

## APEX–Agents

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### Abstract

We introduce the AI Productivity Index for Agents (**APEX–Agents**), a benchmark for assessing whether AI agents can execute long-horizon, cross-application tasks created by investment banking analysts, management consultants, and corporate lawyers. APEX–Agents requires agents to navigate realistic work environments with files and tools. We test eight agents for the leaderboard using Pass@1. Gemini 3 Flash (Thinking=High) achieves the highest score of 24.0%, followed by GPT-5.2 (Thinking=High), Claude Opus 4.5 (Thinking=High), and Gemini 3 Pro (Thinking=High). We open source the APEX–Agents benchmark ( $n = 480$ ) with all prompts, rubrics, gold outputs, files, and metadata. We also open-source **Archipelago**, our infrastructure for agent execution and evaluation.

### 1 Introduction

If AI agents can reliably execute professional services work, the economic and social consequences will be profound. A large team of skilled, diligent experts will be available on-demand to anyone, fundamentally reshaping knowledge work and dramatically increasing productivity. Enterprises such as Box, Salesforce, and Databricks are beginning to deploy agentic systems at scale, and AI labs are investing substantial resources in expanding agentic capabilities.

Agents present a new frontier for AI – yet existing agentic evals have a large sim-to-real gap and do not capture how professionals work day-to-day (Kapoor et al., 2024; Chezelles et al., 2025; Froger et al., 2025; Meimandi et al., 2025; Vidgen et al., 2025). They are often narrow and simplistic, providing limited signal into agents’ actual performance.

To assess whether AI agents can execute highly complex professional services work, we present

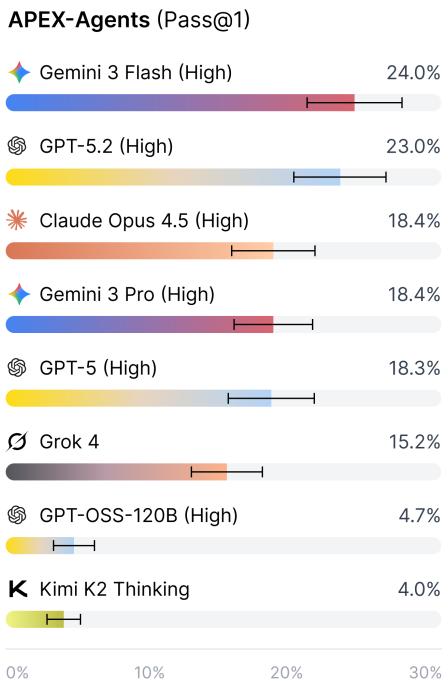


Figure 1: Performance of agents on the APEX–Agents benchmark using Pass@1. Thinking settings are in parentheses.

**APEX–Agents**, a new benchmark for frontier AI evaluation. The tasks were created by investment banking analysts, management consultants, and corporate lawyers, and require agents to reason, demonstrate advanced knowledge, use multiple applications, and plan over long horizons.

**APEX–Agents** was built in three steps. First, we created data-rich worlds, each based on a unique project scenario. Industry professionals were assigned to teams, given roles (e.g., partner, associate), and tasked with delivering the project over 5–10 days. They planned work, conducted research, and produced high-quality customer-ready deliver-

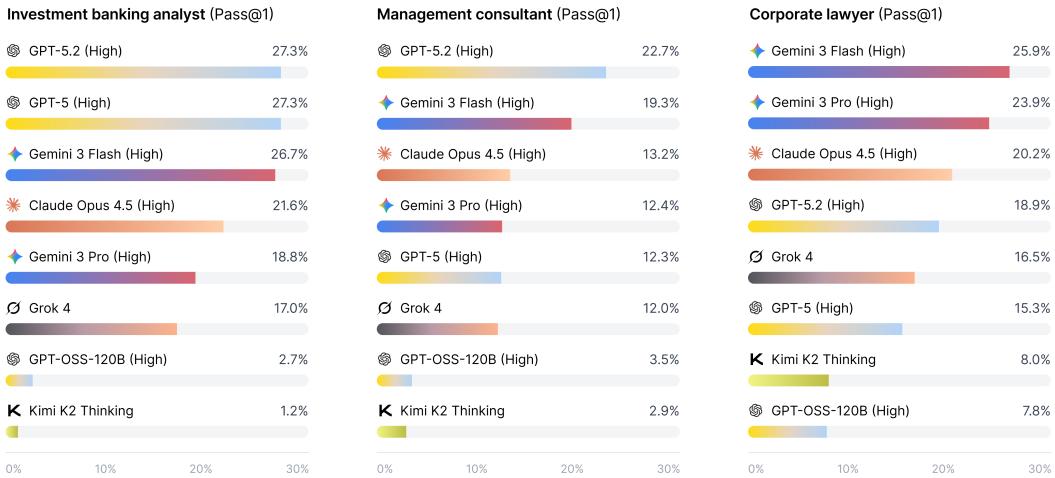


Figure 2: Performance of agents on the APEX–Agents benchmark using Pass@1, segmented by job. Thinking settings are in parentheses.

ables from scratch. Second, professionals created realistic and challenging tasks using the files from within each world. Third, we gave agents access to each world so they could execute the tasks (with all of the data and software that a human would use). This approach is inspired by findings from the APEX Survey (Section 2) and feedback from industry experts and our partners. Tasks are complex and, on average, experienced professionals estimated they take 1–2 hours to complete.

