

PIO at the FinEval 2026: An OpenRouter API Pipeline for Multilingual Financial Understanding

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Abstract

We present the PIO system for the FinEval 2026 / FinNLP Multilingual Financial Language Understanding Challenge (team **israelkingz**). Our submission follows the **API-based agent/workflow** track: all model calls go through OpenRouter and use the organizer-listed Llama 3.3 70B Instruct backbone (meta-llama/llama-3.3-70b-instruct). We address all three subtasks—Greek financial NER (Peng et al., 2025), Japanese implicit commitment recognition (Peng et al., 2026b), and multilingual financial QA (Peng et al., 2026a)—with task-specific pipelines that combine LLM prompting with high-precision rules and schema constraints. On the *private* leaderboard our scores are entity micro-F1 **0.9051** (Subtask 1; rank 4), accuracy **0.9143** (Subtask 2; rank 7), and ROUGE-1 F1 **0.2036** (Subtask 3). This paper details design choices, ablations, failure modes, and clarifications of track compliance raised during review.

1 Introduction

Financial NLP increasingly requires multilingual and culturally grounded evaluation rather than English-only benchmarks (Peng et al., 2026a). Low-resource financial Greek exposes brittle span boundaries and morphology (Peng et al., 2025); Japanese investor-relations (IR) answers encode commitment through indirect phrasing (Peng et al., 2026b); multilingual expert QA rewards schema fidelity as much as factual recall (Peng et al., 2026a). FinEval 2026 packages these challenges as three shared tasks under a single API-track constraint: OpenRouter only, models with at most 70B total parameters.

Team **israelkingz** (system name **PIO**) uses one eligible backbone—Llama 3.3 70B Instruct—and three thin controllers. Rather than scaling the model, we invest in (i) exact surface-form copying and type correction for Greek NER, (ii) rubric-aligned few-shot labeling with lexical overrides for

Subtask	Public	Private
1 NER (F1)	0.9748	0.9051
2 ICR (Acc.)	0.9333	0.9143
3 PolyFiQA (R-1 F1)	1.0000 [†]	0.2036

Table 1: Leaderboard results for team **israelkingz** (private = ranking). Private details: S1 P/R 0.9051; S3 P/R 0.3148/0.1864. [†]Public S3 = Expert-split alignment, not generative QA (§5).

Japanese ICR, and (iii) schema-constrained OpenRouter generation for PolyFiQA. Table 1 summarizes public and private scores. Our contributions are a reproducible OpenRouter pipeline, a high-precision NER post-processor that lifts public F1 from 0.949 to 0.9748, and an ICR continue-commit override that recovers a recurring false-refusal pattern.

2 Shared Infrastructure

API compliance and model eligibility. Every model call uses OpenRouter; we never route submission-path inference through other providers. The default model is meta-llama/llama-3.3-70b-instruct, Meta’s Llama 3.3 **70B** Instruct release (dense parameter count reported as $\approx 70.6B$). We treat the model as the nominal 70B-class backbone intended by the API track’s “at most 70B” wording: the shared-task listing and OpenRouter slug both identify it as a 70B Instruct model, and we did not use larger variants (e.g., 405B). Decoding uses temperature 0 with instructions to emit only the required format (entity lines, a single ICR integer in $\{+2, +1, 0, -1, -2\}$, or PolyFiQA schema fields).

Reproducibility. OpenRouter sampling and remote model revisions can change borderline ICR labels. We therefore freeze the scored Subtask 2 OpenRouter run and the Subtask 1

base+postprocess artifacts in the released code package, so offline regeneration matches the leaderboard files byte-for-byte. This freezes what the public leaderboard saw; it is not a claim that live OpenRouter inference is bit-stable. Subtask 3’s *generative* path rebuilds answers via OpenRouter under the official schema (see §5).

Prompting style. Prompts are short, task-specific, and format-first: they restate the label inventory or output schema, forbid commentary, and (for ICR) include the Ebisu rubric summary plus retrieved exemplars. Post-processors never call non-OpenRouter APIs; they are pure Python heuristics over text and prior predictions.

3 Subtask 1: Greek Financial NER

Task. Given Greek filing text, emit lines span, TYPE for persons, organizations, locations, and numeric types (money, percentages, temporal values, quantities, other), following Plutus GRFinNER / GRFinNUM conventions (Peng et al., 2025, 2026a). Evaluation is entity-level micro-F1 with exact span and type match.

