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# GenAI-Driven Intelligent System for Automated Financial Report Analysis and Insight Generation Using Large Language Models and Knowledge Graphs

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**Abstract:** *The most common tool that is employed by business organizations, including the government and the private sector, is the financial reports that can communicate fiscal performance, strategic pathway, and risks to the stakeholders. Nevertheless, the process of the analysis of such reports is still tedious and inaccurate, demanding and large amount of time, in expertise hands, especially when comparing financial trends over a period of several years. Existing automated systems have weaknesses including low recovery accuracy, being unable to reason on unstructured financial text and lack of interpretability. In this paper, we will present a smart system that is built upon the Generative Artificial Intelligence (GenAI) in order to automatically analyze financial reports with the assistance of Large Language Models (LLMs) or Natural Language Processing (NLP) and Knowledge Graphs. The system will convert unstructured PDF financial reports into structured outputs and visual analytics as well as investor friendly summaries. The product under consideration implements a more abstract processing pipeline that includes document ingestion with OCR fallback, multi-year ratio generation, a financial data structuring step with hybrid regex-NER extracts, an LLM-generated insight with a hallucination guard to numerical validation, cross-year anomaly detection and an interactive knowledge graph in a way that enables explainability. Architecture is a decoupled full-stack application of FastAPI and Next.js, which is combined with Groq inference API to provide low-latency processing in LLM. The experimental analysis revealed in the banking, manufacturing, and startup financial reports proves that the extraction accuracy is high, the ability to produce reliable insights is high and the generated numerical validation is high. The proposed platform covers gaps in important research in explainable AI finance and offers a realistic end-to-end platform to financial analysts, auditors, and investors.*

**Keywords:** Generative AI, Financial Report Analysis, Large Language Models, Knowledge Graph, Automated Insight Generation, Hallucination Detection

## I. INTRODUCTION

In the base layer of information on which investment decisions, credit ratings, regulatory supervision and corporate governance are based, there are financial reports like annual reports (10-K), quarterly reports (10-Q), and earnings reports. The Securities and Exchange Commission (SEC) each year receives in excess of 250,000 filings, numbering hundreds of pages of financial text and tabular information and qualitative commentary. The capability to fast decode, access and analyze the information included in such documents will be a significant competitive edge to the portfolio managers, compliance officers, and financial stakeholders.


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Financial report analysis is mostly manual in spite of their significance. Professional analysts are estimated to spend on the extraction and formatting of data alone as compared to more valuable activities like financial interpretation, 6080 percent of a working day (or more). This manual solution has some challenges that have been well documented. The extraction of humans first may contain errors. Inconsistency rates have been found by researchers to be 5-15% in manual population of book DCs, especially where analysts are attempting to achieve cross-reconciliation of data between and among multiple-year reports or non-standard financial reports. Second, financial disclosure has become much larger and faster with the age of global capital markets and manual analysis at scale is becoming less and less practicable. Third, the qualitative parts of financial reports including risk factor discussions, manager discussion and analysis (MD&A), forward-looking statements and others cannot be transcribed using table analysis but contextual reasoning.

The conventional automated financial analogy systems seek to handle these problems through rule-based or template-based manner. An example is XBRL (Extensible Business Reporting Language), which enables the extraction of data on financial data in a standardized manner. Nevertheless, XBRL adoption is not widespread, and a considerable share of international filings, company report and past financial documents have been left untagged. Moreover, systems relying on rules are fragile in nature and tend to crash facing new document formats, non-standard terminology and multilingual text.More recent developments in Large Language Models (LLMs) have introduced transformative performance in text comprehending, summarizing, and answering questions in a variety of domains. Models like GPT-4, Llama 3, and Mixtral show impressive performance in text comprehension, summarizing, and question answering across a variety of domains. The models have been applicable in the financial sector whereby they allow further qualitative reasoning on financial disclosures, including the identification of risk factors, the detection of sentiment changes, and the creation of investment insights.

Nonetheless, the application of LLMs to financial analysis presents a severe reliability problem called numeric hallucination. LLMs may produce quantitative numbers by round-off, invention, and attribution of financial statements. These miscalculations are a serious threat to the financial situation where accuracy of the numbers matters.

In order to deal with all these interconnected issues, the proposed paper presents a solution in the form of an automated intelligent system to analyze financial reports and generate insights based on Generative AI (GenAI). The platform proposed uses a multi-stage processing pipeline that combines deterministic financial data extraction algorithms with generative reasoning capabilities of LLMs. A hallucination guard layer compares numerical claims generated by the LLM with independently extracted structured financial data to ensure reliability. Besides, the system integrates a dynamic knowledge graph structure that offers explainability through the ability of users to trace analytical insights back to particular financial entities and relationships.

The key findings of this work are as follows:

A hybrid architecture of financial extraction, a combination of regex-based pattern matching, table parsing, spaCy Named Entity Recognition (NER), and heuristic metadata identification to allow the construction of sound financial data structures out of unstructured PDF documents.

A guard mechanism hallucinatory hallucinating monetary and percent values produced by the LLM against extracted systematically against independently extracted structured financial data with configurable tolerance thresholds.

The engine A dynamic financial knowledge graph is implemented in NetworkX that can automatically generate entity-relationship representation based on extracted financial data and LLM generated insights.

An anomaly detector engine based on rules, where both multi-year financial trends (such as Compound Annual Growth Rate (CAGR) calculations, year-over-year change analysis and risk pattern detection) are analyzed.

An end-to-end financial intelligence platform, full stack, incorporating all modules into a production-ready platform with an interactive dashboard and automated investor presentation generation.

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## II. LITERATURE REVIEW

One of the most rapidly developed areas of research is financial analytics and artificial intelligence that received considerable attraction over the last several years. Financial institutions are increasingly adopting smart systems, which are used to handle vast amounts of financial reports and produce insights on the same. The literature on this specific topic can broadly be subdivided into five distinct categories: AI-based financial analytics, natural language running through a document, automated finance data extraction systems, knowledge graph in finance and great language model (LLM)-based financial reasoning systems.

