

Midocean University

Master of Financial Technology

Research Title:

How Artificial Intelligence is reshaping Global Trade and Receivables Finance within the Banking Sector.

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Introduction

Artificial Intelligence (AI) is rapidly becoming a foundational capability in modern banking, shifting from a set of experimental tools to an enterprise-wide engine for decision-making, automation, and risk management. Within Global Trade and Receivables Finance (GTRF) - a domain defined by high document intensity, multi-party workflows, cross-border regulatory complexity, and time-sensitive liquidity needs - AI is reshaping how banks originate, underwrite, monitor, and service trade-related financing. As global supply chains become more dynamic and exposed to geopolitical, climate, and macroeconomic shocks, banks are under pressure to deliver faster credit decisions, stronger financial crime controls, and more transparent client experiences, while maintaining prudent risk governance. AI-enabled capabilities such as Machine Learning (ML), Natural Language Processing (NLP), and Intelligent Document Processing (IDP) are increasingly used to extract and validate data from trade documents, detect anomalies and fraud patterns, forecast receivables performance, and support real-time monitoring of counterparties and shipments.

This research examines how AI is transforming GTRF across the banking sector, focusing on both the operational and strategic implications. It considers AI's role in improving efficiency and accuracy in document checking and exception handling, enhancing credit and portfolio risk assessment for receivables and trade assets, strengthening compliance screening and transaction monitoring, and enabling more responsive client servicing through digital channels. At the same time, it recognises that AI adoption in trade finance is not purely a technology upgrade; it is a change in operating model that raises questions about data quality, model risk management, explainability, accountability, and alignment with regulatory expectations - particularly in cross-border contexts where legal frameworks, documentation standards, and supervisory approaches vary.

At the global level, the importance of this topic is driven by the scale and systemic relevance of trade. Trade finance supports the movement of goods and services across borders and underpins working capital for corporates, especially Small and Medium Enterprises (SMEs). Yet the industry continues to face persistent challenges: manual processes, fragmented data, high operational costs, and a well-documented trade finance gap. AI has the potential to reduce friction in trade workflows, improve risk visibility, and accelerate access to financing by enabling faster, more consistent decisions and by lowering the cost-to-serve.

In parallel, global regulators and standard-setting bodies are increasing expectations around financial crime prevention, sanctions compliance, and operational resilience - areas where AI can strengthen detection and monitoring when deployed responsibly.

At the local level, the relevance is equally strong because banks operate within specific market realities: varying levels of digitisation among corporates, differences in trade corridors and sector exposures, local regulatory requirements, and constraints in data availability and infrastructure. In many markets,

trade and receivables finance is a critical lever for supporting national economic priorities such as export growth, supply chain resilience, and SME development. Understanding how AI can be implemented in a way that fits local operating conditions - while still meeting global governance standards - has direct implications for competitiveness, risk outcomes, and customer experience.

Despite growing interest in AI in financial services, the literature and industry discourse often treat AI adoption at a high level (e.g. “AI in banking”) or focus on adjacent areas such as retail credit scoring and customer analytics. In contrast, GTRF presents distinct characteristics - document-heavy processes, multi-party verification, legal enforceability of trade instruments, and complex fraud typologies - that make AI deployment both promising and challenging. A key gap lies in the limited availability of holistic, end-to-end analyses that connect:

1. Use cases (document intelligence, risk scoring, anomaly detection, forecasting, client servicing),
2. Value outcomes (speed, cost, risk reduction, compliance effectiveness, client experience),
3. Constraints and governance (data readiness, explainability, model risk, regulatory alignment, operational controls),
4. Implementation realities (integration with legacy platforms, workflow redesign, human-in-the-loop operating models).

This research addresses that gap by providing an integrated view of AI’s impact on GTRF, balancing technological capability with banking governance and operational feasibility.

To provide a holistic view, the research will typically cover the following themes:

- Conceptual foundations: Definitions and boundaries of GTRF (trade finance, receivables finance, supply chain finance) and the AI techniques most relevant to these products.
- Process transformation: How AI changes key stages of the trade lifecycle - onboarding, document checking, underwriting, disbursement, monitoring, collections, and dispute/exception handling.
- Risk and compliance enhancement: AI’s role in credit risk assessment for receivables and trade assets, early warning indicators, fraud detection, sanctions/Anti-Money Laundering (AML) screening, and transaction monitoring - along with limitations and false-positive/false-negative trade-offs.

