1. Concept (40%)

Understanding of Problem & Objectives:

Financial apps and banks must automatically categorise raw transactions (e.g., “Starbucks,” “Amazon,” “Shell Fuel”) into categories like *Dining*, *Shopping*, or *Fuel*. The challenge lies in noisy merchant names, unseen vendors, and strict privacy policies that prevent cloud-based solutions.
My goal is to design an **autonomous, high-accuracy, offline AI system** that classifies financial transactions securely, transparently, and efficiently—giving developers full control without external APIs.

Technical Architecture & Design Approach:

The proposed **LightEmbed + GBDT** pipeline merges a lightweight semantic encoder (**MiniLM**) with a **Gradient Boosted Decision Tree (LightGBM)** classifier.

1️⃣ **Preprocessing:** Text cleaning, alias normalization, and fuzzy matching.

2️⃣ **LightEmbed:** Converts merchant text into 384-dimensional semantic vectors.

3️⃣ **Feature Fusion:** Adds numerical features (amount, time, MCC, frequency).

4️⃣ **LightGBM:** Predicts category and confidence score.

5️⃣ **Explainability & Feedback:** Uses SHAP to explain predictions and collects user feedback for retraining.

Data Strategy & Evaluation Methodology:

A hybrid dataset will be used—public transaction data from Kaggle plus **synthetic anonymised records** to simulate diverse merchants. Evaluation will cover **macro/per-class F1, precision, recall, confusion matrix, latency**, and reproducibility.

Model Selection & Performance Targeting:

MiniLM was chosen for its ability to understand unseen merchant names semantically, while LightGBM ensures **CPU-only, sub-15ms inference**.
Performance goal: **macro F1 ≥ 0.90** with stable results across categories.

Responsible & Robust AI Considerations:

All processing occurs **locally**, ensuring data privacy. Preprocessing and augmentation handle text noise, and bias checks are performed across merchant type, region, and amount ranges.

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2. Innovation (30%)

Novelty in Technical Approach:

This hybrid design uniquely combines **semantic understanding (NLP)** with **fast decision-based reasoning (GBDT)**, offering cloud-like intelligence in a **completely**

offline, low-power system. It delivers transformer-level accuracy at a fraction of computational cost.

Explainability & Transparency:
Each prediction includes **confidence levels** and **feature attributions (SHAP values)**, making the system auditable and suitable for financial regulations.

Feedback & Continuous Learning:
A **human-in-the-loop** mechanism lets users correct low-confidence predictions, enabling **continuous self-improvement** through incremental retraining.

Adaptability & Customisation:
A **JSON/YAML-based taxonomy file** allows easy category modification, supporting different financial domains without code changes.

Bias Mitigation & Ethical Innovation:
No personal data or sensitive identifiers are used. Fairness checks ensure unbiased predictions across all merchant categories.

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3. Impact (30%)

Business & Cost Impact:
The system removes dependency on paid enrichment APIs, drastically reducing operational costs while ensuring complete privacy. Its **CPU-only inference** makes it ideal for fintech startups, personal finance tools, and embedded banking platforms.

User & Developer Empowerment:
Developers have **end-to-end ownership** of model logic and taxonomy, while users gain **explainable, editable categorizations** for better trust and clarity.

Scalability & Performance:
Capable of processing **thousands of transactions per second** using <100 MB memory, making it highly scalable for both personal and enterprise applications.

Measurable Outcomes & Broader Impact:
Expected outcomes include **macro F1 ≥ 0.90**, robust explainability, and reproducible evaluation reports.
This project demonstrates that **AI can be accurate, private, transparent, and sustainable**, setting a benchmark for **responsible financial intelligence**.