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A Consent-Gated Early-Warning Framework for Open Banking Credit Monitoring in Uzbekistan

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Abstract: General Background: Open banking can make post-disbursement credit monitoring more timely, but repeated data access also raises questions of lawful purpose, optional consent, data reliability, explainability, and adverse decisions based on missing digital traces. Specific Background: Uzbekistan's loan portfolio rose from UZS 277.0 trillion at year-end 2020 to UZS 604.0 trillion at year-end 2025. Remote-banking customer registrations also expanded sharply; these are bank-level registrations rather than a count of unique citizens and are reported at dates that may differ from year-end banking stocks. Knowledge Gap: Existing digital creditworthiness models focus mainly on origination, while monitoring frameworks rarely separate genuine financial deterioration from consent withdrawal, stale data, or source failure. Aims: This study develops a consent-gated early-warning framework for open banking credit monitoring in Uzbekistan. Methods: Documentary analysis, banking-system trend analysis, process mapping, indicator design, and a synthetic borrower case were combined. An optional-consent gate and a data-reliability gate precede a four-domain Financial Trajectory Score covering recurring inflows, debt-service burden, payment discipline, and cash-flow volatility. Compliance and identity events are treated through a separate categorical flag. Results: The synthetic case produces a baseline score of 53.3 and remains in the review band under alternative weights (50.0–59.8). A stricter coverage or freshness requirement can fail the data gate and route the account to manual review without treating missing evidence as higher risk. Novelty: The framework combines a non-adverse-use rule for optional consent withdrawal with reproducible component transformations, a separate compliance flag, boundary safeguards, and a validation protocol. Implications: Banks can integrate the framework with open banking, Chief Data Officer functions, model-risk validation, restructuring workflows, and RegTech reporting.

Keywords: Security, open banking; credit monitoring; early warning; borrower consent; data quality; Uzbekistan.

1. Introduction

Digital lending increasingly depends on data that are generated after the original credit decision. Transaction histories, recurring inflows, account balances, payment attempts, card activity, and verified information from external providers can reveal changes in a borrower's financial position before a conventional overdue indicator appears. This capacity is central to open banking, where the borrower authorizes standardized data exchange among banks, payment organizations, and other regulated participants. The expansion of formal and mobile account ownership also broadens the digital transaction record available for risk analysis [1]. Research on digital footprints and

alternative data shows that such information can improve risk differentiation and expand access for borrowers with limited formal credit histories [2].

The same data environment creates new governance problems. Machine-learning and digital-scoring models may reproduce historical disparities, rely on unstable proxies, or become difficult to explain when they influence credit limits, pricing, restructuring, or collection [3]. The use of open banking data therefore requires more than predictive accuracy. Banks need purpose limitation, valid consent, data lineage, quality controls, human review, and a documented connection between alerts and proportionate interventions [4].

Uzbekistan is entering this stage of financial digitalization. Presidential Resolution PP-359 of 27 November 2025 requires the introduction of open banking by 1 September 2026, Chief Data Officer functions in the Central Bank and commercial banks, and a RegTech-based system for transmitting statistical, financial, and supervisory data [5]. These reforms coincide with rapid banking-system growth. The credit portfolio increased from UZS 276.975 trillion at year-end 2020 to UZS 604.002 trillion at year-end 2025, deposits rose from UZS 114.747 trillion to UZS 417.258 trillion, and the non-performing loan ratio moved from 2.1% to 3.0% after peaking at 5.2% in 2021 [6]. Remote-banking statistics describe customer registrations across banks, not necessarily unique persons; the latest value used in this study is reported as of 1 October 2025 and is therefore not temporally identical to the year-end balance-sheet stocks [7].

Previous digital creditworthiness frameworks have concentrated predominantly on loan origination and static borrower classification. The operational problem addressed here is different: how should a bank monitor the trajectory of an active loan without treating missing digital evidence as proof of borrower deterioration? The research question is therefore how open banking monitoring can detect genuine risk deterioration while preserving lawful purpose, optional consent, data quality, explainability, and the borrower's right to human review.