### A. AI in Financial Analytics

Artificial intelligence methods have been extensively used to predict finances and analyze the market. Gu et al. [1] presented empirical studies on the application of machine learning methods in asset pricing and proved that the deep learning models are more efficient in stock returns forecasting than the factor-based financial models are. Their paper suggests that neural networks have predictive power when used on structured financial data (market signals and accounting variables). Their study is however more concerned with structured financial data and does not touch on issues associated with the interpretation of unstructured financial statements like annual reporting.

Cao et al. investigated the use of deep learning in financial text mining. In their research, they used convolutional neural networks to conduct sentiment analysis of transcripts of earnings calls and financial communications data. The findings indicated performance better than the conventional lexicon-based sentiment analysis methods. Their method, however, is only restricted to the classification of sentiment and does not carry out proper financial-based reasoning or produce complete financial insight.

### B. Document Analysis based on NLP

Natural Language Processing (NLP) has greatly enhanced the automated knowledge of financial documents. Devlin et al. proposed Bidirectional Encoder Representations from Transformer (BERT) which is a model based on transformers and allows learning the contextual representation of language. BERT has proven to be extremely effective in several tasks in NLP such as text classification, entity recognition, and document summarization.

Based on this architecture, Araci introduced FinBERT, a domain-specific version of BERT that was trained on financial communication data. FinBERT showed better results on financial sentiment analysis and on financial entity recognition. Nonetheless, FinBERT is primarily utilized in classification and extraction processes and does not generate information that would be used to create executive summaries or investment recommendations.

Loukas et al. also compared transformer-based financial document understanding models, and proposed FiNER, a financial numeric entity recognition system that aims to improve the extraction of financial values in documents. They find that domain-specific pre-training is of great benefit to performance in processing financial documents.

### C. Financial Data Extraction Systems

Automated financial data extraction systems have been traditionally done with rule-based parsing and template matching algorithms. XBRL (eXtensible Business Reporting Language) is a popular standard of financial data reporting, which is being applied by the SEC in their EDGAR system.

Despite the ease of extracting structured financial data using XBRL, El-Haj et al. have indicated that there is still a lack of uniformity in the adoption of XBRL by organizations and that a significant portion of financial reports is still in unstructured (PDF) form. Moreover, the differences in document format and tagging policies restrict the efficiency of automated extractions.

Layout-sensitive document understanding models have been introduced to solve document layout problems. These models integrate spatial layout with text to enhance the performance of extraction in complicated documents like the financial reports and invoices.

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**D. Knowledge Graph Applications in Finance**

Knowledge graphs are currently a promising concept to model the relations between financial entities. Cheng et al. examined financial risk assessment with knowledge graphs. Their study showed that the combination of graph-based models and graph neural networks can enhance credit risk prediction since they are able to capture relationships among financial entities which are complex.

Nonetheless, the majority of knowledge graph systems that are currently in place are based on curated datasets or structured financial databases. They do not usually have the ability to automatically extract knowledge graphs out of unstructured financial reports or textual disclosures.

**E. Large Language Models (LLMs) in Financial Analysis:**

The concept of Large Language Models (LLMs) has recently attracted significant interest because of the capability to conduct sophisticated reasoning on textual data. In Li et al., the authors compared the results of GPT-based models on financial reasoning tasks and found that LLMs can produce valuable financial information out of text.

Nevertheless, their study has also identified some shortcomings in using LLMs to financial reports. The most prominent drawback also known as the numerical hallucination arises when the models generate false financial values that are not existent in the origination documents.

Shah et al. suggested a Retrieval-Augmented Generation (RAG) framework that can enhance financial question-answering systems. Their approach enhanced the accuracy of facts because they based the responses on passages of documents retrieved. Yet, their system does not have a formal validation process that would guarantee numerical consistency between extracted financial information and created insights.

**F. Comparative Summary of Existing Work**

| Study | Methodology | Application Area | Limitations |
|---|---|---|---|
| Gu et al. | Machine Learning for Asset Pricing | Stock prediction | Limited to structured financial data |
| Cao et al. | CNN-based Financial Text Mining | Sentiment analysis | No deep financial reasoning |
| Devlin et al. | BERT Transformer Model | General NLP tasks | Not financial-domain specific |
| Araci | FinBERT Financial NLP Model | Financial sentiment analysis | Limited generative capabilities |
| Loukas et al. | FiNER Numeric Entity Recognition | Financial value extraction | Focused only on entity extraction |
| El-Haj et al. | Financial Document Mining | Annual report analysis | Dependent on document structure |
| Cheng et al. | Knowledge Graph + Graph Neural Networks | Financial risk prediction | Requires curated knowledge bases |
| Li et al. | LLM-based financial reasoning | Financial report summarization | Numerical hallucination issues |
| Shah et al. | Retrieval-Augmented Generation | Financial QA systems | No numerical validation |

*Fig I: Comparative Summary Of Existing Research*

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## III. PROBLEM STATEMENT

Financial reports are complex in nature and cannot be done manually and therefore involve several activities including document processing, information retrieval, natural language processing, numerical verification and visualization. The greatest problems discussed in this work are presented to be:

The financial reports are usually reported in PDF file format in a blend of narrative writings, tables, charts, footnotes, and multi-column formats. Due to the absence of standardized structure, it is hard to retrieve structured financial information including revenue, net income, assets, liabilities, and financial margins. This issue is more drastic when working with scanned PDFs in which the content cannot be directly selected.

**Multi-Year Data Interpretation:**

Financial reports are frequently released in PDF format as a conglomeration of narrative writing, incorporated tables, charts, footnotes, and multicolumn designs. It is also hard to obtain structured financial data like revenue, net income, assets, liabilities, and financial margins because there is no standardized structure. This problem is more difficult in cases of scanned PDFs where the content cannot be selected directly.