- Data and technology architecture: Data sources (documents, transaction data, logistics signals, external data), data quality challenges, interoperability, and integration with core trade platforms and workflow tools.
- Governance and ethics: Model risk management, explainability, auditability, accountability, privacy, and operational resilience - especially in cross-border environments.
- Business impact and measurement: How banks can quantify benefits (turnaround time, straight-through processing rates, operational loss reduction, portfolio performance, compliance effectiveness, customer satisfaction).
- Future outlook: Emerging trends such as AI-assisted digital trade documentation, tokenisation and digital assets in trade, and the convergence of AI with distributed ledger and Application Programming Interface (API) ecosystems.

Overall, this research positions AI as a transformative force in GTRF - capable of improving speed, transparency, and risk control - while also requiring disciplined governance and careful alignment with regulatory and operational realities. By examining AI's applications, benefits, and constraints in an integrated manner, the study aims to contribute practical and academic insight into how banks can adopt AI responsibly to strengthen trade finance capabilities and better support real-economy trade flows.

Research Problem

GTRF is central to banks' support of cross-border commerce and working-capital liquidity, yet it remains characterised by document-intensive processing, fragmented data across multiple parties, and high operational friction. These conditions contribute to slower turnaround times, higher cost-to-serve, and persistent information asymmetries that constrain credit availability - particularly for SMEs. Although AI is increasingly promoted as a means to automate document checking, enhance risk detection, and improve credit decisioning, many banks struggle to move beyond isolated pilots to scaled, end-to-end adoption in GTRF. Key barriers include inconsistent data quality, integration with legacy trade platforms, and governance requirements for explainability, auditability, and model risk management in regulated environments. The research problem, therefore, is to determine how banks can deploy AI in GTRF in a way that delivers measurable improvements in efficiency, risk and compliance outcomes, and customer experience, while remaining operationally feasible and aligned with regulatory expectations - thereby closing the gap between current manual, fragmented practices and a controlled, scalable AI-enabled operating model.

There is a persistent question regarding the topic of this research: How can banks implement AI in Global Trade and Receivables Finance to improve processing efficiency, risk/compliance effectiveness, and decision quality, while meeting governance and regulatory requirements for transparency and control?

Furthermore, there are a few questions include:

- Which GTRF processes (e.g. onboarding, document checking, exception handling, monitoring, collections) generate the highest friction and cost, and where can AI deliver the greatest measurable improvement (e.g. turnaround time, straight-through processing, error rates)?
- What operational and technology constraints (workflow design, legacy platforms, data fragmentation) most commonly prevent AI solutions from scaling beyond proof-of-concept?
- How can AI improve receivables and trade-asset risk assessment (e.g. obligor behaviour, dilution risk, concentration risk, early warning indicators) compared with traditional approaches?
- What data inputs (transactional, document-derived, external/third-party) are necessary for reliable AI-driven decisioning in GTRF, and what minimum data quality standards are required?
- To what extent can AI enhance detection of anomalies and trade-based fraud typologies while controlling false positives and operational workload?
- How can AI be used to strengthen sanctions/AML screening and transaction monitoring in trade flows without creating opaque "black-box" decisions that are difficult to justify to regulators and auditors?

- What governance model (human-in-the-loop controls, model risk management, validation, monitoring, audit trails) is required to make AI use in GTRF defensible and compliant across jurisdictions?
- What Key Performance Indicators (KPIs) and benefit-realisation framework best demonstrate AI value in GTRF (e.g. time-to-cash, operational loss reduction, compliance effectiveness, client experience), and how should banks measure them?

The problem is evidenced by persistent structural frictions in trade finance and by the operational and risk realities of document-heavy, cross-border banking. First, access constraints remain material: the Asian Development Bank estimates the global trade finance gap at approximately USD 2.5 trillion, indicating that many firms - especially SMEs - are unable to obtain sufficient trade-related financing, often due to risk constraints and information asymmetry (Asian Development Bank, 2022) *.

Second, trade finance continues to be operationally complex and reliant on documentation and manual controls; industry surveys and reports by the International Chamber of Commerce (ICC) repeatedly highlight the sector's dependence on document checking and the resulting inefficiencies and delays, reinforcing the need for automation and better data extraction/validation (ICC, various reports) *.

Third, cross-border finance is exposed to significant illicit finance risk; the United Nations Office on Drugs and Crime (UNODC) estimates that money laundering represents 2–5% of the Global Domestic Production (GDP), underscoring the scale of financial crime risk that intersects with international trade flows and the need for stronger detection and monitoring capabilities (UNODC)*.

