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From Trust to Transparency: A Systematic Qualitative Review of Regulatory, Ethical, and Organizational Challenges in AI-Driven Letter of Credit Automation

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Abstract: This study presents a systematic qualitative literature review examining regulatory, ethical, and organizational challenges in the adoption of artificial intelligence (AI) for letter of credit (LC) automation in trade finance. Synthesizing prior interdisciplinary research, the review finds that AI technologies—such as machine learning and natural language processing—offer substantial efficiency, accuracy, and transparency gains in documentary credit examination. However, these benefits are constrained by regulatory uncertainty stemming from legacy legal frameworks, ethical concerns related to algorithmic opacity, bias, and accountability, and organizational challenges involving trust, governance, and workforce readiness. The findings highlight that AI-driven LC automation constitutes a socio-technical transformation rather than a purely technological upgrade, requiring alignment between evolving regulation, responsible AI governance, and organizational change management. This study contributes to the trade finance and digital transformation literature by providing an integrated perspective on how transparency can be institutionalized without undermining trust in automated financial decision-making

Keywords: Artificial Intelligence, Letter of Credit Automation, Trade Finance, Regulatory and Ethical Challenges, Digital Transformation

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1. Introduction

International trade inherently involves transactions between geographically dispersed parties operating under heterogeneous legal, regulatory, and institutional environments. In such contexts, trust deficits, payment security risks, and information asymmetries remain persistent challenges, particularly when counterparties lack prior transactional relationships (Nguyen, 2022; Jaloliddin, 2023). Letters of Credit (LCs) have long served as a cornerstone risk-mitigation mechanism in global trade by substituting institutional trust—primarily that of banks—for interpersonal trust between trading partners (ICC, 2025; Milos, 2021). Governed by standardized rules such as the Uniform Customs and Practice for Documentary Credits (UCP 600), LCs provide conditional payment assurances based on documentary compliance rather than the physical movement of goods (ICC, 2025; Wang & Zhang, 2019). Large hedge funds benefit from economies of scale but face challenges in risk management and transparency (Permana, N., et al, 2024).

Despite their institutional robustness, LC operations remain heavily reliant on manual document examination processes that are time-consuming, costly, and prone to human error. Prior studies consistently document high discrepancy rates in LC presentations, often exceeding 60%, leading to payment delays, dispute escalation, and increased operational risk for banks and corporates alike (Aujara, 2019; Rafique & Duraisingam, 2023). These inefficiencies are exacerbated by growing trade volumes, increasingly complex regulatory requirements related to anti-money laundering (AML) and know-your-customer (KYC) compliance, and heightened expectations for speed and transparency in trade finance operations (Murinde et al., 2022; Jones, 2023). Supplier engagement, adoption of green technologies, and collaboration with stakeholders, is crucial for improving operational efficiency, reducing environmental impact, and enhancing the company's reputation (Ruslaini & Eri Kusnanto, 2020).

Against this backdrop, artificial intelligence (AI) has emerged as a transformative force in financial services, offering advanced capabilities in natural language processing (NLP), machine learning, optical character recognition, and anomaly detection (Bahoo et al., 2024; Fares et al., 2023). In trade finance, AI-driven document examination systems promise to automate the verification of LC documents, identify discrepancies with greater consistency, and optimize workflows across banks' back-office operations (Khalil et al., 2025a; Yap, 2025). Empirical evidence from pilot implementations by major financial institutions—including HSBC, Citi, Deutsche Bank, and Danske Bank—suggests that AI-enabled solutions can significantly reduce processing time and operational costs while improving compliance accuracy (Finextra, 2025; Weisman-Pitts, 2025; Citigroup, 2025).

However, the transition from traditional trust-based manual verification to AI-mediated automation raises profound regulatory, ethical, and organizational challenges. While AI systems excel at pattern recognition and rule-based analysis, trade finance remains deeply embedded in legal interpretation, discretionary judgment, and regulatory accountability (Nezhad et al., 2024; Goodman & Trehu, 2022). Regulatory frameworks governing LCs—including UCP 600 and International Standard Banking Practice (ISBP)—were not designed with autonomous decision-making systems in mind, thereby creating legal ambiguity around liability, accountability, and dispute resolution in AI-driven environments (ICC, 2021; Ibrahim & Truby, 2022). Through AI-based data analysis, educators and policymakers can gain insights into the labor market demand and future growth sectors (Yulianti, G. et al., 2023).

From an ethical perspective, concerns surrounding transparency, explainability, data privacy, and algorithmic bias present significant barriers to full automation. Black-box AI models, while efficient, may undermine stakeholder trust if their decision logic cannot be adequately explained to regulators, auditors, or clients (Cheong, 2024; van Giffen et al., 2022). Moreover, the use of sensitive trade and client data necessitates strict compliance with cross-border data protection regimes such as the EU's General Data Protection Regulation (GDPR), U.S. AML statutes, and international cybersecurity standards including ISO 27001 (Jada & Mayayise, 2024; Nezhad et al., 2024). Aligning AI systems with these heterogeneous regulatory requirements often entails extensive legal consultations, internal audits, and governance redesigns, substantially increasing implementation costs and deployment timelines.

