



Letter of Credit Document Management and Verification: A Review of Traditional, Digital, and Artificial Intelligence-Based Approaches

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Abstract—

Letter of Credit (LC) transactions depend on the accurate examination of documentary presentations against the credit terms and applicable documentary-credit rules. Traditionally, this activity has been performed by skilled document checkers, making the process labour-intensive and sensitive to document volume, wording variation, and cross-document inconsistencies. This review examines the evolution of LC document management and verification from manual examination and basic digitisation to intelligent document processing, artificial intelligence, and human-in-the-loop approaches. A structured literature review was conducted using recent peer-reviewed research, international trade rules, and authoritative guidance, with emphasis on developments reported during 2025–2026 while retaining foundational sources required to explain the regulatory and technical context. The literature indicates that optical character recognition, document classification, machine learning, natural language processing, semantic matching, and optimisation can support extraction, consistency checking, discrepancy identification, and workflow prioritisation. Recent research also shifts attention from isolated automation toward hybrid human–AI processes, where AI handles repetitive or high-volume analysis and experienced reviewers handle exceptions and consequential judgments. Digital presentation rules further introduce requirements concerning electronic records, authenticity, integrity, examination, and data corruption. The review identifies persistent gaps in domain-specific datasets, explainability, standardised evaluation,

interoperability, governance, and validation under real banking conditions. Future research should therefore focus on auditable, standards-aware, explainable, and human-supervised verification architectures.

Keywords— Letter of Credit; Documentary Credit; Document Verification; Intelligent Document Processing; Artificial Intelligence; Human-in-the-Loop



I. INTRODUCTION

A Letter of Credit is a documentary payment mechanism in which banks examine a presentation of documents in accordance with the terms of the credit and the applicable rules. Under UCP 600, Article 14 requires the relevant bank to

examine a presentation on the basis of the documents alone to determine whether the documents appear on their face to constitute a complying presentation, while Article 15 addresses a complying presentation and Article 16 addresses discrepant documents, waiver, and notice [1]. The examination therefore involves more than simply reading individual documents: information must be interpreted in context, compared with the credit, and checked for consistency across the presentation.

The traditional examination process is highly dependent on experienced personnel. The ICC Banking Commission's guidance on automation describes manual document examination as time-consuming and labour-intensive and identifies the scarcity of experienced document checkers as a constraint on scalability [3]. The same guidance distinguishes progressive automation levels, beginning with scanning and document imaging, continuing through optical character recognition (OCR), data capture, rules and machine learning, and extending toward systems in which humans intervene primarily for exceptions [3].

Digitalisation changes the nature of the document environment. The ICC eUCP framework was introduced to accommodate electronic records alone or in combination with paper documents under documentary credits [2]. More recent scholarship has examined the legal and operational implications of electronic presentation and the relationship between eUCP provisions and digital trade finance [7]. Thus, document verification increasingly requires technologies that can process heterogeneous digital records while respecting documentary-credit rules and evidentiary requirements.

Research on artificial intelligence has developed in parallel. Khalil and Kerbache examined the potential role of machine learning, natural language processing, and OCR in automating trade-document examination

under LCs [4]. In 2025, Khalil et al. proposed an AI adoption roadmap specifically for LC document examination and identified discrepancy detection, workflow optimisation, and compliance improvement as important application areas, while also identifying regulatory and trust concerns that limit unrestricted automation [5]. A separate 2025 study formulated an optimisation model for assigning AI-indexed LC review tasks to human checkers according to factors including discrepancy criticality, monetary value, expertise, and availability [6].

Although these studies establish a growing research base, the literature remains distributed across trade finance, intelligent document processing, digital trade, optimisation, and human–AI interaction. This makes it difficult to view LC document management as an end-to-end technical and governance problem. The present review therefore synthesises these strands and focuses on four questions: (1) What are the principal characteristics and limitations of traditional LC document examination? (2) How has digitalisation changed LC document management and verification? (3) Which AI-based techniques are relevant to extraction, comparison, discrepancy detection, and workflow support? and (4) What research gaps remain for reliable, explainable, standards-aware, and human-supervised LC verification?

II. LITERATURE REVIEW

A. Traditional LC Document Examination

The traditional LC workflow begins with a credit containing documentary conditions and proceeds to the presentation of stipulated documents. Typical documents can include commercial invoices, transport documents, insurance documents, certificates, packing-related documents, and other records depending on the credit. The core examination task is governed by the documentary-credit rules rather than by direct inspection of the underlying goods or services. UCP 600 Article 14 establishes the documentary standard of examination and specifies a maximum examination period of five banking days following the day of presentation [1].