APEX–Agents contains 480 tasks, split across 33 worlds. We tested eight models (see Figure 1). Gemini 3 Flash performs best, scoring 24.0% on Pass@1, followed by GPT-5.2 at 23.0%. The difference between these models is not statistically significant. Claude Opus 4.5 and Gemini 3 Pro follow at 18.4% and 18.4%, respectively.<sup>1</sup> The two open-source models we tested are much worse than the closed-source models, scoring under 5%. Tasks are split evenly across the three jobs ( $n = 160$  each). They vary in difficulty, with the top-performing model scoring 27.3% for investment banking tasks (GPT-5 and GPT-5.2), 22.7% for management consulting tasks (GPT-5.2) and 25.9% for legal tasks (Gemini 3 Flash). See Figure 2.

The APEX–Agents dataset is on Hugging Face with a CC-BY license.<sup>2</sup> Archipelago, our infras-

tructure for agent execution and evaluation, is also open-source.<sup>3</sup>

## 2 APEX Survey

We surveyed 227 experts from the Mercor platform to understand their day-to-day work, informing the creation of worlds and tasks in APEX–Agents. Participants are a diverse representation of elite professionals, including 58 financial and investment analysts (O\*NET 13-2051), 77 management consultants (O\*NET 13-1111), and 92 lawyers (O\*NET 23-1011). On average, they had 10.8 years of professional experience.

**Work activities** We asked participants what percentage of their time is spent on core activities, learning, admin, communications, meetings, and non-productive time. Results for each job are shown in Table 7 in the Appendix, with core activities comprising 47% of the total. We asked participants to segment how they spend their time on core activities, providing a free text description of each activity and a percentage time allocation. We manually reviewed these descriptions and grouped them into one of 18 inductively-identified categories. This analysis was shared with contributors, and informed task creation for the APEX–Agents benchmark. The five most frequent categories for each job are shown in Table 8 in the Appendix.

<sup>1</sup>Where available, we implement models with thinking / reasoning effort set to high. In the remainder of the paper we refer to models by their names alone.

<sup>2</sup>[huggingface.co/datasets/mercorm/apex-agents](https://huggingface.co/datasets/mercorm/apex-agents)

<sup>3</sup>[github.com/Mercor-Intelligence/archipelago](https://github.com/Mercor-Intelligence/archipelago)

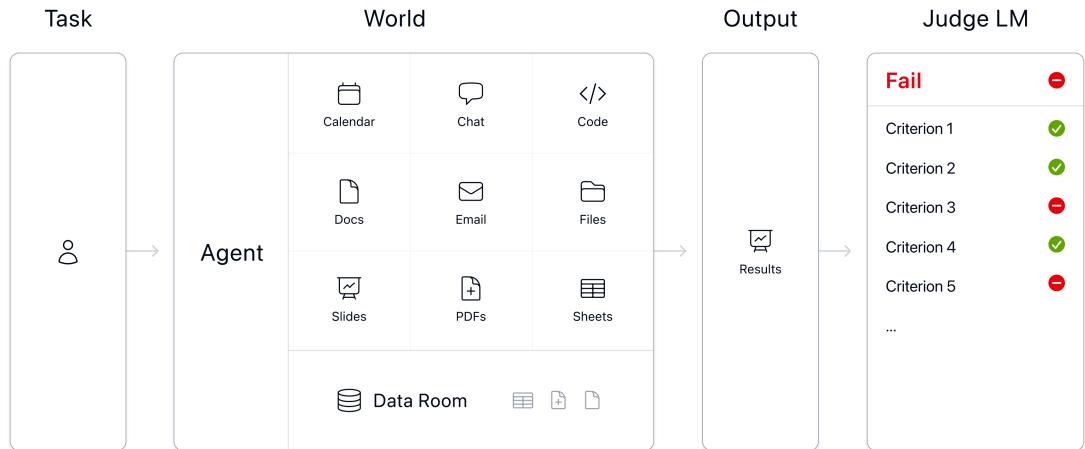


Figure 3: Overview of the approach in APEX–Agents to agentic AI evaluation.

### 3 Benchmark design and dataset

The composition of the APEX–Agents benchmark is described in Table 1 and an overview of our approach is shown in Figure 3.

#### 3.1 World creation

Each world starts from a project scenario created by the experts, and inspired by projects from their professional work. The scenario provides context about the delivery company, the customer, the project background and goals, and relevant constraints, such as:

A team of consultants from NorthPoint Strategy Partners are working on behalf of PureLife Wellness to develop a five-year market expansion and growth strategy by mapping global demand, assessing consumer trends, evaluating market entry options, and prioritizing high-potential international markets and product opportunities.