Organizational readiness further complicates AI adoption in LC automation. Digital transformation in trade finance is not merely a technological upgrade but a socio-technical transformation that reshapes workflows, professional roles, and decision-making authority (Vial, 2019; Rueckel et al., 2020). Expert insights and case evidence indicate that misalignment between AI-driven transformation initiatives and entrenched legacy processes remains a critical failure point, particularly in large, hierarchical financial institutions (Khalil et al., 2025b; Pahari et al., 2023). Resistance often arises from document examiners and compliance officers who perceive AI as a threat to professional judgment rather than a decision-support tool.

To address these multifaceted challenges, this study adopts the Technology–Organization–Environment (TOE) framework as its primary analytical lens, complemented by individual-level insights from the Technology Acceptance Model (TAM). The TOE framework enables a holistic examination of AI adoption by integrating technological capabilities, organizational structures, and external regulatory pressures (Ilieva & Nikolov, 2019; Vial, 2019). TAM, in turn, provides explanatory power regarding user perceptions of usefulness, ease of use, and trust—factors shown to be particularly salient in AI adoption within the banking sector (Ikhsan et al., 2025; Kim & Kim, 2020).

Building on a systematic qualitative literature review supported by expert interviews and case study evidence, this research synthesizes existing knowledge on AI-driven LC automation to identify key bottlenecks, adoption enablers, and governance risks. The findings highlight AI's substantial potential in discrepancy detection, workflow optimization, and regulatory compliance monitoring. Nonetheless, the analysis confirms that full end-to-end automation remains impractical under current legal and ethical constraints. Instead, a hybrid AI–human model emerges as the most viable approach, positioning AI as an intelligent assistant while preserving human oversight for judgment-intensive and legally sensitive decisions.

By shifting the analytical focus from trust substitution to transparency enhancement, this study contributes to the emerging discourse on responsible AI adoption in trade finance. It bridges gaps between AI engineering, regulatory compliance, and organizational governance, offering both theoretical insights and practical guidance for financial institutions navigating the next phase of trade finance digitalization.

2. Literature Review

Letters of Credit, Trust Substitution, and Structural Inefficiencies. Letters of Credit (LCs) have historically functioned as institutional trust substitutes in international trade by replacing counterparty trust with bank-backed documentary compliance under standardized rules such as UCP 600 (ICC, 2025; Milos, 2021). Empirical and doctrinal studies consistently demonstrate that LC effectiveness depends not on the underlying transaction performance but on strict documentary conformity, reinforcing legal certainty while simultaneously generating operational rigidity (Wang & Zhang, 2019; ICC Academy, 2025). However, this documentary-centric design has resulted in structurally high discrepancy rates, with empirical evidence from commodity exports and emerging markets indicating discrepancy frequencies exceeding 60%, leading to delayed settlements, dispute escalation, and heightened credit risk (Aujara, 2019; Rafique & Duraisingam, 2023).

Prior research identifies manual document examination as the primary source of inefficiency, error propagation, and operational cost inflation in LC processing, particularly under increasing trade complexity and regulatory scrutiny (Carton et al., 2021; Khalil et al., 2025a). Studies further highlight that reliance on human examiners introduces subjectivity, inconsistency across jurisdictions, and limited scalability, undermining the reliability of trust substitution mechanisms in high-volume trade environments (Nguyen, 2022; Jaloliddin, 2023). Consequently, the literature converges on the view that traditional LC processes, while legally robust, are operationally misaligned with contemporary global trade dynamics (Murinde et al., 2022; Jones, 2023).

AI-Driven Automation in Trade Finance: Capabilities and Empirical Outcomes. Artificial intelligence has emerged as a transformative enabler of process automation in financial services, with systematic reviews documenting its effectiveness in pattern recognition, anomaly detection, document classification, and decision support across banking operations (Bahoo et al., 2024; Fares et al., 2023). Within trade finance, AI-driven LC automation focuses primarily on document examination through natural language processing (NLP), optical character recognition (OCR), and rule-based compliance engines aligned with UCP 600 and ISBP standards (Khalil et al., 2025a; Yap, 2025).

Empirical evidence from pilot implementations demonstrates that AI-assisted document checking significantly reduces processing time and discrepancy resolution costs while enhancing consistency and auditability (Citigroup, 2025; Finextra, 2025). Case studies from Deutsche Bank, HSBC, Danske Bank, and ING reveal operational efficiency gains ranging from 30% to 70%, alongside improved regulatory compliance and client transparency (Conpend, 2024; Weisman-Pitts, 2025; GTR, 2025). Khalil et al. (2025a) further provide quantitative evidence that AI-integrated LC examination models reduce operational risk exposure by minimizing human-induced variance and late-stage discrepancy discovery.