The article contributes a consent-gated early-warning framework. An optional-consent gate and a minimum data-reliability gate precede a Financial Trajectory Score (FTS). The FTS evaluates changes in recurring inflows, debt-service burden, payment discipline, and cash-flow volatility, while compliance and identity issues are represented by a separate flag. A non-adverse-use rule prevents consent withdrawal, stale data, or an interrupted interface from being interpreted automatically as higher credit risk. The framework is an operational pilot design rather than a validated probability-of-default model.

2. Methodology

Research design. The study combines documentary analysis, structural-dynamic analysis of the Uzbek banking system, process mapping, indicator design, and a synthetic borrower case. The regulatory analysis covers open banking, personal-data protection, bank secrecy, credit-information exchange, banking activity, payment systems, model governance, and loan monitoring [8]. The quantitative context uses official Central Bank publications and open-data series [9]. No individual borrower records were used.

Unit of monitoring. The unit is one active loan or credit line linked to a borrower profile whose monitoring data may be refreshed through internal bank systems, credit bureaus, payment channels, or open banking interfaces. The framework is product-sensitive: mortgage, consumer, microbusiness, and corporate loans may use different monitoring frequencies and thresholds, but the governance sequence remains the same.

Consent gate. Before optional external open banking data or newly repurposed data are used, the bank verifies that the authorization is active, purpose-specific, linked to identifiable sources, time-limited where appropriate, and revocable through an accessible

channel. Withdrawal of optional open banking consent terminates the corresponding external data flow but does not prohibit the bank from using internal or other lawfully available information for contractual and prudential monitoring. A failed consent gate blocks new external-data collection and automated adverse action; it does not code the borrower as riskier [10].

Legal allocation of responsibilities. The personal-data law governs lawful purpose and data protection; the credit-information law governs credit-data exchange; the bank-secrecy law restricts disclosure; the banking and payment-system laws define institutional duties and permitted operations. Accordingly, consent is one legal basis for optional external data sharing, not a universal basis for all internal bank monitoring. Contractual, prudential, anti-fraud, and statutory duties remain subject to their own legal conditions [11].

Data-reliability gate. Data must meet product-specific standards for coverage, freshness, identity matching, reconciliation, and source traceability. The pilot benchmark is 80% coverage of expected observations, no unresolved identity mismatch, and a maximum data age aligned with the payment cycle. These parameters are provisional. Sensitivity is examined at 70%, 80%, and 90% coverage and at alternative freshness limits. A failed gate blocks automated adverse action and triggers correction or manual assessment.

Financial trajectory score and compliance flag. When both gates pass, four financial deterioration domains are transformed to a 0–100 scale and aggregated as follows:

$$FTS_t = 0.30R_t + 0.30D_t + 0.25P_t + 0.15V_t; \quad CTA_status_t = \{\text{consent gate, data gate, } FTS_t, CIF_t\}$$

R measures deterioration in recurring inflows; D measures deterioration in debt-service burden; P measures failed payments and arrears; and V measures increased cash-flow volatility. CIF is a categorical compliance/identity flag: 0 = no verified concern, 1 = unresolved anomaly requiring verification, and 2 = confirmed red-line event. The function $\text{clip}(x, 0, 1)$ limits a normalized value to the unit interval. Table 2 specifies reproducible pilot transformations, baseline periods, and critical conditions. The weights are policy weights rather than estimated causal coefficients.

Red-line events and human review. $CIF = 2$, more than 30 days past due, prohibited-data use, or an unexplained automated adverse action overrides the numeric score. $CIF = 1$ requires identity or compliance verification and freezes automated adverse action until resolution. The FTS supports, but does not replace, professional judgment, contractual rights, regulatory classifications, or independent model-risk review.

Ethics and reproducibility. The empirical table contains aggregate public statistics and clearly identified reporting dates. The borrower case is synthetic. The formulas, policy weights, data gates, provisional bands, and intervention rules are reproduced in the article and in a supplementary workbook. The framework must not be used for automated adverse action until back-testing, fairness testing, calibration, and independent validation are completed.

Table 1. Banking-system growth and differently dated digital-monitoring indicators in Uzbekistan.