After each scenario was finalized, experts were assigned in-world roles (e.g., partner, analyst, associate). They assumed role-appropriate responsibilities, working toward the project objectives under similar information, challenges, and trade-offs as an actual customer engagement. They sent emails and messages, conducted research, planned, and iterated on deliverables such as spreadsheets, in-

sight reports, and slide decks. For each project, one expert role-played the customer.

The benchmark comprises 33 worlds: 10 in investment banking, 11 in management consulting, and 12 in law. On average, each world contains 166 files. Of the 33 worlds, 22 involve entirely fictional entities, 9 involve real companies placed in fictional scenarios, and 2 combine both. Each world has nine applications, comprising 63 tools: Calendar, Chat, Code Execution, Documents, File system, Mail, PDFs, Spreadsheets, and Presentations. Two investment banking worlds also have Edgar SEC, an application for data on Equities and Financial Markets, and an application for data on Fixed Income Markets, adding 187 tools. Web search is turned off for the benchmark to keep evaluations reproducible. To maintain validity, worlds contain all files required to execute tasks.

#### 3.2 Tasks

Once each world was completed, experts created long-horizon tasks that are realistic, challenging, and diverse. Worlds have between 8 and 20 tasks, with 14.5 on average. Each task is provided as a single-turn prompt and can only be executed by using the in-world files and applications. Tasks were informed by the APEX Survey (Section 2), based on the contributors’ real-world work. When creating tasks, contributors selected from a pool of frontier agents (GPT-5, Claude Opus 4.5, Gemini 3 Pro) to collect outputs, allowing them to adver-

Table 1: Overview of the APEX–Agents benchmark dataset. The average estimated hours to complete tasks are provided by the experts. See Section 3.5 for the results of the Baseling study.

Split	Number of worlds	Avg files per world	Number of tasks	Avg criteria per task	Avg estimated hours to complete	Tasks with file outputs
Investment banking	10	172	160	2.93	1.36	27 (16.9%)
Law	12	161	160	4.57	2.40	20 (12.5%)
Management consulting	11	165	160	4.68	1.69	11 (6.9%)
Benchmark	33	166	480	4.06	1.82	58 (12.1%)

sarielly iterate. Tasks underwent multiple rounds of review during production.

The task prompts make explicit what output is required from the agent. 422/480 tasks require a message in the console. For the other 58, the agent has to either create spreadsheets (14), documents (20) or presentations (5), or edit existing spreadsheets (16), documents (2) or presentations (1). An example task, selected for brevity, is given below.

Reply back to me with the P/E ratio for KVUE, rounded to two decimal points. Use the implied share price in the DCF model and diluted EPS from the annual financials dated 12/23/2025.

### 3.3 Rubrics and gold outputs

Experts created rubrics to grade agents’ output. Rubrics contain criteria: self-contained, short descriptive statements, which can be graded as true or false against an agent’s output. Each criterion also has a “grading target”, which specifies the type of output required by the prompt. Criteria only reward critical aspects of the output, i.e., elements that are required for the task to be considered complete.

There are between 1 and 10 criteria per task, with a mean of 4.06. Investment banking has fewer criteria than law and management consulting, on average, because there are more tasks that require just a single value to be returned (e.g., an updated EBITDA). These single value outputs can only be achieved by meeting many new constraints and updating numerous intermediary values.

For each task, experts also created gold outputs. Gold outputs contain the exact information to address the prompt and are in the output type requested (e.g., message, document). Experts manually graded gold outputs against the rubric when

creating them to ensure prompt–rubric alignment. Experts also tagged each prompt and rubric with metadata, including the expected output type, the workflow, and the expected time to complete the task in the real-world. The number of tasks associated with each workflow is in Table 6 in the Appendix.

### 3.4 Contributors to APEX–Agents

256 experts contributed to APEX–Agents, sourced from Mercor’s talent marketplace. Experts’ mean experience is 12.9 years and the median is 11.0 years. Experts include former consultants from BCG and McKinsey, investment bankers from Morgan Stanley and Citigroup, and corporate lawyers at Disney and other Fortune 500 companies. Experts worked as both contributors and reviewers; creating project scenarios, building worlds, creating tasks, auditing quality, and checking gold outputs and rubrics.

### 3.5 Baseling study

For 20% of the tasks ( $n = 96$ ), experts who had not created or reviewed them independently executed them from scratch. This checks (1) whether the tasks can actually be completed, (2) the fairness of the rubric, and (3) the time estimates provided by the experts. In 10% of tasks, we identified a minor problem with the prompt, rubric, or metadata that needed to be fixed. We then cascaded these fixes to the rest of the dataset. For these sample tasks, experts estimated the time to complete the tasks at 1.70 hours (note that the estimate for the whole benchmark is 1.81 hours) whereas the true time was 1.37 hours. This is an over-estimate of 0.33 hours or 24%.

## 4 Evaluation

### 4.1 Collecting agent outputs

Each agent executes each task eight times, yielding a total of 30,720 trajectories (8 agents  $\times$  8 runs  $\times$  480 tasks). Trajectories comprise multiple steps taken by an agent, where each step involves using a tool or reflecting / planning. We apply a maximum of 250 steps per task, marking any trajectories that exceed it as a failure. Inspection of trajectories showed that beyond this, the agent is typically stuck in a loop.

