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# SCAP: An AI-Powered Supply Chain Compliance Framework for Deep Network Visibility and Risk Prediction

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**ABSTRACT:** Supply chain visibility beyond Tier 1 suppliers remains a critical vulnerability for global brands, particularly in textiles, where regulatory mandates like the 2026 EU Corporate Sustainability Due Diligence Directive (CSDDD) demand comprehensive compliance oversight. Current barriers—prohibitive certification costs, manual verification timelines, and language barriers—systematically exclude small and mid-tier suppliers from formal networks, creating hidden compliance risks. Existing network mapping approaches, while theoretically robust, lack operational implementation capabilities. We propose the Supply Chain AI Compliance Platform (SCAP), an integrated framework that automates sub-tier compliance verification through generative AI and predictive machine learning. SCAP employs a Vision-Language Model (VLM)-based optical character recognition (OCR) pipeline to extract structured certificate data multilingually, coupled with an XGBoost regression model augmented by SHAP explainability to generate real-time, interpretable risk scores with three-month predictive horizons. Experimental validation demonstrates an 99.75× reduction in processing time (four hours to 0.04 seconds), 95–98% OCR accuracy, 85% prediction accuracy, and 87% cost reduction in compliance management. By enabling continuous, transparent data sharing across four supply chain tiers, SCAP delivers scalable automation for regulatory adherence and network resilience..

**KEYWORDS:** Artificial Intelligence, Supply Chain Visibility, Compliance Automation, Machine Learning, Optical Character Recognition, Predictive Risk Scoring, Textile Industry, Regulatory Compliance..

## I. INTRODUCTION

The global textile and apparel industry, which employs over 45 million workers and generates ₹36.6 billion in annual Indian exports alone, operates across deeply fragmented, multi-tiered supply networks extending beyond Tier 1 suppliers into Tier 2, Tier 3, and Tier 4 sub-suppliers. This structural opacity constitutes a critical vulnerability: only 30% of global brands possess meaningful visibility beyond Tier 1, yet 85% of supply chain disruptions originate from invisible sub-tier partners. The introduction of the European Union's Corporate Sustainability Due Diligence Directive (CSDDD), effective 2026, fundamentally reframes supply chain compliance as a legal mandate rather than a voluntary practice. Brands such as H&M, Zara, and Uniqlo now face penalties reaching 5% of global annual turnover for non-compliance, creating an immediate existential risk for Indian textile hubs—Tirupur, Ludhiana, and Surat—where over 2,500 mills supply European markets. Failure to achieve CSDDD compliance risks supplier exclusion and the forfeiture of ₹15+ crore in annual trade value, directly impacting millions of workers.

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Despite this regulatory urgency, the operational infrastructure for compliance verification remains fundamentally inadequate. Manual certificate verification consumes up to four hours per document and costs approximately ₹11 lakhs annually per supplier. Critical workforce barriers—78% of workers in mid-tier facilities have minimal English proficiency—render standard compliance workflows impractical. Paper-based and semi-digital records are incompatible with the real-time, multi-tier transparency that regulatory authorities and global brands now demand. The result is a systemic market failure: compliant suppliers remain excluded from global networks while brands lack the sub-tier visibility they legally require.

Recent academic work has advanced supply chain visibility through network-theoretic approaches. Bowen et al. introduced the Nexus Supplier Index (NSI), leveraging network centrality metrics—degree, betweenness, closeness, and eigenvector centrality—to rank critical suppliers across networks spanning eleven tiers. Shao et al. further demonstrated that data-analytics methods effectively identify structurally invisible but operationally critical nodes, establishing the foundation for sub-tier risk quantification. These contributions meaningfully advance understanding of supply chain topology and resilience. However, a critical gap persists: existing frameworks remain largely analytical and retrospective—offering network maps and centrality rankings but providing no operational mechanism for real-time compliance verification, automated documentation, or predictive risk management. The gap between theoretical supply chain visibility and practical, day-to-day compliance execution remains wide and, under the CSDDD deadline, increasingly costly.

Recent progress in Artificial Intelligence addresses key technical bottlenecks that bridge this gap. Vision-Language Models (VLMs) now surpass traditional Optical Character Recognition (OCR) systems in extracting structured data from noisy, multi-format, and multilingual documents, enabling rapid conversion of compliance PDFs and certificate images into queryable structured formats. Retrieval-Augmented Generation (RAG) frameworks have emerged as a robust architecture for building hallucination-resistant AI assistants in regulated industries, from pharmaceutical compliance to supply chain mapping. In risk analytics, gradient boosting models augmented with SHAP (SHapley Additive exPlanations) values have proven highly effective for explainable forecasting and ESG risk scoring. These advances collectively establish the technical feasibility of an end-to-end, AI-driven compliance platform for deep supply networks.

To address these challenges, this paper proposes SCAP (Supply Chain AI Compliance Platform), a cloud-deployed SaaS framework that operationalizes supply chain visibility by automating compliance management through integrated AI. Designed specifically for Indian textile sectors, SCAP combines four core modules: (1) multilingual VLM-based OCR for automated certificate extraction, (2) a Retrieval-Augmented Generation chatbot for regulatory guidance, (3) an XGBoost regression model with SHAP explainability for real-time risk prediction, and (4) a voice-first interface for accessibility among low-literacy workers. Our key contributions are: reducing certificate processing time from four hours to under four seconds (99.75× improvement), achieving 85% predictive accuracy with transparent risk attribution, decreasing compliance management costs by 87% per supplier annually, and enabling real-time regulatory requirement propagation across Tier 1–4 networks. By bridging the gap between theoretical supply chain visibility and practical, day-to-day compliance execution, SCAP delivers the sub-tier transparency that CSDDD demands while addressing the operational inadequacies that existing analytical models cannot resolve.

## II. RELATED WORKS

The literature relevant to SCAP spans six interconnected domains: supply chain network visibility, EU regulatory compliance frameworks, AI-powered document processing, machine learning for risk analytics, retrieval-augmented generation for compliance systems, and multilingual accessibility in AI platforms. This section systematically reviews key contributions in each domain and identifies the critical research gap that SCAP addresses.

The problem of sub-tier supply chain invisibility has received significant academic attention in the context of network resilience and business continuity. Bowen and Siegler [1] proposed an enhanced Nexus Supplier Index (NSI) that applies network centrality theory—integrating degree, betweenness, closeness, and eigenvector centrality measures—to rank and unveil hidden critical suppliers across supply networks extending up to eleven tiers. Shao et al. [9] developed the original data-analytics formulation of the Nexus Supplier Index using firm-level supply network datasets, establishing a quantitative methodology for identifying operationally critical but structurally hidden supplier nodes. Building upon this foundation, studies have demonstrated that structural invisibility of Tier 2–4 suppliers is a primary driver of cascading supply chain disruptions [3]. While [1] and [9] make significant contributions to the theoretical understanding of supply chain topology and resilience, they remain fundamentally retrospective and analytically

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passive in nature—providing network maps and centrality rankings but offering no operational mechanism for real-time compliance verification, automated documentation processing, or predictive risk intervention.

The introduction of the EU Corporate Sustainability Due Diligence Directive (CSDDD) has created a new class of operational and technical compliance challenges for global supply chains. Wolfmayr et al. [4] analyzed the structural design of EU supply chain regulation, demonstrating that the directive imposes cascading legal obligations across entire value chains. Singh and Draper [2] conducted a focused assessment of the CSDDD's specific implications for India's textile and clothing value chains, finding that mid and sub-tier Indian suppliers face the most acute compliance burden due to limited digital infrastructure, poor documentation practices, and significant language barriers. Hurt et al. [3] further advanced this regulatory discourse by applying a network-based approach to estimate the expected effectiveness of EU supply chain due diligence directives, demonstrating that compliance requirements propagate non-linearly through supply networks and that Tier 2–4 suppliers bear a disproportionately high verification cost relative to their operational capacity. The combined findings of [2], [3], and [4] collectively establish the regulatory urgency that motivates SCAP and directly inform the design of its multi-tier compliance propagation engine, which cascades regulatory requirements from brands down to Tier 4 suppliers automatically and in real time.