Period reporting date	/	Loans, UZS tn	Deposits, UZS tn	Loans deposits, %	/ NPL, %	Remote-banking registrations, million
2020 (1 Jan 2021)		276.975	114.747	241.4	2.1	14.6 (1 Jan 2021)
2022 (1 Jan 2023)		390.050	216.700	180.0	3.6	30.0 (1 Jan 2023)
2024 (1 Jan 2025)		533.121	308.692	172.7	4.0	52.9 (1 Jan 2025)
2025 (1 Jan 2026)		604.002	417.258	144.8	3.0	74.2 (1 Oct 2025)
Change 2020–2025		+118.1%	+263.6%	–96.6 pp	+0.9 pp; peak 5.2% in 2021	5.1 times; dates differ

Note: Loan, deposit, and NPL values are year-end stocks reported as of 1 January of the following year. Remote-banking values are customer registrations across banks and should not be interpreted as unique citizens. The 2025 remote-banking observation is as of 1 October 2025 and is not synchronous with the 1 January 2026 balance-sheet stocks. Sources: Central Bank publications, open-data set 4-009-0046, and author's calculations [12].

3. Results

Why post-disbursement monitoring requires separate governance

Table 1 shows why a static origination score is insufficient. The loan portfolio more than doubled between the 2020 and 2025 year-end positions, while deposits grew more rapidly. Remote-banking customer registrations also expanded sharply, although their reporting dates differ from the balance-sheet dates and the counts are not unique-person measures. The movement in the NPL ratio and the absolute scale of credit exposures demonstrate the need for early identification of deterioration after origination.

Open banking can shorten the information lag only when missing observations are interpreted correctly. A broken interface, revoked optional consent, expired authorization, or source outage may produce the same technical symptom as a financial decline: less data. Treating those events as equivalent creates false-positive and rights risks. The framework therefore separates legal permission and data reliability from financial deterioration and from categorical compliance events.

Consent and data gates

Table 2. Mandatory gates, reproducible financial transformations, and the compliance flag.

Element	Operational definition	Pilot calculation or condition	Output	Management rule
Optional-consent gate	Authorization for specified external sources and monitoring purpose	Active, unexpired, revocable authorization; documented purpose and sources	Pass / fail	Failure stops new external-data collection and automated adverse action; internal lawful monitoring may continue.
Data-reliability gate	Coverage, freshness, reconciliation, identity match, and lineage	Baseline: coverage $\geq 80\%$; age within payment-cycle limit; no unresolved identity mismatch	Pass / fail	Failure triggers correction or manual assessment.
Recurring inflows (R)	Three-month seasonally adjusted median compared with 12-month stable baseline	$R = 100 \times \text{clip}[(I_{\text{base}} - I_{3m}) / (0.40 \times I_{\text{base}}), 0, 1]$	0–100	100 corresponds to a decline of at least 40% from baseline.
Debt-service burden (D)	Current debt-service ratio compared with baseline and product limit LD	$D = 100 \times \text{clip}[(DSR_t - DSR_{\text{base}}) / (LD - DSR_{\text{base}}), 0, 1]$	0–100	Use total known obligations and verified recurring inflows.
Payment discipline (P)	Failed debits, days past due, recurrence, and cure behavior	Up to 40 for failed debits; 35 for 1–7 DPD; 70 for 8–30 DPD; +5 for recurrence; cap 100	0–100	More than 30 DPD is a red-line event outside the score.
Cash-flow volatility (V)	Current coefficient of variation compared with borrower baseline	$V = 100 \times \text{clip}[(CV_t - CV_{\text{base}}) / (2 \times \max(CV_{\text{base}}, 0.05))], 0, 1]$	0–100	Use product-specific seasonality and a minimum history requirement.
Compliance/identity flag (CIF)	Verified status of identity, fraud, prohibited data, or compliance concern	0=no concern; 1=unresolved anomaly; 2=confirmed red line	0 / 1 / 2	CIF=1 freezes automated adverse action; CIF=2 requires escalation and remedy.

