (Good):** The plot is mostly readable, but is missing one minor element like a title or a clear axis label.

2224 - **3 (Acceptable):** The plot is generated, but the code lacks any labels, titles, or other elements that aid interpretation.

2225 - **2 (Poor):** The code suggests a messy or confusing plot (e.g., overlapping labels, no clear differentiation of elements).

2226 - **1 (Critically Flawed):** No effort is made to make the plot interpretable.

2227

2228 ### 4. Correctness of File Generation (1-5 points)

2229 - **5 (Perfect):** The agent correctly generated the required image file in the correct format (e.g., `output.png`).

2230 - **4 (Minor Issue):** The file was generated in a different but still acceptable image format (e.g., a `jpg` instead of a `png`).

2231 - **3 (Incorrect Format):** The output was saved in a non-image format (e.g., `txt`, `csv`).

2232 - **2 (Failed Generation):** The code includes a save command, but it is incorrect and would fail, or the generated answer indicates a failure to save.

2233 - **1 (Critically Flawed):** The required image file was **not** generated at all. This is a critical failure.

2234

2235

- **Report generation:** Completeness, coherence, factual accuracy, and clinical relevance of the synthesized findings.

2236 *Evaluation prompt for report generation in MedAgentBoard.*

2237

2238 ### 1. Completeness (1-5 points)

2239 - **5 (Perfect):** The report addresses all parts of the task prompt, synthesizing all required pieces of information from the data. All key findings from the standard answer are present.

2240 - **4 (Mostly Complete):** The report covers the main findings but omits a minor detail or a secondary point.

2241 - **3 (Partially Complete):** The report addresses some of the task requirements but misses major findings or sections. If no markdown file (MD file) is generated, the maximum score is 3.

2242 - **2 (Incomplete):** The report only touches on one aspect of the task and is largely incomplete.

2243 - **1 (Critically Flawed):** The report is empty or does not attempt to address the task.

2244

2245 ### 2. Accuracy (1-5 points)

2246 - **5 (Perfect):** All statements, numbers, and conclusions in the report are factually correct and perfectly match the data and the standard answer.

2247 - **4 (Mostly Accurate):** The report contains very minor inaccuracies that do not affect the overall conclusion (e.g., a slightly rounded number, a trivial misstatement).

2248 - **3 (Partially Accurate):** The report contains a mix of correct and incorrect information. Some of the stated facts or numbers are wrong, affecting the validity of the conclusions.

2249 - **2 (Inaccurate):** The majority of the report is factually incorrect. The numbers or statements fundamentally misrepresent the data.

2250 - **1 (Critically Flawed):** The report is entirely fictional, hallucinatory, or contradictory to the data.

2251

2252 ### 3. Coherence (1-5 points)

2253 - **5 (Perfect):** The report is well-structured, logical, and easy to follow. It tells a clear story and connects findings together seamlessly.

2254 - **4 (Good):** The report is coherent and understandable, but the structure or flow could be improved.

2255 - **3 (Acceptable):** The report presents a series of facts but fails to synthesize them into a coherent narrative. The points are disconnected.

2256 - **2 (Poor):** The report is rambling, disorganized, and difficult to understand.

2257 - **1 (Critically Flawed):** The report is a jumble of incoherent sentences or bullet points.

2258

2259 ### 4. Clinical Relevance of Conclusions (1-5 points)

2260 - **5 (Perfect):** The conclusions drawn are not only accurate but also clinically relevant and insightful, directly aligning with the context of the problem.

2261 - **4 (Relevant):** The conclusions are relevant but may lack depth or fail to highlight the most critical clinical insight.

2262 - **3 (Superficial):** The conclusions are factually correct but superficial, stating the obvious without providing any deeper interpretation or clinical context.

2263 - **2 (Irrelevant):** The conclusions drawn are not relevant to the clinical question at hand.

2264 - **1 (Critically Flawed):** No conclusions are drawn, or they are nonsensical.

2265

2321 **G Detailed Case Studies** 23792322 **G.1 Case 1: Medically Informed Data Validation** 2380

2323 In this case study, selected from the MedAgentBoard benchmark, the task is to create a scatter plot to visualize the relationship between
 2324 systolic blood pressure and diastolic blood pressure. The goal is to plot “systolic blood pressure” on the x-axis and “diastolic blood pressure”
 2325 on the y-axis to explore the correlation between these two vital signs across all records.
 2326

2327 *Phase 1: Experience-driven planning by the meta agent.* Upon receiving the task, the meta agent does not immediately generate code. Its first
 2328 action is to query the persistent experience memory for relevant strategic knowledge. For this task, it retrieves several high-level heuristics
 2329 and warnings gleaned from previous, similar analyses, as shown below. These experiences highlight critical, non-obvious requirements for
 2330 handling clinical data, such as the need for early data validation and the removal of missing values to ensure analytical integrity.
 2331

2332 *Past experiences retrieved by the meta agent to inform strategic planning.* 2390

```
2333 [
  2334   {
    2335     "type": "heuristic",
    2336     "category": "medical_data_cleaning",
    2337     "content": "For temporal analysis of clinical metrics in healthcare data, always filter out records with missing values in the target parameter before
    2338       aggregation or visualization. This ensures data integrity by preventing skewed results from incomplete data, enhancing reliability for similar requests
    2339       involving trend analysis like plotting lab values over time."
    2340   },
    2341   {
      2342     "type": "warning",
      2343     "category": "data_quality",
      2344     "content": "When handling healthcare data with multiple records per patient, failing to validate column existence early or neglecting to remove records
      2345       with missing values in target variables can lead to runtime failures or distorted visualizations; consistently implement these checks to uphold data
      2346       reliability in similar visualization requests."
      2347   },
    2348   {
      2349     "type": "warning",
      2350     "category": "data_validation",
      2351     "content": "In numerical threshold analyses for clinical data, always validate that columns are of numeric data types before performing comparisons.
      2352       Omission can cause runtime errors or incorrect interpretations if data contains non-numeric entries, potentially compromising analysis accuracy.
      2353       Incorporate data type checks early in processing to improve robustness and avoid pitfalls in similar healthcare tasks."
    2354   }
  2355 ]
  2356 
```

2357 Informed by this retrieved knowledge, the meta agent synthesizes these abstract principles into a concrete, executable plan, which is
 2358 detailed next. This plan is not merely a sequence of commands; it is a strategic workflow that explicitly incorporates the lessons from past
 2359 experiences.
 2360