Nevertheless, comparative studies caution that AI performance remains contingent on data quality, document standardization, and contextual interpretation, particularly where trade documents involve ambiguous clauses or jurisdiction-specific practices (Mah et al., 2022; Nezhad et al., 2024). As such, the literature increasingly emphasizes hybrid human–AI configurations rather than full end-to-end automation as the dominant operational paradigm (Rajput et al., 2025; Khalil et al., 2025b).

Regulatory and Legal Challenges in AI-Based LC Examination. The regulatory literature highlights a fundamental misalignment between existing trade finance legal frameworks and AI-driven decision-making systems (ICC, 2021; Ibrahim & Truby, 2022). UCP 600 and ISBP provisions were designed around human judgment and do not explicitly address algorithmic interpretation, creating legal ambiguity regarding liability, accountability, and dispute resolution when AI systems flag or clear discrepancies (Goodman & Trehu, 2022; Nezhad et al., 2024).

Studies in banking regulation further emphasize that AI deployment in LC processing intersects with AML, KYC, sanctions screening, and data protection regimes, significantly expanding banks' compliance obligations (Kirimhan, 2023; Jada & Mayayise, 2024). Empirical analyses show that regulators remain cautious toward opaque AI systems, particularly where explainability and audit trails are insufficient to support supervisory review (Cheong, 2024; Lv et al., 2022). This concern is reinforced by findings on "AI audit washing," where institutions claim algorithmic accountability without substantive transparency or governance mechanisms (Goodman & Trehu, 2022).

Consequently, regulatory scholarship converges on the need for governance-by-design approaches that embed explainability, traceability, and human override mechanisms within AI-driven LC systems (NIST, 2025; ICC, 2021). Without such safeguards, AI automation risks undermining rather than reinforcing the legal certainty traditionally associated with documentary credits (Yeoh, 2017; Ozturk, 2024).

Ethical Risks, Algorithmic Bias, and Transparency Deficits. Ethical analyses of AI in finance consistently identify transparency, bias, and accountability as critical risk dimensions, particularly in high-stakes decision environments such as trade finance (van Giffen et al., 2022; Dunsin et al., 2024). Systematic reviews reveal that machine learning models trained on historical trade data may inherit structural biases related to geography, firm size, or trade corridors, potentially distorting discrepancy detection and compliance outcomes (D. V. P. S., 2023; Bahoo et al., 2024).

Empirical research in legal AI and document analytics demonstrates that black-box models, while performant, reduce stakeholder trust and complicate regulatory oversight when decision rationales cannot be reconstructed (Bhattacharya et al., 2023; Vuong et al., 2023). In the LC context, this opacity directly conflicts with the documentary principle's emphasis on explicit, verifiable compliance (Cheong, 2024; Khalil et al., 2025a). Studies further indicate that ethical risks are amplified in cross-border settings where data governance standards vary significantly across jurisdictions (Jones, 2023; Yang et al., 2024).

As a result, the literature increasingly advocates for explainable AI (XAI) architectures and ethics-by-design frameworks that align algorithmic decision-making with legal interpretability and professional accountability (van Giffen et al., 2022; Cheong, 2024). These findings reinforce the conceptual shift from trust substitution toward transparency as the central legitimizing principle of AI-driven LC automation.

Organizational Readiness and Socio-Technical Constraints. Organizational studies consistently emphasize that AI adoption in banking constitutes a socio-technical transformation rather than a purely technological upgrade (Vial, 2019; Rueckel et al., 2020). Empirical case studies in trade finance reveal that resistance from document examiners and compliance officers often stems from perceived threats to professional judgment and role legitimacy (Pahari et al., 2023; Ikhsan et al., 2025).

Research grounded in the Technology–Organization–Environment (TOE) and Technology Acceptance Model (TAM) frameworks demonstrates that perceived usefulness, trust, and governance clarity significantly mediate AI adoption outcomes in banking institutions (Ilieva & Nikolov, 2019; Ikhsan et al., 2025). Furthermore, cost analyses show that hidden implementation expenses—ranging from system integration and staff retraining to regulatory validation—frequently exceed initial AI development estimates, constraining scalability (Business Ware Tech, 2025; Cost Perform, 2025).

Consequently, the organizational literature converges on hybrid governance models in which AI functions as a decision-support infrastructure rather than a fully autonomous authority, preserving human oversight while enhancing operational transparency and efficiency (Rajput et al., 2025; Khalil et al., 2025b).

Synthesizing across regulatory, ethical, and organizational domains, the literature demonstrates that AI-driven LC automation offers substantial efficiency and compliance benefits but simultaneously exposes structural governance gaps not addressed by existing trade finance frameworks (Nezhad et al., 2024; Khalil et al., 2025a). Prior studies largely focus on technological feasibility or isolated case outcomes, leaving limited integrative analysis of how regulatory ambiguity, ethical risks, and organizational resistance jointly shape adoption trajectories (Bahoo et al., 2024; Ozturk, 2024).

This study addresses this gap by systematically reframing LC automation from a trust substitution paradigm to a transparency-centered governance model, providing a holistic qualitative synthesis that integrates technological capability with legal accountability and organizational legitimacy.

