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End-To-End Automation: Impact of Programmable Credit Decisions on SME Cash Conversion Cycles

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Abstract: ***This paper examines the impact of end-to-end automation-where AI underwriting is integrated with smart-contract-based settlement- on the cash conversion cycles of small and medium enterprises (SMEs). Through a conceptual framework and a field-experiment design with a supply-chain finance (SCF) provider, the study quantifies the effects of programmable credit decisions and automated settlement on time-to-cash, days-sales-outstanding (DSO), days-payable-outstanding (DPO), inventory days, reconciliation effort, error rates and counterparty disputes. The findings are expected to shed light on whether AI+ smart- contract automation materially shortens the cash conversion cycle (CCC), reduces operational frictions and lowers error/risk rates, and how these effects vary by firm characteristics and supply-chain complexity. The paper also discusses governance, data-privacy and fairness considerations for deploying automated credit decisions in SCF workflows.***

Keywords: programmable credit, smart contracts, supply-chain finance, AI underwriting, cash conversion cycle, SME financing, time-to-cash, reconciliation, field experiment

1. Introduction

Small and medium enterprises (SMEs) frequently face working-capital constraints stemming from slow receivables, tight supplier terms, and costly reconciliation processes. Supply-chain finance (SCF) fintech platforms have emerged to provide invoice financing, dynamic discounting and other cash-flow solutions, but many processes remain semi-manual: underwriting decisions, invoice validation, settlement, and reconciliation often involve human intervention and asynchronous bank rails. The convergence of two technologies—AI for credit underwriting and programmable settlement via smart contracts—promises to create end-to-end automated workflows. Such automation could instantaneously underwrite eligible invoices, trigger conditional payments on delivery confirmations, and settle funds to suppliers with minimal manual reconciliation, potentially reducing the cash conversion cycle and operational errors.

This paper asks: What is the causal impact of integrating AI underwriting with smart-contract settlement on SME cash conversion cycles? How does automation affect time-to-cash, reconciliation burden, dispute frequency, and perceived trust? What governance, fairness and operational risks arise from this automation? To answer these questions, the paper proposes a field-experiment design (pilot) in collaboration with an SCF provider and outlines measurement, analytical methods and interpretative frameworks.

2. Literature Review

a) **AI in credit underwriting:** Advances in machine learning and alternative data have enabled lenders to assess creditworthiness faster and for thin-file borrowers. Studies on AI credit scoring emphasise predictive gains and scalability, while noting concerns about explainability, bias and model governance.
b) **Smart contracts and programmable settlement:** Smart contracts- self-executing code that enforces agreements on distributed ledgers or interoperable platforms—enable conditional, automatic settlement once predefined triggers are satisfied (e.g., delivery confirmation, invoice approval). Literature on smart contracts highlights potential efficiency and automation benefits as well as challenges around oracle reliability, legal enforceability and interoperability.
c) **Supply-chain finance and SME working capital:** Empirical work on SCF shows improvements in supplier liquidity and occasionally in buyer working-capital metrics. However, operational frictions (manual verification, delays in payment runs, mismatched invoice data) moderate these gains. Combining AI underwriting with programmable settlement is relatively under-explored empirically; existing studies tend to analyse isolated pieces (AI scoring or invoice tokenisation) rather than end-to-end pilots measuring SME CCC impacts.
d) **Gaps addressed:** Few studies provide causal evidence from field experiments evaluating the joint effect of AI underwriting and smart-contract settlement on SME liquidity and operational metrics. This paper fills that gap by proposing a rigorous experimental design and a comprehensive set of outcome measures.

3. Conceptual Framework

The hypothesised causal pathway is:

AI underwriting + smart contracts → faster eligibility decision + conditional automation → immediate settlement upon verification → reduced time-to-cash and reconciliation effort → shortened CCC (lower DSO, potentially lower inventory days) and lower operational error rates.

Mediators and moderators include: quality and timeliness of data inputs (ERP, e-invoicing, delivery confirmations), reliability of oracles (for real-world event verification), SME digital maturity, supply-chain complexity (number of tiers), platform trust and buyer participation, and regulatory environment.

Hypotheses

Primary hypotheses:
H1: SMEs participating in AI-underwritten + smart-contracted SCF experience a statistically significant reduction

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in time-to-cash compared to SMEs on a standard SCF workflow (human underwriting + manual settlement).

H2: End-to-end automation reduces reconciliation time per invoice and lowers error/dispute rates relative to control.

H3: The effect size on CCC is larger for digitally mature SMEs (with clean ERP/e-invoicing) and for supplier invoices with standardized data formats.

Secondary hypotheses:

H4: Automated decisions increase the proportion of invoices accepted for financing (approval rate), conditional on model thresholds designed to keep portfolio risk constant.

H5: There is a measurable improvement in supplier satisfaction and perceived predictability of cash flows under automation.

Research design and methods

Field experiment/pilot overview

Partner with an SCF fintech that offers invoice financing to suppliers of several medium-to-large corporate buyers. The platform must be capable of: (a) running an AI underwriting model (trained on historical repayments, transaction and alternative data) to score invoices in real time, (b) deploying smart contract templates that automatically execute settlement when predefined conditions are confirmed, and (c) logging detailed operational metrics (timestamps, error messages, manual interventions).

Population and sampling: Enrol a sample of supplier SMEs (N target: 600–1000 invoices per arm across several supplier firms) whose buyers consent to participate. Randomly assign invoices (or suppliers) to treatment and control arms at invoice level (preferred) or supplier level if operational constraints require blocking.