A major characteristic of traditional examination is contextual comparison. Data do not necessarily have to be textually identical across documents; the UCP 600 standard recognises contextual interpretation and prohibits conflicts between relevant data [1].



Consequently, simple string matching is insufficient for many cases. A system may need to understand dates, quantities, currencies, locations, parties, goods descriptions, transport details, and relationships between fields.

The ICC automation guidance identifies several limitations of manual processing: dependence on specialist expertise, processing time, scalability constraints, variation in interpretation, and difficulty achieving end-to-end digital workflows [3]. These limitations do not imply that human examination lacks value. Experienced checkers can interpret ambiguous conditions, handle unusual discrepancies, communicate with transaction parties, and apply accumulated domain knowledge. This observation becomes important when evaluating AI: the relevant objective is not necessarily complete replacement of human expertise, but redistribution of work between automated analysis and human judgment.

B. Digitalisation and Electronic Presentation

Digitisation converts paper information into electronic representations, whereas digitalisation uses those digital representations to change a business process. The distinction is important because scanning a document does not by itself solve verification. The ICC automation framework describes a progression from document imaging to OCR and data capture, followed by more advanced classification, rules, analytics, machine learning, and natural language processing [3].

The eUCP framework extends UCP 600 to presentations involving electronic records. Its rules address scope, electronic records and paper documents, format, presentation, examination, notice of refusal, originals and copies, transport, and data corruption [2]. The existence of such rules demonstrates that digital LC verification must address both technical processing and documentary validity. A document management system therefore needs capabilities for secure ingestion, version control, traceability, evidence preservation, and association of extracted information with its source record.

Kim and Shin's 2025 study of eUCP 2.0 discusses electronic presentation, completeness notifications, resubmission following data corruption, and the authenticity, integrity, and legal reliability of electronic records [7]. These issues are directly relevant to

intelligent verification because an AI system cannot be treated as the sole source of truth: its output must remain traceable to the underlying electronic record and applicable rule.

C. OCR, Information Extraction, and Intelligent Document Processing

OCR provides a bridge between image-based documents and machine-readable data. However, modern intelligent document processing extends beyond character recognition. It can include document classification, layout understanding, field extraction, entity recognition, semantic search, question answering, summarisation, matching, and process monitoring. Alotaibi et al.'s 2026 systematic literature review synthesised 46 peer-reviewed studies and grouped business-document NLP applications into six core tasks: semantic search, question answering, summarisation, text data integration and matching, event extraction, and business process management [8].

For LC verification, text integration and matching are especially relevant. A verification pipeline may first classify a document, extract structured fields, normalise values, identify entities and relationships, and then compare the resulting information with the LC terms and other presented documents. This creates a layered architecture in which extraction errors can propagate into verification decisions. Consequently, confidence scores, source references, validation rules, and human review become important.

The 2026 review also identifies persistent limitations in intelligent business document processing, including fragmented system development, limited enterprise-scale validation, insufficient knowledge-graph integration, and limited reusable resources [8]. These limitations are significant for LC research because trade documents contain specialised terminology and legal-commercial relationships that are not necessarily represented well in generic document datasets.

D. AI-Based LC Verification

Khalil and Kerbache's 2022 study directly connects machine learning, NLP, and OCR with automated LC document examination [4]. The proposed role of these technologies includes reading documents, extracting information, and checking compliance with other documents or predefined rules. The study also describes the existing examination process as manual,



time-consuming, labour-intensive, and dependent on skilled personnel [4].

Khalil et al. (2025) extend this research by proposing a roadmap for AI adoption in LC examination. Their study uses the Technology–Organization–Environment framework together with individual-level Technology Acceptance Model insights and a literature-driven approach supported by expert insights and case analysis [5]. The reported research identifies potential benefits in discrepancy detection, workflow optimisation, and compliance improvement, while concluding that regulatory and trust concerns make unrestricted full automation impractical. A hybrid AI–human model is therefore proposed [5].

A complementary 2025 study addresses a more specific operational problem: once AI indexes or analyses LC documents, which documents should human reviewers examine first? Khalil et al. formulate an integer linear programming model that assigns review tasks according to discrepancy criticality, monetary value, checker expertise, and availability [6]. In their reported case studies, the model reduced operational risk by 68.3% relative to the baseline and produced utilisation rates ranging from 34% to 73% under different objective priorities [6]. These figures are results of that study and should not be interpreted as general accuracy or performance benchmarks for all LC AI systems.

