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Original Article

Analysing The Application Of Agentic AI In Automating Invoice Processing

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ABSTRACT

This research investigates the application of Agentic AI to automate the extraction of invoice details from multi-format invoices and validate extracted data against ERP system records through confidence-based product description matching. Situated within business process automation and intelligent document processing, this study addresses operational challenges including OTIF performance degradation and manual labor inefficiencies. Agentic AI, as a paradigm for autonomous, goal-oriented au-tomation, offers an alternative to traditional rule-based systems by orchestrating format detection, preprocessing, data extraction, semantic matching, and visualization. The proposed framework leverages n8n workflow automation integrated with GPT-5 Mini for intelligent extraction and Levenshtein-based fuzzy matching with a 75% confidence threshold for reconciliation decisions. Operational analysis from a mid-sized FMCG supplier revealed distributors spend 225 minutes weekly on manual ERP entry across three suppliers. The developed system processes the same workload in 9 minutes weekly, representing a 96% reduction in processing time, complete elimination of manual data entry er-rors, and real-time dashboard analytics for transparent decision-making.

Keywords: Agentic AI, Invoice Processing, ERP Reconcili-ation, Semantic Matching, n8n, XAI

INTRODUCTION

A. Background and Motivation

The digital transformation of enterprise operations has made efficient invoice processing a critical requirement for modern businesses. Invoices arrive in heterogeneous formats-PDFs, Excel spreadsheets, scanned images, and Word documents-each requiring distinct handling approaches. Traditional man-ual processing of these documents is labor-intensive, error-prone, and fundamentally unscalable. Industry studies indi-cate that manual invoice processing consumes approximately 25 minutes per document, with error rates ranging from 3% to 5% depending on document complexity and operator experience [2]. These errors propagate through downstream systems, causing inventory discrepancies, payment disputes, and delivery failures that directly degrade On-Time-In-Full (OTIF) performance metrics [1].

Cloud-based ERP systems have streamlined data consolida-tion and analysis, yet the integration of external unstructured invoice data remains problematic. Suppliers use varied termi-nologies, abbreviations, and formatting conventions that create semantic mismatches when matched against standardized ERP master data. For example, an invoice may list “SS Bolt M8x40 Hex” while the ERP system records “Stainless Steel Hexagon Head Bolt, Metric 8mm x 40mm, Grade A2-70.”

Such discrepancies necessitate intelligent automation capable of semantic understanding rather than rigid template matching.

B. Agentic AI for Invoice Automation

Agentic AI represents a paradigm shift from both tradi-tional rule-based automation and generative AI. Defined as autonomous systems capable of independent planning, exe-cution, and optimization through feedback loops [3], Agen-tic AI orchestrates multiple specialized capabilities toward goal-oriented outcomes. Unlike conventional Robotic Process Automation (RPA) that relies on predefined rules and brittle templates, Agentic AI dynamically adapts extraction strategies based on input characteristics, evaluates context for semantic matching, and makes

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

calibrated decisions regarding automa-tion versus human escalation.

C. Research Contributions

This research makes the following contributions: (1) a multi-format document ingestion and preprocessing pipeline capable of handling PDF, Excel, and image invoices without template dependencies; (2) semantic matching algorithms us-ing fuzzy string comparison and numeric token overlap with a calibrated 75% confidence threshold; (3) an Explainable AI (XAI) dashboard providing real-time transparency into match quality and confidence distributions; and (4) empirical validation demonstrating 96% processing time reduction and complete elimination of manual data entry errors in a live FMCG distributor environment.

II. Literature Review

A. AI-Driven Automation in Business Processes

Modern AI-powered automation extends beyond traditional Optical Character Recognition (OCR) by combining machine learning, natural language processing, and intelligent matching techniques [2]. While OCR systems effectively extract header-level fields such as vendor names, invoice numbers, and dates, line-item extraction remains challenging due to inconsistent table structures, multi-page layouts, and merged cells [5]. Fur-thermore, OCR struggles with scan noise, skewed layouts, and low-resolution images, necessitating preprocessing techniques such as de-skewing, binarization, and contrast enhancement [4]. Despite these advancements, end-to-end integration of extracted data with ERP systems remains under-explored, particularly for unstructured or semi-structured invoice formats [7].