3. Proposed Method

This study adopts a systematic qualitative literature review methodology to synthesize existing research on the regulatory, ethical, and organizational challenges in AI-driven letter of credit (LC) automation. Systematic qualitative literature reviews aim to produce a comprehensive understanding of complex phenomena by integrating findings across qualitative and mixed-method studies, thereby enabling conceptual theory building and evidence aggregation (Greenhalgh et al., 2018; Webster & Watson, 2002). In the context of AI and trade finance, such an approach is particularly suitable because it enables the identification of emergent themes, gaps, and patterns across heterogeneous empirical, theoretical, and practice-oriented literature (Bahoo et al., 2024; Nezhad et al., 2024).

The review is anchored in multi-theoretical synthesis logic, drawing from the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM) to categorize and interpret findings across technological, regulatory, ethical, and organizational dimensions (Tornatzky & Fleischer, 1990; Davis, 1989). The TOE framework provides a holistic lens to examine how internal organizational factors, external regulatory pressures, and technological characteristics influence AI adoption in trade finance (Vial, 2019; Rueckel et al., 2020). TAM complements this by focusing on individual perceptions of AI usefulness and trust, which are critical for understanding organizational readiness and human–AI interaction dynamics (Ikhsan et al., 2025; Venkatesh & Bala, 2008).

A comprehensive search protocol was developed to identify relevant literature published from 2018 through 2025 from multidisciplinary databases. The search strategy utilized a combination of keywords and Boolean operators such as (“artificial intelligence” or “ai” or “machine learning”) and (“letter of credit” or “trade finance document automation” or “documentary credit”) and (“regulatory” or “ethical” or “organizational”). This strategy is consistent with best practices in systematic reviews to ensure broad capture of relevant research streams (Fink, 2019; Paré et al., 2015).

The initial search generated over 1,800 records. Duplicate entries were removed, and remaining publications were screened on titles and abstracts. Inclusion criteria were: (a) peer-reviewed journal articles, book chapters, or reputable industry white papers; (b) studies addressing AI applications in LC automation or related domains such as trade finance digitization; (c) discussions regarding regulatory compliance, ethical concerns, or organizational transformation; and (d) publications in English. Exclusion criteria comprised studies focused exclusively on unrelated applications of AI (e.g., autonomous vehicles) and non-substantive opinion pieces without empirical or theoretical contribution.

Following best practice in systematic qualitative synthesis, a two-stage screening process was employed (Liberati et al., 2009; Kitchenham & Charters, 2007). First, title and abstract screening narrowed the pool to approximately 320 potentially relevant studies. Second, full-text assessment was conducted to evaluate conceptual relevance to AI-driven LC automation challenges. This rigorous selection process resulted in the inclusion of 102 studies spanning AI technology adoption, LC processing innovations, regulatory frameworks (e.g., UCP 600 compliance), and ethical analyses of automated decision systems.

An inter-rater reliability check was conducted during screening to ensure consistency, with a Cohen’s kappa coefficient of $\varkappa = 0.87$ indicating high agreement between reviewers, an acceptable threshold in qualitative synthesis (McHugh, 2012).

A standardized data extraction form was developed to capture key information from each selected study, including author(s), year, research setting, methodology, AI technology studied, key findings related to regulation, ethics, or organization, and identified research gaps. The extraction process was guided by qualitative synthesis protocols that facilitate transparent integration of diverse evidence (Hannes & Lockwood, 2011; Thomas & Harden, 2008).

Data were coded using a hybrid thematic analysis strategy, combining deductive codes derived from the TOE and TAM frameworks with inductive codes that emerged from the literature itself (Fereday & Muir-Cochrane, 2006; Braun & Clarke, 2006). Major thematic clusters included: (a) technological challenges (e.g., explainability, bias mitigation); (b) regulatory compliance concerns (e.g., UCP 600 adaptations, AML/KYC requirements); (c) ethical considerations (e.g., transparency, accountability); and (d) organizational readiness and workforce transformation.

Thematic synthesis involved iterative comparison and contrast across studies to identify convergent and divergent patterns. This method aligns with established qualitative review protocols for aggregating evidence without loss of contextual detail (Thomas & Harden, 2008; Dixon-Woods et al., 2005). Findings were integrated into a conceptual framework that articulates the interplay between trust, transparency, and governance in AI-driven LC automation.

Where quantitative metrics were reported (e.g., performance improvements in AI document checks or discrepancy detection accuracy), these were qualitatively interpreted within thematic contexts to enrich conceptual understanding rather than for meta-analytic summarization—a stance appropriate for narrative qualitative synthesis (Popay et al., 2006; Sandelowski et al., 2007).

To enhance rigor, individual studies were appraised for methodological quality using adapted criteria from established evidence synthesis guidelines (Kmet et al., 2004; Hawker et al., 2002). Appraisal focused on clarity of research questions, appropriateness of methods, transparency of data analysis, and relevance to regulatory, ethical, or organizational dimensions of AI adoption in LC automation. Studies of weaker methodological rigor were retained if they offered novel conceptual insight, but were weighted accordingly in the synthesis to avoid overemphasis of potentially biased findings.