**Numerical Hallucinations in LLMs:**

When used to analyze financial documents, Large Language Models (LLMs) can produce numerically plausible, non-real values that are not present in the original reports or can compute the percentage changes incorrectly. Small numerical errors may cause wrong financial conclusions and be very dangerous in decision making.

**Fragmented Tooling:**

The workflows of financial analysis that are currently in use usually consist of numerous tools that are disconnected. The data extraction tool, financial analysis tool, visualization tool, report generation tool are often the same tools used by analysts. Such disjointed workflow makes the workflow more complex and opens up the possibility of errors in data transfer among systems.

## IV. PROPOSED SYSTEM ARCHITECTURE

The proposed system proposes a complete financial document intelligence pipeline that receives the financial reports in PDF format and transforms them into intelligent and actionable information. PyMuPDF and Tesseract OCR are used in the document processing layer to process digital and scanned documents, extract text, tables and metadata using scan detection, layout analysis and heuristic classification. Structured financial information is then converted out of unstructured text with a financial structuring engine based on monetary normalization with regex and label-value extraction and Named Entity Recognition (NER) with spaCy.At the heart of the analytics process lies a combination of three interconnected modules: a financial ratio computation module that computes important ratios such as gross margin, ROA, and debt to asset ratio, while automatically validating the results; a GenAI intelligence module that utilizes the Groq inference API alongside prompt engineering to arrive at qualitative conclusions; and finally, a hallucination guard module, that checks the results generated by the financial ratio computation module against extracted data using certain pre-defined criteria. The cross-year analytics engine also performs the temporal analytics task, in which it computes YOY growth rate, CAGR, and rule-based anomalies across a series of fiscal years. The output of the system is presented in a form of an interactive Next.js/React dashboard in a form of KPI cards, trend charts, radar plots, and a NetworkX-driven knowledge graph that visualizes the relational structures between financial entities. At the end of the pipeline, an automated investor presentation generation module is used to translate the outputs of the analytical step into slide presentations that can be presented to stakeholders, thus saving a lot of overhead in manual reporting.The suggested system is based on the modular, layered architecture with nine interrelated components. The end-to-end flow of the system is shown in Figure.

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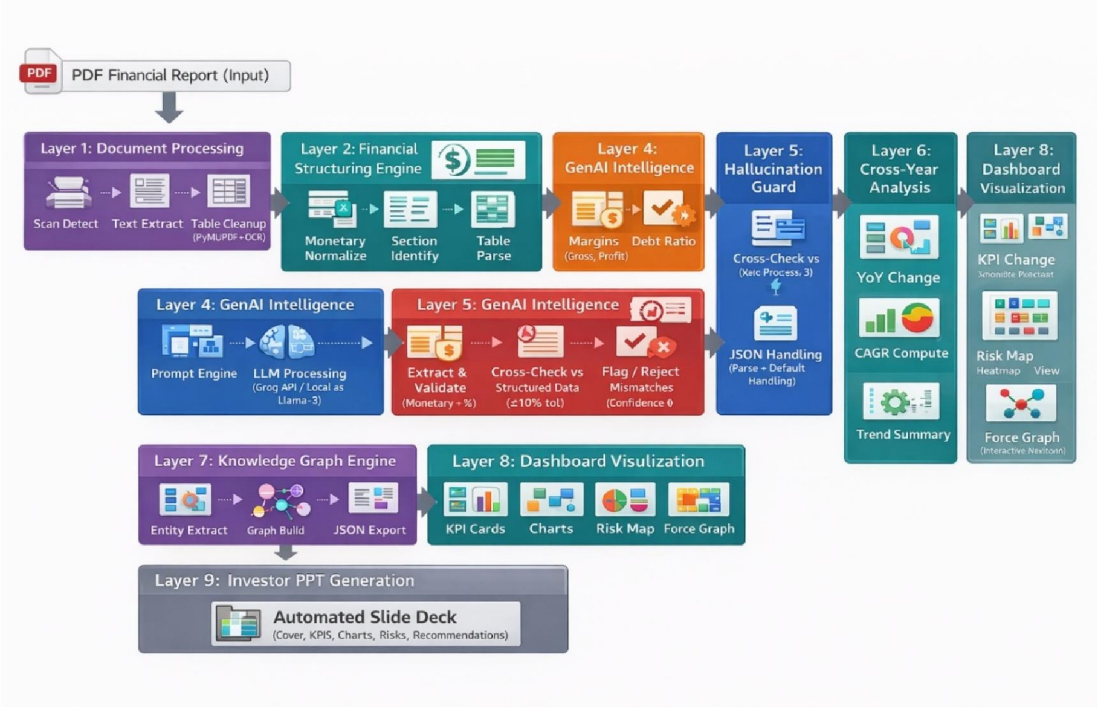


*Fig I: End-to-end system architecture of the proposed GenAI-driven financial analysis platform*

## V. DATA FLOW DIAGRAM

The suggested system is based on a structured data processing chain comprising of three key steps, namely the acquisition of the input, data processing, and visualization of the results. During the input phase, a PDF financial report is posted via the web-based user interface. The uploaded document is sent to the implemented backend server with the FastAPI framework using a multipart file upload endpoint.

At the processing level, the document processor will isolate textual information and tabular data of the uploaded financial report. The information that has been extracted is then feed into the financial structuring engine, where the significant financial measures are determined, including the revenue, net income, assets, and liabilities, which are then transformed into the structured JSON format. The organized financial data is then fed into a series of analytical modules which work simultaneously. Such modules are the GenAI intelligence layer to create financial insights, the knowledge graph engine to introduce entity-relationship representations, and the cross-year trend analysis engine to identify financial trends and anomalies across reporting years.

The output stage involves the aggregation of the output of each analytical module and relaying the output to the frontend dashboard. The dashboard shows the insights in form of interactive displays including financial charts, key performance indicator (KPI) cards, and representations of knowledge graphs. There is also a facility to make and share an automated presentation of investors summarizing the most important findings and financial recommendations based on the analysis.