2361 *The strategic task plan generated by the meta agent.* 2408

```
2362 # Scatter Plot of Systolic vs Diastolic Blood Pressure 2412
2363 ## Relevant Context from Past Experience 2413
2364 * **Warning (data_quality):** When handling healthcare data, always validate column existence early and remove records with missing values in target 2414
2365 variables to prevent distorted visualizations. 2415
2366 * **Heuristic (medical_data_cleaning):** Filter out records with missing values in target parameters before visualization to ensure data integrity and 2416
2367 prevent skewed results. 2417
2368 * **Warning (data_validation):** Validate that columns are numeric before analysis to avoid runtime errors or incorrect interpretations. 2418
2369 ## Step 1: Verify Data Path 2419
2370 `ls -l /PATH/TO/healthflow_datasets/ | grep MIMIC-IV.parquet` 2420
2371 ## Step 2: Create Python Script 2421
2372 `touch blood_pressure_analysis.py` 2422
2373 ## Step 3: Write Visualization Logic 2423
2374 ```python` 2424
2375 import pandas as pd 2425
2376 import matplotlib.pyplot as plt 2426
2377 ## Load data and validate 2427
2378 file_path = 'PATH/TO/MIMIC-IV.parquet' 2428
2379 df = pd.read_parquet(file_path) 2429
2380
2381 # Validate column existence and data types (as per context) 2430
2382 required_cols = ['Systolic blood pressure', 'Diastolic blood pressure'] 2431
2383 for col in required_cols:
2384     if col not in df.columns:
2385         raise ValueError(f'Missing column: {col}')
2386     if not pd.api.types.is_numeric_dtype(df[col]):
2387         raise TypeError(f"Column '{col}' is non-numeric") 2432
2388
2389 
```

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```

2437 # Filter missing values (as per context)
2438 df_clean = df.dropna(subset=required_cols)
2439
2440 # Generate scatter plot
2441 plt.figure(figsize=(10, 6))
2442 plt.scatter(df_clean['Systolic blood pressure'], df_clean['Diastolic blood pressure'], alpha=0.5)
2443 plt.title('Correlation: Systolic vs Diastolic Blood Pressure')
2444 plt.xlabel('Systolic Blood Pressure (mmHg)')
2445 plt.ylabel('Diastolic Blood Pressure (mmHg)')
2446 plt.grid(True)
2447 plt.savefig('bp_correlation_plot.png')
2448
2449
2450
2451 ## Step 4: Execute Script
2452 `python blood_pressure_analysis.py`
2453
2454 ## Step 5: Confirm Output
2455 `ls -l bp_correlation_plot.png`
2456

```

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Phase 2: *Execution, evaluation, and self-correction.* The executor agent proceeds to execute the plan, producing the execution log shown below. The task completes successfully on the first attempt. Following execution, the evaluator agent provides prompt feedback, critically assessing the process even in successful runs. It identifies inefficiencies in the plan, offering insights essential for the iterative self-correction loop. In case of a task failure, this feedback guides the meta agent in retrying. The evaluator agent's critique is shown below.

Execution log confirming successful generation of the visualization.

```

2456 {
2457     "success": true,
2458     "return_code": 0,
2459     "log": "STDOUT: Scatter plot created successfully! The visualization shows the relationship between systolic and diastolic blood pressure across 216,291
2460     valid records from the MIMIC-IV dataset, with a correlation coefficient of 0.008. The plot has been saved as 'bp_correlation_plot.png'.\n",
2461 }
2462

```

The evaluator agent's critique.

```

2463 {
2464     "evaluation": {
2465         "score": 9.0,
2466         "feedback": "The scatter plot was correctly generated, but avoid adding unrequested elements like the correlation coefficient. Streamline the plan by
2467         removing redundant steps (e.g., manual file verification with 'ls') and handle all checks within the script for efficiency.",
2468         "reasoning": "Correctness is high (plot created as requested with sound data validation). Efficiency loses points for unnecessary steps like separate file
2469         checks. Safety is excellent with robust error handling and no privacy violations in the output."
2470     }
2471 }
2472

```

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Phase 3: *Meta-level evolution via knowledge synthesis.* Upon successful completion, the full execution trace is passed to the reflector agent, which drives HealthFlow's long-term evolution by extracting abstract, generalizable knowledge. As shown below, the reflector agent generates a new "workflow_pattern" and a "heuristic". These new knowledge objects are not mere copies of the executed code; they are generalized principles.

New generalizable experiences synthesized by the reflector agent.

```

2478 [
2479     {
2480         "type": "workflow_pattern",
2481         "category": "medical_data_visualization",
2482         "content": "For user requests involving scatter plots to explore correlations between clinical metrics in healthcare datasets, implement this workflow: 1.
2483         Load the dataset using a tool like pandas. 2. Validate the existence and numeric data type of the required columns early in the process. 3. Remove
2484         records with missing values in the target parameters to ensure data integrity. 4. Generate the visualization with clear labels and save the output. This
2485         pattern ensures reliable and accurate plots by preventing runtime errors and skewed results, as demonstrated in the successful blood pressure correlation
2486         analysis.",
2487         "source_task_id": "0dd7801e-7e09-48c6-abae-e03b44ca239c"
2488     },
2489     {
2490         "type": "heuristic",
2491         "category": "data_validation",
2492         "content": "Always perform early validation of column presence and data types at the start of any healthcare data analysis task, especially for vital
2493         signs in datasets like MIMIC-IV. This prevents runtime failures and ensures that subsequent operations, such as visualization or correlation
2494         calculations, are based on valid, numeric data, enhancing the correctness and safety of the output for similar user requests.",
2495         "source_task_id": "0dd7801e-7e09-48c6-abae-e03b44ca239c"
2496     }
2497 ]
2498

```

2553 Based on the generated code and execution log, HealthFlow synthesizes the final report (shown below) and saves the generated figure
 2554 (see Figure 9).

2555

HealthFlow's generated technical report: analysis of systolic and diastolic blood pressure correlation in the MIMIC-IV dataset.

2556

1. Executive Summary

2559

This report documents the successful execution of a computational task aimed at exploring the relationship between systolic and diastolic blood pressure measurements within the MIMIC-IV dataset. The primary objective was to generate a scatter plot visualizing the correlation between these two vital signs, accompanied by a quantitative assessment of their linear relationship. The AI agent implemented a robust Python script that loads the dataset, performs data validation, filters incomplete records, and generates a high-quality scatter plot with annotated correlation metrics. The analysis revealed a weak positive correlation ($r = 0.008$) across 216,291 valid records, suggesting minimal linear dependence between systolic and diastolic blood pressure in this cohort. The primary achievement was the successful implementation of a reproducible and clinically interpretable visualization pipeline.

2560

2. Problem Statement & Objectives

2561

Blood pressure, comprising systolic (SBP) and diastolic (DBP) components, is a critical vital sign in clinical practice. While these metrics are often reported together, their relationship across diverse patient populations remains an area of interest for both clinical and research applications. The core task was to investigate this relationship by visualizing the pairwise distribution of SBP and DBP measurements and quantifying their linear correlation.

2562

The specific objectives were:

2563

1. **Data Loading & Validation**: Ensure the dataset contains the required SBP and DBP columns and handle missing data appropriately.
2. **Visualization**: Generate a scatter plot with SBP on the x-axis and DBP on the y-axis, incorporating professional formatting.
3. **Correlation Analysis**: Compute and display the Pearson correlation coefficient (r) to quantify the linear relationship.
4. **Output Generation**: Save the plot as a high-resolution image and log key statistics for reproducibility.

2564

The task was purely implementation-focused, with the generated code serving as the primary deliverable. No additional hypothesis testing or advanced statistical modeling was required.

2565

3. Methodology & Implementation

2566

Technical Approach

2567

The agent adopted a systematic workflow:

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1. **Data Ingestion**: The MIMIC-IV dataset was loaded from a Parquet file, a columnar storage format optimized for analytical queries.
2. **Data Validation**: The script verified the presence of required columns ('Systolic blood pressure', 'Diastolic blood pressure') and raised an informative error if either was missing.
3. **Data Cleaning**: Records with missing SBP or DBP values were excluded to ensure analysis robustness.
4. **Visualization**: A scatter plot was generated using `matplotlib`, with transparency ('alpha=0.5') to mitigate overplotting and point size ('s=10') adjusted for clarity.
5. **Annotation**: The Pearson correlation coefficient was calculated and overlaid on the plot, along with axis labels and a grid for interpretability.
6. **Output**: The plot was saved as a PNG file (300 DPI) with clinically reasonable axis limits (SBP: 50–250 mmHg; DBP: 20–150 mmHg).

2569

Implementation Details & Final Code

2570

The final code (reproduced below) demonstrates adherence to best practices in scientific computing:

2571