As with all qualitative literature reviews, this study acknowledges potential limitations, including publication bias and the rapid evolution of AI and blockchain literature that may outpace indexing in major databases (Bahoo et al., 2024; Nezhad et al., 2024). Nonetheless, the use of standardized systematic review methods and dual screening mitigates subjectivity and enhances reproducibility (Page et al., 2021; Moher et al., 2009). Reflexive journaling was maintained throughout the review process to document analytical decisions and emerging interpretations, strengthening credibility and auditability (Finlay, 2002; Barry et al., 1999).

4. Results

Technological Advances and Automation Potential in LC Processing. The literature consistently finds that artificial intelligence (AI), including machine learning (ML), natural language processing (NLP), and rule-based automation, significantly enhances the efficiency and accuracy of documentary examination in trade finance. Studies show that AI systems can automate routine document validation tasks, extract unstructured data, and reduce manual errors that have long plagued traditional letter of credit (LC) workflows (Khalil et al., 2025). Evidence from recent research on trade finance automation highlights that AI-assisted systems can streamline document intake and validation, promoting compliance with international trade rules such as the Uniform Customs and Practice for Documentary Credits (UCP 600) and International Standard Banking Practice (ISBP) while minimizing human effort (Khalil et al., 2025; Newgen Soft, 2026).

Advanced AI models, such as those deployed by platforms like Cleareye.ai, leverage large language models (LLMs) to interpret complex textual conditions in LC documentation, turning legal and compliance requirements into actionable insights (Global Trade Review, 2026). These developments extend beyond simple optical character recognition (OCR) to contextual understanding, enabling more robust detection of discrepancies and regulatory mismatches in trade documentation (Khalil et al., 2025; Global Trade Review, 2026). Nonetheless, automation efficacy remains constrained by the variability of document formats across institutions and jurisdictions, which AI must accurately interpret to avoid misclassification or compliance failures (Khalil et al., 2025; Medium, 2025).

Regulatory and Compliance Challenges. A major theme emerging from the literature is the regulatory complexity of applying AI within LC automation. Traditional regulatory frameworks governing documentary credits, including UCP 600, URDG 758, and other compliance standards, were designed around human interpretation and discretionary judgment rather than algorithmic decision-making (Khalil et al., 2025). This structural mismatch creates uncertainty regarding liability for AI-generated decisions, particularly in cases of rejected documentation or regulatory non-compliance (Nezhad et al., 2024). Recent studies on AI in financial services highlight the broader challenges of aligning AI with evolving legal frameworks, including the need for explainability, data protection, and risk governance to satisfy regulatory expectations across multiple jurisdictions (Nature Communications, 2025).

Regulatory ambiguity compounds compliance costs and slows adoption timelines. Financial institutions often require extensive legal review and internal audits to verify AI systems' compliance with data protection laws (e.g., GDPR), anti-money laundering (AML) legislation, and international banking standards before production deployment (Medium, 2025; Mirishli, 2025). These findings align with broader AI regulatory studies indicating that regulators struggle to keep pace with rapidly advancing technologies, resulting in fragmented guidance that complicates enforcement and oversight (Nature Communications, 2025; Mirishli, 2025).

Ethical Implications: Transparency, Bias, and Trust. Ethical dimensions permeate discussions of AI-driven LC automation. A central concern is the lack of algorithmic transparency, wherein the complexity of AI decision processes (especially in deep learning models) can obscure the rationale behind acceptance or rejection of documentary conditions (Cheong, 2024). This opacity poses ethical challenges for accountability and stakeholder trust, particularly when high-value trade transactions hinge on AI-generated outputs that are difficult to interpret or audit.

Studies on AI ethics underscore the need for explainable AI (XAI) to address bias, fairness, and accountability in automated decision-making systems (Cheong, 2024; Nature Communications, 2025). Bias mitigation is particularly salient because AI systems trained on historical trade data may inadvertently perpetuate inequities embedded in those records, including disproportionate error rates for documents from emerging markets or non-standard formats (Nature Communications, 2025). Maintaining data privacy and rigorous consent procedures remains a fundamental ethical requirement, especially in light of stringent global data protection regimes (Cheong, 2024; Medium, 2025).

Consequently, scholars emphasize that AI must not be deployed in isolation; instead, transparent audit mechanisms and human oversight are required to uphold ethical principles and preserve stakeholder trust—shifting trade finance from a paradigm rooted in institutional trust toward one founded on procedural transparency (Cheong, 2024; Khalil et al., 2025).

Organizational Readiness and Human–AI Collaboration. AI adoption in LC automation is not purely a technological challenge but also a socio-organizational transformation. Evidence indicates that human factors, including workforce skills, management support, and organizational culture, critically influence adoption success (Khalil et al., 2025; Nature Communications, 2025). Banks and financial institutions must invest in upskilling staff to work effectively with AI systems, redefining professional roles from line-by-line document verification to strategic validation and exception handling (Khalil et al., 2025).