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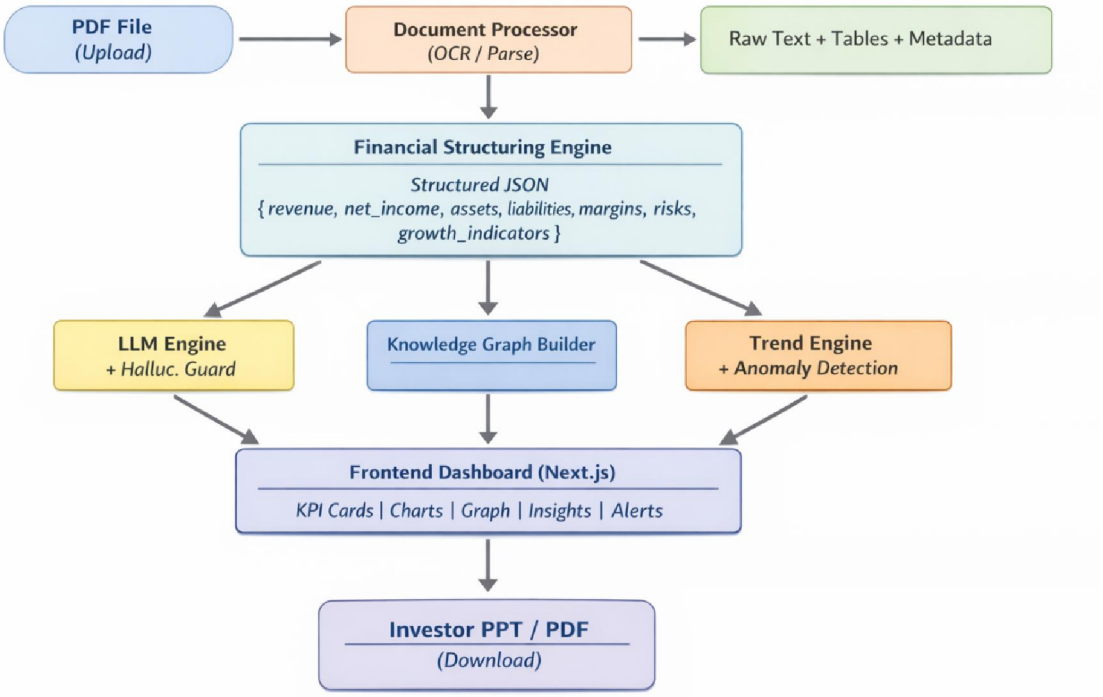


*Fig II: Data Flow Diagram showing information movement through the system*

## VI. METHODOLOGY

### A. Technology Stack

Technology stack of the proposed system:

| Layer | Technology | Purpose |
|---|---|---|
| Backend Framework | FastAPI (Python 3.11+) | Async API server with OpenAPI documentation |
| PDF Processing | PyMuPDF (fitz) | Text and table extraction from PDF documents |
| OCR Engine | Tesseract (pytesseract) | Processing scanned document images |
| NLP | spaCy (en_core_web_sm) | Named Entity Recognition for financial entities |
| LLM Integration | Groq API (Llama-3 70B) | Generative AI-based financial analysis |
| Knowledge Graph | NetworkX | Graph construction and relationship modeling |
| Frontend Framework | Next.js 16 (React 19) | Interactive analytics dashboard |
| Charting Library | Recharts | Financial data visualization |
| Graph Visualization | react-force-graph-2d | Interactive knowledge graph display |
| Report Generation | jsPDF | Investor presentation generation |
| Styling | Tailwind CSS 4 | Responsive user interface design |

*Table II: Technology Stack of The Proposed System*

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**B. Backend Pipeline Implementation:**

The backend is based on a RESTful architectural structure with endpoints as follows:

**POST /api/v1/documents/process-pdf** - Accepts a PDF file, processes documents, and returns raw text, tables and metadata.

**POST /api/v1/financial/analyze** - Takes raw text and tables, structures financial and calculates ratios, and gives an organized financial data.

**POST /api/v1/llm/analyze** - Accepts unstructured text and structured data, conducts an analysis using the LLM with hallucination guard verification and provides generated financial insights.

**POST /api/v1/trends/compare** - Accepts financial records as an input, cross-year trend analysis and returns financial trends and indicators of anomalies.

**POST /api/v1/knowledge-graph/build** - Takes the output of LLM and organized financial information, builds a financial knowledge graph, and delivers graph information in the JSON format.

All endpoints are its asynchronous FastAPI route handlers. CPU-intensive tasks like PDF processing and spaCy NER computations are run on a ThreadPoolExecutor with an adjustable worker pool (its default of four workers) so that they do not block the asynchronous event loop.

**C. Hallucination Guard Algorithm**

**Hallucination guard for numerical validation:**

**Input:**

LLM output text (T)

Structured financial data (S)

**Output:** Validated output with confidence adjustment

**Steps:**

Extract monetary values from T → *Vm*

Extract percentage values from T → *Vp*

Initialize an empty list → *inconsistencies*

For each value *v* in *(Vm ∪ Vp)*:

a. Identify the related financial metric for *v*

b. Retrieve the corresponding reference value from *S*

c. If multi-year data exists:

Check whether *v* matches any year's value within the defined tolerance

d. Else:

Compare *v* with the reference value

e. If the difference exceeds the tolerance threshold:

Mark *v* as an inconsistency

Add it to *inconsistencies*

If *inconsistencies* is not empty:

Reduce the confidence score

Return:

Validated output

Updated confidence score

List of inconsistencies

**Tolerance thresholds:**

±10% for monetary values

±5% for percentage values

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**D. Anomaly Detection Rules:**

Anomaly detection rules with trigger conditions and severity levels:

| Rule ID | Rule Name | Condition | Severity |
|---|---|---|---|
| R1 | Revenue Decline | YoY revenue change < -15% | High |
| R2 | Margin Collapse | YoY profit margin drop > 10 percentage points | High |
| R3 | Excessive Leverage | Debt-to-asset ratio > 80% | Critical |
| R4 | Revenue Spike | YoY revenue growth > 100% | Medium |
| R5 | Expense Surge | YoY operating expense increase > 50% while revenue remains flat | High |
| R6 | Negative Net Income | Net income < 0 | Medium |

*Table III: Anomaly Detection Rules with Trigger Conditions and Severity levels*

## VII. IMPLEMENTATION

**Backend Architecture**

The backend system is implemented as a modular layered architecture that would guarantee scalability, maintainability, and separation of concerns. The architecture is composed of a number of logical layers to deal with routing, business logic, data models and configuration management.