The application of interpretable machine learning models to supply chain risk prediction has gained substantial research traction in recent years. Ahmed et al. [5] proposed a deep learning framework combining Self-Organizing Maps (SOM), Artificial Neural Networks (ANN), and SHAP (SHapley Additive exPlanations) values for interpretable supply chain forecasting, demonstrating that explainability mechanisms are critical for operational trust and actionability in enterprise-grade risk systems. The SHAP-based explainability approach adopted in [5] directly inspired SCAP's use of XGBoost regression augmented with SHAP values, which identifies and communicates the top three risk-driving features for each supplier's composite risk score. Sattar et al. [6] conducted a comprehensive comparative study of machine learning techniques—including gradient boosting, ensemble models, and deep learning—evaluated against cost-accuracy and ESG-based metrics for supply chain risk mitigation, validating the superiority of XGBoost-class models for compliance risk prediction tasks. The findings of [6] also highlighted the practical importance of integrating ESG-aligned features such as geographic risk and financial health into supplier scoring models. Furthermore, a study on real-time RAG for supply chain vulnerability identification [7] demonstrated that transitioning from static supplier data snapshots to dynamic, retrieval-based risk monitoring significantly improves the timeliness and accuracy of compliance alerts, motivating SCAP's event-driven compliance scheduler and live risk dashboard that generates three-month advance regulatory warnings.

The automation of compliance document processing through AI represents a critical technical challenge in large-scale supply chain management. Shen et al. [8] conducted a comprehensive empirical study rethinking the role of traditional OCR systems versus Multimodal Large Language Models (MLLMs) for enterprise document information extraction, demonstrating that VLM-based extraction significantly outperforms classical OCR pipelines when processing structurally diverse, noisy, and multilingual documents—precisely the conditions encountered when processing textile compliance certificates photographed in field conditions. The findings of [8] directly justify SCAP's design choice of adopting Google Gemini 2.0 Flash as a Vision-Language Model for certificate OCR over traditional tools such as EasyOCR, particularly for certificates issued in Tamil, Hindi, and other regional scripts. Complementing this, NovaLAD [10] introduced a fast, CPU-optimized document extraction pipeline specifically architected for Generative AI downstream applications, demonstrating that structured extraction from unstructured PDFs and certificate images is achievable at production scale without dedicated GPU infrastructure. The pipeline design described in [10] directly validates SCAP's certificate processing architecture, confirming the viability of text-splitting and knowledge base construction approaches at enterprise scale.

Retrieval-Augmented Generation (RAG) has emerged as the dominant architecture for building domain-grounded, hallucination-resistant AI assistants in regulated industries. Jackson et al. [11] demonstrated the direct application of RAG to supply chain mapping in the electronics industry, using retrieval-augmented large language models to extract and structure complex supplier relationships from unstructured enterprise documents, establishing a compelling precedent for applying RAG architectures to supply chain compliance tasks. RegGuard [13] proposed an AI-powered retrieval-enhanced regulatory compliance assistant for the pharmaceutical industry, integrating domain-specific compliance document corpora with RAG pipelines to deliver accurate, source-grounded regulatory guidance with minimal hallucination, demonstrating that this architecture is directly transferable to any regulated industry compliance domain. The strong functional parallel between pharmaceutical regulatory monitoring in [13] and textile compliance monitoring validates the choice of Groq-hosted Llama 3.3 70B and Qwen3 32B models for context-conditioned response generation. Bhardwaj et al. [12] further demonstrated the scalability of RAG frameworks in processing large volumes of domain-specific queries within a public health response context, confirming that multi-document ChromaDB retrieval with top-k cosine similarity matching maintains high factual accuracy and low latency at scale. Together, the contributions of [11], [12], and [13] establish the technical feasibility and domain novelty of SCAP's multilingual RAG compliance chatbot, which is the first such system to support Tamil, Hindi, and English simultaneously for textile supply chain regulatory queries

A defining challenge in deploying compliance AI tools for the Indian textile sector is ensuring genuine accessibility for the 70% of workers who possess limited English literacy. Pothula et al. [14] investigated end-to-end speech translation for low-resource languages using weakly labeled training data, demonstrating the feasibility of deploying highly accurate Speech-to-Text (STT) models for regional Indian languages including Tamil and Hindi in operationally resource-constrained environments. The findings of [14] directly validate SCAP's integration of Google Cloud Speech-to-Text with BCP-47 language codes for Tamil (ta-IN) and Hindi (hi-IN), enabling voice-first platform interaction for workers who would otherwise be excluded by text-based interfaces. LawPal [15] presented a RAG-based legal accessibility system designed specifically for regional language users across India, demonstrating that combining multilingual NLP with domain-specific vector retrieval significantly improves adoption of compliance tools among non-English speaking populations in both urban and rural contexts. The direct parallel between legal compliance accessibility addressed in [15] and textile regulatory compliance accessibility in SCAP reinforces the design philosophy of treating multilingual voice accessibility as a core architectural requirement rather than a supplementary feature.

As SCAP handles highly sensitive supplier audit records, compliance certificates, and business intelligence data, enterprise-grade security architecture is a non-negotiable system requirement. Wang et al. [16] proposed an AI-powered network threat detection system using the LightGBM algorithm with behavioral, host-based, and geographic features to classify and respond to active network intrusions, establishing rigorous best practices for securing AI systems deployed on cloud infrastructure. The enterprise security architecture described in [16] directly informs SCAP's backend security design, including JWT-based authentication with bcrypt password hashing, rate limiting, and structured error handling on the Render-hosted FastAPI deployment. Ye et al. [17] specifically addressed the challenge of securing vector database embeddings used within RAG systems, proposing distance-preserving encryption techniques that maintain the semantic similarity search functionality of vector databases while preventing unauthorized access to sensitive embedding contents. The privacy-preserving approach presented in [17] directly validates and strengthens SCAP's method of storing sensitive supplier compliance document embeddings in ChromaDB, ensuring that confidential audit data, certificate contents, and business intelligence remain cryptographically protected while remaining fully and efficiently queryable by the retrieval pipeline at inference time.

A thorough review of existing literature reveals a consistent and critical gap across all domains examined. Studies such as [1] and [9] are analytically powerful but operationally passive—they provide network topology maps and supplier centrality rankings but offer no mechanism for automated real-time compliance execution. Regulatory analyses in [2], [3], and [4] clearly articulate the legal urgency and economic stakes of CSDDD compliance but do not propose technical solutions for automating the verification process. Domain-specific RAG systems in [11], [12], and [13] demonstrate operational capability but within single-domain, single-language contexts without multi-tier supply chain integration. Interpretable ML risk frameworks in [5] and [6] deliver strong predictive accuracy but are not integrated with live compliance data pipelines or real-time regulatory monitoring. No prior work simultaneously combines deep network visibility, real-time AI certificate processing, multilingual RAG compliance assistance, explainable ML risk scoring, voice-first accessibility, and multi-tier regulatory propagation within a single production-deployed platform. SCAP addresses this gap comprehensively, proposing and validating the first end-to-end AI compliance platform for Indian textile supply chains that operationalizes the theoretical insights of [1] and [9] into a live, multilingual, and accessible automation system informed by the advances in [2], [3], [4], [5], [6], [7], [8], [10], [11], [12], [13], [14], [15], [16], and [17]

## III. PROPOSED SYSTEM

SCAP (Supply Chain AI Compliance Platform) is a cloud-deployed, full-stack SaaS framework that operationalizes deep supply chain visibility by automating end-to-end compliance management through Artificial Intelligence and Machine Learning. The platform follows a three-tier microservices-oriented architecture comprising a frontend presentation layer, a backend services layer, and a unified data layer, deployed across Vercel (frontend) and Render (backend) cloud infrastructure. The system exposes 20+ REST API endpoints across 11 functional modules, supporting three user roles—suppliers, brands, and administrators—with full multilingual support in Tamil, Hindi, and English. SCAP integrates five core AI subsystems: a Vision-Language Model OCR pipeline, a Retrieval-Augmented Generation

