

# QuickLoan Mobile

## Data Governance Review Report

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### Executive Summary

This report presents findings from an independent data governance review of QuickLoan Mobile, a Ghana-based fintech startup offering instant micro-loans through a mobile application. The review identified critical risks across data quality, legal compliance, and algorithmic fairness that require immediate remediation to ensure ethical operations and regulatory compliance with Ghana's Data Protection Act (Act 843).

### Deliverable 1: Governance Review Card

#### 1. Data Quality Risk

Issue/Definition	Inconsistent and incomplete customer data formatting in the Raw Data Database, particularly for phone numbers, addresses, and identity verification fields. Missing standardization leads to duplicate customer records and inaccurate creditworthiness assessments.
Impact	ML model receives unreliable training data, resulting in inaccurate risk predictions. This compromises loan approval decisions, increases default rates, and creates unfair outcomes for legitimate customers who may be denied loans or approved incorrectly.

<b>Suggested Fix/Mitigation</b>	Implement data quality validation rules at the Preprocessing Service level: (1) Standardize phone numbers to E.164 format (+233XXXXXXXX), (2) Validate Ghana Card numbers against official format, (3) Implement address parsing and normalization, (4) Add deduplication logic to detect and merge duplicate customer records, (5) Establish data quality monitoring with automated alerts for completeness thresholds below 95%.
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## 2. Legal & Compliance Risk

<b>Data Classification</b>	SENSITIVE
<b>Issue/Definition</b>	The system collects highly sensitive personally identifiable information (PII) including Ghana Card numbers, financial transaction history, geolocation data, and complete contact lists WITHOUT explicit, informed consent. This violates Ghana's Data Protection Act (Act 843), specifically Section 18 (lawful processing), Section 19 (consent requirements), and Section 25 (data minimization principle).
<b>Impact</b>	QuickLoan faces severe regulatory penalties from the Data Protection Commission (DPC), including fines up to GHS 5 million or 4% of annual turnover (whichever is higher). Potential criminal liability for directors under Section 112. Reputational damage could devastate customer trust and market position. Operational shutdown risk if DPC issues enforcement orders.
<b>Suggested Fix/Mitigation</b>	IMMEDIATE ACTIONS: (1) Implement explicit consent capture at app onboarding with clear, granular opt-ins for each data category, (2) Eliminate collection of entire contact lists - only collect emergency contact information (2-3 contacts maximum), (3) Add Privacy Notice with transparent disclosure of data processing purposes, retention periods, and third-party sharing, (4) Implement data classification tagging in database with field-level sensitivity markers, (5) Establish data retention policy (maximum 7 years for financial records per Bank of Ghana guidelines), (6) Register as Data Controller with DPC if not already registered, (7) Appoint Data Protection Officer (DPO) as required under Section 39 of Act 843.

## 3. Bias & Fairness Risk

<b>Source of Bias</b>	The ML Scoring Model at Step 5 introduces algorithmic bias through proxy discrimination. Contact list size, smartphone type/price, and geolocation patterns serve as proxies for socioeconomic status, which correlates with protected characteristics including gender, region, and ethnicity in Ghana. Rural users and women (who statistically have smaller professional networks and lower-cost devices) face systematic disadvantage in loan approvals.
<b>Impact</b>	Disparate impact on vulnerable populations violates Ghana's constitutional guarantee of equality (Article 17) and may breach Act 843's fairness requirements. Systematic denial of financial services to women and rural populations perpetuates economic inequality. Risk of public backlash and regulatory action if bias patterns are exposed. Undermines financial inclusion mission that microfinance should serve.

<b>Suggested Fix/Mitigation</b>	(1) Conduct fairness audit using demographic parity and equalized odds metrics, stratified by gender, region (Greater Accra vs. rural), and age cohorts, (2) Remove or reduce weight of proxy features (contact list size, device price) from ML model, (3) Implement fairness constraints in model training to ensure approval rates do not vary by more than 10% across protected groups with similar credit profiles, (4) Add human review layer for all marginal rejection cases (scores within 5% of approval threshold), (5) Establish Model Monitoring Dashboard tracking approval rates by demographic segment weekly, (6) Create algorithmic impact assessment documentation per emerging AI governance best practices.
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## 4. Storytelling / Reporting Recommendation