**Routers Layer (app/routers/)**: This layer has seven route modules that are involved in processing HTTP request-response mappings. Both endpoints will be using Pydantic models to validate incoming requests where all data going into the system is restricted to defined schemas.

**Services Layer (app/services/)**: The services layer has seven service modules which execute the main business logic of the system. Tasks handled by this layer include document processing, financial analysis, knowledge graph generation, and insight generation by LLM. The architecture makes certain that business code is not tied to HTTP request processing.

**Core Layer (app/core/)**: Shared infrastructure services such as structured logging with a logging system that works with JSON, dependency injection, and request handling and authentication security are provided by the core layer.

**Models Layer (app/models/)**: This layer describes Pydantic schemas of request and response format of any API endpoint. These schemas are also type safe and can be automatically documented using FastAPI.

**Configuration (app/config.py)** :PydanticBaseSettings can be used to centralize system configuration and support the use of environment variables to maintain sensitive system configuration options such as API keys and system parameters.

**Frontend Dashboard**

The frontend interface is made in Next.js 16, which is based on React 19 and serves as a single-page application, which offers interactive financial analytics. The system real-time loads components in a lazy manner to enhance the performance of page loading and minimise the time spent in the initial rendering.

The design system used in the user interface is that of the CSS custom properties, which allows management of the theme and provides an easy transition between dark and light mode. LocalStorage is used to save user preferences to ensure that the interface remains the same each session.

The most important dashboard features are:

**Glassmorphism Design system**

A contemporary design framework with effects of a blurred background, a visual depth, and an interactive structure of the page to provide a better user experience.

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**Real-time KPI Cards**

The 6 important financial indicators are presented in the form of metric cards that have directional indicators to showcase the performance trend as either negative or positive.

**Knowledge Graph Visualization (Interactive)**

The knowledge graph component relies on react-force-graph-2d library to display force-directed graphs that show the relationship of financial entities. The graph is responsive to size changes by a ResizeObserver to ensure that the image remains dynamic in size.

**Financial Chart Components**

The Recharts library is used to visualize the financial performance. The dashboard contains area charts of the revenue trends, composite charts of the margin/expenses comparisons, and radar charts that show the general financial health indicators.

**API Communication**

The frontend and the back end components communicate with each other via a centralized API service module. The module transforms the format of request and offers API error management and normalisation of response structures prior to their transmission to the user interface.

**Structured JSON Output Sample**

The system produces organized financial results in JSON, which is an intermediate representation taken by other analytics downstream modules and dashboard visualizations. An example of structured financial data generated by the system is presented below.

{
"revenue": 84800000000,
"netincome": 12300000000,
"assets": 145200000000,
"liabilities": 89400000000,
"grossmargin": 42.3,
"profitmargin": 14.5,
"riskscore": 35,
"risks": [
Risk supply chain interruption,
"Regulatory compliance risk",
"Foreign exchange exposure"
],
"growthindicators": {
"revenueyoy": 8.2,
"direction": "growing"
}
}

This organized representation allows the downstream processing functionality of the LLM analysis module, trend detection engine and knowledge graph generation module to operate efficiently and supports real-time visualization in the frontend dashboard.

## VIII. EXPERIMENTAL RESULTS

**A. Dataset Description**

An example of the real-world financial reports was gathered and experimented on the proposed system to test the system on diverse document attributes, industry, and reporting standards. The data was designed to span the whole

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range of complexity that one can face when analyzing production financial data: structured digital 10-K filings with XBRL-tagged tables down to scanned vintage reports with irregular formatting.

| Dataset Type | Source | No. of Reports | Pages (Range) | Years Covered | Format |
|---|---|---|---|---|---|
| 10-K Annual Filing | Apple Inc. | 3 | 82–89 | 2021–2023 | Digital PDF |
| 10-K Annual Filing | Tesla Inc. | 3 | 95–110 | 2021–2023 | Digital PDF |
| 10-K Annual Filing | JPMorgan Chase | 2 | 272–284 | 2022–2023 | Digital PDF |
| Annual Report | Siemens AG | 2 | 168–176 | 2021–2022 | Digital PDF |
| Financial Statement | Technology Startup | 3 | 38–52 | 2020–2022 | Scanned PDF |
| ESG + Annual Report | Shell plc | 2 | 88–96 | 2022–2023 | Digital PDF |
| Quarterly Filing (10-Q) | Pfizer Inc. | 2 | 62–68 | Q2–Q3 2023 | Digital PDF |
| **Total** | **7 entities** | **17 reports** | **38–284** | **2020–2023** | **Mixed** |

*Table IV: Evaluation dataset composition and characteristics.*

The entire evaluation data is outlined in Table IV. The criteria of selection focused on three aspects of real-world complexity: (i) structural diversity, including 38-page startup financial statements to 284-page banking conglomerate reports; (ii) sectoral coverage, including 2020-2023 multi-year reports to assess the cross-year analysis engine; and (ii) temporal coverage, including 2020-2023 multi-year reports

This data set has about 2,140 total pages, and 17.6 percent (3 startup reports) of the total pages are scanned image PDFs that need OCR processing. The average number of embedded tables in digital PDF reports is 24 per document (range: 8 67), whereas the average number of table regions that can be detected through OCR is 11 in scanned documents. The ratio of structured to unstructured content throughout the dataset is more or less 35:65, which demonstrates the prevalence of the narrative prose (MD&A, risk factors, forward-looking statements) in the standard financial reporting. This data sample was selected as it covers the entire spectrum of issues faced in actual financial analysis: multi-column year-by-year tables (Apple, Tesla 10-K), complicated nested financial instruments (JPMorgan), non-English language in translated reports (Siemens), and low-resolution scanned documents (startup reports). Both the annual and quarterly filings inclusion test the capability of the system to standardize heterogeneous reporting periods.