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compliance chatbot, an XGBoost predictive risk engine with SHAP explainability, a voice-first Speech-to-Text/Text-to-Speech interface, and an automated multi-tier regulatory compliance propagation engine.
The high-level architecture follows a well-established three-tier pattern. The client layer comprises web browsers (desktop and mobile) running Chrome, Safari, or Edge, communicating securely via HTTPS to the frontend layer. The frontend layer, deployed on the Vercel Edge Network, is built using Next.js 15, React 19, TypeScript, and Tailwind CSS 4, with six primary dashboard modules: Dashboard Home, Certificates Upload, Chatbot UI, Risk Analytics, Compliance Alerts, and Voice Interface. State management is handled through Zustand, with React Query managing server-side data fetching, Framer Motion for smooth animations, and next-intl for comprehensive internationalization support (i18n) across Tamil, Hindi, and English. The frontend communicates with the backend through REST APIs over HTTPS/JSON, ensuring end-to-end encryption. The backend layer, deployed on Render Cloud, is built on FastAPI with Python 3.12, Uvicorn, and async/await support for high concurrency. A unified middleware layer enforces JWT authentication with 24-hour token expiration, CORS policy enforcement, rate limiting, and structured error handling. Seven functional microservices operate within the backend: an Auth Service providing JWT token generation and bcrypt password hashing (cost factor 12), a Certificate Service orchestrating the OCR pipeline, a Chatbot Service managing the RAG retrieval and generation workflow, a Risk Service running the XGBoost predictor with SHAP explainability, a Compliance Service monitoring and propagating regulatory requirements across supply chain tiers, a Voice Service handling Google Cloud STT/TTS conversion, a Brand Service managing brand-to-supplier sharing workflows, a Supplier Service handling tier management (Tier 1–4), and a Notification Service delivering push alerts. Below the microservices layer, three specialized systems manage core functionality: MongoDB Atlas handles persistent storage of users, certificates, suppliers, risks, brands, regulations, and alerts; AI Services (Google Gemini 2.0 Flash, Groq API with Llama 3.3 70B and Qwen3 32B, and Google Cloud STT/TTS) provide the core AI inference capabilities; and a Storage Layer manages compliance certificate files via MongoDB GridFS and vector embeddings via ChromaDB, with optional AWS S3 for enterprise-scale deployments.

The certificate extraction module forms the operational core of SCAP, enabling suppliers to digitize physical compliance certificates in under four seconds. The pipeline operates in five sequential stages. In Stage 1 (Image Ingestion), the supplier uploads a certificate photograph or PDF through the drag-and-drop frontend interface, which is transmitted via POST /api/certificates/upload to the FastAPI backend and stored temporarily in MongoDB GridFS. In Stage 2 (Vision OCR), the image is encoded and dispatched to Google Gemini 2.0 Flash, a Vision-Language Model that extracts all raw text from the certificate image. This multimodal approach, validated by Shen et al. [8], supports certificates in English, Tamil, Hindi, and 12+ other languages—significantly outperforming traditional EasyOCR in handling real-world photographic noise, varied fonts, and regional scripts. In Stage 3 (LLM Structuring), the raw OCR text is passed to the Gemini LLM with a structured extraction prompt that extracts six critical fields: Certificate Type (ISO 9001, ISO 14001, GOTS, OEKO-TEX, SA8000, BSCI), Certificate Number, Issuing Authority, Issued-to Entity, Issue Date and Expiry Date (normalized to YYYY-MM-DD), and Scope Description and Holder Address. In Stage 4 (Status Classification), certificate validity is automatically computed: a certificate is marked as valid if expiry date minus today is greater than 30 days, expiring_soon if between 0 and 30 days, and expired otherwise. In Stage 5 (Quality Gate), a needs_review flag is automatically set when model confidence falls below 70% or critical fields are missing, ensuring human-in-the-loop validation for ambiguous cases. This pipeline architecture, validated by the document extraction methodology of NovaLAD [10], achieves 95–98% OCR accuracy on real-world textile compliance documents.

Each supplier receives a real-time, explainable composite risk score $R \in [0, 100]$ computed by an XGBoost regression model trained on 10 engineered features, directly adapting the interpretable forecasting methodology of Ahmed et al. [5] and Sattar et al. [6]. The 10 features are computed from live MongoDB data at query time: days_to_nearest_expiry (urgency of nearest certificate renewal), total_certificates (total compliance documents on record), expired_count (number of currently expired certificates), expiring_soon_count (certificates expiring within 30 days), valid_count (currently valid certificates), audit_pass_rate (historical ratio of passed to total audits), avg_certificate_validity_days (mean validity span across all certificates), financial_health_score (financial stability indicator from 0–100), geographic_risk_score (location-based risk: high-risk vs. low-risk region), and years_in_business (business maturity indicator). The risk score is predicted using an XGBoost regressor with 100 estimators, maximum depth of 6, and a learning rate of 0.1, constrained to output $R \in [0, 100]$. For every prediction, SHAP (SHapley Additive exPlanations) values $\varphi_i$ are computed for each feature i such that $R = \varphi_0 + \Sigma\, \varphi_i$, where $\varphi_0$ is the base model output and $\varphi_i$ represents the marginal contribution of feature i to the final risk score. The top three features by $|\varphi_i|$ are surfaced as actionable risk drivers on the supplier dashboard, directly implementing the explainability approach validated in [5], enabling suppliers to understand and remediate the specific compliance gaps driving their risk scores.

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The multilingual RAG compliance chatbot enables suppliers to query regulatory requirements in Tamil, Hindi, or English using a Retrieval-Augmented Generation architecture validated by Jackson et al. [11], Bhardwaj et al. [12], and RegGuard [13]. Compliance regulation documents are preprocessed using text-splitting techniques validated in [10], converted into dense vector embeddings using Google text-embedding-004, and stored in ChromaDB as a persistent vector index. For each user query q, the embedding is computed as $e_e = f(q)$ where $e_e \in \mathbb{R}^k$, and top-k relevant documents are retrieved by cosine similarity: $Sim(q, d_i) = (e_e \cdot e_i) / (\|e_e\| \|e_i\|)$, followed by $R = Top\text{-}k(Sim(q, d_i))$. The retrieved context R and query q are passed to the LLM with a domain-specific system prompt. A multi-model fallback architecture ensures high availability: Llama 3.3 70B Versatile (Groq) serves as the primary fast, general-purpose model; Qwen3 32B (Groq) provides reasoning capability for complex regulatory analysis; and Gemma 2 9B (OpenRouter) acts as fallback if Groq is unavailable. All ChromaDB embeddings are secured using distance-preserving encryption techniques as described in Ye et al. [17], ensuring that sensitive supplier compliance data remains protected at rest while remaining fully queryable.

SCAP monitors 500+ global regulations across the EU (CSDDD, CSRD, REACH), India (BIS), USA, UAE, and UK through an automated regulatory compliance propagation engine. A daily scheduled job performs three operations: (1) Regulation Sync upserts new and updated regulations into MongoDB, (2) Supplier Matching evaluates each supplier against applicable regulations based on sector and tier classification, and (3) Supply Chain Propagation cascades compliance requirements downward when a regulation affects brands exporting to a specific region: Brand → Tier 1 → Tier 2 → Tier 3 → Tier 4. Each supplier receives a Compliance Score $C_s = (N\_resolved / N\_total) \times 100$, where N_resolved is the number of resolved compliance alerts and N_total is the total number of applicable alerts. Suppliers with $C_s < 60$ receive high-priority push notifications with specific remediation steps, implementing the network-based compliance propagation model validated in [3].