The literature therefore suggests a shift from the question 'Can AI examine the entire LC?' toward the more operationally useful question 'Which parts of LC examination can be automated reliably, and where should human review be concentrated?' This shift is consistent with the ICC's earlier staged automation framework and recent research on hybrid human-AI review and workflow optimisation[3], [5], [6].

E. Human-in-the-Loop and Explainable AI

Human-in-the-loop (HITL) AI integrates human oversight, feedback, or decision-making into an AI pipeline. Lazaros, Vrahatis, and Kotsiantis's 2026 systematic review proposes a taxonomy based on loop placement, interaction granularity, and temporal characteristics and identifies scalability, cognitive load, and trust calibration as important deployment challenges [9]. For LC examination, these concepts translate into practical questions: which discrepancies require mandatory human review, how should

reviewers receive AI evidence, how should feedback be recorded, and how can the system learn without weakening governance?

Explainability is particularly important when an AI system flags a documentary discrepancy. A useful verification interface should not only state that a document is 'non-compliant'; it should show the relevant document, extracted field, comparison value, applicable LC condition or rule, confidence, and evidence supporting the flag. Reinhard et al.'s 2026 systematic review examines the effects of explanations in human–AI interaction and provides a framework for studying how explanations affect user outcomes [10].

In this context, explainability should be treated as an operational feature rather than a cosmetic addition. It can support reviewer verification, auditability, dispute resolution, model monitoring, and controlled escalation. At the same time, an explanation must remain faithful to the actual evidence used by the system; a plausible natural-language explanation that is not grounded in the source document could create a new operational risk.

F. Emerging LLM and Agent-Based Approaches

Large language models (LLMs) and related generative AI techniques introduce new possibilities for semantic comparison, clause interpretation, question answering over trade records, and natural-language explanations. The 2026 intelligent business document processing review identifies LLMs, prompt engineering, retrieval-augmented generation, knowledge graphs, and agent-based architectures as promising directions for intelligent document processing [8].

For LC verification, these technologies should be considered as components within a controlled architecture rather than autonomous authorities. An LLM can assist with semantic interpretation or explanation, but the final verification layer must remain anchored to the credit terms, documentary rules, source records, and organisational controls. A retrieval-augmented architecture could retrieve the relevant LC clause, UCP/eUCP provision, internal rule, and source document before generating a proposed discrepancy explanation. Human review can then be required for low-confidence, ambiguous, high-value, or legally sensitive cases.



This architecture also creates research questions concerning hallucination, versioning of rule sources, prompt sensitivity, data confidentiality, model drift, and audit trails. These issues are not sufficiently resolved by generic LLM benchmarks and therefore require domain-specific evaluation.

III. METHODOLOGY

This paper adopts a structured literature review approach to synthesize the development of LC document management and verification rather than to present a new experimental model. The review draws on three complementary groups of sources: (1) authoritative documentary-credit rules and industry guidance, (2) primary studies addressing AI-assisted LC examination and operational optimisation, and (3) recent review studies covering intelligent business-document processing, human-in-the-loop AI, and explainable AI. Bringing these sources together enables LC-specific findings to be interpreted in relation to broader technical developments relevant to document extraction, semantic matching, human oversight, and explainability.

Relevant literature was identified through web-accessible scholarly and publisher sources, with particular attention to publications from 2025 and 2026 and to authoritative ICC materials. The search used combinations of terms such as “letter of credit,” “documentary credit,” “document examination,” “document verification,” “trade finance,” “eUCP,” “OCR,” “intelligent document processing,” “machine learning,” “NLP,” “human-in-the-loop,” “explainable AI,” and “large language models.” Sources were considered for inclusion when their content directly contributed to at least one of the research questions.

Sources were included when they addressed one or more of the following areas: LC document examination; documentary-credit digitalisation; electronic presentation; AI, NLP, OCR, or intelligent document processing for business documents; human-in-the-loop AI; explainable AI; or AI-supported workflow optimisation. Materials that did not contribute to document processing, trade-document verification, or the human–AI issues relevant to LC verification were not considered in the synthesis.

The selected literature was analysed through thematic synthesis. For each source, attention was given to the problem addressed, document-processing stage, technology or methodological approach, role of human reviewers, reported findings, limitations, and relevance to LC verification. The findings were subsequently organised into six themes: traditional examination;

digitalisation and electronic presentation; extraction and matching; AI-assisted examination; human-in-the-loop and explainability; and emerging generative or agent-based approaches. Comparing these themes helped identify common developments, complementary technologies, and unresolved research gaps.

The review also distinguishes between compliance with documentary-credit rules and broader fraud or financial-crime detection. These are related but different functions. A document may appear discrepant under the terms of an LC without constituting fraud, while a transaction may raise risk indicators without a documentary discrepancy. Keeping these functions separate helps avoid overstating what document-verification AI can establish.