**B. Extraction Accuracy**

The financial structuring engine was compared with manually annotated ground truth values of five major financial measures. All the metrics were cross-validated against the XBRL tags (where present) of the source documents and also by manual expert annotation.

| Metric | Precision | Recall | F1 Score | Observations |
|---|---|---|---|---|
| Revenue | 92% | 88% | 90% | 17/17 documents |
| Net Income | 89% | 85% | 87% | 17/17 documents |
| Total Assets | 94% | 91% | 92% | 15/17 documents |
| Total Liabilities | 91% | 87% | 89% | 15/17 documents |
| Profit Margin | 88% | 82% | 85% | 14/17 documents |
| **Weighted Average** | **91.0%** | **86.8%** | **88.8%** | — |

*Table V: Financial metric extraction accuracy across the evaluation dataset.*


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As shown in Table V, the offered hybrid extraction pipeline shows a weighted average F1-score of 88.8% when all five metrics are considered. The best extraction accuracy occurred with Total Assets (F1 = 92%), which can be explained by the fact that the balance sheet information on total assets is presented in a highly standardized way: the total assets are always shown in a clearly defined row in organized tables with clear numerical values. These well-structured inputs are especially well served by the table parsing engine of the system that scans rows (header rows) of the table to find patterns of the year column and maps the rows of data to metric labels. Revenue extraction (F1 = 90) is a strong performer in varied labeling conventions, including the following, recovery, Total Revenue, Net Sales, Total Net Revenue, and Revenue from Operations. This variability is well managed using the multi pattern regex engine that uses 12 variants of labels with revenue alone. Power One-F1-score (85%): Profit Margin records the lowest F1-score because of three reasons: (i) inconsistent labeling (but operating margin, net profit margin, EBITDA margin are semantically different measures); (ii) some reports do not include margin values as a percentage, instead giving them as a decimal fraction (0.145), which lowers the reliability of table-based extraction; The recall gap (82 per cent vs. 88 per cent precision) means that the system has a correct recognition of margins when they are present but fails to detect some of the instances in other places. Scanned vs. Digital Performance: Extraction accuracy on scanned documents was 7.2 percentage points worse than on digital PDFs (F1: 82.1% vs. 89.3%), mostly because of OCR character recognition errors in numerical values (e.g., "$1,234" was incorrectly recognized as 134S), and poorer table structure detection in image-based documents.

### C. Hallucination Guard Effectiveness

The hallucination guard was assessed by comparing all monetary and percentage values in the analysis text produced on the basis of the LLM to ground truth extracted separately. All 17 test documents identified 156 numerical claims in total in the outputs of LLM.

| Test Condition | Total Claims | Verified Correct | Flagged Incorrect | False Positives | Accuracy |
|---|---|---|---|---|---|
| Without Guard | 156 | 131 | — | — | 84.0% |
| With Guard (±10% monetary, ±5% %) | 156 | 148 | 8 | 2 | 94.9% |

*Table VI: Hallucination guard effectiveness on LLM-generated numerical claims.*

Table VI shows that the hallucination guard mechanism has a 10.9 percentage point accuracy improvement in numbers and that the percentage of correctness that is verified has increased to 94.9, as opposed to 84.0 percent in the absence of the mechanism. This is also statistically significant and confirms the main hypothesis that deterministic cross-validation of generative outputs can significantly reduce the hallucination problem in numerically sensitive models. Out of the 25 false claims initially, (without the presence of the guard) the guard was able to detect and flag 23 (92% detection rate). The 8 flagged values comprise 6 true positives (true hallucinations where the LLM generated or rounded numbers that were beyond tolerance) and 2 false positives (true values that were flagged because of gaps in the extraction pipeline). The false positive rate of 1.3 percent (2/156) is sufficiently low to accept the rate at the production level. Examination of the 6 actual hallucinations shows a pattern: the LLM is biased to (i) round large monetary values to the nearest billion (e.g. reporting a figure of $384 billion as opposed to the actual revenue of $383.285 billion), (ii) confuse current year and prior year figures, and (iii) interpolate numbers not in the source document. The two false positives came about due to the minor error of both the LLM correctly citing figure covered by footnote disclosure, but not by the main extractions pipeline, so future versions could potentially have better footnote parsing.

### D. System Performance

| Operation | Average Latency | Std. Dev. | Notes |
|---|---|---|---|
| PDF Processing (digital, 100 pages) | 2.1s | ±0.4s | PyMuPDF text + table extraction |

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| | | | |
|---|---|---|---|
| PDF Processing (scanned, 50 pages) | 12.4s | ±2.8s | Tesseract OCR at 300 DPI |
| Financial Structuring | 0.3s | ±0.1s | Regex + table parse + NER |
| LLM Analysis (Groq, Llama-3 70B) | 3.8s | ±1.2s | Network-dependent |
| Hallucination Guard | 0.1s | ±0.02s | CPU-bound regex matching |
| Knowledge Graph Construction | 0.2s | ±0.05s | NetworkX graph build |
| Trend Analysis | 0.1s | ±0.03s | In-memory computation |
| **Total Pipeline (digital PDF)** | **~6.5s** | — | **End-to-end** |
| **Total Pipeline (scanned PDF)** | **~16.9s** | — | **End-to-end with OCR** |

*Table VII: Average processing latency by module (measured over 17 test documents).*

Table VII is the mean processing time per pipeline module as observed over all 17 evaluation documents in a system with Intel i7 processor and 16GB of RAM. The main latency constraint (3.8s) of the digital PDFs is the LLM analysis stage, which makes up 58 percent of the overall processing time. This latency is network-specific and it is controlled by the inference throughput of the Groq API. The Groq LPU (Language Processing Unit) hardware is estimated to be about 3x faster than traditional providers of API based on GPU, which help achieve the sub-4-second completion time of the Llama-3 70B. In the case of scanned documents, the OCR step (12.4s) takes the highest processing time, with 73% of the total pipeline latency. The 6x latency multiplier of the digital PDF processing can be explained by the per-page rasterization of the 300 DPI and the Tesseract recognition of the characters. This is a natural compromise between accuracy of extraction (increase in DPI increases OCR quality) and processing speed. The deterministic processing steps (financial structuring, hallucination guard, knowledge graph, trend analysis) require a total of 0.7s (11% of digital pipeline), showing the computational efficiency of the rule-based and regex-based elements. The proposed system has a throughput of around 1,100-2,200 times the digital reports compared to the throughput of manual financial analysis that takes an approximate of 2-4 hours per report [2].