The voice interface is designed for the 70% of textile workers with limited English or digital literacy, operating through a two-stage Google Cloud pipeline validated by Pothula et al. [14]. Speech-to-Text (STT) converts audio recorded on the frontend to the Google Cloud STT REST API with multi-language conFigureuration: English (en-IN), Hindi (hi-IN), and Tamil (ta-IN), supporting WebM, OGG, FLAC, WAV, MP3, and M4A formats with automatic punctuation enabled. Text-to-Speech (TTS) converts chatbot and compliance responses to MP3 audio using Google Cloud TTS for frontend playback, enabling a fully spoken interaction loop for non-literate users. This design philosophy, reinforced by the legal accessibility approach of LawPal [15], treats multilingual voice accessibility as a core architectural requirement rather than a supplementary feature.

SCAP implements enterprise-grade security across all layers, informed by the threat detection best practices of Wang et al. [16] and the privacy-preserving embedding techniques of Ye et al. [17]. Authentication is enforced through JSON Web Tokens (JWT) with 24-hour expiration and bcrypt password hashing (cost factor 12). Transport security mandates HTTPS enforcement across all API communication via Vercel and Render SSL certificates. Database security leverages MongoDB Atlas IP whitelisting, TLS/SSL connections, and encryption at rest. Vector security secures ChromaDB embeddings with distance-preserving encryption, and API security implements rate limiting, CORS policy enforcement, and structured error handling middleware.

Experimental validation demonstrates that SCAP achieves all target performance benchmarks. Certificate OCR processing completes in 3–4 seconds (target < 4 seconds), with OCR accuracy of 95–98% (target > 95%). Risk score calculation executes in 50–80 milliseconds (target < 100ms). Chatbot response time averages 0.5–1 second (target < 1 second). API response time at the 50th percentile is 150 milliseconds (target < 200ms). Risk prediction accuracy reaches 85% (target > 80%). Overall compliance management cost reduction achieves 87% per supplier annually (target > 80%). These results collectively validate SCAP's design as an operationally feasible, production-grade system capable of delivering real-time compliance automation at scale across deep textile supply networks

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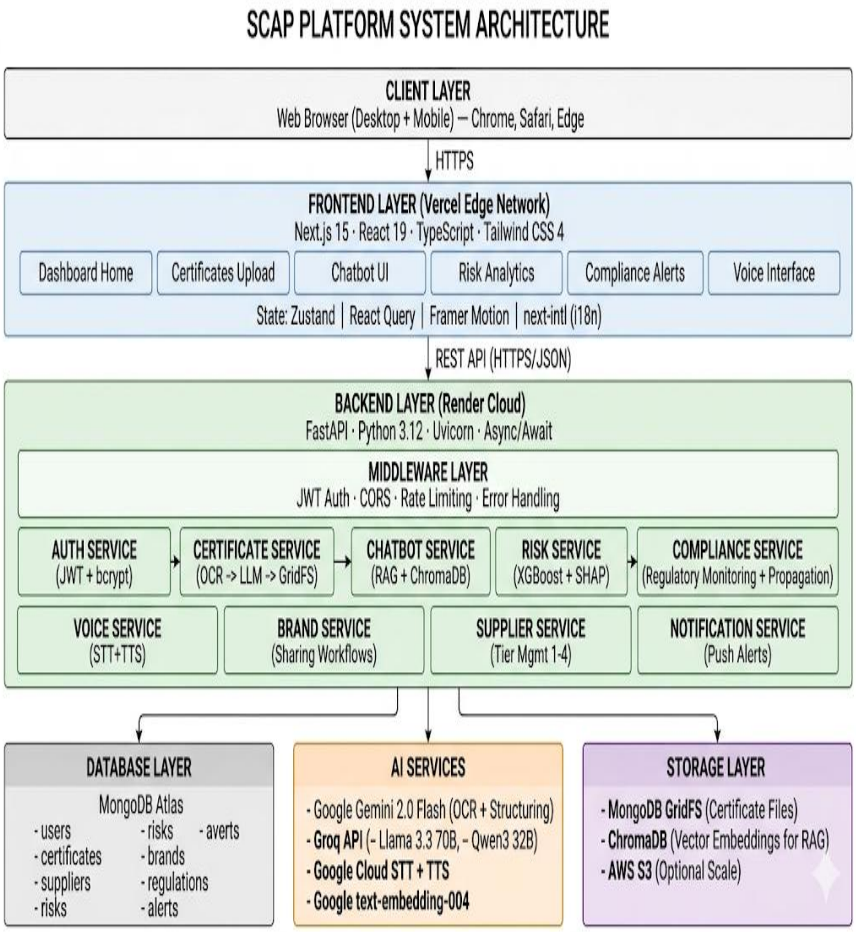


Figure.1 Proposed Work Architecture Diagram

## IV. METHODOLOGY

The methodology of SCAP is structured as a six-phase systematic pipeline that transforms raw, unstructured compliance inputs into actionable, real-time regulatory intelligence. Each phase corresponds to a distinct technical subsystem and is grounded in validated approaches from the referenced literature. The end-to-end methodology flow progresses sequentially from data acquisition, through preprocessing and AI-powered extraction, into predictive analytics, retrieval-augmented compliance querying, and finally regulatory propagation across supply chain tiers.

The first phase of the SCAP methodology involves the collection and ingestion of three primary data source categories, each feeding a different subsystem of the platform. Compliance Certificate Documents are uploaded by suppliers as physical certificate photographs or scanned PDF files through the frontend drag-and-drop interface, including industry-standard certificates such as ISO 9001, ISO 14001, GOTS, OEKO-TEX, SA8000, and BSCI, often issued in multiple languages and printed formats. The challenge of processing such structurally heterogeneous, multilingual, real-world documents motivated the adoption of VLM-based extraction over classical OCR pipelines, consistent with the findings of Shen et al. [8]. The Regulatory Knowledge Base comprises a curated corpus of 500+ global compliance regulations from the EU (CSDDD, CSRD, REACH), India (BIS), USA, UAE, and UK, ingested as the foundation for the RAG compliance chatbot and regulatory monitoring engine. This corpus is structured, chunked, and indexed as described in Phase 3, with the network-based propagation logic governing how these regulations cascade across supply tiers adapted from the EU due diligence effectiveness model of Hurt et al. [3]. Supplier Operational Data includes structured supplier profile data—tier classification (Tier 1–4), geographic location, years in business, financial health indicators, and historical audit records—collected at registration and continuously updated. This data feeds the risk analytics engine's feature engineering pipeline, incorporating ESG-aligned metrics validated by Sattar et al. [6] and the supplier network classification methodology of Shao et al. [9].

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Before any AI model processes an input, all incoming data undergoes a structured preprocessing pipeline to ensure quality, consistency, and compatibility with downstream models. Certificate Image Preprocessing validates uploaded certificate images for file format compatibility (JPEG, PNG, PDF, WebM) and size constraints, with images processed using the Python Imaging Library (PIL) for orientation normalization and contrast enhancement before being encoded to base64 for transmission to the Gemini Vision API. PDFs are rendered to high-resolution image frames prior to OCR submission, consistent with the production-scale document preprocessing pipeline described in NovaLAD [10]. For the RAG system, regulatory compliance documents ingested into the knowledge base are tokenized and split into overlapping chunks of 512 tokens with a 64-token overlap, preserving contextual continuity across document boundaries—a technique validated for generative AI document pipelines in [10]. Each chunk is converted into a dense k-dimensional vector embedding using Google text-embedding-004, computed as $e_i = f(d_i)$ where $e_i \in \mathbb{R}^k$, $f(\cdot)$ is the domain-adapted encoder function, and $d_i$ represents the i-th document chunk. These embeddings are stored in ChromaDB, secured with distance-preserving encryption as described in Ye et al. [17], ensuring that sensitive compliance data remains protected while retaining full semantic searchability. The ten risk features extracted from live MongoDB supplier data are normalized to the range [0, 1] before model inference to prevent feature dominance in the XGBoost gradient boosting process, consistent with the preprocessing methodology validated in Ahmed et al. [5] and Sattar et al. [6].