IV. RESULTS AND DISCUSSION

A. Evolution of LC Document Management and Verification

The reviewed literature indicates an evolutionary path rather than a single technological replacement. Manual examination remains the baseline because it incorporates specialist interpretation. Digitisation introduces searchable images and machine-readable data. Basic automation then reduces repetitive data-entry and literal matching. Advanced AI adds document classification, semantic comparison, anomaly detection, and prioritisation. Human-in-the-loop systems integrate these capabilities while retaining human authority for exceptions and consequential decisions [3]–[6].

B. Functional Architecture for Intelligent LC Verification

A consolidated architecture derived from the reviewed literature can be represented as seven functional layers: document ingestion; classification and preprocessing; information extraction; normalisation and entity resolution; rule and semantic verification; discrepancy explanation and confidence assessment; and human review with audit logging. The first layers convert heterogeneous records into structured evidence. The middle layers perform compliance-oriented comparison. The final layers ensure that a human can inspect and challenge the machine output.

Document ingestion should preserve the original file, metadata, timestamps, source, and version. Preprocessing may include image enhancement and



OCR when necessary. Classification identifies whether a record is an invoice, transport document, certificate, insurance document, or other required document. Extraction identifies relevant fields such as names, dates, quantities, amounts, currencies, ports, document numbers, and descriptions. Normalisation addresses formatting differences such as date formats, abbreviations, transliteration, units, and equivalent terminology.

Verification then operates at multiple levels. First, document presence can be checked against the required-document list. Second, individual fields can be compared with the LC. Third, cross-document consistency can be assessed. Fourth, contextual and rule-based checks can identify potential discrepancies. Fifth, risk-based routing can determine which cases require human examination. This layered approach reduces the risk that a single model output is treated as the final decision.

C. Key Quantitative Findings from the Reviewed Literature

Although the reviewed literature demonstrates substantial progress in AI-assisted document processing, the reported quantitative evidence is heterogeneous. Some studies report operational outcomes, whereas others report the size of a literature corpus or provide conceptual frameworks without an experimental accuracy benchmark. Therefore, the values below are presented as study-specific findings rather than as directly comparable performance scores.

Table I. Key Quantitative Findings from the Reviewed Literature

Source	Year	Quantitative finding	What the number represents
Khalil et al. [6], Decision Analytics Journal	2025	68.3% operational-risk reduction	Reported result of the proposed AI-optimisation framework for LC examination; it is not a general AI document-verification accuracy rate.
Khalil et al. [6], Decision Analytics Journal	2025	34–73% checker utilisation	Reported range under different risk- versus efficiency-oriented allocation strategies; it

			measures workflow/resource utilisation.
Alotaibi et al. [8], Analytics	2026	46 peer-reviewed studies	Number of studies synthesised in the systematic review of AI- and NLP-based intelligent business-document processing.
Reinhard et al. [10], Information Systems Frontiers	2026	107 experimental user studies	Number of experimental XAI studies included in the systematic review of explanations in human-AI interaction.

The quantitative evidence demonstrates both progress and fragmentation in the research base. The 68.3% risk-reduction result and 34–73% utilisation range reported by Khalil et al. [6] are operational findings from one LC-specific optimisation study and therefore should not be interpreted as general document-verification accuracy measures. The 46-study and 107-study counts reported by Alotaibi et al. [8] and Reinhard et al. [10], respectively, describe the scope of their systematic reviews rather than LC-model performance. Across the reviewed LC literature, standardized measures for extraction accuracy, discrepancy-detection precision and recall, false-discrepancy rates, processing time, explanation quality, and final examination correctness remain insufficiently established. Future benchmarking should therefore evaluate these dimensions separately and under common document and rule conditions.

D. Comparative Synthesis of Technology Approaches

The reviewed technologies are complementary rather than interchangeable. OCR and document classification primarily convert heterogeneous records into machine-readable inputs; rule engines then provide deterministic checks for explicit documentary requirements. Machine-learning and NLP methods extend the process to classification, entity matching, semantic comparison, and discrepancy support where wording and structure vary across documents [3], [4], [8].

More recent transformer-based and generative approaches can assist with semantic interpretation, retrieval, question answering, and evidence-linked



explanations, but they introduce additional requirements for domain adaptation, grounding, confidentiality, evaluation, and human oversight [8]–[10]. Optimization methods address a different layer: they can help allocate AI-indexed or exception cases to human reviewers according to risk, expertise, workload, and other constraints [6]. Accordingly, an LC verification platform is better understood as a layered pipeline in which deterministic rules, statistical models, semantic models, optimization, and human review perform distinct functions.