The two gates solve an identification problem, while the separate CIF solves a measurement problem. A borrower can be financially stable when the data channel is incomplete, and an unresolved identity inconsistency is not the same construct as income deterioration. Only the four financial domains are averaged; legal permission, data usability, and compliance status remain explicit decision controls.

Synthetic borrower application and sensitivity

A synthetic case illustrates the calculation. The borrower has active optional consent, 84% observation coverage, a maximum data age of 20 days, and no source-lineage break. Relative to the baseline, recurring inflows have weakened, debt-service burden has increased, one installment has entered short arrears, and cash-flow volatility has risen. A minor identity inconsistency is unresolved, so CIF=1. The financial scores are illustrative outputs of the pilot transformations, not observations from a real customer.

Table 3. Synthetic Financial Trajectory Score and separate compliance/identity flag.

Domain	Illustrative evidence	Score, 0–100	Weight	Weighted contribution
Recurring inflows (R)	Persistent decline relative to seasonally adjusted baseline	35	0.30	10.50
Debt-service burden (D)	Increase toward product limit	50	0.30	15.00
Payment discipline (P)	Repeated failed debit and short arrears	75	0.25	18.75
Cash-flow volatility (V)	Material increase in monthly variability	60	0.15	9.00
Financial Trajectory Score (FTS)			1.00	53.25
Compliance/identity flag (CIF)	Minor unresolved inconsistency; no confirmed fraud	1	Separate flag	Verification required; no automated adverse action

The FTS is 53.25, within the provisional review band. CIF=1 independently requires verification and blocks automated adverse action. The result therefore triggers borrower contact, verification of the identity inconsistency and payment event, confirmation of income changes, and consideration of a proportionate intervention. If the optional-consent gate failed, the bank would use existing lawful information and manual review without coding the absence of new open banking data as deterioration.

Table 4. Sensitivity of the synthetic FTS to alternative policy weights.

Specification	Weights R / D / P / V	FTS	Interpretation
Baseline	0.30 / 0.30 / 0.25 / 0.15	53.25	Review
Equal	0.25 / 0.25 / 0.25 / 0.25	55.00	Review
Payment-heavy	0.20 / 0.20 / 0.45 / 0.15	59.75	Review; close to upper boundary
Cash-flow-heavy	0.35 / 0.20 / 0.15 / 0.30	51.50	Review
Income-and-debt-heavy	0.35 / 0.35 / 0.15 / 0.15	50.00	Review

The classification remains in the review band across all five specifications, with scores from 50.00 to 59.75. This does not validate the weights. It shows only that the illustrative classification is not driven by a single weight vector. The payment-heavy scenario lies near the 60-point boundary and therefore activates the boundary rule: scores within ± 2 points of a cut-off receive the stricter adjacent review standard until empirical calibration is completed.

Sensitivity of the data-reliability gate

Table 5. Synthetic sensitivity of coverage and freshness thresholds.

Scenario	Required coverage	Maximum data age	Synthetic profile: 84% coverage, 20 days	Governance result
Broad pilot	70%	30 days	Pass	FTS may be calculated; monitor missingness risk.
Baseline pilot	80%	30 days	Pass	FTS may be calculated; CIF and human-review rules remain.
Strict coverage	90%	30 days	Fail	No automated adverse action; correct data or review manually.
Strict freshness	80%	15 days	Fail	No automated adverse action; refresh data or review manually.

This one-profile sensitivity exercise does not estimate portfolio pass rates. A bank pilot must report how alternative thresholds change the share of accounts eligible for automated calculation, the manual-review workload, false positives, and exclusion of borrowers with irregular or cash-intensive income [13].

Intervention bands and institutional responsibilities

Table 6. Provisional FTS bands and proportionate response.