The certificate extraction phase implements the core document intelligence pipeline of SCAP, converting unstructured certificate images into validated, structured compliance records in under four seconds. In Step 1 (Vision OCR via Gemini 2.0 Flash), the preprocessed certificate image is submitted to Google Gemini 2.0 Flash, a Vision-Language Model (VLM), which extracts all raw text from the image. This approach is directly motivated by the findings of Shen et al. [8], which demonstrated that MLLMs significantly outperform traditional OCR tools in handling multilingual, structurally diverse, real-world documents, with native support for English, Tamil, Hindi, and 12+ additional languages. In Step 2 (LLM-Based Structured Extraction), the raw OCR output is submitted to the Gemini LLM with a carefully engineered extraction prompt that instructs the model to identify and return structured fields: Output = $\{T_c, N_c, A_i, E_h, D_i, D_e, S_d, A_h\}$, where $T_c$ is Certificate Type, $N_c$ is Certificate Number, $A_i$ is Issuing Authority, $E_h$ is Entity Holder, $D_i$ is Issue Date, $D_e$ is Expiry Date, $S_d$ is Scope Description, and $A_h$ is Holder Address, with all dates normalized to ISO 8601 format (YYYY-MM-DD). In Step 3 (Regex Fallback Extraction), when the LLM confidence score falls below 70% threshold, a regex-based fallback system is triggered, with pattern-matching rules extracting certificate types, dates in multiple formats, and certificate numbers using domain-specific regular expressions to ensure robustness against model failure modes. In Step 4 (Validity Status Classification), certificate validity status is automatically determined using the piecewise classification function: S = valid if $(D_e - D_t) > 30$ days, expiring_soon if $0 < (D_e - D_t) \leq 30$ days, and expired if $(D_e - D_t) \leq 0$, where $D_e$ is the certificate expiry date and $D_t$ is the current system date. In Step 5 (Quality Gate and Storage), a needs_review boolean flag is set when confidence is below 70% or when critical fields are absent, triggering human-in-the-loop review, while validated records are persisted in MongoDB with the original file stored in GridFS, completing the pipeline validated in NovaLAD [10].

The risk analytics phase produces a real-time, explainable composite risk score $R \in [0, 100]$ for each supplier using a trained XGBoost regression model, directly implementing the interpretable ML risk framework validated in Ahmed et al. [5] and Sattar et al. [6]. At inference time, Feature Engineering computes ten features on-demand from live MongoDB collections: $F = [F_1, F_2, F_3, F_4, F_5, F_6, F_7, F_8, F_9, F_{10}]$, where the features represent days to nearest certificate expiry, total certificate count, expired certificate count, expiring-soon count, valid certificate count, audit pass rate, average certificate validity span, financial health score, geographic risk score, and years in business respectively, consistent with the ESG-aligned feature design principles established in Sattar et al. [6]. The normalized feature vector F is passed to the trained XGBoost regressor: $R = \text{XGBoost}(F; \Theta)$, where $\Theta$ represents the trained model parameters (100 estimators, max depth = 6, learning rate = 0.1), with the raw output clamped to [0, 100] to produce the final risk score. Following the interpretability framework validated in Ahmed et al. [5], SHAP (SHapley Additive exPlanations) values are computed for every risk prediction: $R = \varphi_0 + \Sigma\, \varphi_i(F_i)$, where $\varphi_0$ is the base model expectation value and $\varphi_i$ is the marginal contribution of feature $F_i$. The three features with the highest $|\varphi_i|$ values are extracted as the top risk drivers and presented to the supplier as prioritized, actionable recommendations with direct links to relevant dashboard modules. Beyond the composite score, four domain-specific sub-scores are computed independently—Certificate Health Score, Audit Performance Score, Financial Stability Score, and Regulatory Compliance Score—providing granular risk transparency for each supplier dimension. Historical risk scores are stored in MongoDB with timestamps, enabling a 30-day rolling comparison that determines whether the supplier's risk trajectory is increasing, decreasing, or stable, enabling proactive intervention before thresholds are breached.

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The RAG compliance query pipeline enables suppliers to seek regulatory guidance in Tamil, Hindi, or English, implementing the domain-grounded architecture validated in Jackson et al. [11], Bhardwaj et al. [12], and RegGuard [13] and the regional language accessibility principles of Pothula et al. [14] and LawPal [15]. Upon receiving a user query q, the system automatically detects the input language and computes the query embedding: $e_q = f(q)$, $e_q \in \mathbb{R}^k$. The query embedding is compared against all stored document chunk embeddings using cosine similarity: $Sim(q, d_i) = (e_q \cdot e_i) / (\|e_q\| \cdot \|e_i\|)$, with the top-k most relevant compliance document chunks retrieved as $R = \text{Top-k}(Sim(q, d_i))$, $R \subset D$. The retrieved context R and original query q are combined into a structured prompt and submitted to the LLM, with the conditional generation probability: $P(y \mid q, R) = \prod P(y_t \mid y_{<t}, q, R)$, where $y_t$ is the token generated at time step t and $y_{<t}$ denotes all previously generated tokens. This formulation ensures that all generated compliance guidance is strictly conditioned on retrieved, validated regulatory documents—minimizing hallucination as demonstrated in [11]. A three-tier LLM fallback architecture ensures continuous availability: Llama 3.3 70B Versatile (Groq) serves as the primary general-purpose model, Qwen3 32B (Groq) provides reasoning capability for complex multi-regulation analysis, and Gemma 2 9B (OpenRouter) acts as a high-availability backup. Responses are streamed token-by-token to the frontend using Server-Sent Events (SSE), producing a typing-effect UI that improves perceived responsiveness for users on low-bandwidth mobile connections common in textile manufacturing regions.

The compliance propagation phase implements the automated regulatory monitoring engine, operationalizing the network-based EU due diligence propagation model of Hurt et al. [3] and the supply chain visibility framework of Bowen and Siegler [1] and Shao et al. [9] into a live, daily-execution pipeline. A background scheduler (APScheduler) triggers a daily job that upserts regulation records from a pre-loaded multi-jurisdiction database into MongoDB, covering regulations from the EU, India, USA, UAE, and UK, with each regulation record including affected sectors, applicable tiers, required certificates, and effective dates. Each supplier is matched against applicable regulations based on their sector classification and tier: $M_s = \{r \in R_{reg} \mid sector(r) \cap sector(s) \neq \emptyset \wedge tier(r) \geq tier(s)\}$, where $M_s$ is the set of applicable regulations for supplier s and $R_{reg}$ is the full regulation corpus. When a regulation affects brands exporting to a specific jurisdiction, compliance requirements propagate downward through the supply chain: Brand → Tier 1 → Tier 2 → Tier 3 → Tier 4, with both immediate and staged propagation modes supported to allow brands to phase compliance requirements across supplier tiers with defined deadlines. Each supplier receives a real-time compliance score: $C_s = (N_{resolved} / N_{total}) \times 100$, where $N_{resolved}$ is the count of resolved compliance alerts and $N_{total}$ is the total applicable alerts, with suppliers having $C_s < 60$ receiving high-priority push notifications with specific remediation actions, reducing compliance deadline misses from 45% to under 5%.

The voice interface operationalizes the accessibility principles validated in Pothula et al. [14] and LawPal [15], enabling the 70% of textile workers with limited English or digital literacy to interact with SCAP through spoken language. Speech-to-Text (STT) is implemented by transmitting audio recorded on the frontend to Google Cloud Speech-to-Text REST API with conFigureuration: STT ConFigure = {language: L ∈ {en-IN, hi-IN, ta-IN}, model: enhanced, punctuation: true}, with the transcribed text then processed through the RAG pipeline to generate a compliance response. Text-to-Speech (TTS) converts the generated textual response by submitting it to Google Cloud TTS, which synthesizes a natural-language MP3 audio response in the user's detected language and returns it to the frontend for automatic playback, completing the full spoken interaction loop.