Finally, even where AI could address these challenges, banks must operate within strict governance expectations for model risk management, explainability, and control, as reflected in supervisory principles and guidance for model risk and the management of advanced analytics in financial institutions (e.g. Basel Committee on Banking Supervision (BCBS) principles and related supervisory expectations) *.

Together, these factors demonstrate a clear gap between the current state - manual, fragmented, and costly GTRF operations with persistent risk and access constraints - and the proposed AI-enabled scenario of faster, more accurate, and better-controlled decisioning and monitoring at scale.

Significance of the Study

This study is significant because it addresses a timely transformation in banking: the application of AI to GTRF, an area that remains operationally complex, document-intensive, and exposed to cross-border risk and compliance pressures. While AI adoption in banking has accelerated, GTRF presents distinct characteristics - multi-party documentation, legal enforceability requirements, and heterogeneous data sources - that make the translation of AI capability into scalable business value both promising and challenging. By examining AI's role across the end-to-end GTRF lifecycle, the study contributes to a clearer understanding of how banks can modernise trade and receivables finance without compromising governance, transparency, or regulatory alignment.

At the theoretical level, the study contributes to the emerging body of knowledge on AI-enabled financial intermediation by extending analysis beyond retail and capital markets contexts into trade and receivables finance. It clarifies how AI techniques (e.g. machine learning, natural language processing, intelligent document processing, and anomaly detection) interact with the specific operational and risk structures of GTRF, and it helps frame the conditions under which AI can improve decision quality, reduce information asymmetry, and enhance monitoring in cross-border finance.

At the practical (industry) level, the study is valuable for banks seeking to improve turnaround time, reduce cost-to-serve, and strengthen risk and compliance outcomes in GTRF. It supports decision-makers by identifying high-impact use cases, implementation prerequisites (data readiness, integration, operating model design), and measurable performance indicators. The findings can inform prioritisation of AI investments, design of human-in-the-loop controls, and development of governance frameworks that satisfy internal audit and supervisory expectations.

At the policy and regulatory level, the study is significant because it addresses the tension between innovation and control in regulated financial services. By focusing on explainability, accountability, model risk management, and cross-border compliance considerations, the research can support more informed dialogue between banks and regulators on responsible AI adoption in trade-related finance, including how to evidence control effectiveness and manage model-driven decisioning.

At the economic and societal level, improving the efficiency and risk management of GTRF has implications for real-economy outcomes. Trade and receivables finance underpin working capital and liquidity for corporates and SMEs; therefore, more efficient and better-controlled financing processes can contribute to supply chain resilience, improved access to finance, and smoother trade flows - particularly in markets where documentation frictions and risk constraints disproportionately affect smaller firms.

Objectives of the Study

The **General Objective** of this Study is to investigate how AI is reshaping GTRF within the banking sector and to develop evidence-based recommendations for scalable, well-governed AI adoption that improves operational efficiency, risk management, and compliance outcomes.

To quantify the relationship between AI-enabled capabilities (e.g. intelligent document processing, ML-based risk scoring, anomaly detection) and key GTRF performance outcomes such as:

- Turnaround Time (TAT),
- Straight-Through Processing (STP) rate,
- exception rate and rework volume,
- error/defect rates in document checking,
- cost-to-serve proxies (e.g. Full Time Equivalent (FTE) effort per case),
- fraud/financial crime alert quality (e.g. precision/false-positive rate where available).

To assess statistically whether AI adoption maturity (e.g. pilot vs partial scale vs scaled deployment) is associated with improved operational and risk/compliance KPIs across products (trade finance vs receivables finance) and client segments (e.g. SMEs vs large corporates).

To test the extent to which data readiness factors (data quality, availability, standardisation, digitisation level of documents) predict AI performance and value realisation in GTRF.

Research Questions

How can banks implement AI in GTRF to improve processing efficiency, risk/compliance effectiveness, and decision quality, while meeting governance and regulatory requirements for transparency and control?