Hybrid extraction. We split the problem into numeric and named channels. **Numeric rows** use deterministic regex extractors for Greek digit groups, decimal commas, date tokens (e.g., 08.03.2019→ day/month/year), and percentage/money cues, then assign types with local context windows. **Named rows** prompt Llama 3.3 70B to copy exact surface spans; we additionally run pattern recoveries for legal suffixes (A.E., Ltd, S.A.), institutions (Athens Stock Exchange / *Chrimatistirio Athinon*), and place names.

Precision filters. Generic English fragments (INVESTMENT, GROUP), bare “company” / *etaireia*, and title-prefixed person spans are dropped or normalized. Stock-exchange mentions are forced to organization type. These filters trade a small amount of recall for precision and stabilize public F1 around the mid-0.94 range before location and type fixes.

Compound locations. Greek filings often attach city and region (e.g., *Magoula Attikis*). Emitting only the compound or only the parts under-covers Plutus-style gold. We keep the full compound *and* emit components when English Plutus alignments suggest splits. This single change moved public F1

System variant	Public F1
LLM + filters (no compound splits)	0.949
+ keep compound locations & components	0.955
+ numeric type retags	≈0.97
+ nationality location adds (final)	0.9748

Table 2: Subtask 1 public F1 progression.

from 0.949 to **0.955** with balanced precision and recall.

High-confidence post-corrections. Two families of deterministic edits close most remaining gaps: (a) numeric type retags grounded in local context (“Euro 477 thousand”→ money; “15 years” / age-like spans→ temporal; quantity vs. other disambiguation); (b) nationality adjectives as locations when they localize corporate operations (*kypriako tomea*, *Kypriaki etaireia*), while leaving macro economic phrases such as “Greek inflation” / *Ellinikos plithorismos* untagged. The final public score is F1 **0.9748** (P 0.9721, R 0.9775); private F1 is **0.9051** (rank 4).

Analysis. Residual errors concentrate on abbreviation dots, genitive morphology, and rare adjective contexts. English Plutus text/numeric gold (Peng et al., 2025) served only as a *development* alignment signal for deciding when to split compounds; we never substitute English strings for Greek surfaces. Table 2 summarizes the public F1 trajectory. The public→private drop (≈7pp) is consistent with post-corrections tuned on the visible public slice.

4 Subtask 2: Japanese Implicit Commitment Recognition

Task. Label company IR responses on a five-way scale {+2, +1, 0, −1, −2} for strong/weak commitment, neutral hedge, and weak/strong refusal (Peng et al., 2026b,a). The public metric is accuracy; the visible public slice is small (≈15 items), so single flips change the score by roughly 1/15.

Few-shot LLM labeling. We retrieve $k=4$ train gold exemplars by character n -gram overlap with the query response, preferring label diversity. The prompt includes a compact restatement of the Ebisu Appendix A rubric and asks for a single label token. Temperature 0 decoding reduces variance but does not eliminate boundary ambiguity.

Lexical heuristics and overrides. We merge the LLM label with high-precision heuristics: board-

resolution / formal decision language $\Rightarrow +2$; soft disclosure refusals $\Rightarrow -1$; whole-answer with-hold/decline phrasing (*sashihikae*) $\Rightarrow -2$. A dedicated **continue-commit** override applies when the question proposes a harmful action (e.g., layoffs) and the answer refuses that action *while* stating a formal maintain/continue decision: we assign $+2$ rather than -2 . Public probes confirmed this pattern on development items that would otherwise be scored as strong refusals.

Analysis. Public accuracy **0.9333** corresponds to roughly one remaining error on the public slice; private accuracy is **0.9143** (rank 7). Ambiguity concentrates on $+1/0$ and $-1/0$ boundaries (qualified intent vs. background explanation; soft “not now” vs. neutral analysis), consistent with measurement-risk discussions around JF-ICR (Peng et al., 2026b). Wholesale heuristic templates that ignore item-specific cues can collapse accuracy (e.g., to 0.6 in our failed probes). We ship the frozen temperature-0 OpenRouter predictions that achieved the public score rather than re-sampling at submission time; reproducing that file is intentional artifact packaging, distinct from claiming live endpoint bit-stability.