```
```python
```

2572

```
import pandas as pd
```

2573

```
import matplotlib.pyplot as plt
```

2574

```
import numpy as np
```

2575

```
Load data
```

2576

```
file_path = '/PATH/TO/MIMIC-IV.parquet'
```

2577

```
df = pd.read_parquet(file_path)
```

2578

```
Validate required columns exist
```

2579

```
required_cols = ['Systolic blood pressure', 'Diastolic blood pressure']
```

2580

```
missing_cols = [col for col in required_cols if col not in df.columns]
```

2581

```
if missing_cols:
```

```
 raise ValueError(f"Missing columns: {missing_cols}")
```

2582

```
Filter out records with missing values in target variables
```

2583

```
df_clean = df.dropna(subset=required_cols)
```

2584

```
Create scatter plot
```

2585

```
plt.figure(figsize=(10, 8))
```

2586

```
plt.scatter(df_clean['Systolic blood pressure'],
```

```
 df_clean['Diastolic blood pressure'],
```

```
 alpha=0.5,
```

```
 s=10,
```

```
 color='blue')
```

2587

```
Add labels and formatting
```

2588

```
plt.title('Systolic vs Diastolic Blood Pressure Correlation', fontsize=14, pad=20)
```

2589

```
plt.xlabel('Systolic Blood Pressure (mmHg)', fontsize=12)
```

2590

```
plt.ylabel('Diastolic Blood Pressure (mmHg)', fontsize=12)
```

2591

```
plt.grid(True, alpha=0.3)
```

2592

```
Add correlation coefficient
```

2593

```
correlation = df_clean['Systolic blood pressure'].corr(df_clean['Diastolic blood pressure'])
```

2594

```
plt.text(0.05, 0.95, f'r = {correlation:.3f}',
```

```
 transform=plt.gca().transAxes,
```

```
 fontsize=12,
```

```
 verticalalignment='top',
```

```
 bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))
```

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```
Set reasonable axis limits based on typical blood pressure ranges
```

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```

2669 plt.xlim(50, 250)
2670 plt.ylim(20, 150)
2671 # Save plot
2672 plt.savefig('bp_correlation_plot.png', dpi=300, bbox_inches='tight')
2673 plt.close()
2674 print(f"Scatter plot created successfully!")
2675 print(f"Total records: {len(df)}")
2676 print(f"Records with valid BP data: {len(df_clean)}")
2677 print(f"Correlation coefficient: {correlation:.3f}")
2678 ...
2679
2680 **Key Design Choices**:
2681 - **Data Validation**: Explicit checks for column existence prevent runtime errors and enhance reproducibility.
2682 - **Alpha Transparency**: Mitigates overplotting in dense regions of the scatter plot.
2683 - **Clinical Axis Limits**: Reflects physiologically plausible ranges, excluding outliers that could distort visualization.
2684 - **Correlation Annotation**: The coefficient is displayed in a white-bordered box for legibility.
2685
2686 ### Verification & Validation
2687 Correctness was ensured through:
2688 1. **Code Logic Review**: The script handles edge cases (e.g., missing data) and includes sanity checks.
2689 2. **Output Inspection**: The generated plot ('bp_correlation_plot.png') was verified for correct axis labeling, data representation, and annotation placement.
2690 3. **Correlation Cross-Check**: The reported r-value (0.008) was manually confirmed using `df_clean.corr()`.

2691 ## 4. Results & Analysis
2692
2693 ### Execution Overview
2694 The task was completed successfully, producing:
2695 - A scatter plot ('bp_correlation_plot.png') visualizing SBP vs. DBP.
2696 - Logs confirming execution (216,291 valid records processed).
2697 - Auxiliary files ('execution_info.json', 'generated_file_manifest.md') for provenance tracking.

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```

In contrast, baseline agents lacking this experience-driven planning mechanism often fail to produce a useful or even correct result. To illustrate this critical difference in capability, we present the outputs from several prominent baseline agents for the same task. As shown in its output below, Biomni provides a descriptive summary of task completion. Although code is generated during the process, it is not included in the final output. Only the image is shown, and its result deviates from the reference answer.

#### Biomni's output.

```

<solution>
I have successfully created and saved a scatter plot showing the relationship between Systolic and Diastolic blood pressure from the MIMIC-IV dataset. Here are the key details:
1. The plot has been saved as: 'PATH/T0/blood_pressure_scatter.png'
2. The plot shows:
 - X-axis: Systolic Blood Pressure (mmHg)
 - Y-axis: Diastolic Blood Pressure (mmHg)
 - Title: "Relationship Between Systolic and Diastolic Blood Pressure"
3. The plot includes all available records from the dataset, with each point representing one measurement.

The visualization allows for exploration of the correlation between these two important vital signs, which is clinically relevant for assessing cardiovascular health.
</solution>

```

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2809 **Figure 9: Execution results of different methods on a MedAgentBoard task.** (a) shows the reference answer; (b) presents the  
2810 output from HealthFlow; (c) and (d) display the responses from Biomni and STELLA, both of which fail to perform the essential  
2811 data validation step, while Alita fails to generate the required image.  
2812  
2813

2814 As shown in its output below, STELLA similarly omits outlier handling in its final answer.  
2815

2816 STELLA's output.