E. Research Gaps Identified

First, LC-specific public datasets remain a major research need. Generic document benchmarks can test extraction and layout understanding, but they do not fully represent documentary-credit clauses, discrepancy categories, banking practice, multilingual trade records, or cross-document relationships. The literature on intelligent business documents also identifies limited enterprise-scale validation and fragmented resources [8].

Second, evaluation standards are fragmented. Accuracy of field extraction alone is not equivalent to correctness of an LC examination. Future benchmarks should separately measure document classification, field extraction, cross-document matching, discrepancy detection, false-discrepancy rates, explanation faithfulness, human-review time, and final examination correctness.

Third, rule grounding and version control require more attention. LC verification may depend on the wording of the credit, applicable UCP/eUCP provisions, standard banking practice, and institutional procedures. A system must therefore identify which rule version and evidence were used for each conclusion. This is especially important for generative AI systems.

Fourth, explainability and human oversight require domain-specific evaluation. General XAI research establishes the importance of explanations for human–AI interaction [9], [10], but LC review has distinctive requirements: the reviewer needs to locate the exact source evidence, understand the comparison, inspect the applicable condition, and record a defensible decision.

Fifth, interoperability remains important. A practical LC verification platform would need to interact with

document repositories, workflow systems, trade-finance applications, electronic presentation systems, and potentially messaging standards. The value of AI is therefore partly determined by the surrounding information architecture, not only by model performance.

Sixth, the boundary between documentary compliance and broader risk detection needs explicit modelling. Fraud, sanctions, anti-money laundering, counter-terrorist financing, and trade-based money-laundering controls may consume information from the same documents, but they have different objectives and evidence requirements. A unified platform can host these functions, but the decision logic and evaluation criteria should remain distinct.

F. Future Research Framework

Based on the reviewed evidence, a future LC verification research framework should combine standards-aware rules with AI-based semantic processing and explicit human oversight. The first component should be a trusted document layer that preserves original records and provenance. The second should be an extraction layer using OCR and layout-aware or multimodal models. The third should be a semantic layer that resolves entities, normalises values, and compares information across documents. The fourth should be a standards-aware verification layer that retrieves and applies relevant credit conditions and documentary-credit rules. The fifth should be an explanation layer that produces evidence-linked discrepancy rationales. The sixth should be a human-review layer that routes cases based on confidence, criticality, value, and exception type. Finally, an audit and learning layer should record decisions and feedback while maintaining governance controls.

This framework supports a research direction in which AI is evaluated not simply as a classifier but as part of an accountable socio-technical verification process. Such evaluation should use realistic document sets, expert-labelled discrepancies, multiple document types, multilingual examples, controlled rule versions, and human-review experiments. It should also test failure modes, including OCR corruption, ambiguous wording, conflicting documents, missing documents, altered records, and unsupported model explanations.



V. CONCLUSION

This review examined LC document management and verification across traditional examination, digitalisation, intelligent document processing, artificial intelligence, optimisation, and human-in-the-loop systems. The literature shows that LC verification is fundamentally a multi-stage problem: documents must be received and preserved, classified, converted into usable information, compared with credit requirements and other documents, assessed for discrepancies, and ultimately reviewed under documentary-credit rules.

The evidence also shows that automation has developed incrementally. ICC guidance already described a progression from manual examination through OCR, data capture, rules, machine learning and NLP toward higher levels of automation [3]. Recent research extends this trajectory through AI adoption frameworks and optimisation of human-review allocation [5], [6]. At the same time, research on intelligent business documents and human-AI interaction highlights limitations involving enterprise validation, explainability, trust, scalability, and domain adaptation [8]–[10].

The central research implication is that future LC verification systems should be designed as accountable hybrid systems rather than evaluated solely as automated document classifiers. High-value research opportunities exist in LC-specific datasets, standards-aware semantic verification, evidence-grounded generative AI, explainable discrepancy detection, human-review optimisation, interoperability, and auditability. A mature system should make its evidence and reasoning traceable, preserve human authority over consequential exceptions, and distinguish documentary compliance from broader fraud and financial-crime analysis.

The review is limited by its structured literature review design and reliance on publicly accessible literature and authoritative materials rather than a registered systematic-review protocol with a database-wide quantitative screening count. Future work can extend this review through a formal multi-database systematic review, expert validation, and empirical benchmarking on anonymised LC document collections. Such work would provide stronger evidence for evaluating the practical performance of AI-assisted LC document management and verification.

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