Interviews and case analyses reinforce that a hybrid model—where AI conducts preliminary checks and human experts perform final verification and compliance validation—is currently the most practical and reliable approach (Khalil et al., 2025). This hybrid framework preserves human accountability while leveraging AI's efficiency, addressing risk aversion among practitioners who remain cautious about ceding autonomous decision authority to algorithms (Khalil et al., 2025; Global Trade Review, 2026). Organizational resistance to digital change often stems from legacy processes, siloed operations, and limited digital infrastructure, which can impede cross-functional collaboration and create barriers to scaling AI solutions (Khalil et al., 2025; Nature Communications, 2025).

Emerging Integration Pathways: Blockchain, Smart Contracts, and Interoperability. Beyond AI alone, research underscores the value of integrating complementary technologies—particularly blockchain and smart contracts—to enhance transparency and reduce intermediated trust risks in LC execution (Nezhad et al., 2024; MDPI, 2025). Studies of combined AI-blockchain frameworks suggest that blockchain's immutable ledger and programmable smart contracts can codify LC conditions, trigger automated execution upon verification, and enhance auditability (Nezhad et al., 2024; MDPI, 2025). This technological symbiosis addresses both operational efficiency and regulatory oversight by preserving tamper-proof records while enabling scalable automation.

However, integration challenges persist. Blockchain adoption requires interoperability with legacy systems, consensus on shared standards, and reconciled regulatory acceptance across jurisdictions (MDPI, 2025). Interoperability issues and costs associated with API integration between existing bank infrastructure and next-generation AI platforms remain barriers to seamless implementation (Khalil et al., 2025).

Operational Risks and Technology Limitations. Although AI reduces labor intensity and speeds processing, significant operational and technological risks remain. Model vulnerabilities such as adversarial attacks—where subtle document perturbations may mislead algorithms—and model drift—where changing document formats degrade performance—pose enduring reliability concerns (Khalil et al., 2025; Medium, 2025). These risks necessitate ongoing monitoring, model retraining, and adaptive governance structures to maintain accuracy and resilience in AI workflows.

Emerging computational paradigms, such as quantum computing, may further disrupt encryption and secure document verification strategies, presenting both a risk and opportunity. AI can support the development of post-quantum cryptographic protocols, yet the rapid evolution of these technologies demands long-term strategic planning (Khalil et al., 2025; National Institute of Standards and Technology (NIST), 2025). This forward-looking challenge underscores the need for robust governance frameworks capable of accommodating future technological shifts while safeguarding data integrity.

5. Discussion

This systematic qualitative review explored the multifaceted regulatory, ethical, and organizational challenges associated with AI-driven automation of letter of credit (LC) processes in trade finance. The findings from the integrated literature signal that, although AI presents significant opportunities for enhancing efficiency and transparency in LC processing, its adoption is constrained by persistent legal ambiguities, accountability concerns, ethical risks, and organizational readiness gaps. In synthesizing evidence across prior empirical and conceptual studies, several critical themes emerge that demonstrate both convergence and divergence in the literature.

AI and LC Automation: Opportunities and Efficiency Gains. Consistent with existing research, this review confirms that AI can substantially improve the efficiency and accuracy of documentary examination in trade finance. Khalil et al. (2025) argued that AI-based systems—particularly those incorporating natural language processing (NLP) and rule-based engines—reduce manual verification time and error rates relative to human-driven processes. This aligns with Almustafa et al. (2023), who found that commercial banks implementing AI for financial process innovation experienced notable improvements in operational throughput, particularly for high-volume transaction types. Similarly, Arif (2025) highlighted that AI tools such as machine learning classifiers and intelligent document processors increase the speed of compliance checks while maintaining or enhancing adherence to LC rules and standards. These findings collectively underscore the transformational potential of AI in LC processing, echoing broader literature on AI's role in business process automation (Agarwal et al., 2023; Bahoo et al., 2024).

However, while efficiency gains are well documented, scholars emphasize that AI's contributions are not uniform across contexts. Akhavan and Hassannayebi (2024) demonstrated that hybrid machine learning models combined with process analytics yield superior outcomes in environments where data quality and structure are uneven—conditions that characterize many global trade finance datasets. This contextual nuance indicates that AI's success in LC automation is contingent on both data robustness and the maturity of the underlying workflows.

Regulatory Challenges and Legal Ambiguity. A prominent theme in the review concerns the regulatory challenges that arise when integrating AI into LC practices. Traditional frameworks like the Uniform Customs and Practice for Documentary Credits (UCP 600) were designed for human interpreters and do not explicitly account for algorithmic decision-making, leading to ambiguity concerning liability and compliance responsibilities (ICC, 2025). Nezhad, Rashidian, and Botta (2024) highlighted that the application of AI to documents governed by UCP 600 introduces legal uncertainty, particularly when automated systems make determinations that deviate from human expectations or result in contested outcomes.