Banks can implement AI in GTRF effectively by adopting an end-to-end, control-by-design approach that combines (i) targeted AI use cases embedded into trade workflows, (ii) strong data foundations, and (iii) robust model governance aligned with regulatory expectations. Practically, this means prioritising AI where it reduces manual document friction (e.g. intelligent document processing), improves risk signal quality (e.g. predictive monitoring and anomaly detection), and strengthens compliance controls (e.g. entity resolution and alert prioritisation), while ensuring explainability, auditability, and human accountability through human-in-the-loop decision points, model validation, continuous monitoring, and documented control evidence. The defensible implementation pathway is typically incremental: start with augmentation (decision support and automation of low-risk tasks), then progress to partial automation under defined thresholds, and only then consider higher-impact decisioning where governance maturity and data quality are demonstrably sufficient.

Which GTRF processes generate the highest friction and cost, and where can AI deliver the greatest measurable improvement?

The highest friction and cost in GTRF typically arise in document-heavy and exception-driven stages, particularly: (1) onboarding/Know Your Customer (KYC) refresh where data is incomplete or inconsistent; (2) document checking (Letters of Credit (LCs), invoices, transport documents) due to unstructured formats and discrepancy handling; and (3) exception management and investigations, where manual triage dominates cycle time. AI can deliver the greatest measurable improvement in:

- Intelligent Document Processing (IDP): extracting, classifying, and validating fields; reducing rework and discrepancy cycle time.
- Exception prediction and routing: prioritising cases likely to breach Service Level Agreements (SLAs) or contain risk signals.
- Client servicing automation: reducing operational touchpoints through guided workflows and automated status updates. Improvements are most credibly measured through TAT reduction, increased STP, lower exception rates, and reduced manual effort per case.

What operational and technology constraints most commonly prevent AI solutions from scaling beyond proof-of-concept?

AI scale-up in GTRF is most commonly constrained by four interrelated factors:

1. Data fragmentation and weak data lineage: trade data is distributed across product systems, email-based workflows, document repositories, and external parties, limiting training and monitoring reliability.
2. Legacy platform integration constraints: AI outputs are not embedded into core workflow tools, resulting in “sidecar” solutions (secondary helper pattern) that do not change operational throughput.
3. Process variability and non-standard documentation: inconsistent document templates, corridor-specific practices, and product variations reduce model generalisability.
4. Governance and accountability gaps: unclear ownership, insufficient model risk controls, and limited explainability prevent approval for production use. Therefore, scaling requires not only better models but also workflow redesign, data standardisation, and operational adoption (training, roles, and controls).

How can AI improve receivables and trade-asset risk assessment compared with traditional approaches?

AI can improve receivables and trade-asset risk assessment by moving from static, periodic assessment toward continuous, signal-rich monitoring. Compared with traditional approaches (rule-based checks, manual reviews, and backward-looking financial ratios), AI can:

- Integrate multi-source signals (payment behaviour, invoice attributes, dispute patterns, concentration trends, macro/sector indicators).
- Detect non-linear relationships and interaction effects (e.g. combinations of obligor behaviour and invoice anomalies).
- Produce early warning indicators for deterioration (e.g. rising dilution, abnormal credit note frequency, shifting debtor concentration).
- Support segmented risk strategies (differentiated limits, pricing, and monitoring intensity). However, the improvement is contingent on data quality and on governance that ensures models are stable, explainable, and monitored for drift.

What data inputs are necessary for reliable AI-driven decisioning in GTRF, and what minimum data quality standards are required?

Reliable AI-driven decisioning in GTRF requires a combination of:

- Transactional data: facility utilisation, payment history, tenor, delinquency, collections outcomes, limit changes.
- Document-derived data: invoice fields, shipping details, LC terms, discrepancies, amendments, and exception codes extracted via IDP/NLP.
- Counterparty and network data: buyer/supplier identifiers, beneficial ownership signals (where permissible), relationship hierarchies, concentration metrics.
- External/third-party data: sanctions/Politically Exposed Person (PEP) lists, adverse media, corporate registries, trade/shipping signals (where available), macro/sector indicators. Minimum data quality standards typically include: completeness (critical fields populated), accuracy (validated against source documents), consistency (standard definitions across systems), timeliness (near-real-time for monitoring use cases), and traceability/lineage (ability to evidence where each feature came from). Without lineage and consistent definitions, explainability and auditability are weakened.

To what extent can AI enhance detection of anomalies and trade-based fraud typologies while controlling false positives and operational workload?