B. Semantic Matching and NLP

Natural Language Processing provides the foundation for extracting structured data from unstructured invoice text. Named Entity Recognition (NER) identifies and categorizes entities such as products, quantities, and prices [4]. However, the critical challenge lies in semantic matching-aligning in-voice descriptions with ERP master data despite terminological variations. Word embeddings and sentence transformers enable cross-terminology product alignment by understanding contex-tual similarity [8]. Research indicates that semantic similarity algorithms can recognize that "Organic Tea" and "Green Tea" may refer to the same product, yet confidence calibration for invoice-specific matching contexts lacks formalized metrics [9].

C. Agentic AI Paradigm

Agentic AI distinguishes itself from both generative AI and traditional automation through autonomous goal-oriented behavior. Bandi et al. [3] define Agentic AI as systems capable of independent planning, execution, and continuous optimiza-tion via feedback loops. In invoice processing, this agential nature enables dynamic selection of extraction methods based on invoice templates, adaptive semantic similarity assessment against ERP records, and calculated decisions regarding auto-matic posting versus human review. Unlike RPA tools that require pre-programmed actions for each step, Agentic AI evaluates input variability in real-time and adjusts strategies accordingly.

D. Explainable AI in Financial Contexts

Explainable AI (XAI) addresses the opacity of complex machine learning models by providing interpretable insights into decision-making processes [10]. In business-critical appli-cations such as invoice reconciliation, confidence scores func-tion as primary explainability mechanisms, communicating system certainty to stakeholders [11]. Hamida et al. confirm that visualizing model confidence effectively builds user trust, while Arunraju Chinnaraju [12] argues that interpretability is a prerequisite for responsible AI deployment in organizational settings. This research operationalizes XAI principles through a real-time dashboard surfacing confidence scores and match status for transparent decision-making.

III. Methodology

A. Research Design

This research employs Design Science Research Method-ology (DSRM) to provide an organized framework for the development, implementation, and evaluation of the proposed Agentic AI solution. DSRM is particularly suited for this study as it focuses on creating and evaluating innovative artifacts-in this case, an automated invoice reconciliation workflow- that address practical business problems while contributing to aca-demic knowledge. The methodology encompasses six iterative phases: problem identification, objective definition, design and development, demonstration, evaluation, and communication.

The research investigates how Agentic AI can automate invoice data extraction and validation against master data through a multi-step n8n workflow. The study aims to improve the accuracy and efficiency of invoice reconciliation by au-tomating the process from invoice reception to final reporting, reducing manual effort and improving operational performance metrics such as OTIF.

B. System Architecture and Workflow

The proposed system architecture consists of seven inte-grated components, each implemented as nodes within the n8n visual workflow automation platform. Fig. 1 illustrates the end-to-end workflow from invoice reception to dashboard reporting.

