Governance Review Card

| Section | Issue/Definition | Impact | Suggested Fix/Mitigation |
|---|---|---|---|
| **1. Data Quality Risk** | Incomplete and inconsistently formatted customer data entering the preprocessing service without validation rules or standardization protocols. | The ML model receives unreliable inputs, producing inaccurate credit scores that may wrongly deny loans to creditworthy applicants or approve risky borrowers. This degrades model performance and business outcomes. | Implement field-level validation at the API Gateway (Step 2) with mandatory format checks for phone numbers, national IDs, and income figures. Add a data quality dashboard in the Preprocessing Service (Step 5) that flags records with missing or malformed fields before they reach the ML model. |
| **2. Legal & Compliance Risk** | The system collects entire contact lists, GPS location logs, and device metadata without explicit, granular consent. Ghana's Data Protection Act (Act 843, Section 18) requires informed consent for processing personal data, and Section 27 mandates data minimization. | QuickLoan faces regulatory penalties from the Data Protection Commission, potential lawsuits from users, and reputational damage. The company cannot demonstrate lawful basis for processing excessive personal data unrelated to creditworthiness assessment. | Insert a consent management layer between the API Gateway (Step 2) and Raw Data DB (Step 3). Users must explicitly opt in to each data category collected, with clear explanations of purpose. Collect only loan-relevant data: income verification, repayment history, and basic identity information. Remove contact list and GPS tracking entirely. |

| Section | Issue/Definition | Impact | Suggested Fix/Mitigation |
| --- | --- | --- | --- |
| **Data Classification** | **Sensitive** | The data includes financial information (income, loan history), identity documents (national ID), and potentially contact lists that reveal social networks. Under Ghana's DPA, this qualifies as sensitive personal data requiring the highest protection standards. | Apply encryption at rest and in transit for all databases. Implement role-based access controls limiting who can view unmasked sensitive data. |
| **3. Bias & Fairness Risk** | The ML model may inherit bias from historical loan data if past lending decisions systematically disadvantaged certain regions, genders, or age groups. The current pipeline has no demographic fairness checks. | Automated loan approvals could perpetuate discrimination, violating Ghana's DPA Section 43 (prohibition of discriminatory processing) and harming vulnerable populations who already face financial exclusion. | Add a bias audit step in the Decision Service (Step 7) that logs approval rates segmented by gender, region, and age bracket. Set alert thresholds if any group's approval rate deviates more than 10% from the baseline. Retrain the model quarterly using balanced sampling techniques. |
| **Source of Bias** | Historical training data likely reflects past human lending biases, and the model's feature set (GPS logs, contact lists) may proxy for | | |

| Section | Issue/Definition | Impact | Suggested Fix/Mitigation |
| --- | --- | --- | --- |
| | protected characteristics like ethnicity or socioeconomic status. | | |
| **4. Storytelling / Reporting Recommendation** | | | |
| **Metric to Monitor (name & definition)** | **Demographic Approval Parity Index**: The ratio of loan approval rates across demographic groups (gender, region, age cohort), calculated weekly. A score of 1.0 means perfect parity; scores below 0.85 or above 1.15 indicate significant disparity requiring investigation. | | |
| **Visualization Type** | Grouped bar chart showing approval rates by demographic category, with a reference line at the overall approval rate. Include a | | |

| Section | Issue/Definition | Impact | Suggested Fix/Mitigation |
|---|---|---|---|
| | trend line chart tracking the parity index over time. | | |
| **Why It Matters** | This metric makes algorithmic fairness measurable and actionable, allowing QuickLoan to detect and correct discriminatory patterns before they cause regulatory violations or harm to customers. | | |

**Annotations Of Corrected Data Flow Diagram**

**1. Add Consent Capture (between API Gateway and Raw Data DB):**

Insert a simple consent screen that asks users to agree before their data is stored. Show them exactly what data you're collecting and why. This meets Ghana DPA's consent requirements and builds user trust. Keep a timestamped record of each consent in a separate audit log.

**2. Add Data Validation (Preprocessing Service):**

Check that incoming data is complete and properly formatted before it reaches the ML model. Flag records with missing phone numbers, invalid ID formats, or unrealistic income figures. This prevents bad data from producing bad loan decisions and improves model accuracy.

**3. Add Decision Logging (Decision Service):**

Record every automated loan decision with the applicant's demographic info (age, region, gender), the model's confidence score, and which factors influenced the decision. This creates an audit trail you can review for bias patterns and helps explain decisions to customers who ask why they were rejected.

**4. Mask Personal Data (Analytics DB):**

Before data goes to the analytics team or external partners, replace national IDs with anonymous codes, remove full names, and round ages to ranges like "25-30." This lets analysts do their work without exposing individual customer identities, reducing privacy risk.

Summary of Review Process

I approached this review by mapping QuickLoan's data flow against the data lifecycle stages: collection, storage, processing, sharing, and deletion. At each stage, I applied classification principles to determine whether the data handling matched the sensitivity level of the information.

During collection (Step 1), I identified that contact lists and GPS logs are excessive for a loan decision. Data minimization requires collecting only what is necessary for the stated purpose. Since creditworthiness depends on income verification and repayment history, not social networks or location tracking, I recommended removing those fields entirely.

At the storage stage (Step 3), I noticed the absence of classification labels. I classified the dataset as "Sensitive" because it includes financial and identity information. This classification dictates specific controls: encryption, access restrictions, and explicit consent. The lack of consent capture between the API Gateway and database represented a direct violation of Ghana's Data Protection Act, which requires informed consent before processing personal data.

In the processing stage (Steps 5-7), I found two critical gaps. First, the Preprocessing Service had no data quality checks, allowing malformed records to corrupt the ML model's training data. Second, the Decision Service lacked transparency logging, making it impossible to audit for bias. I recommended validation rules and demographic logging to address these gaps.

The Demographic Approval Parity Index I proposed directly addresses the ethical governance requirement. By tracking approval rates across demographic groups weekly, QuickLoan can detect discriminatory patterns early. If women in the Northern Region have a 60% approval rate while men in Accra have 85%, the metric flags this disparity for investigation. The grouped bar chart visualization makes the data accessible to non-technical executives, turning abstract fairness principles into concrete operational targets. This metric transforms ethical compliance from a checkbox exercise into a measurable business process, allowing QuickLoan to demonstrate responsible AI use to regulators, investors, and customers.