Metric to Monitor	<b>Demographic Approval Rate Disparity (DARD)</b>
<b>Definition</b>	The percentage point difference in loan approval rates between demographic groups (gender, region, age cohort) among applicants with similar creditworthiness profiles (defined as applicants within the same ML score quintile). Calculated weekly as:   Approval Rate Group A - Approval Rate Group B  for each score band.
<b>Visualization Type</b>	Grouped Bar Chart with trend line overlay. X-axis shows weeks, Y-axis shows approval rate (%), grouped bars compare demographic segments (Male/Female, Urban/Rural), horizontal reference line at 10% disparity threshold (red alert zone), trend line shows 4-week moving average to identify systematic patterns vs. random variation.
<b>Why It Matters</b>	This metric provides early warning of algorithmic bias, enables Board/Executive oversight of fairness commitments, demonstrates regulatory compliance with equality obligations, and creates accountability for ethical AI deployment in financial services impacting vulnerable populations.

## **Deliverable 2: Corrected Data Flow Diagram**

**The following corrections must be implemented in the QuickLoan data flow to address governance, compliance, and ethical risks:**

### **Required Corrections with Annotations**

#### **Correction 1: Data Minimization at User Mobile App (Step 1)**

**Issue:** App collects excessive personal data including entire contact lists, precise geolocation history, and non-essential device information.

**Fix:** Implement data minimization principle per Ghana DPA Section 25.

**Collect ONLY:** (a) Basic identity (name, Ghana Card number, phone number), (b) 2-3 emergency contacts (not entire contact list), (c) Approximate location (district level, not GPS coordinates), (d) Essential financial data (bank account for disbursement/repayment). Remove collection of: contact lists, precise geolocation, device metadata, social media profiles.

**Rationale:** Reduces privacy invasion, limits data breach exposure, ensures compliance with data minimization obligation, prevents proxy discrimination based on socioeconomic proxies.

#### **Correction 2: Explicit Consent Capture Between API Gateway and Raw Data DB (Steps 2-3)**

**Issue:** No consent mechanism exists. Data flows directly from app to database without user authorization, violating Act 843 Section 19 consent requirements.

**Fix:** Insert Consent Management Service between API Gateway and Raw Data DB. Implementation: (a) Display clear Privacy Notice before data collection, (b) Obtain granular opt-in consent for each processing purpose (credit scoring, marketing, third-party sharing), (c) Record consent timestamp, version, and scope in Consent Registry database, (d) Validate consent status before allowing data writes to Raw Data DB, (e) Provide easy withdrawal mechanism in app settings, (f) Log all consent changes for audit trail.

**Rationale:** Establishes legal basis for processing under Act 843, enables regulatory compliance demonstration, empowers users with control over their data, creates audit trail for DPC inspections.

### **Correction 3: Data Classification & Retention Policy at Raw Data DB (Step 3)**

**Issue:** No field-level classification, no retention schedules, indefinite data storage creates unnecessary risk exposure.

**Fix:** Implement data classification framework: (a) Tag all fields with sensitivity levels (Public/Internal/Confidential/Sensitive), (b) Ghana Card numbers, financial data = SENSITIVE classification, (c) Establish automated retention policy: Active loans = full data; Closed loans = 7 years financial records (Bank of Ghana compliance) then deletion; Rejected applications = 1 year then pseudonymization, (d) Schedule automated data deletion jobs monthly, (e) Implement encryption at rest for all SENSITIVE fields using AES-256.

**Rationale:** Limits breach impact through data minimization over time, demonstrates storage limitation compliance (Act 843 Section 26), reduces infrastructure costs, enables efficient data governance.

### **Correction 4: Data Quality Validation at Preprocessing Service (Step 4)**

**Issue:** No standardization, validation, or deduplication. Poor quality data flows to ML model, compromising decision accuracy.

**Fix:** Add data quality validation layer: (a) Phone number standardization to E.164 format (+233XXXXXXXXX), (b) Ghana Card validation against official 15-digit format (GHA-XXXXXX-X), (c) Address parsing and normalization to standard Ghana postal format, (d) Completeness checks (reject records with >10% missing critical fields), (e) Deduplication algorithm using fuzzy matching on name + phone + Ghana Card, (f) Data quality scoring metric tracked in monitoring dashboard.