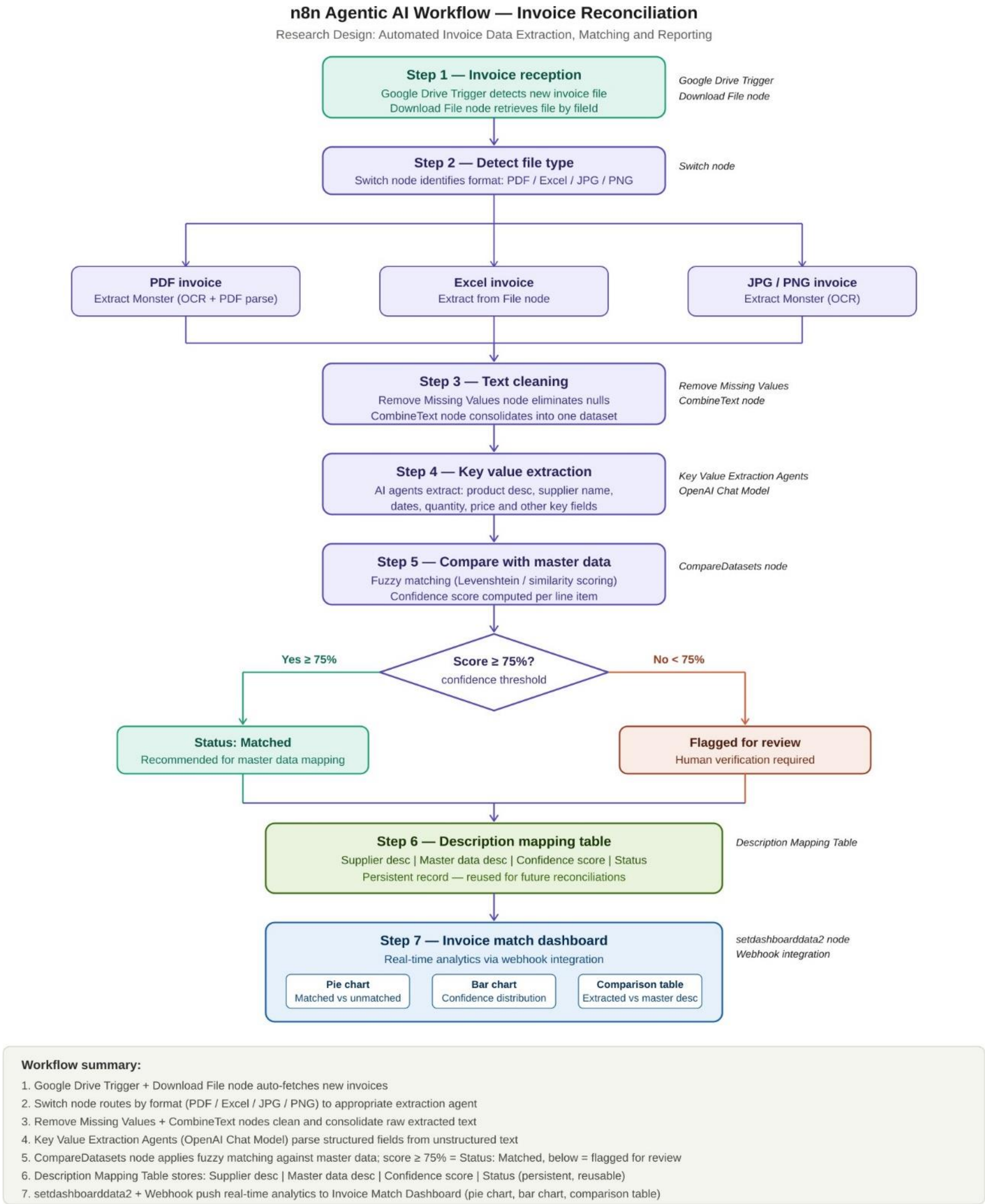

Fig. 1: End-to-end methodology workflow for agentic invoice reconciliation.

1) ***Invoice Reception and Download:*** The workflow initi-ates with the Google Drive Trigger node, which continuously monitors a designated folder for newly uploaded invoice files. Upon detection, the Download File Node retrieves the file using its unique fileId, enabling automatic invoice retrieval without manual intervention. This trigger-based architecture ensures real-time processing as invoices arrive from suppliers.

2) ***File Type Detection and Format-Specific Extraction:*** Following download, the Switch node determines the file format (PDF, Excel XLSX, JPG, or PNG) and routes the work-flow accordingly. For image-based documents (JPG/PNG) and PDF files, the Extract Monster node performs OCR-based text extraction. For Excel documents, the Extract From File node parses structured spreadsheet data. This format-agnostic approach eliminates template dependencies and accommodates heterogeneous supplier invoice formats.

3) ***Text Cleaning and Preprocessing:*** Extracted data un-dergoes preprocessing to remove null values, empty fields, and noise using the Remove Missing Values node. The Com-bineText node then consolidates all cleaned text segments into a unified dataset, standardizing inputs for subsequent AI processing regardless of original format.

4) ***Key Value Extraction via AI Agents:*** The OpenAI Chat Model (GPT-5 Mini) functions as an Agentic AI extraction agent, processing consolidated text to identify and extract structured fields including product descriptions, invoice dates, supplier names, quantities, and unit prices. Unlike template-based extraction, this agent interprets semantic context, en-abling accurate field identification across varying invoice lay-outs and terminologies.