Treatment arms:

- Treatment A (Full automation): AI underwriting + smart contract settlement. Eligibility decisions are made automatically; once invoice and delivery confirmation (via certified oracle or integrated ERP event) are matched, the smart contract triggers settlement to the supplier's wallet/bank account.
- Control (Standard workflow): Human-review underwriting (or existing automated scoring with human override) + manual settlement processes (bank payment runs, manual reconciliation).

Optional intermediate arm:

- Treatment B (AI underwriting only): AI decisioning but manual settlement, to isolate underwriting vs settlement effects.

Randomisation: Stratify randomisation by supplier size, industry, and historical invoice volume to ensure balance.

Duration: 6–12 months to capture sufficient invoice flows and observe short-term CCC changes and dispute cycles.

Outcome measures

Primary outcomes:

- Time-to-cash (hours/days from invoice issuance to funded receipt by supplier).
- Cash conversion cycle components: DSO (accounts receivable days), inventory days (if data available), and DPO (if buyer behaviour changes).
- Reconciliation time: person-hours per invoice required to reconcile and clear payment.
- Error/dispute rate: percentage of invoices with mismatches, disputes or failed settlements.

Secondary outcomes:

- Approval rate for financing (percentage of invoices offered financing).
- Effective financing cost (discount rates or fees charged).
- Supplier satisfaction and perceived predictability (survey measures).
- Operational cost per financed invoice for platform (to assess scalability).

Data sources and measurement procedures

- Platform logs: timestamps for invoice submission, underwriting decision, verification events, smart contract execution, settlement confirmation.
- ERP/invoicing data: invoice metadata, PO matching, delivery confirmations.
- Receipts: Bank/wallet settlement confirmations to verify receipt.
- Manual logs: record of interventions, exceptions, and reconciliation steps.
- Surveys: short supplier questionnaires on satisfaction and perceived time to cash.
- Risk/performance: default or repurchase events, repayment performance for financed invoices.

Identification and estimation

Intent-to-treat (ITT) analysis comparing mean outcomes across arms. If compliance issues occur (e.g., failures in automated oracle or manual overrides), instrumental variables (IV) using assignment as instrument for actual automated settlement can estimate complier average causal effects.

a) Statistical tests: difference-in-means with clustering at supplier level, regression adjustment with covariates (supplier size, industry, seasonality). Survival analysis (time-to-cash as a duration outcome) can model time dynamics and censoring. Heterogeneity analysis by digital maturity and invoice standardisation is recommended.
b) Power calculations: prior to fieldwork, simulate expected reductions in time-to-cash (e.g., from median 7 days to 1–2 days) to compute required sample sizes; even moderate reductions yield high economic significance.

Operational and technical implementation considerations

AI underwriting model considerations

Model development should prioritise predictive performance, fairness, and explainability. Use diverse data sources (historical repayment, buyer creditworthiness, invoice metadata, ERP transactional patterns). Implement thresholds aligned with platform risk appetite. Maintain human-in-the-loop governance for edge cases.

Smart contract and oracle reliability

Smart contract templates should be auditable and legally reviewed. Oracles that feed real-world events (delivery confirmations, inventory scans, customs entries) must be robust and tamper-resistant. Where possible, integrate with buyer ERP systems or certified logistics providers to reduce oracle risk. Fallback mechanisms for oracle failure (grace period, human adjudication) must be defined.

Settlement rails and liquidity management
Decide settlement mechanics: push payment from platform trustee account to supplier bank vs on-chain wallet transfers convertible to bank. Ensure AML/KYC compliance and alignment with bank partners' liquidity operations.

Governance, audit trails and dispute resolution
Maintain immutable audit trails for decisions and settlements. Create clear dispute resolution workflows and SLA commitments. Record model explanations and decision-rationale snippets for supplier transparency.

Risk, ethics and regulatory considerations
- Explainability and fairness: Provide suppliers with human-readable reasons for approvals/rejections and monitor for demographic or structural biases.
- Data privacy and consent: Ensure suppliers consent to use of ERP, transaction and alternative data; comply with data protection laws.
- Legal enforceability: Verify that smart-contracted conditional settlements are legally enforceable in relevant jurisdictions.
- Operational risk: Prepare contingency plans for oracle failures, cyber incidents or settlement delays.
- Systemic considerations: Monitor for potential concentration risk if many suppliers become dependent on a single platform.

Expected contributions and practical implications
This study offers empirical evidence on whether combining AI underwriting with programmable settlement materially shortens SME time-to-cash and reduces reconciliation costs. Practical implications include:
- For SCF providers: evidence to justify investments in automation, or to identify where hybrid approaches (AI underwriting + manual checks) are preferable.
- For SMEs: insights on which digital practices (standardised invoicing, ERP integration) amplify benefits.
- For corporates/buyers: understanding of how buyer participation (providing delivery confirmations and ERP connectivity) increases supplier liquidity.
- For regulators: clarity on necessary governance and consumer protection measures when credit decisions and settlement are automated.

4. Limitations and Robustness Checks

Limitations include external validity (pilot results may depend on platform features, buyer cooperation and country legal frameworks), short-run focus (long-term effects on credit pricing and buyer behaviour may diverge), and potential Hawthorne effects (participants change behaviour because they are in a study). Robustness checks: replicate across industries and geographies, conduct placebo tests (simulate automation logs without live settlement), and re-estimate effects excluding invoices subject to manual override.

5. Conclusion

End-to-end automation that couples AI underwriting with smart-contract settlement has the potential to significantly reduce SME time-to-cash and operational friction in supply-chain finance. A carefully designed field experiment—attentive to model governance, oracle reliability and legal enforceability—can provide causal evidence on these effects and guide fintech providers, corporates and policymakers on best practices for implementing programmable credit decisions.

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