**Rationale:** Improves ML model accuracy and fairness, prevents duplicate customer records, reduces operational errors, supports regulatory requirement for data accuracy (Act 843 Section 24).

### **Correction 5: Decision Logging & Transparency at Decision Service (Step 7)**

**Issue:** No transparency into automated decision-making. Users receive approve/reject with no explanation, violating right to explanation.

**Fix: Implement Decision Audit Log and Explainability Service:** (a) Log every decision with: user ID, timestamp, ML score, decision (approve/reject), top 5 contributing features with weights, model version, (b) Generate plain-language explanation sent to user: 'Your application was [approved/rejected] based primarily on: [payment history/income stability/debt ratio]', (c) Provide appeal mechanism for rejected applicants with human review, (d) Store decision logs for minimum 3 years for regulatory audit, (e) Enable user access to their decision history via app.

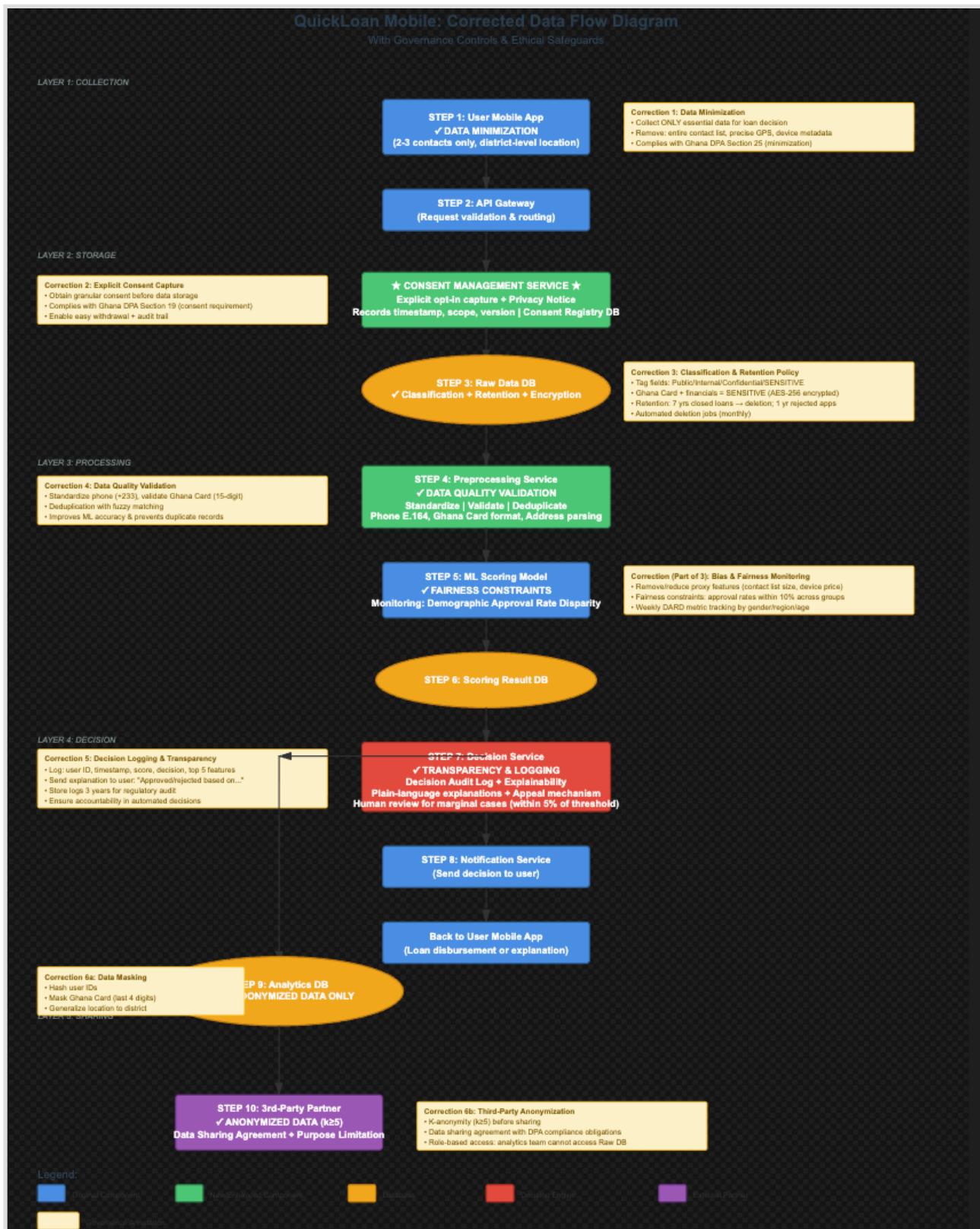
**Rationale:** Ensures accountability and transparency in automated decision-making, enables bias detection and investigation, supports regulatory compliance with automated processing rules, builds customer trust through transparency.