FTS band / flag	Provisional meaning	Primary action	Borrower protection	Reassessment
0–19	Stable trajectory	Routine monitoring	No adverse change based only on minor fluctuations	Standard cycle
20–39	Watch	Soft contact or data verification	Explain purpose; allow correction of inaccurate data	Next payment cycle
40–59	Review	Human review and borrower dialogue	No automated adverse action; document reasons and evidence	Within 10 business days
60–79	Intensive intervention	Affordability reassessment; restructuring options; limit review	Proportionate response; preserve appeal and explanation	Monthly or product-specific

FTS band / flag	Provisional meaning	Primary action	Borrower protection	Reassessment
80–100	Critical financial deterioration	Senior risk review; protective measures; possible restructuring or collection	Contractual and legal safeguards; human decision required	Immediate
CIF=1 / CIF=2	Unresolved anomaly / confirmed red line	Verification / immediate escalation and evidence preservation	Freeze automated harm; correction, notification, and remedy where required	After verified resolution

The response ladder is non-punitive at the early stages. A watch signal leads first to verification and communication, not automatic credit tightening. The cut-offs are provisional pilot bands. A score within ± 2 points of 20, 40, 60, or 80 receives the stricter adjacent review standard. Empirical calibration should optimize timely intervention subject to controlled false-positive, complaint, and exclusion rates [14].

Consent-gated monitoring architecture

Consent-Gated Early-Warning Cycle for Open Banking Credit Monitoring

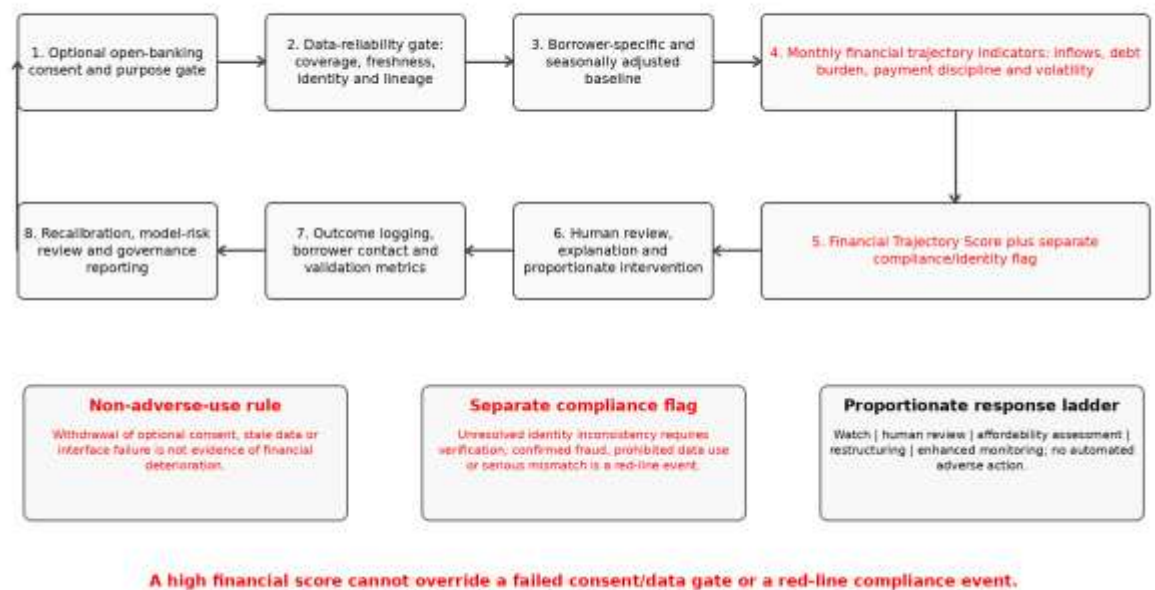


Figure 1. Consent-gated early-warning cycle for open banking credit monitoring.
Source: developed by the author.

Figure 1 frames monitoring as a closed governance cycle. Optional consent and data reliability are checked before current behavior is compared with the borrower-specific baseline. The financial score and separate CIF produce a management recommendation, but a trained human reviewer determines the intervention and records the rationale. Cures, false positives, complaints, restructuring outcomes, defaults, and gate failures feed back into threshold calibration and model-risk validation [15].

4. Discussion

The framework extends digital creditworthiness assessment from origination to trajectory governance. Alternative and transactional data can improve prediction and access [16], but predictive improvement does not resolve fairness, explanation, or data-rights questions [17]. A post-disbursement system repeatedly observes and reinterprets the borrower; lawful purpose, data quality, and human review therefore become recurring controls rather than one-time onboarding formalities.