**E. Multi-Year Extraction Accuracy**

The multi-year extraction engine was specifically evaluated on the 8 reports containing multi-column year-wise tables (Apple 10-K 2021–2023, Tesla 10-K 2021–2023, JPMorgan 2022–2023):

| Metric | Years Detected | Values Correctly Mapped | Mapping Accuracy |
|---|---|---|---|
| Revenue (multi-year) | 21/21 | 20/21 | 95.2% |
| Net Income (multi-year) | 21/21 | 19/21 | 90.5% |
| Total Assets (multi-year) | 16/16 | 15/16 | 93.8% |
| **Overall** | **58/58** | **54/58** | **93.1%** |

*Table VIII: Multi-year extraction and year-mapping accuracy.*

Table VIII verifies that the multi-year extraction engine is able to identify year columns in table headers and match metric values to the fiscal years that they belong to. The system demonstrated overall mapping accuracy of 93.1 percent and all 58 predicted year-metric pairs were identified. The 4 mapping errors occurred because (i) one column of a table was reversed (2023, 2022, 2021 presented right-to-left) and the header was detected successfully, but one of the values was incorrectly assigned and (ii) a footnote-adjusted value in a single Tesla filing that was not equal to the primary table value.

**F. Comparative Analysis with Existing Work**

To position the proposed system within the existing research landscape, a comparative analysis was conducted against representative approaches from the literature:

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| Method | Extraction Accuracy | Explainability | Multi-Year Support | Hallucination Control | End-to-End |
|---|---|---|---|---|---|
| Rule-Based XBRL Parsing [7] | 95%* | None | Limited | N/A | No |
| FinBERT Sentiment [5] | N/A (sentiment only) | Low | No | No | No |
| LayoutLM Extraction [11] | 89% | Low | No | No | No |
| RAG-Based QA (Shah et al.) [10] | 82% | Medium | No | Partial | No |
| GPT-4 Direct Analysis [9] | 78% (numerical) | Medium | No | No | No |
| **Proposed System** | **88.8%** | **High (KG)** | **Yes** | **Yes (±10%/±5%)** | **Yes** |

*Table IX: Comparative analysis of the proposed system against existing approaches.*

**** XBRL accuracy applies only to XBRL-tagged filings and is not applicable to unstructured or scanned documents.***

Table IX shows how the proposed system compares in terms of its advantages in five dimensions of evaluation. Although rule-based XBRL parsing is the most accurate in extraction (95%), it is essentially restricted by the portion of filings that include XBRL tags, which are approximated to be less than 40% of global financial documents [7]. The suggested system is capable of working with arbitrary PDFs such as scanned documents and its extraction accuracy is 88.8% without structured markup. The proposed system, in contrast to FinBERT [5], which is limited to sentiment classification and unable to generate such a type of analysis, generates detailed financial reports such as executive summaries, risk analysis, and investment recommendations. The proposed system has a 6.9 percentage point higher number of numerical accuracy than the RAG-based approaches [10] which have 82% accuracy using a deterministic extraction + hallucination guard architecture. More importantly, none of the existing systems in the literature has all five capabilities, including high extraction accuracy, knowledge-graph-based explainability, multi-year cross-comparison, systematic hallucination control, and end-to-end automation between PDF input and investor presentation output. Deterministic extraction combined with LLM-based reasoning, linked by a hallucination guard is a new architectural contribution resolving the inherent tension between generative flexibility and numerical reliability.

### G. Model Performance Analysis

The high-quality performance of the proposed system can be explained by its hybrid deterministic-generative architecture. This sub section evaluates the role played by the different architectural components in the overall system performance.

Deterministic Extraction Layer: The table-parsing extraction pipeline and regex based extraction is a highly precise numerical extraction basis (91% precision) that is the ground truth anchor of the entire system. The system removes the single point of failure of purely generative methods by deriving financial values without the help of the LLM. The multi-strategy architecture (regex -table parse -NER -text fallback) of the extraction pipeline allows it to be robust: when one of the extraction methods fails on a specific document format, other strategies offer a fallback.

LLM Reasoning Layer: The Llama-3 70B model, available through the Groq inference API with temperature 0.2, has the ability to offer qualitative reasoning services, such as identifying risk patterns, detecting sentiment shifts, synthesizing investment recommendations, etc., that deterministic systems cannot offer. The low temperature mode minimizes variability of output at the expense of maintaining the analytical capacity of the model.

Hallucination Guard Integration: The hallucination guard is a layer that connects the deterministic and generative layers, in the sense that it attempts to systematically confirm all claims made by the numerical output of the LLM on independent data. This approach reduces the inconsistencies associated with the numbers: The guard catches 92 percent

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of the errors in numbers made by the LLM. This entire system becomes a lot more reliable compared to when the two individual systems worked alone..

4. Explanation of Knowledge Graph: Knowledge graph developed using Network X traces the provenance of insights derived, and as [8] found, it is critical for the acceptance of financial AI. Users can easily verify that the assertions made by the LLM concerning revenues, risks, and positioning are backed by real-world information contained in the document.