5) ***Semantic Matching and Confidence Scoring:*** The Com-pare Datasets node implements fuzzy matching between ex-tracted invoice descriptions and ERP master data. The Leven-shtein Distance algorithm measures string similarity, supple-mented by numeric token matching for quantities and specifications. A confidence score is computed for each potential match; values exceeding the 75% threshold trigger automatic approval, while lower scores escalate to manual verification.

6) ***Data Mapping and Persistent Storage:*** Matched results populate the Description Mapping Table, recording supplier descriptions, master data equivalents, confidence levels, and match status. This persistent repository eliminates redundant re-matching for recurring invoices and provides historical data for system improvement.

7) ***Real-Time Reporting and Analytics:*** The setdashboard-data2 node transmits reconciliation results via webhook to the Invoice Match Dashboard. This dashboard visualizes match distributions through pie charts, confidence score distributions via bar charts, and detailed comparison tables, providing stake-holders with immediate visibility into system performance and exceptions requiring attention.

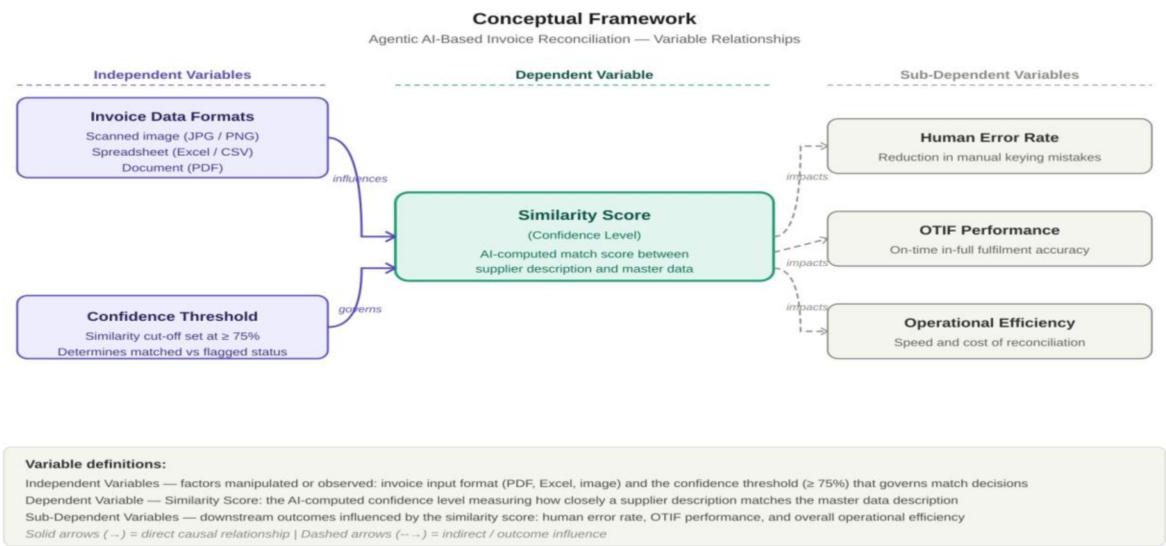

Fig. 2: Conceptual framework mapping variables to operational outcomes.

D. Variable Operationalization and Hypotheses

Variable	Definition	Measure
Similarity Score	Fuzzy match between in-voice and master data	0%–100%
Invoice Format	File type category	Categorical
Confidence Threshold	Match approval cutoff	Binary: 75%

TABLE I: Variable Operationalization

Hypothesis 1 (H1): H_0: Agentic AI does not significantly improve the accuracy of invoice reconciliation compared to traditional manual methods. H_1: Agentic AI significantly improves the accuracy of invoice reconciliation compared to traditional manual methods.

Hypothesis 2 (H2): H_0: Using a 75% confidence threshold does not improve the reliability of AI-driven invoice reconcil-iation. H_1: Using a 75% confidence threshold improves the reliability of AI-driven invoice reconciliation.