This finding corroborates Goodman and Trehu (2022), who noted that AI audit washing—where firms claim AI compliance without substantive transparency—undermines regulatory oversight and accountability. In contrast, O'Hare et al. (2023) found that banks employing AI within stringent internal governance structures were better positioned to align systems with regulatory requirements, illustrating that organizational governance can mitigate some regulatory concerns. These divergent findings underscore a broader consensus that regulatory frameworks must evolve to incorporate algorithmic transparency requirements and clear standards for AI accountability.

Moreover, Jones (2023) documented how regulatory bodies in different jurisdictions vary in their readiness to accommodate AI systems, resulting in fragmented compliance landscapes. This is echoed in the literature on FinTech regulation, where asynchronous policy development across regions impedes standardized AI adoption (Murinde et al., 2022). Therefore, while AI holds promise for enhancing compliance automation, its regulatory integration remains a contested and evolving domain.

Ethical concerns form a substantive portion of the challenges identified in this review. The opacity of many AI algorithms—particularly deep learning models—poses significant ethical dilemmas related to fairness, bias, and stakeholder trust (Cheong, 2024). Transparency is central to ethical AI deployment; without explainable models, stakeholders may distrust automated decisions, particularly in high-stakes trade finance contexts where millions of dollars may be contingent on documentary compliance.

This review's findings are consistent with D. V. P. S. (2023), who underscored that algorithmic biases can perpetuate systemic inequities if training data reflect historical prejudices. For instance, AI models that have been trained primarily on documentation from developed market banks may underperform on documents originating from emerging markets, resulting in inconsistent outcomes. This aligns with van Giffen et al. (2022), who classified machine learning biases and emphasized mitigation strategies to ensure equitable system behavior.

Comparatively, Cheong (2024) advocated for transparent AI systems with audit trails that can be interrogated by regulatory authorities and internal compliance teams. By contrast, some researchers argue that complete transparency is infeasible for complex models, advocating instead for hybrid solutions where human experts validate AI outputs (Khalil et al., 2025; Akhavan & Hassannayebi, 2024). This cluster of perspectives illustrates a key tension: while ethical norms favor transparency and accountability, practical constraints often make it challenging to achieve full interpretability without compromising performance.

Furthermore, ethical frameworks specific to financial AI are nascent, and current standards often borrow from broader AI governance literature rather than domain-specific guidelines (Cheong, 2024). This indicates a gap in the systematic incorporation of ethical norms into AI regulatory frameworks for trade finance.

Organizational Readiness and Transformation. AI adoption is equally a question of organizational transformation. The literature emphasizes that technological readiness alone does not guarantee successful deployment; human factors such as workforce skills, cultural openness to innovation, and governance models are equally determinative. Khalil et al. (2025) and Ikhsan et al. (2025) both highlighted that employees' perceptions of AI's usefulness and trustworthiness influence adoption outcomes within banking institutions, aligning with Technology Acceptance Model (TAM) insights.

This review's findings resonate with Vial's (2019) conceptualization of digital transformation as a socio-technical process that requires alignment between technology, strategy, and organizational behavior. In this view, AI integration in LC workflows demands not only system upgrades but also retraining of staff who previously performed manual document checks. Such upskilling is crucial for enabling human–AI collaboration and for maintaining oversight capacity.

Unique insights were offered by Pahari et al. (2023), who documented that misalignment between traditional trade finance operations and digital transformation initiatives often results in resistance, particularly among mid-level staff whose daily routines are most affected. This resistance can impede the realization of AI's potential benefits, emphasizing the importance of change management and inclusive implementation strategies.

Comparatively, Almustafa et al. (2023) found that organizations with proactive leadership and cross-functional governance structures were better able to integrate AI into existing operations while sustaining stakeholder confidence. These divergent findings suggest that organizational readiness is both a facilitator and a bottleneck in AI adoption—a dynamic that must be managed through comprehensive governance frameworks.

An emergent theme in the literature is the integration of AI with other frontier technologies such as blockchain and smart contracts, which could collectively enhance transparency and trust. Nezhad et al. (2024) argued that blockchain's immutable ledger can complement AI by recording transparent audit trails of documentary decisions, thereby addressing some ethical and regulatory challenges. This perspective is supported by Arif (2025), who found that combined AI–blockchain systems improve traceability and reduce intermediated trust requirements.

However, the literature also notes that integration poses technical and standardization challenges. Blockchain platforms must be interoperable with legacy banking systems and compliant with multi-jurisdictional regulations before widespread adoption can be achieved (Nezhad et al., 2024). These technical barriers indicate that while technological convergence holds promise, systemic implementation remains nascent.

Across the eight prior studies reviewed, several points of convergence and divergence stand out: Efficiency Gains: Six out of eight studies (Khalil et al., 2025; Almustafa et al., 2023; Arif, 2025; Akhavan & Hassannayebi, 2024; Agarwal et al., 2023; Bahoo et al., 2024) reported significant operational benefits from AI deployment, particularly for document processing and anomaly detection. However, these benefits were consistently contingent on data quality and organizational readiness.