#### **Correction 6: Data Masking/Anonymization at Analytics DB and Third-Party Sharing (Steps 9-10)**

**Issue:** Full PII exposed in analytics database and shared with third-party partners without anonymization, creating excessive breach risk and compliance violations.

**Fix: Implement Privacy-Preserving Analytics:** (a) Analytics DB receives only pseudonymized data: hash user IDs, mask Ghana Card numbers (show only last 4 digits), generalize location to district level, remove direct identifiers, (b) Third-party data sharing requires: anonymization ( $k$ -anonymity with  $k \geq 5$ ), data sharing agreement with DPA compliance obligations, purpose limitation restrictions, (c) Implement role-based access control: analytics team cannot access Raw Data DB with full PII, (d) Regular privacy impact assessments for third-party partnerships.

**Rationale:** Minimizes breach impact and third-party misuse risk, complies with purpose limitation and data minimization principles, enables valuable analytics while protecting privacy, reduces regulatory exposure from third-party violations.



## **Deliverable 3: Summary of Review Process**

**My governance review process employed a systematic lifecycle-based analysis framework combined with classification principles to identify risks across QuickLoan's data pipeline. I began by mapping the data lifecycle stages—collection, storage, processing, decision-making, and sharing—against each component in the flow diagram. This revealed critical gaps at lifecycle transition points where governance controls should exist but were absent.**

**At the collection stage (User Mobile App), I applied the data minimization principle to identify excessive PII gathering, particularly the entire contact list collection that violates proportionality. Moving to storage (Raw Data DB), I used classification frameworks to determine that Ghana Card numbers and financial data constitute SENSITIVE information requiring encryption and strict retention schedules, yet none existed. During processing (Preprocessing Service and ML Scoring Model), I analyzed feature engineering to detect proxy discrimination where socioeconomic indicators serve as proxies for protected characteristics, creating algorithmic bias against women and rural populations.**

**The decision-making review (Decision Service) exposed the lack of transparency and explainability, violating fundamental fairness principles in automated processing. Finally, examining the sharing stage (Analytics DB and Third-Party Partners) revealed PII exposure without anonymization, creating unnecessary breach risk and potential secondary processing violations.**

**My proposed Demographic Approval Rate Disparity (DARD) metric ensures ethical and transparent governance by operationalizing fairness monitoring into concrete, measurable outcomes. Unlike abstract commitments to non-discrimination, DARD provides quantitative evidence of bias (or its absence) through weekly tracking of approval rate differences across demographic groups within similar creditworthiness cohorts. The grouped bar chart visualization**

**makes patterns immediately visible to executives and the Board, creating accountability for fairness outcomes rather than just fairness intentions.**

This metric transforms ethical governance from compliance checkbox to operational reality. When DARD shows disparities exceeding 10%, it triggers mandatory investigation and model recalibration. When trends move toward parity, it demonstrates measurable progress. Most importantly, DARD enables transparent reporting to regulators and the public, building trust through demonstrated fairness rather than asserted values. By making bias visible and actionable, this metric embeds ethics into QuickLoan's operational DNA while meeting Ghana's constitutional equality obligations and Act 843's fairness requirements.

## **Recommendations & Next Steps**

QuickLoan must prioritize immediate implementation of the six corrections outlined in Deliverable 2, particularly consent management and data minimization, to avoid regulatory enforcement. I recommend establishing a Data Governance Committee with executive accountability, appointing a qualified DPO, and conducting quarterly fairness audits. The DARD metric should be incorporated into executive dashboards and Board reporting within 30 days.

These changes will transform QuickLoan from a compliance liability into an ethical fintech leader, demonstrating that profitable growth and responsible data stewardship are complementary, not competing, objectives.