The non-adverse-use rule is the principal conceptual contribution. Withdrawal of optional open banking consent or failure of an external provider means that the bank loses a particular evidence stream; it does not gain evidence of deterioration. The bank may continue to use internal and other lawfully available information for contractual, prudential, anti-fraud, and regulatory purposes. What is prohibited by the framework is the automatic conversion of missing optional data into a higher-risk score or adverse treatment.

The approach is compatible with risk-data governance. Basel principles emphasize accuracy, completeness, timeliness, adaptability, and traceability [18]. Uzbekistan's legal framework allocates complementary responsibilities across personal-data protection, credit-information exchange, bank secrecy, banking activity, and payment systems [19]. The Chief Data Officer function under PP-359 can define ownership, quality thresholds, reconciliation, and escalation; risk management calibrates the FTS; compliance verifies lawful processing; internal audit examines adherence; and independent model validation evaluates discrimination, stability, and performance [20].

The framework does not assume that more data always improve decisions. High-frequency transaction data may be noisy, seasonal, or affected by account switching. Digital traces can disadvantage cash-intensive households and small firms. The 12-month baseline, three-month comparison window, and transformations in Table 2 are pilot defaults rather than universal parameters. Borrowers must have protected channels to correct inaccurate data and explain exceptional cash-flow patterns [21].

A second contribution is the separation of alerting from adverse action and the separation of financial trajectory from compliance status. The FTS is an information and workflow instrument. CIF=1 initiates verification; CIF=2 or another red line requires escalation. Neither the score nor the flag independently changes pricing, limits, or collection treatment without a documented human decision and applicable contractual and legal safeguards [22].

Implementation should begin with salary-linked consumer loans, merchant-account microbusiness loans, and revolving facilities. A validation pilot should observe at least 12 months of performance and include either 5,000 exposures per major product or enough accounts to record at least 200 deterioration events [23]. Reporting should cover sensitivity, specificity, precision, recall, false-positive rates, calibration, temporal and regional stability, Population Stability Index, subgroup disparities, gate-failure frequency, overrides, complaints, cures, successful restructurings, and cases in which a gate prevented automated adverse action. Validation must be independent from model development [24].

The system-level statistics provide context rather than causal proof. Credit growth, remote-banking registration growth, and the NPL trajectory do not demonstrate that open banking monitoring reduces defaults. In addition, remote-banking counts are customer registrations across banks and may include the same person more than once [25]. Causal evaluation requires a bank-level pilot, a comparison design, a sufficiently long outcome window, and safeguards against selection bias [26].

Several limitations remain. The weights, transformations, 80% baseline data threshold, and FTS bands are provisional. The case is synthetic, and aggregate banking indicators cannot validate account-level performance [27]. The categorical CIF requires separate governance and should not be interpreted as a continuous measure of financial risk. Future research should test whether the gates reduce false positives, whether FTS predicts transitions into arrears, and whether early intervention improves both borrower and bank outcomes [28, 29].

5. Conclusion

This study developed a consent-gated early-warning framework for open banking credit monitoring in Uzbekistan. The framework first verifies optional external-data authorization and minimum data reliability. It then calculates a four-domain Financial Trajectory Score from recurring inflows, debt-service burden, payment discipline, and cash-flow volatility, while compliance and identity events remain a separate categorical flag.

The synthetic application produces an FTS of 53.25 and remains in the provisional review band under alternative weights ranging from 50.00 to 59.75. CIF=1 requires verification but is not averaged into financial deterioration. A stricter coverage or freshness condition can fail the data gate and route the case to manual review. Optional-consent withdrawal, stale data, or an interrupted interface cannot be treated automatically as evidence of borrower deterioration.

For Uzbekistan, the framework can support implementation of open banking, Chief Data Officer functions, and RegTech reporting under PP-359. Banks should pilot the method, recalibrate transformations and thresholds against observed outcomes, publish internal documentation for explanations and overrides, and connect alerts with proportionate borrower-contact and restructuring procedures. Institutional acceptance should depend on predictive value, controlled false positives, lawful data governance, subgroup fairness, and effective human review.

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