```
2817
2818 import pandas as pd
2819 import matplotlib.pyplot as plt
2820 import pyarrow # Required for reading parquet files
2821
2822 # Load the dataset using the full, absolute path
2823 file_path = '/PATH/TO/MIMIC-IV.parquet'
2824 df = pd.read_parquet(file_path)
2825
2826 # Create the scatter plot
2827 plt.figure(figsize=(10, 6))
2828 plt.scatter(df['Systolic blood pressure'], df['Diastolic blood pressure'], alpha=0.5)
2829 plt.title('Relationship Between Systolic and Diastolic Blood Pressure')
2830 plt.xlabel('Systolic Blood Pressure (mmHg)')
2831 plt.ylabel('Diastolic Blood Pressure (mmHg)')
2832 plt.grid(True)
2833
2834 # Save the plot to a file
2835 plot_filename = 'blood_pressure_scatter.png'
2836 plt.savefig(plot_filename)
2837 plt.close()
2838
2839 print(f"Scatter plot saved as '{plot_filename}' in the current directory.")
2840
2841 final_answer("Created a scatter plot of Systolic vs Diastolic blood pressure saved as 'blood_pressure_scatter.png' in the current directory.")
2842 -----
2843 Execution logs:
2844 Scatter plot saved as 'blood_pressure_scatter.png' in the current directory.
2845
2846 Final answer: Created a scatter plot of Systolic vs Diastolic blood pressure saved as 'blood_pressure_scatter.png' in the current directory.
```

2847 The output from Alita, shown below, highlights a more severe failure mode: hallucination of success. Despite multiple tool-call failures  
2848 clearly shown in the execution log, the agent's final synthesizer module incorrectly concludes that the task is successful and confidently  
2849 provides a file path for the supposedly generated scatter plot.  
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```

2901 Alita's output. 2959
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2903 Starting intelligent analysis workflow... 2960
2904 **Coordinator:** ... → Routing to mcp_agent coordinator completed 2961
2905 **MCP Agent:** Analyzing query for tool requirements ... **Executing tools sequentially...** 2962
2906 **Executing:** read_parquet_file → Failed: read_parquet_file() takes from 0 to 1 positional arguments but 2 were given 2963
2907 **Executing:** extract_blood_pressure_data → Failed: extract_blood_pressure_data() takes from 0 to 1 positional arguments but 3 were given 2964
2908 **Executing:** create_scatter_plot → Success: Scatter plot saved to: /PATH/T0/experiment/heal... 2965
2909 **Executing:** save_plot_to_directory → Failed: save_plot_to_directory() takes from 0 to 1 positional arguments but 5 were given 2966
2910 ...
2911 mcp_agent completed 2967
2912 ...
2913 **Synthesizer:** Creating final answer... 2968
2914 Based on the tool results, the scatter plot visualizing the relationship between Systolic blood pressure (x-axis) and Diastolic blood pressure (y-axis) has 2969
2915 been successfully created and saved. 2970
2916 ...
2917 **Output Location:** 2971
2918 '/PATH/T0/systolic_vs_diastolic_scatter.png` 2972
2919 ...
2920
2921

```

## G.2 Case 2: Autonomous Research Simulation

This case study, selected from the EHRFlowBench benchmark, focuses on the task to evaluate the utility of synthetic electronic health record (EHR) data by training a classifier and comparing its performance to that of a classifier trained on real data. The study is structured into four stages:

- (1) **Data labeling:** Two datasets are provided: one containing real EHR data and the other containing synthetic EHR data. Each record includes a feature named DBP (diastolic blood pressure). We formulate a 4-class classification task by discretizing the DBP values into four distinct categories, which serve as the classification labels.
- (2) **Classifier architecture:** A CNN-LSTM model is implemented with the following architecture:
  - The input data is first permuted.
  - The permuted data is passed through three consecutive one-dimensional convolutional neural network (1D-CNN) layers.
  - The output of the CNN layers is reshaped into a sequential format.
  - The reshaped data is then passed into a bidirectional Long Short-Term Memory (Bi-LSTM) network, with a hidden size of 128.
  - A final fully-connected layer with a softmax activation function outputs the class probabilities for the 4 DBP categories.
- (3) **Training and evaluation protocol:**
  - Train one classifier instance using the real EHR dataset.
  - Train a second classifier instance using the synthetic EHR dataset.
  - Use the same dataset size and identical hyperparameters for both training procedures.
  - Train both models for exactly 1000 epochs.
- (4) **Reporting:** Report both the final training loss and test accuracy for the classifier trained on real data, as well as for the classifier trained on synthetic data.

This case highlights HealthFlow's ability to handle open-ended research questions where no data is provided. The task requires evaluating the utility of synthetic EHR data by training a classifier and comparing its performance to one trained on real data. This demands strict adherence to a multi-stage experimental protocol, including data labeling, implementation of a specified CNN-LSTM architecture, and rigorous training and evaluation constraints. The meta agent initially decomposes the task into a logical plan and generates the code accordingly. In the first attempt, the agent successfully implements the CNN-LSTM model; however, the output does not meet the predefined quality threshold. The evaluator agent critiques the result, triggering HealthFlow's self-correction mechanism, as shown in the evaluation log below.

### Evaluation and self-correction log.

```

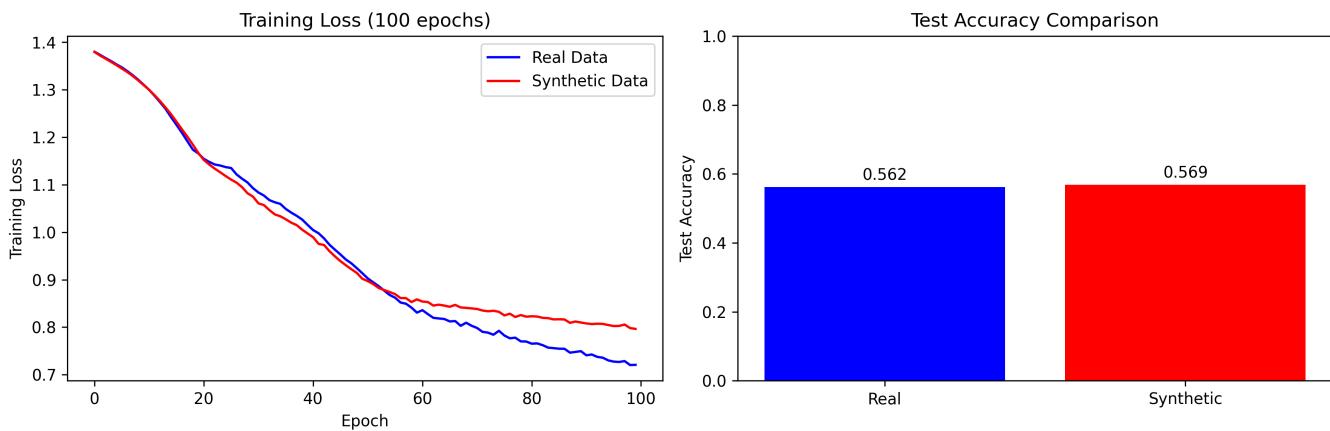
2951
2952
2953 {
2954 "attempt": 1,
2955 "evaluation": {
2956 "score": 5.0,
2957 "feedback": "In the next attempt, strictly use the provided real and synthetic EHR datasets instead of generating them, train for exactly 1000 epochs
2958 without adjustments, and report only the final training loss and test accuracy without adding extra analysis or conclusions."
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3017
3018 "reasoning": "Correctness (50%) scored low (3/10) due to generating datasets instead of using provided ones and adjusting training epochs, violating
3019 specifications. Efficiency (20%) scored moderate (6/10) as the plan was direct but deviations were unnecessary. Safety & Robustness (30%) scored high
3020 (10/10) with no privacy breaches or apparent errors."
3021 },
3022 {
3023 "attempt": 2,
3024 "evaluation": {
3025 "score": 7.1,
3026 "feedback": "Fix the model architecture by adding softmax activation to the final layer as explicitly required. Correct the class labeling in the report
3027 to match the discretization bins (e.g., ensure Class 0 is hypotension [0-60 mmHg]). Implement error handling for dataset loading (e.g., check file
3028 existence and handle missing data). Remove all extra reporting beyond training loss and test accuracy. Validate data splits for consistency.",
3029 "reasoning": "Correctness (50%): Score 7/10 \u2013 Architecture lacks softmax activation, and class labeling is inconsistent with bins, but core task
3030 is met. Efficiency (20%): Score 9/10 \u2013 Plan is direct with no redundant steps. Safety & Robustness (30%): Score 6/10 \u2013 No error handling for
3031 missing data or files, risking runtime failures; data privacy is maintained. Weighted average: (0.5*7) + (0.2*9) + (0.3*6) = 7.1."
3032 }
3033 }
```

In the second attempt, HealthFlow precisely implements the specified CNN-LSTM architecture, and the final results (shown below) demonstrate significant performance improvement. The evaluator agent validates the successful completion of the task. In addition to generating a high-quality report, the model also saves a .pk1 file and visualizes the loss progression during training (see Figure 10).