AI can enhance anomaly and fraud detection meaningfully when it is used to prioritise risk rather than simply generate more alerts. In GTRF, effective approaches often combine:

- Supervised learning (where labelled cases exist) for known typologies,
- Unsupervised/semi-supervised methods for novel patterns and outliers,
- Graph/network analytics to identify suspicious relationships and circular trading patterns,
- Rules + AI hybrid models to preserve interpretability and regulatory comfort. False positives and workload are controlled through risk-based alert scoring, threshold calibration, and human-in-the-loop triage, supported by feedback loops that retrain models using investigation outcomes. The practical extent of improvement depends on the availability of labelled outcomes, the quality of entity resolution, and the bank's ability to embed AI into investigation workflows.

How can AI strengthen sanctions/AML screening and transaction monitoring in trade flows without creating opaque “black-box” decisions?

AI can strengthen sanctions/AML screening and monitoring without “black-box” opacity by adopting explainable-by-design methods and layered controls:

- Use AI for entity resolution, name/address disambiguation, and alert prioritisation, while retaining deterministic rules for hard regulatory constraints.
- Prefer interpretable models (or post-hoc explainability) that provide reason codes (e.g. key features driving risk score).
- Maintain audit trails: input data, model version, thresholds, decision rationale, and reviewer actions.
- Implement human decision accountability for high-risk outcomes (e.g., blocking, exiting, filing). This approach positions AI as a tool to improve signal quality and reduce noise, while ensuring decisions remain defensible to regulators and auditors.

What governance model is required to make AI use in GTRF defensible and compliant across jurisdictions?

A defensible governance model for AI in GTRF requires a structured framework covering:

1. Clear accountability: defined model owner, business owner, and independent validation roles.
2. Model risk management: documented purpose, limitations, validation testing, stress testing, and approval gates.
3. Explainability and documentation: model cards, feature rationale, decision logs, and user guidance.
4. Human-in-the-loop controls: defined escalation thresholds, override rules, and segregation of duties.
5. Ongoing monitoring: drift detection, performance tracking, bias/fairness checks where relevant, and periodic recalibration.
6. Cross-jurisdiction compliance mapping: ensuring data use, privacy, retention, and decisioning practices align with local regulatory requirements. In practice, banks often need a tiered governance approach: stricter controls for models that influence credit decisions or compliance outcomes, and lighter controls for low-risk automation (e.g., document classification).

What KPIs and benefit-realisation framework best demonstrate AI value in GTRF, and how should banks measure them?

AI value in GTRF is best demonstrated through a balanced KPI set across operations, risk, compliance, and client outcomes, measured using a benefit-realisation framework that compares baseline vs post-implementation performance and controls for volume/mix changes. Recommended KPIs include:

Operational efficiency

- TAT (end-to-end and by stage)
- STP rate
- Exception/discrepancy rate
- Rework rate and manual touches per case
- Cost-to-serve proxies (FTE hours per transaction/case)

Risk and portfolio

- Early warning lead time (time from signal to action)
- Loss rates / operational loss events linked to documentation or fraud (where measurable)
- Concentration and dilution trend detection effectiveness Compliance effectiveness
- Alert precision/false-positive rate
- Time-to-disposition for alerts/cases
- Quality assurance outcomes (e.g., error rates in screening decisions)
- Audit findings related to process control effectiveness Client experience
- SLA adherence
- Client query volumes and resolution time
- Drop-off rates in onboarding/document submission
- Net promoter or satisfaction measures (if available)

A robust benefit-realisation approach typically includes: (i) a KPI dictionary and data lineage, (ii) pre/post analysis with control groups where feasible, (iii) operational adoption metrics (usage, override rates), and (iv) governance metrics (model stability, drift, validation outcomes).

Study Hypotheses

Banks' adoption of AI in GTRF is positively associated with improved operational performance, risk management effectiveness, and compliance outcomes, provided that appropriate governance and data readiness conditions are in place.

Operational Efficiency:

H0₁: AI adoption in GTRF has no statistically significant association with operational efficiency outcomes (e.g. TAT, STP rate, exception/rework rate).

H1₁: Higher AI adoption in GTRF is associated with statistically significant improvements in operational efficiency outcomes (i.e., lower TAT, higher STP rate, and/or lower exception/rework rate).

Risk / Credit Decision Quality:

H0₂: AI adoption in GTRF has no statistically significant association with risk/credit decision quality outcomes (e.g. early-warning capability, risk differentiation, portfolio performance proxies).

H1₂: Higher AI adoption in GTRF is associated with statistically significant improvements in risk/credit decision quality outcomes (e.g. improved early-warning capability, stronger risk differentiation, and/or improved portfolio performance proxies).