Outputs are collected from closed-source models via their respective APIs. For open-source models, we use Baseten. LiteLLM is used as a wrapper to handle calls uniformly. See Appendix E for information on model configs. We lightly optimized the system prompt used by the agents to help them execute tasks. It is given in Appendix D, along with details on the ReAct toolbelt used by the agents.

### 4.2 Judge model

Agents’ outputs are graded against the task rubric, with each criterion graded independently by a judge model. This results in  $\sim$ 125,000 grades (30,720 trajectories  $\times$  4.06 criteria). Based on several rounds of internal testing, we use Gemini 3 Flash, with thinking set to low, as the judge. The judge takes in the task prompt, the agent output, a log of the changes induced by the agent’s actions, and the criterion – but not the agent trajectory. It returns a binary score per criterion (Met, Not met) and a concise free text explanation. To identify what needs grading, such as a message printed to the console or an edited spreadsheet, we use an auxiliary judge that identifies the right artifact from the “grading target” associated with each criterion. The content of files is extracted using Reducto.<sup>4</sup>

To assess the performance of the judge model, we

<sup>4</sup>[reducto.ai](https://reducto.ai)

Table 2: Confusion matrix for the judge model, evaluated against human-labeled ground truth ( $n = 747$  labels, based on  $n = 249$  criteria).

		Predicted	
Actual	Met	Failed	
Met	208	4	
Failed	7	528	

constructed a ground truth eval set of labels for 60 tasks (20 per job), comprising 249 criteria. For each task, we sampled outputs from three models, equating to 747 criteria (3  $\times$  249). The ground truth labels were created independently, with experts not able to see LM judge grades. On a per-criterion basis, the eval set contains 212 passes (28.4%) and 535 fails (71.6%), similar to the distribution of criterion scores in the benchmark. Judge model grades are shown in Table 2. Accuracy is 98.5%, precision is 96.7%, recall is 98.1%, and Positive-class F1 is 97.4%. This corresponds to a false negative rate of 1.9% and a false positive rate of 1.3%. Differences in benchmark scores that are below 1 percentage point should be interpreted cautiously. After the benchmark was finalized, we ran the judge model over the  $n = 480$  gold outputs and it graded all of the associated criteria correctly.

Gemini 3 Flash serves as the judge model and is also evaluated on the leaderboard, creating a risk of self-preference. This is mitigated by the judge not viewing the trajectories when grading. Self-preference can be lower when grading well-defined criteria in a rubric, rather than abstract concepts like “helpfulness” or “preference”. Out of 84 criteria for Gemini 3 Flash in the ground truth eval set, the judge returned 1 false positive. This equates to a false positive rate of 1.2%. Acknowledging the small sample, this rate is in line with the other agents we tested.

### 4.3 Metrics

The APEX–Agents leaderboard uses Pass@1, the proportion of tasks where the agents’ outputs meet all criteria. We use Pass@1 because the criteria are all must-haves – if any are not met, the task is incomplete. Pass@1 answers a clearly-defined question: if you select a task uniformly from the benchmark data and run an agent once, what is the probability that it passes (i.e., meets all criteria)?

We collect 8 trajectories for each agent–task pair, and score each trajectory as pass or fail. For each agent and task, we compute the pass rate and report Pass@1 as the task-uniform mean of these per-task pass rates across the 480 tasks. We compute 95% confidence intervals using task-level bootstrapping: we resample tasks with replacement ( $n = 480$ ) and recompute the task-uniform mean over 10,000 resamples.

Beyond the leaderboard, we report Pass@8 as an indicative ceiling on current frontier agent capabilities, showing whether the agent passes at least once when given eight attempts. We also report Pass<sup>8</sup>, which assesses consistency by measuring whether the agent produces a correct output on every attempt out of eight. For  $k < 8$ , we estimate Pass<sup>k</sup> per task by sampling without replacement from each agent’s observed runs. Finally, we report the mean percentage of criteria passed per task. For training, this percentage can be more informative than Pass@1 because it provides a dense signal that rewards partial progress.

## 5 Results on APEX–Agents

**Pass@1 (Leaderboard)** Agents’ performance on Pass@1 is shown in Table 3 and Figure 1. Gemini 3 Flash performs best, scoring 24.0%. The next best agents are GPT-5.2, Claude Opus 4.5, and Gemini 3 Pro at 23.0%, 18.4%, and 18.4% respectively. The open-source agents perform substantially worse than the closed-source ones, both scoring under 5%.

We use McNemar’s exact tests to evaluate whether Pass@1 differences between agents are statistically significant. A Benjamini–Hochberg correction controls the false discovery rate at 5%. Under this correction, the difference between the two best-performing agents, Gemini 3 Flash and GPT-5.2, is not significant, but both models are significantly better than all other models. All pairwise differences between the commercial agents and the two open-source agents are significant, and the difference between the two open-source agents is not. See Section F in the Appendix.