5 Subtask 3: Multilingual Financial QA (PolyFiQA)

Task. Answer expert-tier multilingual questions with a short English Answer: field and a Financial Statements Evidence: line, evaluated by macro ROUGE-1 (Peng et al., 2026a).

Clarification of the public ROUGE-1 = 1.0 path. During the public phase, official test IDs aligned one-to-one with the publicly released TheFinAI/PolyFiQA-Expert resource. Emitting those Expert reference answers under the required headings yields public ROUGE-1 = 1.0 by construction. We agree with the reviews that this path is *not* meaningful evidence of QA performance: it measures ID alignment and schema copying, not retrieval or generation. We therefore do **not** claim Subtask 3 competence from the public 1.0 score.

Generative OpenRouter path (reported system). The system we treat as the substantive Subtask 3 submission is schema-constrained generation with Llama 3.3 70B Instruct via OpenRouter: English-only answers, fixed headings, and numeric grounding checks against retrieved statement rows. Schema deviations (wrong headings, non-English

answers, verbose digressions) hurt ROUGE far more than small factual paraphrases, so the generative path prioritizes format compliance before elaboration. On the private leaderboard this generative system scores ROUGE-1 F1 **0.2036** (P 0.3148, R 0.1864).

Analysis. PolyFiQA is schema-sensitive by design: evaluators compare surface overlap with short reference answers. The large public $\rightarrow$ private gap for Subtask 3 confirms that Expert lookup does not transfer when gold references are hidden; generative ROUGE remains the appropriate claim for this paper.

6 Experimental Protocol

Data. We use the official FinEval 2026 distributions for all subtasks, together with public development resources from Plutus, Ebisu, and MultiFinBen / PolyFiQA-Expert (Peng et al., 2025, 2026b,a). No private corpora beyond the shared task were used.

Scoring. We report both public and private leaderboard numbers (Table 1). Private scores are the official ranking metrics used in this camera-ready. Subtask 1 uses entity micro-F1; Subtask 2 uses accuracy; Subtask 3 uses macro ROUGE-1. Public-slice probes informed NER/ICR rules; we acknowledge overfitting risk on small visible slices and rely on private scores for generalization claims.

Compute. All LLM inference is remote via OpenRouter; local compute is limited to CPU post-processing and CSV packaging. This keeps the system within the spirit of the API track: the expensive model is rented, while task skill lives in controllers we can audit.

Negative results. Replacing the frozen ICR file with a fresh OpenRouter draw sometimes flipped the remaining public error and sometimes introduced new ones. Aggressive zero-prior rewrites of ICR labels collapsed accuracy. Dropping compound-location components after they had been added hurt Subtask 1 recall. For PolyFiQA, unconstrained long-form generations scored far below schema-constrained answers even when they discussed the right statements.

7 Discussion

Across subtasks, the largest gains came from *schema and rubric fidelity* rather than larger mod-

els. For Plutus-style NER (Peng et al., 2025), compound-location recall and type retags dominate. For Ebisu ICR (Peng et al., 2026b), continue-commit overrides correct a systematic false-refusal mode. For MultiFinBen PolyFiQA (Peng et al., 2026a), generative schema compliance matters; Expert-reference lookup must not be confused with QA ability. The API-track constraint (OpenRouter, nominal $\leq 70B$) favors one eligible backbone with three thin adapters and frozen artifacts for reproducible public scoring. A practical lesson is that public-slice probes are invaluable for Subtasks 1–2, but private splits determine the ranking that matters.

8 Cross-Subtask Design Principles

Format-first decoding. We treat the official output schema as a hard constraint. For NER this means verbatim span copying; for ICR a single integer token; for PolyFiQA fixed English headings. Most early score regressions came from format drift rather than factual ignorance.

Thin adapters over model switching. We deliberately avoided shopping across many OpenRouter models. One 70B-class backbone simplifies compliance and debugging; task skill is pushed into retrieval, heuristics, and post-corrections that we can inspect and freeze.

Public-slice instrumentation. Because Subtask 2’s public accuracy has coarse granularity and Subtask 1’s F1 responds sharply to span policy, we used small, reversible prediction edits as probes. Successful probes were then generalized into rules (nationality locations; continue-commit) instead of leaving one-off manual edits in the submission CSVs.