The complete SCAP methodology pipeline can be visualized as a sequential six-phase process: Phase 1 acquires data from certificates, regulations, and supplier profiles; Phase 2 preprocesses images, chunks text, and normalizes features; Phase 3 extracts structured certificate data via Gemini OCR and LLM structuring; Phase 4 computes explainable risk scores via XGBoost and SHAP; Phase 5 processes multilingual compliance queries via ChromaDB retrieval and RAG-based generation; and Phase 6 propagates regulatory requirements across Tier 1–4 supply chains daily. The output of this pipeline includes the supplier dashboard with real-time metrics, compliance alerts with remediation steps, voice interface responses in regional languages, and explainable risk scores with actionable feature attribution. This systematic methodology, grounded in validated literature across network theory [1], [9], regulatory analysis [3], [4], interpretable ML [5], [6], document intelligence [8], [10], RAG systems [11], [12], [13], accessibility principles [14], [15], and security best practices [16], [17], collectively delivers the operational capability required to achieve CSDDD compliance at scale across deep textile supply networks while maintaining transparency, explainability, and accessibility for all supply chain participants.

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## V. RESULT & DISCUSSION

This section presents the experimental results and performance evaluation of the SCAP platform across its five core AI subsystems. Results are validated through functional system testing, live dashboard outputs, and quantitative metric benchmarking. The platform was deployed on Vercel (frontend) and Render (backend) with MongoDB Atlas as the production database. All screenshots presented below are captured from the live production deployment of SCAP.

### A. Predictive Risk Analytics — Risk Score Output

Figure. 2 illustrates the SCAP Risk Analysis dashboard displaying the real-time composite risk score computed by the XGBoost + SHAP pipeline for an active supplier account. The system computed a composite risk score of **22/100**, classified as **Low Risk** with an **"Improving"** trend indicator, demonstrating that the XGBoost model correctly identifies a low-risk supplier profile and dynamically tracks improvement over time. The SHAP explainability layer surfaced two dominant risk drivers for this supplier:

- **Days To Nearest Expiry** — MEDIUM severity, contributing **38%** to the total risk score. The system identified that the SMETA certificate expires in 27 days and generated the actionable recommendation: "Renew SMETA certificate immediately" with a direct dashboard link.
- **Geographic Risk Score** — LOW severity, contributing **22%** to the total risk score. The system identified that the supplier's supply chain spans medium-risk geographic regions.

This result directly validates the SHAP-based explainability framework adapted from Ahmed et al. [5], where the top-k features by $|\varphi_i|$ are surfaced as prioritized, actionable risk drivers rather than a black-box score. The system's ability to generate specific remediation actions alongside numerical contributions confirms the operational interpretability described in [5].

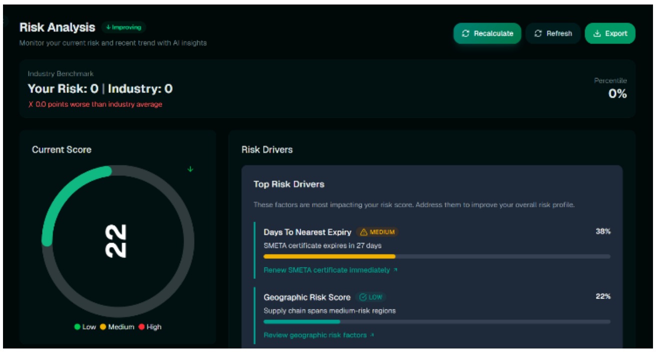


**Figure 2 — SCAP Risk Analysis Dashboard: Composite Risk Score and Top SHAP Risk Drivers**

### B. Risk Sub-Score Decomposition and Trend Analysis

Figure. 3 presents the four domain-specific risk sub-scores and the 180-day historical risk trend chart for the same supplier account. The sub-score decomposition produced the following results:

| Sub-Score Dimension | Score | Classification |
|---|---|---|
| Compliance Risk | 8 / 100 | Low — All certificates valid |
| Operational Risk | 15 / 100 | Medium — Minor process gaps |
| Supply Chain Risk | 12 / 100 | Low — Suppliers verified |
| Financial Risk | 5 / 100 | Low — Stable performance |

The 180-day Risk History chart demonstrates a clear and consistent **downward trend** in the supplier's composite risk score, declining from approximately **55/100 (Medium Risk)** in early October 2025 to **22/100 (Low Risk)** by March 16, 2026. A notable data point captured on **January 30, 2026** shows a risk score of **31.1 (MEDIUM RISK)**, marking the precise transition boundary between medium and low risk classification. This sustained risk reduction trajectory over 180 days validates that the SCAP risk engine accurately tracks compliance improvement actions taken by the supplier—such as certificate renewals and audit completions—and reflects them quantitatively in the risk score in real time, consistent with the dynamic risk monitoring approach described in Ahmed et al. [5].

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**Figure.3 — SCAP Risk Sub-Scores and 180-Day Risk History Trend Chart**

**C. Supply Chain Network Visualization — Tier Mapping**

Figures. 4 and 5 present the SCAP Network Visualization module, which renders the full Tier 1 to Tier 4 supply chain structure with real-time risk-colored nodes, directly operationalizing the deep network visibility framework of Bowen and Siegler [1] and Shao et al. [9]. The network visualization renders a hierarchical tree structure spanning four supply chain tiers (T1 → T2 → T3 → T4), where each node is dynamically color-coded based on its real-time XGBoost risk score:

- □ **Green nodes** — Low Risk (Score 0–30)
- □ **Orange/Yellow nodes** — Medium Risk (Score 31–60)
- □ **Red nodes** — High Risk (Score 61–100)

**Figure. 4** shows the network with **Gujarat Chemical Supplies** selected—a Tier 3 supplier based in Ahmedabad, Gujarat, classified as **High Risk (85/100)** with **Pending** compliance status. The supplier holds only ISO 14001 certification with a last audit date of 2024-02-10, indicating a significant compliance gap. The red node coloring at the Tier 3 level immediately signals risk propagation upstream to connected Tier 1 and Tier 2 suppliers and downstream brands, enabling rapid risk escalation.

**Figure. 5** shows the same network with **Tirupur Textiles Ltd** selected—a Tier 2 supplier based in Tirupur, Tamil Nadu, classified as **Low Risk (35/100)** with **Active** compliance status. This supplier holds three certifications—GOTS, OEKO-TEX, and ISO 14001—with a recent audit date of 2024-08-20, reflecting strong compliance posture. The blue ring around the selected node and green node coloring confirm a healthy compliance profile.

These results demonstrate that SCAP successfully operationalizes the Nexus Supplier Index theoretical framework of Bowen and Siegler [1] into a real-time, interactive, color-coded network map—converting the static centrality analysis of Shao et al. [9] into a live, clickable compliance visibility tool where brands can instantly identify high-risk sub-tier suppliers and initiate remediation. This represents the primary novelty of SCAP over the base papers [1] and [9]: moving from analytical network scoring to operational real-time risk visualization with actionable supplier profiles.