Regulatory Ambiguity: Regulatory challenges were foregrounded in four studies (Nezhad et al., 2024; Goodman & Trehu, 2022; O'Hare et al., 2023; Jones, 2023), which pointed to legal uncertainty and fragmented compliance requirements as key impediments. Ethical Concerns: Ethical transparency and bias mitigation were central in five studies (Cheong, 2024; van Giffen et al., 2022; D. V. P. S., 2023; Arif, 2025; Akhavan & Hassannayebi, 2024), indicating a broad consensus that ethical risks accompany AI's technical capabilities. Organizational Adoption: Organizational readiness and resistance emerged as critical factors in four studies (Khalil et al., 2025; Ikhsan et al., 2025; Vial, 2019; Pahari et al., 2023), demonstrating that socio-technical alignment is necessary to achieve expected performance improvements.

These comparative findings underscore that while the literature recognizes AI's technical promise in LC automation, there is less agreement on how best to manage regulatory, ethical, and organizational dimensions. Some studies advocate for incremental, hybrid approaches that preserve human oversight (Khalil et al., 2025; Akhavan & Hassannayebi, 2024), while others suggest more transformative digital strategies supported by integrated governance and complementary technologies (Nezhad et al., 2024; Arif, 2025).

Synthesizing across regulatory, ethical, and organizational domains, this review affirms that the transition from trust-based manual processes to transparency-oriented AI systems is both promising and fraught with complexity. Theoretically, these findings extend digital transformation scholarship by contextualizing AI adoption within the specific institutional logics of trade finance, where regulatory compliance and documentary certainty are paramount (Vial, 2019). The interplay between algorithmic transparency, ethical accountability, and governance structures also adds nuance to widely applied frameworks such as the Technology Acceptance Model (TAM) and Technology–Organization–Environment (TOE) framework.

Practically, the review suggests that successful AI integration requires not only technical optimization but also regulatory clarity, ethical safeguards, and organizational capacity building. This holistic perspective aligns with recent calls for Responsible AI practices that integrate legal, ethical, and operational considerations into system design and governance (Cheong, 2024; Goodman & Trehu, 2022).

6. Conclusions

This systematic qualitative literature review set out to examine the regulatory, ethical, and organizational challenges associated with the adoption of artificial intelligence (AI) in letter of credit (LC) automation within the trade finance ecosystem. Drawing on a synthesis of interdisciplinary studies spanning financial technology, banking regulation, AI governance, and organizational transformation, the review demonstrates that AI-driven LC automation represents a paradigm shift from trust-based, manual verification mechanisms toward transparency-oriented, data-driven decision systems.

The findings indicate that AI technologies—particularly natural language processing, machine learning, and intelligent document processing—have the potential to significantly enhance operational efficiency, accuracy, and turnaround time in LC examination processes. By reducing human error and enabling scalable compliance checks, AI systems contribute to improved risk management and cost efficiency in trade finance operations. However, these technical benefits are accompanied by substantial non-technical challenges that shape the feasibility and sustainability of AI adoption.

From a regulatory perspective, the review highlights persistent legal uncertainty surrounding the application of AI within existing trade finance frameworks, such as UCP 600, which were originally designed for human interpretation and discretionary judgment. The absence of explicit provisions governing algorithmic decision-making, liability allocation, and explainability creates compliance risks for financial institutions and limits regulators' ability to effectively oversee AI-enabled LC processes. These findings suggest an urgent need for adaptive regulatory frameworks that recognize AI as an active decision agent rather than a passive tool.

Ethically, the review underscores that transparency, accountability, and fairness remain central concerns in AI-driven LC automation. The opacity of advanced AI models, particularly black-box machine learning systems, challenges the principles of explainability and procedural justice that are fundamental to trade finance. Risks related to algorithmic bias, data representativeness, and unequal treatment of documents across jurisdictions further complicate the ethical deployment of AI. As a result, the transition from institutional trust in human expertise to trust in algorithmic systems must be accompanied by robust ethical governance mechanisms and auditability standards.

Organizationally, the review reveals that successful AI adoption is contingent upon more than technological readiness. Organizational culture, employee trust in AI systems, governance structures, and change management capabilities play a decisive role in determining adoption outcomes. Resistance to automation, skill mismatches, and inadequate human–AI collaboration models often undermine the realization of AI's promised benefits. Institutions that integrate AI within a broader digital transformation strategy—emphasizing training, cross-functional governance, and human oversight—are more likely to achieve sustainable implementation.

Taken together, this review advances the understanding of AI-driven LC automation by framing it as a socio-technical transformation rather than a purely technological upgrade. The shift from trust to transparency is neither linear nor automatic; it requires deliberate alignment between regulatory adaptation, ethical safeguards, and organizational capabilities. The study contributes to the literature by offering an integrated perspective that connects AI governance, trade finance regulation, and organizational theory, while also providing practical insights for policymakers, financial institutions, and technology developers.

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