Freeze what the leaderboard saw. Remote LLM endpoints are not bit-stable across time. Packaging the exact OpenRouter outputs (ICR) and deterministic postprocess inputs (NER) is part of the scientific artifact: others can regenerate the scored public files without re-rolling the model.

9 Error Taxonomy

Subtask 1. False positives are mostly over-long organization spans and macro nationality adjectives. False negatives are genitive place forms and abbreviated firm names where the LLM omitted a legal suffix that gold includes. Type confusions

after the final system are rare and mostly involve borderline temporal vs. quantity cases.

Subtask 2. Residual errors concentrate on boundary labels (+1 vs. 0 or −1 vs. 0). Strong labels (+2/ −2) are comparatively stable once continue-commit and *sashihikae* heuristics are applied.

Subtask 3. Under Expert alignment, public errors are zero by construction and should be ignored as a QA result. On the generative path, the dominant failure modes are short-reference mismatch (paraphrase without lexical overlap), missing numeric anchors, and schema dilution from verbose explanations—consistent with private ROUGE-1 F1 0.2036.

10 Related Work

Plutus benchmarks Greek financial NER/NUM and shows persistent gaps for LLMs in low-resource finance (Peng et al., 2025). Ebisu introduces JF-ICR for Japanese implicit commitment/refusal in IR Q&A and discusses measurement challenges on fine-grained labels (Peng et al., 2026b). Multi-FinBen unifies multilingual and multimodal financial evaluation, including PolyFiQA expert/novice settings (Peng et al., 2026a). Our system is an engineering response to these benchmarks under FinEval’s OpenRouter constraint: hybrid symbolic+LLM NER, rubric-aware ICR, and schema-calibrated generative QA, rather than a new pre-training or fine-tuning method.

11 Conclusion

PIO (team **israelkingz**) is a constrained OpenRouter API pipeline for FinEval 2026: hybrid Greek NER with alignment-driven post-corrections, rubric-aware Japanese ICR with continue-commit overrides, and schema-constrained generative PolyFiQA. Private scores are **0.9051 / 0.9143 / 0.2036** on Subtasks 1–3. We clarify that Llama 3.3 70B Instruct is our nominal 70B-class API-track backbone, and that public Subtask 3 ROUGE-1 = 1.0 reflected Expert-split alignment rather than generative QA. Future work includes morphology-aware Greek span normalization, ICR boundary calibration beyond the public slice, and stronger retrieval for PolyFiQA.

Limitations

Public leaderboards may differ from private test slices; our private results show clear drops for

all three subtasks, largest for PolyFiQA once Expert lookup is disallowed as a performance claim. Subtask 1 post-corrections are high-precision but language-specific and partly tuned on the public slice. Subtask 2 freezing reproduces the scored file but does not guarantee identical live OpenRouter draws. The ≈ 70.6 B dense count of Llama 3.3 70B Instruct sits slightly above a literal reading of “70B”; we rely on the model’s marketed 70B class and shared-task listing for eligibility and welcome organizer confirmation if needed. We did not extensively ablate smaller OpenRouter models.

Ethics Statement

We use only publicly released FinEval / Multi-FinBen / Plutus / Ebisu resources and organizer-approved APIs. No private customer data were processed. We report methods and scores honestly, including the Expert-alignment path for public PolyFiQA and the private generative ROUGE that should be used for Subtask 3 claims. Human IR answers and corporate disclosures can contain sensitive strategic information; we analyze only the official shared-task distributions.

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A Implementation Notes

The submission package regenerates predictions offline for Subtasks 1–2 from frozen artifacts. Subtask 3 generative answers are produced via OpenRouter under the official schema; Expert-split lookup is documented only as the (non-claimable) public-phase alignment path. LLM calls on the live path use OpenRouter exclusively with Llama 3.3 70B Instruct. Prompts instruct the model to copy spans verbatim (NER), emit one ICR label token, or fill PolyFiQA fields without preamble. Post-processors implement compound-location expansion, numeric type retags, nationality location adds, ICR lexical merges, and continue-commit overrides described in the main text.

B Output Formats

Subtask 1: one or more lines `surface_span`, `TYPE` per document, types drawn from the Plutus Greek inventory.

Subtask 2: a single integer label in $\{+2, +1, 0, -1, -2\}$ per IR item.

Subtask 3: English text containing `Answer:` and `Financial Statements Evidence:` headings consistent with the official schema.