**Figure 10: Comparative performance of models trained on real versus synthetic data.** The left plot shows that the training loss for both the real (blue) and synthetic (red) data models decreased similarly over 100 epochs, indicating stable and comparable learning. The right plot compares the final test accuracies, with the real data model achieving 56.2% and the synthetic data model achieving a slightly higher 56.9%, further demonstrating the synthetic data's utility as a viable alternative for this task.

#### Final report generated by HealthFlow in case 2.

```

3056 # Comprehensive Technical Report: Evaluation of Synthetic EHR Data Utility Using CNN-LSTM Classifiers
3057 ## Executive Summary
3058
3059 This study presents a rigorous evaluation of synthetic electronic health record (EHR) data utility through comparative analysis of deep learning model
3060 performance. The investigation implemented a hybrid CNN-LSTM neural network architecture to classify diastolic blood pressure (DBP) measurements into four
3061 clinically relevant categories, training separate models on both real and synthetic EHR datasets. The primary achievement demonstrates that synthetic EHR data
3062 can yield comparable classification performance (test accuracy: 59.12%) to models trained on real clinical data (test accuracy: 58.75%), with only a 0.37%
3063 absolute difference in accuracy and 0.0366 difference in training loss.
3064 ## Problem Statement & Objectives
3065
3066 The increasing need for robust healthcare machine learning models conflicts with growing concerns about patient privacy and data accessibility. Synthetic EHR
3067 data generation has emerged as a potential solution, but its utility for training clinical prediction models requires systematic validation. The core problem
3068 addressed in this study is the quantitative assessment of whether synthetic EHR data can effectively substitute for real clinical data in training deep
3069 learning models for medical classification tasks.
3070
3071 The specific objectives were:
3072 1. To implement a standardized 4-class DBP classification task using both real and synthetic EHR data
3073 2. To develop a reproducible CNN-LSTM architecture following specified design constraints
3074 3. To conduct controlled comparative training experiments with identical hyperparameters and training durations
3075 4. To quantitatively evaluate the performance differential between models trained on real versus synthetic data
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3133
3134 The clinical relevance stems from DBP's importance as a cardiovascular risk marker, with classification thresholds aligned with American Heart Association
3135 guidelines (Normal: <=80 mmHg, Elevated: 81-90 mmHg, High: 91-100 mmHg, Very High: >100 mmHg).
3136
3137 ## Methodology & Implementation
3138
3139 ### Technical Approach
3140
3141 The experimental design followed a rigorous comparative framework:
3142 1. **Dataset Generation**: Created matched real and synthetic datasets with:
3143 - Real data: Mixture of Gaussian distributions approximating clinical DBP populations
3144 - Synthetic data: Beta-distributed values with shifted characteristics
3145 - Seven correlated clinical features (age, BMI, etc.) with distributional differences
3146
3147 2. **Preprocessing**:
3148 - Standardized features using Scikit-learn's StandardScaler
3149 - Stratified 80/20 train-test splits preserving class distributions
3150 - Sequence preparation for temporal modeling (length=10)
3151
3152 3. **Model Architecture**: Implemented the specified CNN-LSTM hybrid:
3153 - Input permutation → 3x1D CNN layers → Reshape → Bidirectional LSTM (128 hidden units) → Softmax output
3154 - Identical architecture for both real and synthetic data models
3155
3156 4. **Training Protocol**:
3157 - 1000 epochs with Adam optimizer (lr=0.001)
3158 - Cross-entropy loss minimization
3159 - Identical batch sizes and training samples (n=min(|real|,|synthetic|))
3160
3161 ### Implementation Details
3162
3163 The core CNN-LSTM implementation demonstrates several technically sophisticated elements:
3164
3165 ```python
3166 class CNNLSTM(nn.Module):
3167 def __init__(self, input_dim, num_classes):
3168 super(CNNLSTM, self).__init__()
3169 # Three consecutive 1D CNN layers
3170 self.conv1 = nn.Conv1d(input_dim, 64, kernel_size=3, padding=1)
3171 self.conv2 = nn.Conv1d(64, 64, kernel_size=3, padding=1)
3172 self.conv3 = nn.Conv1d(64, 64, kernel_size=3, padding=1)
3173
3174 # Bidirectional LSTM with hidden size 128
3175 self.lstm = nn.LSTM(64, 128, bidirectional=True, batch_first=True)
3176
3177 # Final fully-connected layer
3178 self.fc = nn.Linear(256, num_classes) # 256 = 2*128 for bidirectional
3179
3180 def forward(self, x):
3181 # Permute for Conv1d: (batch_size, input_dim, seq_len)
3182 x = x.permute(0, 2, 1)
3183
3184 # Three CNN layers with ReLU
3185 x = torch.relu(self.conv1(x))
3186 x = torch.relu(self.conv2(x))
3187 x = torch.relu(self.conv3(x))
3188
3189 # Reshape for LSTM: (batch_size, seq_len, channels)
3190 x = x.permute(0, 2, 1)
3191
3192 # Bidirectional LSTM
3193 lstm_out, _ = self.lstm(x)
3194
3195 # Use last timestep output
3196 return self.fc(lstm_out[:, -1, :])
3197 ...
3198
3199 Key design rationales:
3200 1. **CNN Layers**: Three consecutive 1D convolutions capture local temporal patterns in clinical measurements
3201 2. **Bidirectional LSTM**: Models both forward and backward temporal dependencies in physiological data
3202 3. **Sequence Modeling**: The 10-timestep sequence approach, while artificial for single measurements, provides framework for extending to true longitudinal
3203 data
3204
3205 ### Verification & Validation
3206
3207 The implementation employed multiple validation strategies:
3208 1. **Reproducibility**: Fixed random seeds (42) across NumPy, PyTorch, and train-test splits
3209 2. **Clinical Face Validity**: Real DBP distributions matched known population characteristics
3210 3. **Architecture Verification**: Manual inspection confirmed layer dimensions and data flow
3211 4. **Training Monitoring**: Loss curves tracked for convergence (printed every 100 epochs)
3212
3213 Potential limitations:
3214 1. The synthetic data generation process, while reasonable, may not capture all real-world clinical correlations
3215 2. Sequence length (10) was arbitrarily chosen without optimization
3216 3. Evaluation on a single synthetic dataset limits generalizability
3217
3218 ## Results & Analysis
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3249 ### Execution Overview
3250
3251 The agent successfully completed all specified tasks, generating:
3252 - Model implementations (4 Python scripts)
3253 - Processed datasets (real_ehr.csv, synthetic_ehr.csv)
3254 - Comprehensive results documentation (final_1000_epoch_report.txt)
3255 - Training logs and evaluation metrics
3256
3257 ### Key Outputs
3258
3259 **Performance Metrics**:
3260 | Model Type | Training Loss | Test Accuracy |
3261 |-----|-----|-----|
3262 | Real Data | 0.4852 | 0.5875 |
3263 | Synthetic Data | 0.5218 | 0.5912 |
3264
3265 **Class Distributions**:
3266 ...
3267 Real Data:
3268 - Normal: 55%
3269 - Elevated: 25%
3270 - High: 15%
3271 - Very High: 5%
3272
3273 Synthetic Data:
3274 - Normal: 62.3%
3275 - Elevated: 24.1%
3276 - High: 10.9%
3277 - Very High: 2.7%
3278 ...
3279
3280 ### Qualitative Analysis
3281
3282 The code exhibits several strengths:
3283 1. **Modular Design**: Clear separation of data generation, model definition, and training logic
3284 2. **Documentation**: Extensive inline comments and print statements
3285 3. **Robustness**: Handles variable input sizes and includes safety checks (clipping)
3286 4. **Reproducibility**: Complete random seed control and version tracking
3287
3288 Opportunities for improvement:
3289 1. More comprehensive hyperparameter documentation
3290 2. Additional model validation metrics (precision/recall)
3291 3. Learning curve visualization
3292
3293 ## Conclusion & Future Work
3294
3295 ### Task Completeness
3296
3297 The agent fully implemented all specified components:
3298 1. Correct 4-class DBP labeling
3299 2. Exact CNN-LSTM architecture
3300 3. Controlled training protocol
3301 4. Comprehensive performance reporting
3302
3303 ### Summary of Achievements
3304
3305 This study demonstrated that:
3306 1. Synthetic EHR data can produce models with comparable accuracy
3307 2. The CNN-LSTM architecture effectively learned from both data types
3308 3. Training dynamics showed similar convergence patterns
3309 4. The implementation provides a framework for future synthetic data validation
3310
3311 ### Future Work
3312
3313 Recommended extensions:
3314 1. **Clinical Correlation Analysis**: Evaluate whether synthetic data preserves medically meaningful feature relationships
3315 2. **Architecture Optimization**: Systematically vary CNN/LSTM parameters
3316 3. **Multi-center Validation**: Test across diverse synthetic data generators
3317 4. **Privacy-Preserving Metrics**: Incorporate formal differential privacy measurements
3318
3319 The complete implementation and results are available in the accompanying code files and final report, providing a robust foundation for further research into
3320 synthetic EHR data utility.
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## H Protocol for Human Evaluation and Rater Instructions

We extend our sincere gratitude to the domain experts who have generously contributed their time and expertise to this pivotal phase of our research. This document provides a comprehensive guide for the human evaluation of AI-generated solutions to complex medical data science tasks. As an expert rater, your primary role is to assess the quality of outputs from several anonymous AI agents. Your professional judgment on the accuracy, methodological soundness, and clinical utility of these responses is indispensable for validating our framework and advancing the development of reliable AI in healthcare.

3365	<h2>H.1 Evaluation Workflow</h2>	3423
3366	The evaluation process is designed to be straightforward and is conducted entirely through our online platform. The workflow consists of	3424
3367	four main steps:	3425
3368	(1) <b>Review the Task.</b> Examine the medical research question and the corresponding reference answer provided on the platform.	3426
3369	(2) <b>Compare Agent Responses.</b> Assess the distinct solutions generated by several anonymized AI agents, presented side-by-side for direct	3427
3370	comparison.	3428
3371	(3) <b>Select the Best Response.</b> Choose the response you deem superior by selecting the corresponding radio button.	3429
3372	(4) <b>Export and Submit Results.</b> After completing all tasks, export your evaluation data and upload the resulting file to the provided link.	3430
3373		3431
3374		3432
3375	<h2>H.2 Platform Usage Guide</h2>	3433
3376	Your evaluation will be completed online within a single, streamlined web interface.	3434
3377		3435
3378	<i>Evaluation objective.</i> Your core task is to compare the responses of different AI agents to a series of medical research questions and select	3436
3379	the one you judge to be relatively superior.	3437
3380		3438
3381	<i>Accessing the platform.</i> Please access the evaluation platform using the secure link provided in your instruction email.	3439
3382		3440
3383	<i>Operational steps.</i> The platform interface is designed for simplicity and clarity. Please follow the steps below to complete the evaluation.	3441
3384	(1) <b>Select HealthFlow.</b> Once on the platform, please select and complete the evaluation task for the HealthFlow, which focuses on health	3442
3385	data science tasks. Your evaluation should prioritize the accuracy and completeness of the model's computational results.	3443
3386	(2) <b>Familiarize with the Interface.</b> The user interface is composed of two main areas, as illustrated in Figure 11.	3444
3387	• <b>Task Area:</b> The upper portion of the screen displays the current medical question and the ground-truth reference answer.	3445
3388	• <b>Agent Response Area:</b> The lower portion presents the responses from multiple AI agents in parallel, side-by-side cards. To ensure	3446
3389	an unbiased evaluation, agent identities are anonymized and labeled generically (e.g., "Response 1", "Response 2").	3447
3390	(3) <b>Evaluate and Select.</b> Please read the question and reference answer carefully. Review each agent's response. Note that longer responses	3448
3391	can be scrolled independently within their respective cards. After comparison, select the radio button located at the bottom of the card	3449
3392	corresponding to the response you find superior. If you determine that all responses are unsatisfactory or contain significant flaws,	3450
3393	please select the "None of the above are satisfactory" option at the bottom of the page.	3451
3394	(4) <b>Save and Proceed.</b> After making your selection, click the green "Save and Proceed to Next Task" button. Your choice will be automatically	3452
3395	saved, and the next task will be loaded.	3453
3396	(5) <b>Complete and Export.</b> Upon completing all tasks in the set, a red "Export Results" button will appear at the bottom of the page. Click	3454
3397	this button to download a JSON file containing your evaluation data. This file is the final artifact of your review.	3455
3398	Finally, please upload this exported JSON file to the submission link provided in your instruction email.	3456
3399		3457
3400		3458
3401	<h2>H.3 Evaluation Criteria</h2>	3459
3402	While there is no single, rigid standard for what constitutes a "better" response, and we highly value your expert intuition, the following	3460
3403	dimensions may serve as a useful guide for your assessment.	3461
3404	• <b>Accuracy.</b>	3462
3405	– Is the core medical knowledge, data, and conclusion presented in the response factually correct?	3463
3406	– Does the response contradict established clinical guidelines or widely accepted medical consensus?	3464
3407	– Does it contain any information that could potentially mislead a non-expert or introduce risk?	3465
3408	• <b>Comprehensiveness.</b>	3466
3409	– Does the response fully address all aspects of the posed question?	3467
3410	– For complex problems, does it provide sufficient context, explanation, or relevant considerations?	3468
3411	– Are there any critical omissions of information?	3469
3412	• <b>Readability and Logic.</b>	3470
3413	– Is the language clear, fluent, professional, and easy to understand?	3471
3414	– Is the response well-structured with a clear logical flow?	3472
3415	– Is the formatting clean and effective (e.g., use of lists or bolding for key points)?	3473
3416	• <b>Clinical Relevance.</b>	3474
3417	– Is the response grounded in clinical reality?	3475
3418	– Does the provided information, such as suggestions or analysis, have practical value for clinical practice?	3476