**Pass@1 by job** The top-performing agent with Pass@1 for investment banking analyst tasks (GPT-5 and GPT-5.2, tied) scores 27.3%, for management consulting tasks scores 22.7% (GPT-5.2), and for corporate lawyer tasks scores 25.9% (Gemini 3 Flash). For all jobs, the two open-source agents score lowest. They are comparatively stronger in corporate law, scoring 7.8% (GPT-OSS-120B) and 8.0% (Kimi K2 Thinking).

**Pass@8** The top-performing agent with Pass@8 is GPT-5.2 at 40.0%, followed by Gemini 3 Pro at 37.3%, and Gemini 3 Flash at 36.7%. This is approximately 15 percentage points higher than Pass@1, and shows agents have capabilities but are inconsistent. We find limited evidence of saturation at 8 runs, with agents’ scores increasing by no more than 1 percentage point compared to 7. See Figure 4.

**Pass<sup>8</sup>** The top-performing agent with Pass<sup>8</sup> scores 13.4% (Gemini 3 Flash). Across commercial agents, Pass<sup>8</sup> drops by approximately 10–12 percentage points relative to Pass<sup>1</sup>. Agents’ rank ordering remains unchanged as  $k$  increases, suggesting there are limited differences in how consistent agents are.

**Mean score** Gemini 3 Flash has the highest mean score at 39.5%, followed by GPT-5.2 (38.7%) and Claude Opus 4.5 (34.8%). Mean scores are similar to Pass@8 and much higher than Pass@1, showing that even when they fail to completely execute a task, agents can still create partially useful outputs. Across the eight runs from each agent on each task, the mean standard deviation is 0.14, ranging from 0.09 for GPT-OSS-120B to 0.16 for Grok 4.

Table 3: Performance of agents on the APEX–Agents benchmark. Where available, models have thinking / reasoning effort set to high.

Model	Pass@1	Pass@8	Pass <sup>8</sup>	Mean score	IB analyst Pass@1	Consultant Pass@1	Lawyer Pass@1
Claude Opus 4.5	18.4% [15.5–21.3]	34.0% [29.8–38.3]	8.8%	34.8%	21.6%	13.2%	20.2%
Gemini 3 Flash	24.0% [20.7–27.3]	36.7% [32.3–41.0]	13.4%	39.5%	26.7%	19.3%	25.9%
Gemini 3 Pro	18.4% [15.7–21.1]	37.3% [32.9–41.7]	6.5%	34.1%	18.8%	12.4%	23.9%
GPT-5	18.3% [15.4–21.3]	31.0% [26.9–35.4]	7.7%	32.9%	27.3%	12.3%	15.3%
GPT-5.2	23.0% [19.8–26.2]	40.0% [35.6–44.4]	11.0%	38.7%	27.3%	22.7%	18.9%
GPT-OSS-120B	4.7% [3.3–6.1]	11.5% [8.8–14.4]	1.2%	14.5%	2.7%	3.5%	7.8%
Grok 4	15.2% [12.8–17.7]	32.9% [28.7–37.3]	4.7%	30.3%	17.0%	12.0%	16.5%
Kimi K2 Thinking	4.0% [2.9–5.2]	14.4% [11.5–17.5]	0.3%	11.5%	1.2%	2.9%	8.0%

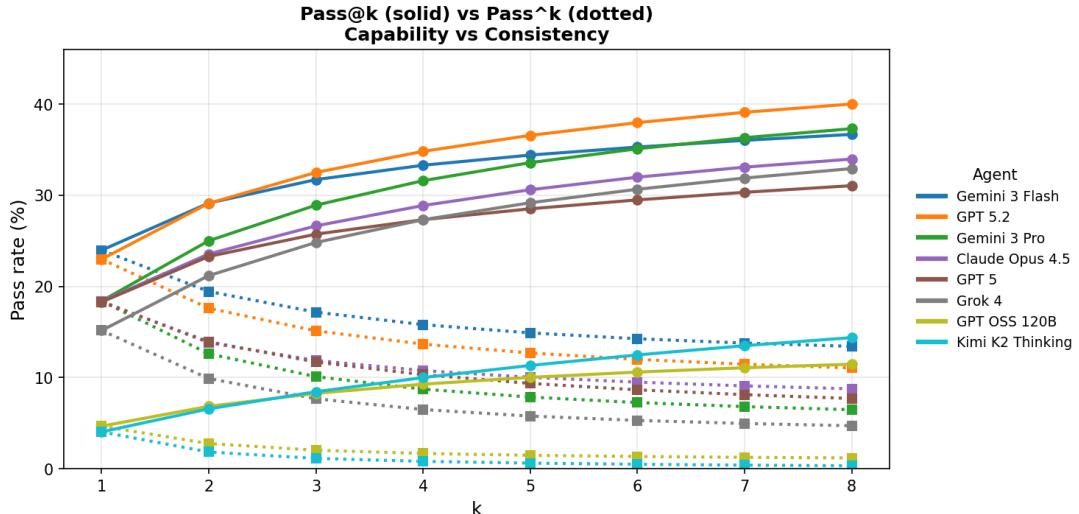


Figure 4: Pass@ $k$  and Pass $^k$  of agents on the APEX–Agents benchmark. Solid lines indicate Pass@ $k$ , and dotted lines indicate Pass $^k$ .