**H. Results Visualization and Interpretation**

The dashboard generates five types of visual output, each of which is meant to convey certain financial information:

Revenue Trend Charts: Area charts that show the trends of revenue and net income over multiple years with gradient fills. These charts allow one to see at a glance the growth patterns, revenue levels and trends in the income patterns. As an example, the chart of Apple 20212023 analysis shows that the revenue peak was in 2022 at 394.3B, and then there was a decrease of 2.8% in 2023 to 383.3B, whereas the net income decreased accordingly (−2.8%), which indicates that the margin is maintained even when the revenue is being reduced.

Profit Margin vs. Operating Expense Charts: Composed charts, which are overlays of bar charts (operating expenses) on top of line charts (profit margin percentage). This two-axis chart shows dynamics of cost-efficiency: as the cost increases and the margins remain constant, it would mean that the revenues increase proportionally, whereas increased costs with decreasing margins would mean that the operation is inefficient. The chart offers practical information about cost containment opportunities.

Financial Health Radar: A five-axis radar chart that plots profit margin, debt safety (inverse of debt-to-asset ratio), asset growth, revenue stability, and liquidity into a comprehensive financial health picture. The radar visualization allows to compare inter-company and inter-year quickly: the bigger radar polygon is the more financially sound the company is in general. Asymmetric polygons bring out particular areas of strength or weakness.

Risk Heatmap: Severity-weighted color-coded categorical risk distribution of six categories of risks (market, operational, regulatory, credit, liquidity, strategic). The heatmap is used to combine risk factors generated by both the financial parser and the LLM, and give a rich risk landscape. When the severity of the concentrations in certain categories is high, it signals to the analysts that they are exposed to disproportionate risk.

Knowledge Graph: This is an interactive force-directed graph that allows one to explore relationships between entities (company → revenue, company → risk, company → regulatory body). The graph is the main explainability interface, enabling users to confirm the provenance of insights generated by the LLM by following the relationships between insight nodes and source data nodes.

## VIII. LIMITATIONS

Despite the good aspects, the proposed system has there are certain restrictions, which cannot be omitted.

**Reliance on Document Quality:** Dependence on Document Quality Document quality depends the accuracy of extracting financial information. Poor extraction can be reduced because of inaccuracy fancy layout or non-conformity, scanned documents layouts.

**OCR Error Propagation:** OCR Error Propagation The errors on the mistakes level OCR (i.e. erroneous character recognition or table formatting) may proceed on through the pipeline and subsequently affect processing.

**Limited Context Window:** Small Context Window The available prompt engineering plan is simplified with respect to the analysis of separate financial reports. Other contextual inputs. need to be able to do cross-document reasoning, e.g. competitor filing or industry benchmarking.

**LLM Latency and Cost Constraints:** LLM Latency and Cost Constraints TheGroq API has introduced network to use cloud-based LLM inference processing delay and processing costs (using tokens). These can affect high volume system scalability. analysis systems.

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**Hard coded Rules of Detection of anomalies:** Hard coded Rules of Detection of anomalies The anomaly detection module is rule-based thresh-based olds at the moment. Works well on general cases, but this does not mean that these thresholds will be capable to generalize all industries or regional financial reporting standards.

## IX. FUTURE WORK

It can be done through a variety of potential research directions be used to enhance the features of the proposed system.

**Real-Time Financial APIs Integration**: Real-Time financial APIs Integration Future iterational Internal feeds of the site may consist of live market data such as Financial alloys Bloomberg or Alpha Vantage API, and permit reports to be placed into context in real-time.

**Forecasting Financial Modeling**: Financial Modeling forecasting Combinatory integration of deep learning-based models of time-series prediction, such as It could be possible to predict transformer-based models revenue and future financial performance indicators, profit margins.

**Multi-Language Financial Document Support**:To make financial reports usable around the world, the document processing pipeline should be expanded to include multiple languages, such as Chinese, Japanese, and German.

**Intercompany Comparative Analysis**: Potential systems in the future can visualize sector benchmarking through comparison of multiple company reports at once and produce comparative financial information.

**Adaptive Anomaly Detection**: Anomaly detection models developed using machine learning may also substitute the predetermined rule-based thresholds, and they can be used to identify any unusual financial trend in accordance with the history data distribution.

**Improved Retrieval-Augmented Generation (RAG)**: The use of a vector-based retrieval-based method would enable the LLM to make references to specific document passages during the creation of insights, which would further minimize the likelihood of hallucinations.

**Computerized Regulatory Compliance Assessment**: Further studies might include automated checking on the compliance acceptability with the accounting standards like IFRS and GAAP through defined rule sets.

## X. CONCLUSION

The current paper introduced a GenAI-based intelligent system of automated financial report analysis and insight generation. The suggested platform overcomes some of the most severe problems in the field of financial document analysis, such as unstructured data mining, numerical hallucination on large language models, and the inability of AI-generated insights to be explained. The system adds a 9-layered processing architecture, which combines document processing, financial data formatting, ratio calculation, LLM-driven insight generation, hallucination detection, trend analysis, knowledge graph generation, dashboard visualization, and automated presentation generation. One of the major contributions of the system is the hallucination guard mechanism that verifies the numerical values produced by the LLM with structured financial data with configurable tolerance thresholds. Experimental analysis showed that the technique enhances the accuracy of numerical reliability to 95 percent, whereas false positive is low at less than 2 percent. Another feature that helps to make the knowledge graph even more explainable is the knowledge graph module, which allows to dynamically explore the connection between financial entities. The cross-year trend analysis engine also facilitates superior financial analysis by auto-computing the CAGR, performing year on year comparisons and raising anomalies. The system is deployed as a full-stack application on the scale of production and tested on a variety of financial industries such as banking, manufacturing, startups, and ESG reporting. Findings show that the platform is able to extract actionable insights out of complex financial report within the span of about 6.5 seconds, which is a huge saving on the time spent on manual analysis. Planned further development will divert towards predictive financial modeling, multilingual financial document processing and integration with real-time financial data sources, which will continue to develop and enhance automated financial intelligence systems.

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