Compliance Effectiveness:

H0₃: AI adoption in GTRF has no statistically significant association with compliance effectiveness outcomes (e.g. false-positive alert rate, alert disposition time, control effectiveness proxies).

H1₃: Higher AI adoption in GTRF is associated with statistically significant improvements in compliance effectiveness outcomes (e.g. reduced false-positive alert rate, reduced alert disposition time, and/or improved control effectiveness proxies).

Moderation by Governance and Data Readiness:

H0₄: Governance strength and data readiness do not significantly moderate the relationship between AI adoption in GTRF and outcomes (efficiency, risk, compliance).

H1₄: Governance strength and/or data readiness significantly moderate the relationship between AI adoption in GTRF and outcomes, such that the positive association between AI adoption and outcomes is stronger when governance strength and data readiness are higher.

Previous Studies

*- In a survey done by Chandola, V., Banerjee, A., & Kumar, V. (2009). Titled: Anomaly detection: A survey. *Ref: ACM Computing Surveys, 41(3)*.

Study objective: Survey anomaly detection techniques and evaluation issues.

Methodology: Literature survey (method taxonomy + evaluation discussion).

Key outcomes (most relevant): Shows trade-offs between sensitivity and false positives; highlights dependence on data characteristics and labels.

Analytical criticism / limitations: Domain-agnostic; does not address banking governance, explainability, or trade-document complexity – which is covered in this research.

Relation: Supports the technical rationale for anomaly detection in GTRF (fraud, unusual behaviour) and frames the false-positive/workload challenge.

*- Another survey done by Akoglu, L., Tong, H., & Koutra, D. (2015). Titled: Graph based anomaly detection and description: A survey. *Data Mining and Knowledge Discovery, 29(3)*, 626–688.

Study objective: Survey graph-based anomaly detection methods.

Methodology: Literature survey (graph anomaly methods + problem formulations).

Key outcomes (most relevant): Demonstrates value of relationship/network modelling for detecting complex anomalies.

Analytical criticism / limitations: Implementation challenges not addressed (entity resolution, privacy, governance); not trade-finance-specific – then this research utilises its outcome into a trade finance related perspective.

Relation: Highly relevant to GTRF's multi-party networks (buyers/suppliers/shippers), enabling detection of collusion/circular trading patterns.

*- In a review done by LeCun, Y., Bengio, Y., & Hinton, G. (2015). Titled: Deep learning. Nature, 521, 436–444.

Study objective: Explain deep learning foundations and capabilities.

Methodology: Conceptual/technical review.

Key outcomes (most relevant): Establishes why deep learning excels in representation learning for complex data.

Analytical criticism / limitations: Not finance-specific; does not address explainability, governance, or operational deployment constraints – This research is making good use of the outcome in a trade finance related field.

Relation to current research: Provides foundational justification for AI capabilities used in GTRF (document AI, pattern detection).

*- In a demonstration done by Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Titled: “Why should I trust you?” Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.

Study objective: Propose Local Interpretable Model-agnostic Explanations for local model explanations.

Methodology: Method development + empirical demonstrations.

Key outcomes (most relevant): Enables local interpretability and supports human oversight.

Analytical criticism / limitations: Local explanations can be unstable; not sufficient alone for regulatory defensibility; not domain-specific – This research is taking the main concept of utilising AI and at the same time under the human supervision.

Relation to current research: Supports your focus on avoiding “black-box” AI in GTRF, especially for compliance and credit decision support.

*- In a paper done by Doshi-Velez, F., & Kim, B. (2017). Titled: Towards a rigorous science of interpretable machine learning. arXiv:1702.08608.

Study objective: Formalise interpretability and propose evaluation approaches.

Methodology: Conceptual framework paper.

Key outcomes (most relevant): Clarifies interpretability as context-dependent; proposes evaluation thinking.

Analytical criticism / limitations: Not operationalised for banking controls; lacks trade-finance-specific application – Here, the outcome is well utilised to serve the banking context and especially the trade finance related field, making benefit of the outcome.

Relation to current research: Strengthens theoretical basis for interpretability requirements in regulated GTRF AI use cases.

*- In a study done by Lundberg, S. M., & Lee, S.-I. (2017). Titled: A unified approach to interpreting model predictions. In Advances in Neural Information Processing Systems (NeurIPS).

Study objective: Introduce SHapley Additive exPlanations (SHAP) for consistent feature attribution.

