AI Expense Categorizer - Technical Documentation

1. Categorization Logic

The categorization system follows a hybrid approach combining rule-based mapping and LLM-based classification to ensure both consistency and flexibility.

Rule-Based Mapping

Known merchant keywords are directly mapped to categories (e.g., SWIGGY → Meals, AWS → Software).

This ensures deterministic results, faster processing, and reduced LLM calls.

Rule-based categorization also improves explainability and auditability.

LLM-Based Classification

If no rule matches, the LLM classifies the transaction using its description context.

The LLM output is validated against a strict JSON schema and enforced category list.

Fallback to 'Other' occurs if the LLM output is invalid.

2. Prompt Structure

The LLM prompt enforces structured output and deterministic behavior.

Temperature is set to 0 to ensure consistent categorization.

The prompt instructs the LLM to return JSON with category, confidence score, and reason.

Category validation ensures outputs remain within predefined categories.

3. Anomaly Detection Approach

Statistical High Amount Detection

Uses Median Absolute Deviation (MAD) to detect unusually high expenses.

Transactions above threshold (median + 4*MAD) are flagged as statistical anomalies.

MAD provides robustness against skewed financial distributions.

Duplicate Detection

Transactions with identical date, amount, and normalized description are flagged as possible duplicates.

Category Outlier Detection

MAD is applied within each category to identify abnormal spending patterns.

Example: unusually high meal expense flagged within Meals category.

4. Limitations

Small datasets may produce false anomaly flags due to limited statistical context.

Currency normalization assumes single-currency datasets.

Anomaly detection is dataset-relative without historical baseline.

Rule-based mapping requires manual updates.

PDF reporting focuses on summary-level insights.