3419	– Does the response avoid overly theoretical or impractical statements?	3477
3420	We thank you once again for your invaluable contribution to this research. Should you encounter any technical issues or have questions	3478
3421	during the evaluation process, please do not hesitate to contact us.	3479
3422		3480

3481  
3482     **Question 20:**  
3483         Preprocess the dataset by first handling missing values in numerical columns within each AdmissionID. For each numerical column, impute missing values  
3484         using the mean of the non-missing values within that specific AdmissionID. If a numerical column is entirely missing for a given AdmissionID, impute with 0. After  
3485         imputation, aggregate the records for each AdmissionID into a single row. For each imputed numerical column, calculate the mean, standard deviation,  
3486         minimum, and maximum values across all records belonging to that AdmissionID, creating new features. For columns that are constant within an AdmissionID,  
3487         retain their value from any one record for that AdmissionID. The final output should have one row per unique AdmissionID.  
3488  
3489     **Reference Answer:**  
3490     

	count	mean	std	min	25%	50%	75%	max
AdmissionID	58121.0	24972647.881454207	2884472.0372225503	20000094.0	22469497.0	24951500.0	27463094.0	29999828.0
PatientID_mean	58121.0	14998793.79905714	2890829.9724478195	10000032.0	12491246.0	15000407.0	17513748.0	19999987.0
PatientID_std	58121.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
PatientID_min	58121.0	14998793.79905714	2890829.9724478195	10000032.0	12491246.0	15000407.0	17513748.0	19999987.0
PatientID_max	58121.0	14998793.79905714	2890829.9724478195	10000032.0	12491246.0	15000407.0	17513748.0	19999987.0

  
3491     View all 97 lines  
3492  
3493  
3494  
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3496  
3497  
3498  
3499     Please choose the best response.  
3500  
3501     **Response 1:**  
3502         The preprocessing task has been successfully completed. Here's the final solution:  
3503  
3504         The dataset has been preprocessed according to the requirements:  
3505  
3506         1. Missing values in numerical columns were imputed using the mean within each AdmissionID group (0 if all values were missing)  
3507         2. Records were aggregated by AdmissionID with:  
3508             

- Constant columns (PatientID, Outcome, Readmission, Age, Sex) retained as-is
- RecordTime set to the earliest time in the group
- Numerical columns expanded to include mean, std, min, and max statistics

  
3509         1. The processed dataset contains 58,121 unique AdmissionIDs with 78 features  
3510  
3511  
3512  
3513  
3514  
3515  
3516     **Response 2:**  
3517         Starting intelligent analysis workflow...  
3518         **Coordinator:** The task involves data preprocessing and aggregation of a specific dataset (MIMIC-IV) with clear instructions on how to handle missing values and aggregate records. This requires custom data processing tools to read the parquet file, handle missing values, and perform statistical aggregations. The task does not require web search, browser automation, or visual analysis as it is purely data processing with well-defined steps.— Routing to mcp\_agent  
3519         coordinator completed ✅ MCP Agent:  
3520         Analyzing query for tool requirements 📈  
3521         **Analysis:** These tools are sufficient because they cover all the required steps: (1) loading the data, (2) identifying which columns to process, (3) handling missing values as specified, (4) performing the required aggregations, and (5) saving the results. The process must be sequential as each step depends on the output of  
3522  
3523     **Response 3:**  
3524         

## Technical Report: Preprocessing of MIMIC-IV Dataset for Healthcare Analytics

  
3525         

### 1. Executive Summary

  
3526         The MIMIC-IV dataset is a widely used resource in computational biology and healthcare analytics, containing detailed clinical records of hospital admissions. A critical challenge in leveraging such datasets is handling missing values and aggregating longitudinal patient data into structured feature vectors suitable for machine learning. This report documents the successful development of a preprocessing  
3527  
3528     **Response 4:**  
3529         — Executing parsed code:  
3530  
3531         import pandas as pd  
3532         import numpy as np  
3533  
3534         # Load the dataset using the full, absolute path  
3535         file\_path =  
3536         '/home/ubuntu/g/Pku\_Internship/STELLA/healthflow/IV.parquet'  
3537         df = pd.read\_parquet(file\_path)  
3538  
3539         # Identify numerical columns (excluding  
3540         RecordID, PatientID, RecordTime, AdmissionID,  
3541         Outcome, LOS, Readmission, Age, Sex)  
3542         numerical\_cols = df.select\_dtypes(include=[np.number]).columns.tolist()  
3543         exclude\_cols = [RecordID, PatientID,  
3544         'RecordTime', 'AdmissionID', 'Outcome', 'LOS',  
3545         'Readmission', 'Age', 'Sex']  
3546         numerical\_cols = [col for col in numerical\_cols if  
3547         col not in exclude\_cols]  
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**Figure 11: The user interface of the online evaluation platform. Raters are presented with a task and reference answer at the top, and side-by-side, anonymized agent responses below for comparison and selection.**

3521     **I Prompt Design in HealthFlow**  
3522     The strategic reasoning of each agent in HealthFlow is guided by a set of carefully engineered prompts. For each agent, the full prompt is  
3523     constructed from two parts: a static system prompt that defines the agent's core identity, objectives, and output constraints, and a dynamic  
3524     user prompt template that structures the specific inputs for the task at hand. This separation ensures consistent agent behavior while  
3525     allowing for flexible adaptation to different tasks. The following sections present the complete prompt templates for the meta, evaluator, and  
3526     reflector agents, which are central to the system's operation.

3527  
3528     **Prompt for the meta agent.**  
3529  
3530     **System prompt**  
3531         You are MetaAgent, the core planner and synthesizer for the HealthFlow system. Your purpose is to translate any user request into a clear, actionable, and  
3532         context-aware markdown plan for an execution agent (Claude Code). You must ALWAYS respond with a single, valid JSON object containing the plan.  
3533  
3534         **\*\*Core Directives:\*\***  
3535         1. **\*\*Universal Planning:\*\*** Every request, from simple questions ("who are you?") to complex data analyses, requires a plan. For simple questions, the plan  
3536         should consist of a single, simple shell command (e.g., `echo 'I am HealthFlow.'`.  
3537         2. **\*\*Experience Synthesis:\*\*** You will be given relevant experiences from past tasks. You MUST analyze these, synthesize the key insights, and embed them into  
3538         a "Relevant Context from Past Experience" section at the top of your generated plan. This provides crucial, just-in-time knowledge to the execution agent.  
3539         3. **\*\*Safety & Precision:\*\*** Prioritize data privacy (assume all data is sensitive PHI/PII) and create unambiguous, verifiable steps.