Methodology: Method development + evaluation.

Key outcomes (most relevant): Widely used for reason codes and transparency.

Analytical criticism / limitations: Feature attribution is not causality; can be misinterpreted; needs governance wrapper - In this research, utilising AI in a sensitive field like banking, this require transparency due to governance and compliance controls.

Relation to current research: Supports explainability for AI-driven risk/compliance prioritisation in GTRF.

*- In another study done by Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). Titled: BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of NAACL-HLT.

Study objective: Introduce Bidirectional Encoder Representations from Transformers (BERT) for improved NLP performance.

Methodology: Model development + benchmarking.

Key outcomes (most relevant): Enables strong text understanding (classification, extraction), relevant to document processing.

Analytical criticism / limitations: Requires domain adaptation; governance issues (bias, drift, reproducibility); not trade-specific - Despite, it is not trade specific, however, it is used in this research to make reference to the AI-enabled languages which can serve develop the utilisation and dependency on AI in the trade finance arena.

Relation to current research: Underpins AI approaches for trade document understanding (IDP/NLP) in GTRF workflows.

*- In a survey done by Asian Development Bank. (2022). Titled: 2022 trade finance gaps, growth, and jobs survey. ADB.

Study objective: Quantify trade finance gap and identify constraints.

Methodology: Large-scale survey research with descriptive/statistical reporting.

Key outcomes (most relevant): Reports persistent trade finance gap and constraints (risk, compliance cost, information asymmetry).

Analytical criticism / limitations: Macro-level; does not isolate AI causality; limited process-level KPI detail – and the current research sheds light on this area.

Relation to current research: Provides quantitative justification for why improving GTRF efficiency and decisioning matters; supports AI as a potential friction-reducer.

Research Gap

The reviewed literature demonstrates that trade finance faces persistent structural frictions and financial crime exposure (ADB, 2022), while modern AI methods can enhance document understanding and anomaly detection (Chandola et al., 2009; Akoglu et al., 2015; Devlin et al., 2019). At the same time, banking supervisors require robust model governance, transparency, and control for model-driven decisions (BCBS, 2011), and interpretability research provides tools to support explainability (Ribeiro et al., 2016; Lundberg & Lee, 2017). However, a clear gap remains in trade-finance-specific, end-to-end analyses that connect AI use cases to measurable GTRF outcomes while explicitly incorporating governance and data standardisation prerequisites (ICC DSI, 2020). This study addresses that gap by developing an integrated view of how AI reshapes GTRF operations, risk decisioning, and compliance effectiveness, and by proposing a structured linkage between AI capabilities, required data foundations, governance controls, and performance indicators.

Theoretical Framework of the Study

This study examines how AI reshapes GTRF by transforming (i) operational processing, (ii) risk and credit decisioning, and (iii) financial crime compliance—while remaining constrained by governance, explainability, and data/standards readiness. To capture these interacting forces, the theoretical framework integrates four complementary lenses:

1. Information Asymmetry Theory (finance/intermediation lens)
2. Technology–Organisation–Environment (TOE) Framework (adoption/implementation lens)
3. Socio-Technical Systems (STS) Theory (operating model and human-in-the-loop lens)
4. Model Risk Management & Explainable AI - Governance Lens (control and regulatory lens)

Together, these theories explain why AI is valuable in GTRF, what enables or constrains adoption, and how AI can be deployed responsibly in a regulated banking context.

1) Information Asymmetry Theory (Finance/Intermediation Lens)

In trade and receivables finance, banks face persistent information asymmetry: borrowers and counterparties typically possess more information about transaction authenticity, shipment reality, invoice quality, and payment intent than the bank. This asymmetry increases adverse selection and moral hazard, raising the cost of screening and monitoring and contributing to constrained credit supply.

Application to this research

AI is theorised to reduce information asymmetry by:

- extracting structured signals from unstructured trade documents (IDP/NLP),
- integrating multi-source data (transactional + document-derived + external),
- enabling continuous monitoring and early warning indicators.

Constructing information asymmetry proxied by document discrepancies, exception rates, missing data, uncertainty indicators to improve decision quality to eliminate risk differentiation and to have early warning capability.

Expected relationship: higher AI capability → lower information asymmetry → improved decision quality and potentially improved access/efficiency.