## 5.1 Tools and token use

The mean number of steps, number of tool calls (note that multiple tools can be used at each step), and token usage for each agent are reported in Table 4. Token usage is split into trajectory tokens (tokens sent from Archipelago, our infra service, to the agent per API call, including the system prompt, conversation history, and any retrieved context) and completion tokens (tokens generated by the agent at each API call, summed across all calls in a trajectory, including response text and any tool call specifications). From the completion tokens, we subset the final answer tokens. The tools most frequently used by agents are given in Appendix G.

Agents’ use of tokens and tools varies substantially, with Gemini 3 Flash using nearly 5 $\times$  as many tokens as GPT-5.2, and about 8 $\times$  as many as Gemini 3 Pro. It also uses approximately 54% more steps

than GPT-5.2 and 22% more tool calls. This suggests that although it is effective, Flash is inefficient. At the other end of the leaderboard, Kimi K2 Thinking averages 92 steps and 91 tool calls per task and 1.6 million tokens, showing that using more resources does not always result in higher-quality output. Final answer token counts are relatively similar across agents (from 191 for Gemini 3 Pro to 472 for Claude Opus 4.5), indicating that agents do not differ substantially in verbosity.

## 5.2 Failure analysis

**Tasks with files as output** For 422 tasks, agents are required to return a message to console, and for 58 tasks they are required to create or edit a file (document, spreadsheet, presentation). Agents’ scores are lower on tasks that require a file. For both sets of tasks, Gemini 3 Flash performs best, followed by GPT-5.2 and Claude Opus 4.5, with drops of 4.9%, 7.2%, and 5.0% respectively.

Table 4: The mean number of steps, tools, and tokens used by agents ( $n = 3,840$ ). Answer tokens are a subset of completion tokens. We round values over 1,000 to the nearest hundred and over 10,000 to the nearest thousand.

Model	Steps	Tools	Per run tokens	Trajectory tokens	Completion tokens	Answer tokens
Claude Opus 4.5	19	27	467,000	458,000	8,500	472
Gemini 3 Flash	54	55	5,315,000	5,266,000	49,000	299
Gemini 3 Pro	24	26	667,000	652,000	16,000	191
GPT-5	34	31	1,011,000	963,000	48,000	307
GPT-5.2	35	45	1,042,000	1,008,000	33,000	330
GPT-OSS-120B	43	26	1,635,000	1,600,000	36,000	328
Grok 4	31	31	632,000	630,000	2,500	166
Kimi K2 Thinking	92	91	1,620,000	1,610,000	10,000	257

**Unwanted file deletion** Deletions are never requested in the task prompts, and can be seen as undesirable ‘rogue’ behavior by the agent. Claude Opus 4.5, GPT-5 and Kimi K2 Thinking make no deletions. 36 trajectories contain deletions (0.12%), with GPT-5.2 deleting the most files ( $n = 21$ ), followed by Grok 4 ( $n = 6$ ), Gemini 3 Flash ( $n = 5$ ), and Gemini 3 Pro ( $n = 2$ ) and GPT-OSS-120B ( $n = 2$ ).

**How agents fail** On trajectories where agents do not meet all of the criteria, we record how many have their trajectories stopped for exceeding 250 steps (reflecting a mixture of reasoning limits, planning inefficiencies, and orchestration overhead), how many score 0%, and how many achieve partial credit (i.e., score more than 0% and less than 100%). See Table 5. All agents score zero in at least 40% of their runs, showing how difficult the tasks are. This partly reflects our evaluation design, where 92/480 tasks have only one criterion and 79/480 have two.

Timeout percentages are substantially higher for the open-source than closed-source models, especially Kimi K2 Thinking, which often doom loops, timing out 29.8% of trajectories. Notably, the top performing agent overall, Gemini 3 Flash, timeouts the most of the closed-source models (3.2%), followed by the second best agent, GPT-5.2, which timeouts 2.7% of the time.

**Tool use in passing trajectories** In trajectories where the agent meets all criteria, code execution accounts for 16.5% of tool calls versus 20.5% in trajectories that do not (-4.0 percentage points). Equally, the inspect tool accounts for 3.2% of tool calls versus 6.4% (-3.3 percentage points), and listing files accounts for 16.7% ver-

Table 5: Agents’ outcomes on APEX–Agents. Each row is 3,840 trajectories (1 x 480 x 8) and sums to 100%.

Model	Pass	Timeout	Zero	Partial
Claude Opus 4.5	18.4%	0.2%	46.4%	35.1%
Gemini 3 Flash	24.0%	3.2%	40.3%	32.6%
Gemini 3 Pro	18.4%	0.1%	46.6%	34.9%
GPT-5	18.3%	1.1%	46.9%	33.7%
GPT-5.2	23.0%	2.7%	40.8%	33.5%
GPT-OSS-120B	4.7%	6.5%	62.2%	26.6%
Grok 4	15.2%	0.0%	50.5%	34.3%
Kimi K2 Thinking	4.0%	29.8%	47.1%	19.1%

sus 12.3% (+4.4 percentage points). However, this aggregate analysis does not control for differences in task difficulty, nor for differences in agents’ problem-solving approaches. Instead, to make a head-to-head comparison, we use the 937 of 3,840 agent–task pairs (reflecting 7,496 trajectories) where the agent has at least one run that passes the task and one run that fails.