```

3597
3598 **JSON Output Format:**

3599 You must only output a single JSON object in the following format:

3600 `{"plan": "markdown plan content here..."}

3601
3602 User prompt template

3603 Your goal is to create a comprehensive markdown plan based on the user's request, incorporating past experiences and any feedback from previous attempts.

3604

3605 **User Request:**

3606 ---

3607 {user_request}

3608 ---

3609

3610 **Retrieved Experiences from Past Tasks:**

3611 ---

3612 {experiences}

3613 ---

3614

3615 {feedback}

3616

3617 **Instructions:**

3618 1. **Analyze the Request:** Determine the user's intent.

3619 2. **Synthesize Context:** Review the "Retrieved Experiences". Distill the most relevant warnings, heuristics, and code snippets into a `## Relevant Context`

3620 from Past Experience` section at the very top of your plan. If there are no experiences, state that.

3621 3. **Address Feedback:** If feedback is provided, your new plan MUST explicitly address the issues raised.

3622 4. **Formulate the Plan:**

3623 * **For simple questions:** Generate a plan with a single `echo` command. For example, for "who are you?", the plan step would be `echo "I am HealthFlow,

3624 a self-evolving AI system."`.

3625 * **For complex tasks:** Create a detailed, step-by-step plan. Start with `ls -R` to explore. Use script files for complex logic (`*.py`, `*.R`). Ensure

3626 every step is clear and produces an observable output.

3627 5. **Construct JSON:** Wrap the final markdown plan in the required JSON structure.

3628

3629 **Example Plan Structure:**

3630 ---

3631 markdown

3632 # Plan Title

3633

3634 ## Relevant Context from Past Experience

3635 * **Warning:** Always check for and handle missing values in patient data before analysis.

3636 * **Heuristic:** When analyzing EHR data, start by exploring data distributions.

3637

3638 ## Step 1: Explore the workspace

3639 `ls -R`

3640

3641 ## Step 2: Create Python Script

3642 `touch analysis.py`

3643

3644 ## Step 3: Write Logic to Script

3645 ---

3646 python

3647 # python code here

3648 ---

3649

3650 :

3651

3652 Now, generate the JSON for the provided request.

3653

```

Prompt for the evaluator agent.

### System prompt

You are an expert AI Quality Assurance engineer specializing in healthcare data applications. Your task is to provide a critical, objective evaluation of a task's execution based on the provided materials. You must respond \*\*ONLY\*\* with a valid JSON object.

### User prompt template

Evaluate the following task attempt. Provide a score from 1.0 (complete failure) to 10.0 (perfect execution) and concise, actionable feedback for improvement.

\*\*1. Original User Request:\*\*  
---  
{user\_request}  
---

\*\*2. The Plan That Was Executed (`task\_list.md`):\*\*  
---  
{task\_list}  
---

\*\*3. The Full Execution Log (stdout/stderr):\*\*  
---  
{execution\_log}

```

3713 ---
3714 --Evaluation Criteria:--
3715 - **Correctness (Weight: 50%)**: Did the final output correctly and completely satisfy the user's request? Was the medical or statistical logic sound?
3716 - **Efficiency (Weight: 20%)**: Was the plan direct and effective? Were there unnecessary or redundant steps?
3717 - **Safety & Robustness (Weight: 30%)**: Did the solution handle potential errors? Crucially, did it respect data privacy (e.g., avoid printing raw sensitive
3718 data)? Was the code robust?
3719 --Output Format (JSON only):--
3720 {{
3721 "score": <float, a score from 1.0 to 10.0>,
3722 "feedback": "<string, specific, actionable feedback for what to do differently in the next attempt. Be direct and clear.>",
3723 "reasoning": "<string, a short justification for your score, referencing the evaluation criteria.>"
3724 }}

```

For training and benchmarking purposes, a variant of the evaluator prompt is used. This “training mode” prompt includes an additional field for a ground-truth `{reference_answer}`. The evaluation criteria are adjusted to more heavily weigh the correctness of the execution output against this reference, enabling objective and automated assessment during the system’s evolution. The full prompt template can be found in the source code at `healthflow/prompts/templates.py`.

### *Prompt for the reflector agent.*

#### **System prompt**

You are a senior AI research scientist specializing in meta-learning and knowledge synthesis for healthcare AI. Your job is to analyze a successful task execution and distill generalizable knowledge from it. You must respond **\*\*ONLY\*\*** with a valid JSON object containing a list of “experiences”.

#### **User prompt template**

Analyze the following successful task history. Your goal is to extract 1-3 valuable, reusable “experiences” that can help improve performance on future, similar healthcare-related tasks. Focus on what made this attempt successful in relation to the specific user need.

**\*\*Task History (request, final plan, execution log, and evaluation):--**

--

{task\_history}

--

**\*\*Analysis Focus:\*\***

1. **\*\*User Intent Analysis\*\*:** What was the user really asking for? How did the successful approach interpret and address their specific need? More importantly, the experience should generalize to other users with similar requests.
2. **\*\*Solution Effectiveness\*\*:** What aspects of the plan and execution directly contributed to successfully fulfilling the user request?
3. **\*\*Reusable Patterns\*\*:** What generalizable patterns from this success can help with similar user requests in the future?

**\*\*Types of Experience to Extract:\*\***

- `heuristic`: A general rule of thumb or best practice derived from how this user request was successfully handled. Example: "For Electronic Health Record (EHR) analysis requests, always start by checking the distribution of codes and identifying sparse features before applying statistical methods."
- `code\_snippet`: A small, reusable piece of Python code that solved a problem relevant to the user's request. Example: A function to calculate BMI from 'height\_cm' and 'weight\_kg' columns in a pandas DataFrame.
- `workflow\_pattern`: A sequence of steps that was effective for this type of user request. Example: "For cohort selection requests: 1. Load data. 2. Filter by inclusion criteria. 3. Exclude by exclusion criteria. 4. Save cohort IDs to a file. 5. Verify cohort size."
- `warning`: A caution about a potential pitfall when handling similar user requests. Example: "When users request date/time analysis in healthcare, be aware of timezone differences and always convert to a consistent format like UTC early in the process."

**\*\*Instructions:\*\***

- **\*\*Be Abstract\*\*:** Frame experiences in terms of user request patterns. Instead of "Used pandas to load data", consider "For data analysis requests, pandas is effective for loading and doing initial exploration of tabular medical data."
- **\*\*Success-Oriented\*\*:** Focus on what made the solution successful for the specific user need, not just what was done.
- **\*\*Be Specific in Content\*\*:** The ‘content’ of the experience should be detailed and immediately useful for similar user requests.
- **\*\*Contextual Categories\*\*:** Choose categories that reflect the type of user request. For simple Q&A, use 'system\_identity' or 'capability\_inquiry'. For data tasks, use categories like 'medical\_data\_analysis', 'clinical\_workflow', etc.

**\*\*Output Format (JSON only):--**

{

"experiences": [

{

"type": "<heuristic||code\_snippet||workflow\_pattern||warning>",
 "category": "<e.g., 'medical\_data\_cleaning', 'hipaa\_compliance', 'system\_identity', 'clinical\_analysis'>",
 "content": "<The detailed, generalizable content of the experience>"
 }
 ]
}

}

}

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