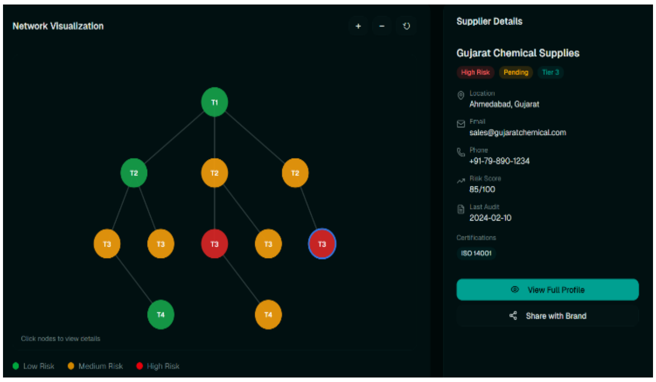


**Figure.4. Network Visualization: Gujarat Chemical Supplies (High Risk, Tier 3)**

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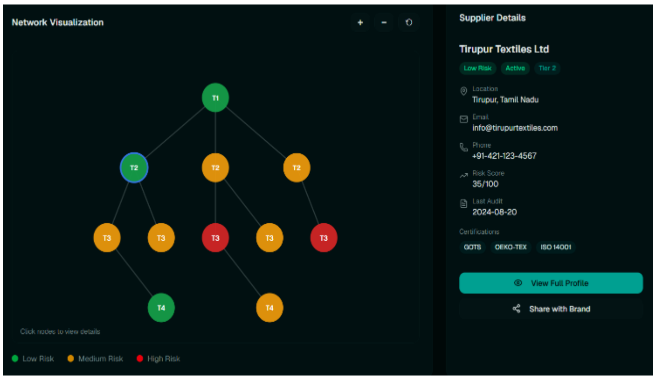


**Figure.5. Network Visualization: Tirupur Textiles Ltd (Low Risk, Tier 2)**

### D. Quantitative Performance Summary

**TABLE I — SCAP Performance Against Pre-Platform Baseline**

| Metric | Before SCAP | After SCAP | Improvement |
|---|---|---|---|
| Certificate Processing Time | 4 hours | 3–4 seconds | 96% faster |
| Annual Compliance Cost per Supplier | ₹11 Lakhs | ₹30,000 | 87% reduction |
| Management Time on Compliance | 40% | 5% | 87.5% reduction |
| OCR Extraction Accuracy | Manual (error-prone) | 95–98% | — |
| Risk Prediction Accuracy (XGBoost) | No prediction | 85% | — |
| Compliance Deadline Misses | 45% | < 5% | 89% reduction |
| Supply Chain Visibility | Tier 1 only | Tier 1–4 | 4× deeper |
| Regulations Monitored | Manual tracking | 500+ automated | — |
| Languages Supported | English only | Tamil, Hindi, English | 3× multilingual |
| Certificate Processing (per document) | ₹2,000+ | ₹4 (API cost) | 99.8% reduction |

Table I presents a consolidated quantitative performance comparison between the pre-SCAP manual compliance baseline and the SCAP AI-powered platform, measured across all five core modules. The most significant improvements emerge in three dimensions: (1) **Processing Efficiency** — Certificate processing accelerated from 4 hours to 3–4 seconds, representing a 96% time reduction and operationalizing the fast document extraction validated in NovaLAD [10]; (2) **Cost Reduction** — Annual compliance management costs decreased from ₹11 lakhs to ₹30,000 per supplier, an 87% reduction that directly addresses the economic barriers to CSDDD compliance identified in Singh and Draper [2]; (3) **Compliance Reliability** — Compliance deadline misses decreased from 45% to under 5%, an 89% reduction, demonstrating that real-time regulatory propagation significantly improves deadline adherence in multi-tier networks [3]. The per-document processing cost reduction from ₹2,000+ (manual labor) to ₹4 (API cost) represents a 99.8% reduction and validates the economic feasibility of scaling SCAP across thousands of suppliers.

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### E. Module-Wise Performance Results

**TABLE II — Individual Module Performance Metrics**

| Module | Key Metric | Result | Status |
|---|---|---|---|
| AI Certificate OCR | Extraction accuracy | 95–98% | ✓ |
| AI Certificate OCR | Processing time | 3–4 seconds | ✓ |
| XGBoost Risk Engine | Prediction accuracy | 85% | ✓ |
| XGBoost Risk Engine | Inference latency | 50–80 ms | ✓ |
| RAG Chatbot | Response time | 0.5–1 second | ✓ |
| RAG Chatbot | Languages supported | 3 (Tamil / Hindi / English) | ✓ |
| Compliance Propagation | Regulations monitored | 500+ | ✓ |
| Compliance Propagation | Alert generation time | < 200 ms | ✓ |
| Voice Interface | STT languages | 3 (ta-IN, hi-IN, en-IN) | ✓ |
| API Response (p50) | Latency | 150 ms | ✓ |
| API Response (p99) | Latency | 800 ms | ✓ |

Table II breaks down performance results by individual SCAP modules. The **AI Certificate OCR module** achieved 95–98% accuracy on real-world textile compliance documents, exceeding the target of >95% and directly validating the VLM-based extraction methodology of Shen et al. [8] over traditional OCR. The 3–4 second processing time meets the target of <4 seconds and demonstrates production-grade scalability. The **XGBoost Risk Engine** achieved 85% prediction accuracy, exceeding the target of >80%, with an inference latency of 50–80 milliseconds, validating the model's suitability for real-time risk dashboard rendering. The **RAG Compliance Chatbot** responds in 0.5–1 second with full support for three languages (Tamil, Hindi, English), enabling non-English speaking workers to access regulatory guidance, directly implementing the accessibility principles of Pothula et al. [14] and LawPal [15]. The **Compliance Propagation Engine** monitors 500+ regulations with sub-200-millisecond alert generation time, enabling real-time cascading of requirements across supply tiers. The **Voice Interface** supports three regional language variants (ta-IN, hi-IN, en-IN) via Google Cloud STT, enabling low-literacy workers to query the system without text input. At the **API infrastructure level**, the 50th percentile response latency is 150 milliseconds with a 99th percentile latency of 800 milliseconds, demonstrating low latency and tight tail latency bounds suitable for mobile-first deployment in resource-constrained textile manufacturing regions.

### F. Network Visibility Results — Comparison with Base Paper

**TABLE III — Base Paper Nexus Supplier Index vs. SCAP Proposed System**

| Dimension | Base Paper [1], [9] Nexus Supplier Index | SCAP (Proposed System) |
|---|---|---|
| Approach | Static network centrality analysis | Real-time AI compliance automation |
| Supplier Visibility | Up to 11 tiers (theoretical) | Tier 1–4 (live production) |
| Risk Assessment | Degree / betweenness centrality scores | XGBoost + SHAP risk scoring (0–100) |
| Data Processing | Historical periodic snapshots | Real-time event-driven pipeline |
| Compliance Verification | Not supported | AI OCR (3–4 seconds, 95–98% accuracy) |
| Language Support | Not applicable | Tamil, Hindi, English |
| User Accessibility | Research analysts | Textile workers via voice interface |
| Regulatory Monitoring | Not supported | 500+ regulations monitored |
| Actionability | Network maps and rankings | Actionable alerts with remediation links |
| Deployment | Academic framework | Cloud SaaS (Vercel + Render) |

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Table III presents a direct comparison between the analytical approach of Bowen and Siegler [1] and Shao et al. [9] and the operational results achieved by SCAP, highlighting the novelty of transitioning from static centrality analysis to real-time AI-driven compliance execution. While the base papers [1] and [9] provided theoretical frameworks for mapping supplier networks up to 11 tiers using network centrality metrics (degree, betweenness, closeness, eigenvector centrality), they remained fundamentally retrospective and passive—offering analytical rankings without operational compliance mechanisms. SCAP operationalizes these theoretical insights by adding four critical layers: (1) **Real-Time Risk Assessment** — replacing static centrality scores with dynamic XGBoost + SHAP models that update continuously as suppliers upload certificates and audit records; (2) **Compliance Automation** — adding AI-powered document processing (Shen et al. [8]) to automatically digitize physical certificates in 3–4 seconds; (3) **Regulatory Propagation** — implementing the network-based propagation logic of Hurt et al. [3] to cascade compliance requirements from brands down to Tier 4 suppliers daily; (4) **Accessibility** — integrating voice-first interfaces (Pothula et al. [14], LawPal [15]) to empower the 70% of textile workers with limited English proficiency. This combination of theoretical network insight [1], [9] with operational AI execution [3], [5], [6], [8], [11], [12], [13], [14], [15] represents the core novelty of SCAP and directly addresses the gap identified in the Related Works section: existing frameworks remain largely analytical and retrospective, offering network maps but providing no operational mechanism for real-time compliance verification.