In a head-to-head comparison, trajectories that pass all criteria use slightly more unique tools (an increase of 0.22 per trajectory) and are 3 percentage points more likely to use code at least once. They also have substantially fewer steps (-5.95) and make far fewer tool calls overall (-5.66). Successful trajectories likely avoid repeatedly using unproductive tools (i.e., “doom looping”).

## 6 Conclusion

The APEX–Agents benchmark evaluates whether frontier agents are capable of performing long-horizon, cross-application tasks in professional services. We find that agents have substantial headroom to improve, with the top-performing agents (Gemini 3 Flash, GPT-5.2, Claude Opus 4.5) all scoring under 25% when measured with Pass@1, and no more than 40% when measured with both Pass@8 and mean score. Failures vary – from running out of steps, to failing to meet any criteria, or achieving partial credit (which indicates some useful output). We also see variance across runs, and a substantial drop from Pass@8 to Pass^8, demonstrating that agents are capable of executing complex professional services work, but often do so inconsistently.

To enable open research, the dataset for APEX–Agents is available open-source, along with Archipelago, our infra service. In future benchmarks, we plan to expand the horizon of tasks, the complexity and depth of worlds, and the difficulty (and value) of tasks.

## 7 Acknowledgments

We thank all the experts from the Mercor marketplace who contributed to APEX–Agents. We thank team members at Mercor who gave feedback on the design of APEX–Agents and supported the project.

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## A Archipelago

Archipelago is open-source infrastructure for running and evaluating AI agents against RL environments. It has three components: (1) the Environment, a containerized sandbox that exposes multiple applications through a unified Model Context Protocol gateway; (2) an Agents runner that runs LMs with different agentic harnesses (for this benchmark, a ReAct toolbelt); and (3) a Grading system that evaluates agent outputs by comparing before-and-after snapshots of the world, using verifiers. All three components are Docker containers that can run on any orchestration platform (e.g., Kubernetes, Modal).

## B Time spent at work by professionals

The time allocation reported by participants in the APEX Survey is given in Table 7.

Table 6: Count of how many times each workflow appears in the tasks.

Job	Workflow	Count
Investment banking analyst	Comparables	16
	DCF	42
	Debt Model	6
	LBO	12
	Market / Sector Research	3
	Merger Model	7
	Sensitivity Analysis	46
	Valuation Analysis	28
Management consultant	Benchmarking / Competitive Analysis	26
	Cost Benefit Analysis	11
	Market Sizing, TAM, SAM	14
	Operations Analysis	23
	Scenario/Sensitivity Analysis	35
	Strategy Recommendations	5
	Survey / Interview Analysis	31
	Variance / Performance Analysis	15
Corporate lawyer	Compliance Program Review	16
	Contract Review	30
	Due Diligence	18
	Internal Investigations	3
	Legal Research	47
	Litigation Strategy	8
	Motion Drafting	6
	Risk Assessment	24
	Other	8

## C Distribution of workflows

The distribution of workflows over the tasks in APEX–Agents is given in Table 6. The five most reported categories of work for each job are given in Table 8.

## D Agent setup

### D.1 ReAct toolbelt

We use a looped toolbelt, following the ReAct paradigm: Reasoning and Acting are interleaved in a single loop. At each step, the agent observes the current state, reasons about the next action, executes tool(s), and repeats.

The agent requires an explicit final\_answer tool call to complete. This ensures intentional termination with structured output (i.e., an answer + status). To ensure tools do not bloat model context, we implement a toolbelt approach where the agent initially only has access to (1) meta-tools for discovering, describing, and managing available tools and (2) task planning (i.e., creating a to-do list with batch

Table 7: Time spent by professionals at work, based on responses from participants in the APEX Survey ( $n = 227$ ).

	All jobs	Investment banking analyst	Management consultant	Lawyer
Core activities	47.4%	47.2%	43.5%	50.0%
Learning	9.2%	8.3%	7.1%	11.4%
Admin	10.5%	10.4%	10.1%	11.1%
Comms	13.5%	13.5%	14.7%	12.8%
Meetings	14.3%	14.7%	18.7%	10.2%
Non-productive	5.1%	6.0%	5.9%	4.5%
Total	100%	100%	100%	100%

Table 8: Breakdown of time spent on core activities by professionals at work, based on responses from participants in the APEX Survey ( $n = 227$ ). We show the five most reported categories of work for each job.