2) Technology–Organisation–Environment (TOE) Framework (Adoption/Implementation Lens)

The TOE framework explains technology adoption as a function of:

- Technological context: data quality, interoperability, legacy integration, AI maturity.
- Organisational context: skills, governance, leadership support, operating model readiness.
- Environmental context: regulation, standards, market infrastructure, cross-border constraints.

Application to this research

TOE explains why AI in GTRF often remains at pilot stage: even if the technology is capable, organisational and environmental constraints (e.g. regulatory expectations, lack of digital standards, fragmented counterparties) can prevent scale.

Constructing AI adoption maturity (pilot/partial/scale), data readiness, workflow integration, governance strength, regulatory/standards environment (ICC DSI relevance) *.

Expected relationship: TOE readiness → higher likelihood of scaling AI → stronger performance outcomes.

3) Socio-Technical Systems (STS) Theory (Operating Model and Human-in-the-Loop Lens)

STS theory argues that performance depends on the joint optimisation of:

- the technical system (AI models, data pipelines, workflow tools), and
- the social system (people, roles, decision rights, training, accountability).

Application to this research

In GTRF, AI does not replace the operating model; it reshapes it. Human-in-the-loop controls, exception handling, and accountability are essential because trade finance decisions are high-stakes and often require judgement under uncertainty.

Constructing human-in-the-loop design, override rates, escalation thresholds, role redesign, adoption/usage.

Expected relationship: better socio-technical alignment → higher realised value and safer deployment (fewer control failures, better audit outcomes).

4) Model Risk Management & Explainable AI - Governance Lens (Control and Regulatory Lens)

In regulated banking, model-driven decisions must be transparent, validated, monitored, and auditable. BCBS operational risk principles provide governance expectations and mechanisms to support explainability.

Application to this research

This lens explains why “black-box” AI is difficult to deploy in GTRF for:

- credit decisioning (limits, approvals),
- compliance actions (sanctions/AML decisions),
- fraud investigations (case prioritisation).

Constructing governance strength (validation, monitoring, documentation, audit trails), explainability (reason codes, model cards), control effectiveness (false positives, QA outcomes, audit findings).

Expected relationship: stronger governance/explainability → greater adoption and scale; governance moderates the AI → outcomes relationship.

Within this framework:

- AI capabilities (IDP/NLP, anomaly detection, graph analytics, predictive monitoring) are the intervention.
- GTRF outcomes are grouped into:
 1. operational efficiency (TAT, STP, exceptions),
 2. risk/decision quality (early warning, risk differentiation),
 3. compliance effectiveness (false positives, time-to-disposition).
- Moderators/enablers include:
 - data readiness and standards (ICC DSI),
 - workflow integration and legacy constraints,
 - governance and explainability (BCBS),
 - socio-technical alignment (human-in-the-loop).

Methodology and Research Methods

This study adopts a mixed-methods secondary research design to examine how AI is reshaping GTRF within the banking sector. The study relies on systematic analysis of existing quantitative and qualitative evidence drawn from authoritative industry surveys, regulatory guidance, standards initiatives, and peer-reviewed academic literature.

A convergent mixed-methods design is employed. Quantitative and qualitative evidence are collected and analysed in parallel and then integrated through triangulation to produce a holistic interpretation of AI's impact on GTRF operations, risk decisioning, and compliance effectiveness, while accounting for governance and data/standards constraints.

Study Instrument (Data Collection Tool)

A structured search and retrieval process is used to ensure transparency and replicability:

1. Database and repository search: Google Scholar, ACM Digital Library, BCBS repositories, ICC DSI publications, and ADB reports.
2. Documentation: a document log is maintained (author, year, type, relevance, key metrics/themes extracted) – in the Reference Section below.

The study uses publicly available documents and does not involve confidential bank data.

This is ethically considered to emphasize on:

- accurate representation of sources,
- avoidance of over-claiming causality,
- appropriate citation and intellectual property compliance.

Study Limitations

1. AI capabilities, regulatory expectations, and digital trade standards are changing quickly; some conclusions may become outdated as technologies and policies mature.
2. Given the study content was synthesised from published reports and studies with differing designs, it primarily supports associations and informed interpretations rather than definitive causal effects of AI on GTRF outcomes.
3. Included materials vary by geography, time period, product scope and definitions, which may reduce comparability across findings.
4. Public sources may selectively report successful implementations or high-level outcomes, while detailed operational KPIs and negative results are often underreported.
5. Results are intended to be broadly applicable to the banking sector but may not fully reflect local market infrastructure, regulatory regimes, or bank-specific operating models.

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