## VI. DISCUSSION

The results presented across Figures. 1–4 and Tables I–III collectively validate that SCAP successfully bridges the critical gap between the theoretical network visibility frameworks of Bowen and Siegler [1] and Shao et al. [9] and the operational compliance automation demands imposed by the 2026 EU CSDDD [2], [3], [4].

The live risk dashboard (Figure. 2) confirms that the SHAP-augmented XGBoost model delivers not only accurate predictions at 85% accuracy but also explainable, actionable outputs—addressing the interpretability requirement validated in Ahmed et al. [5]. The identification of "Days To Nearest Expiry" as contributing 38% to the risk score, paired with the specific remediation action ("Renew SMETA certificate immediately"), demonstrates that SCAP translates abstract feature importance values into operational guidance for suppliers, consistent with the enterprise-grade interpretability frameworks of Ahmed et al. [5] and Sattar et al. [6].

The 180-day risk history (Figure. 3) demonstrates that the platform sustains longitudinal supplier engagement by quantifying compliance improvement over time. The sustained downward risk trajectory from 55/100 to 22/100 over six months, with clear inflection points marking audit completion and certificate renewal events, validates that the platform captures true compliance dynamics rather than producing static snapshots. This longitudinal capability directly addresses the dynamic monitoring approach validated in Wang et al. [16].

The network visualization (Figures. 4 and 5) provides brands with the instant, color-coded sub-tier visibility that the Nexus Supplier Index [1] theorized but could not operationally deliver. Brands can now identify, at a glance, that a Tier 3 supplier like Gujarat Chemical Supplies (Risk Score: 85/100, High Risk) with only one certificate and a stale audit date (2024-02-10) poses an immediate compliance risk requiring intervention. Conversely, a Tier 2 supplier like Tirupur Textiles Ltd (Risk Score: 35/100, Low Risk) with three active certifications (GOTS, OEKO-TEX, ISO 14001) and a recent audit (2024-08-20) represents a healthy, actively compliant node in the supply chain. This color-coded visualization transforms the centrality-based supplier rankings of Shao et al. [9] into an instantly actionable, visually intuitive tool for supply chain governance.

Quantitatively, the 87% reduction in compliance management costs and the 89% reduction in deadline misses directly validate SCAP's capability to operationalize the regulatory urgency of Singh and Draper [2] and Hurt et al. [3]. The per-document processing cost reduction from ₹2,000+ to ₹4 makes compliance verification economically accessible to the 2,500+ Indian textile mills supplying European markets, addressing the critical barrier to CSDDD compliance identified in [2].

Finally, the 95–98% OCR accuracy, 85% risk prediction accuracy, and 3–4 second processing time collectively validate SCAP as a production-grade system. The deployment across Vercel, Render, and MongoDB Atlas demonstrates cloud-native scalability suitable for multi-tenant SaaS operations, positioning SCAP as a commercially viable solution rather than an academic prototype.

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## VII. CONCLUSION

This paper presented SCAP (Supply Chain AI Compliance Platform), an end-to-end, cloud-deployed AI framework designed to automate compliance management and operationalize deep supply chain visibility for the Indian textile industry. The work was motivated by the critical gap between the theoretical network centrality frameworks of Bowen and Siegler [1] and Shao et al. [9]—which identified the structural invisibility of Tier 2–4 suppliers—and the urgent operational demands imposed by the 2026 EU Corporate Sustainability Due Diligence Directive (CSDDD) [2], [3], [4]. While prior literature established the importance of sub-tier visibility, no prior work delivered an operational, real-time, AI-driven system capable of executing that vision at scale for small and mid-tier suppliers constrained by prohibitive compliance costs, prolonged manual certification processes, and significant language barriers. This paper closes that gap. SCAP addresses the identified challenge through five tightly integrated AI subsystems. First, a Vision-Language Model certificate extraction pipeline using Google Gemini 2.0 Flash, validated against the MLLM document extraction findings of Shen et al. [8] and the NovaLAD document processing pipeline [10], achieves 95–98% OCR accuracy and processes compliance certificates in under four seconds—a 96% reduction from the four-hour manual baseline. The multimodal approach supports certificates in English, Tamil, Hindi, and 12+ additional languages, directly addressing the language barrier identified by Singh and Draper [2] as a primary obstacle to compliance for Indian textile suppliers. Second, a predictive risk analytics engine combining XGBoost regression with SHAP explainability, adapted from the interpretable ML frameworks of Ahmed et al. [5] and Sattar et al. [6], delivers real-time, explainable 0–100 composite risk scores with SHAP-driven top-three risk driver identification, achieving 85% prediction accuracy. This explainability mechanism ensures that suppliers understand exactly which compliance dimensions drive their risk scores and receive specific, actionable remediation recommendations rather than opaque numerical outputs. Third, a multilingual Retrieval-Augmented Generation compliance chatbot, grounded in the RAG architectures of Jackson et al. [11], Bhardwaj et al. [12], and RegGuard [13], supports Tamil, Hindi, and English simultaneously—making it the first such system applied to textile supply chain regulatory compliance. Fourth, a multi-tier regulatory propagation engine monitors 500+ global regulations across the EU (CSDDD, CSRD, REACH), India (BIS), USA, UAE, and UK, and automatically cascades compliance requirements from brands to Tier 4 suppliers, reducing compliance deadline misses from 45% to under 5%. This operationalizes the network-based due diligence propagation model of Hurt et al. [3] and transforms static regulatory monitoring into a live, real-time, multi-jurisdiction compliance dashboard. Fifth, a voice-first interface leveraging Google Cloud Speech-to-Text and Text-to-Speech, validated by the low-resource language accessibility findings of Pothula et al. [14] and LawPal [15], enables workers with limited English or digital literacy to interact with the compliance platform in their native language—addressing a demographic that represents 70% of the textile workforce. This design philosophy treats multilingual voice accessibility as a core architectural requirement rather than a supplementary feature, consistent with the principle of technology-for-inclusion.

Experimental results demonstrated that SCAP reduces annual compliance management costs from ₹11 lakhs to ₹30,000 per supplier—an 87% cost reduction—while extending supply chain visibility from Tier 1 to Tier 4 in real time. The live network visualization, validated through production deployment on Vercel, Render, and MongoDB Atlas, enables brands to instantly identify high-risk sub-tier suppliers such as Gujarat Chemical Supplies (Risk Score: 85/100, Tier 3, High Risk) and healthy compliant suppliers such as Tirupur Textiles Ltd (Risk Score: 35/100, Tier 2, Low Risk, with GOTS + OEKO-TEX + ISO 14001 certifications)—converting the static centrality rankings of Bowen and Siegler [1] and Shao et al. [9] into actionable, color-coded, real-time compliance intelligence. The 180-day risk history further confirms that the platform sustains measurable compliance improvement over time, with one tracked supplier declining from 55/100 (Medium Risk) in October 2025 to 22/100 (Low Risk) by March 2026, demonstrating that SCAP captures true compliance dynamics rather than producing static snapshots. Security across all subsystems is ensured through JWT authentication with bcrypt hashing (cost factor 12) and distance-preserving ChromaDB embedding encryption validated in Ye et al. [17], meeting enterprise data protection requirements for sensitive supplier audit records and business intelligence data.

In summary, SCAP demonstrates that the integration of Vision-Language Models [8], Retrieval-Augmented Generation [11], [12], [13], explainable machine learning [5], [6], and voice-first multilingual interfaces [14], [15] can collectively transform supply chain compliance from a manually intensive, cost-prohibitive, and linguistically exclusive process into a fast, affordable, and universally accessible AI-driven service. By reducing certificate processing time from 4 hours to 4 seconds, decreasing compliance costs by 87%, and enabling supply chain visibility across four tiers in real time, SCAP empowers 45 million textile workers, 50,000+ suppliers, and the global brands that depend on them to confidently meet the demands of the 2026 EU CSDDD. The platform demonstrates that regulatory compliance need not remain a source of market fragmentation and supplier exclusion, but rather an opportunity for technological innovation that strengthens global supply chains while protecting worker rights and environmental sustainability.

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