Job	Top activities (share of time)
Investment banking analyst	Financial modelling (23.5%) Research (13.6%) Quantitative data analysis (12.8%) Prep & give presentations (11.9%) Managing stakeholders (6.0%)
Management consultant	Quantitative data analysis (17.8%) Prep & give presentations (15.1%) Customer contact (10.4%) Research (9.9%) Staff feedback & review (8.3%)
Lawyer	Research (24.9%) Docs, reports, memos (16.4%) Contracts and legal docs (14.7%) Customer contact (10.9%) Other legal work (9.4%)

support). The agent also includes context summarization that is triggered when 70% of the context window is utilized and retains the last 10 messages. This efficient context window management minimizes the risk that agents fail a task because they run out of tokens. See our GitHub repository.

## D.2 Agent system prompt

All agents use the same system prompt:

You are an agent that completes tasks independently. Use the tools provided to you to complete the task to the best of your ability. You should use the `code_exec` tool when needed, such as when calculating values. When calculating numbers, unless specified otherwise, use the exact values without rounding them.

You must attempt to execute the task.

You cannot ask for help or further clarification.

For every tool except the `code_exec` tool, you may assume that all relevant files are located under the root path `/`. For the `code_exec` tool, however, you must explicitly use `/filesystem/` as the root path to locate all relevant files.

## E Model details

An overview of the models tested against APEX–Agents is given in Table 9.

## F Significance tests on Pass@1 scores

Pairwise scores for models tested against APEX–Agents, using McNemar’s exact test with a Benjamini–Hochberg correction, are given in Table 10.

## G Tools most frequently used by agents

Rounded to the nearest thousand, the ten tools most frequently used by agents are: Code execution (256,000), Add tool to the toolbelt (200,000), List files in the file system (163,874), Read spreadsheet tab (127,000), Search the PDF (86,000), Inspect tool with the toolbelt (78,000), Read PDF (55,000), Read document content (45,000), List tabs in a spreadsheet (42,000), and Read an image (37,000).

Table 9: Configs of the models tested against the APEX–Agents benchmark.

Model name	Provider	Access	Thinking settings	Other configs
Claude Opus 4.5	Anthropic	Closed-source	High	Temperature = 1.0 Max tokens = 64, 000
Gemini 3 Flash	Google DeepMind	Closed-source	High	Temperature = 1.0 Verbosity = Medium Max tokens = 65, 536
Gemini 3 Pro	Google DeepMind	Closed-source	High	Temperature = 1.0 Verbosity = Medium Max tokens = 65, 536
GPT-5	OpenAI	Closed-source	High	Verbosity = Medium Max tokens = 128, 000
GPT-5.2	OpenAI	Closed-source	High	Verbosity = Medium Max tokens = 128, 000
GPT-OSS-120B	OpenAI	Open-source	High	Temperature = 0.7 Max tokens = 131, 072
Grok 4	xAI	Closed-source	[On by default]	Temperature = 0.8 Max tokens = 16, 000
Kimi K2 Thinking	Moonshot AI	Open-source	[On by default]	Temperature = 0.7 Max tokens = 262, 144

Table 10: Pairwise Pass@1 scores with Benjamini–Hochberg correction (m=28).

Model A	Model B	p (McNemar)	q (BH)
Kimi-K2-Thinking	gemini-3-flash-preview	5.68e-23	1.59e-21
gemini-3-flash-preview	gpt-oss-120b	6.51e-21	9.11e-20
Kimi-K2-Thinking	gpt-5.2	3.21e-20	2.99e-19
gpt-5.2	gpt-oss-120b	8.67e-19	6.07e-18
Kimi-K2-Thinking	claude-opus-4-5	3.60e-13	2.02e-12
claude-opus-4-5	gpt-oss-120b	1.24e-12	5.79e-12
gemini-3-pro-preview	gpt-oss-120b	1.85e-12	7.39e-12
Kimi-K2-Thinking	gemini-3-pro-preview	4.03e-12	1.41e-11
gpt-5	gpt-oss-120b	7.24e-10	2.04e-09
Kimi-K2-Thinking	gpt-5	7.29e-10	2.04e-09
gemini-3-flash-preview	grok-4	2.92e-08	7.43e-08
Kimi-K2-Thinking	grok-4	3.64e-08	8.07e-08
gpt-oss-120b	grok-4	3.75e-08	8.07e-08
gpt-5.2	grok-4	3.69e-06	7.38e-06
gemini-3-flash-preview	gpt-5	3.30e-05	6.15e-05
gpt-5	gpt-5.2	0.0002	0.0004
gemini-3-flash-preview	gemini-3-pro-preview	0.0003	0.0004
claude-opus-4-5	gemini-3-flash-preview	0.0005	0.0008
gemini-3-pro-preview	gpt-5.2	0.0065	0.0096
claude-opus-4-5	gpt-5.2	0.0073	0.0102
claude-opus-4-5	grok-4	0.0503	0.0670
gemini-3-pro-preview	grok-4	0.0893	0.1140
claude-opus-4-5	gpt-5	0.3480	0.4240
gpt-5	grok-4	0.3910	0.4560
gemini-3-pro-preview	gpt-5	0.4970	0.5560
gemini-3-flash-preview	gpt-5.2	0.5550	0.5970
claude-opus-4-5	gemini-3-pro-preview	0.9180	0.9520
Kimi-K2-Thinking	gpt-oss-120b	1.0000	1.0000