IV. Implementation

A. n8n Workflow Design

Fig. 3 shows the n8n workflow architecture integrating Google Drive, AI agents, SQL master data, and dashboard visualization.

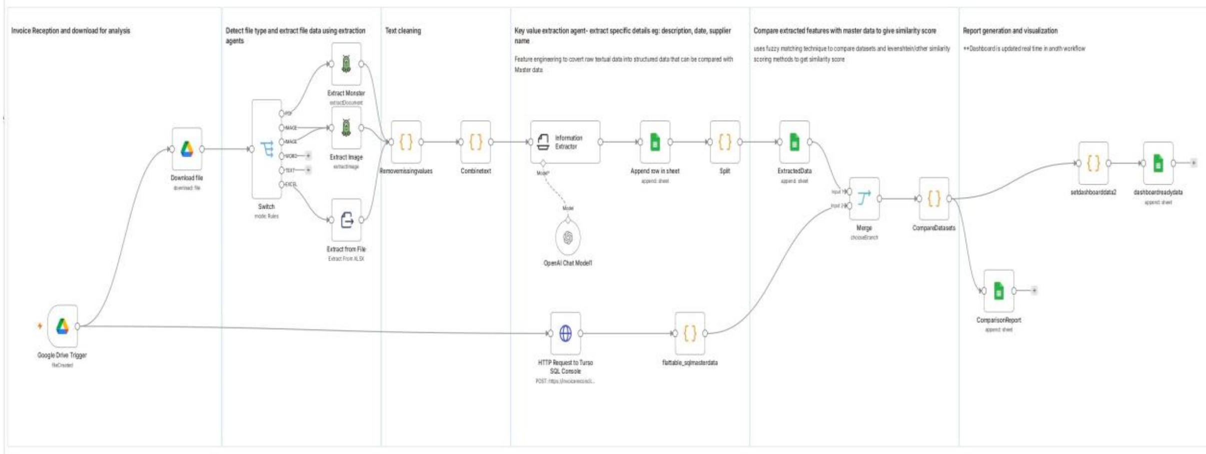

Fig. 3: n8n workflow architecture for agentic invoice recon-ciliation.

B. Key Components

Format Detection: Switch node routes PDF/PNG/JPG to Extract Monster (OCR) and Excel to Extract from File node.

AI Extraction: GPT-5 Mini agent performs semantic un-derstanding of unstructured invoice text, extracting product descriptions, quantities, and prices without template depen-dencies.

Semantic Matching: Levenshtein distance combined with numeric token overlap generates confidence scores. Matches

≥75% auto-approve; others flag for review.

Dashboard: Real-time webhook updates to Loveable dash-board displaying match status, confidence distributions, and side-by-side comparisons.

C. Data Sources

Invoices were collected from a mid-sized supplier upon company approval. These invoices were generated from the internal ERP system. Distributor Master Data was collected from a distributor.

Sensitive information such as customer details are removed from the invoice by masking. These invoices are stored in private Google drive folder. Only the essential data from invoice for research is shown and the rest are masked.e.g.: only line- item description taken for analysis.

In total, 93 samples invoices were taken .Three sample invoices, with different templates and file types were taken-representing the three primary invoice formats encountered in the operational context: PDF, Excel, and scanned PNG image respectively.

Each invoice contained between 3 and 11 line items, with line-item descriptions used as the primary unit of analysis for semantic matching against the product master data. The master data comprised the full product catalogue from distributor SFA system, containing product descriptions across multiple product groups and categories. The distributor master data is stored in SQLite database.

V. RESULTS AND EVALUATION

II. Performance Metrics

Table II presents the comparative performance analysis between manual processing and the Agentic AI system. Oper-ational data from SCB invoice generation records established the baseline: each distributor processes at least three invoices per week per supplier at 25 minutes of manual ERP entry per invoice [2]. Across three suppliers, this totals 225 minutes of manual processing weekly. The Agentic AI system reduced this to 9 minutes weekly-a 96% reduction equivalent to saving approximately 187 hours of administrative labor per distributor annually.

Metric	Manual	Agentic AI
Weekly time (9 inv.)	225 min	9 min
Annual time	195 hrs	8 hrs
Time reduction	-	**96%**
Error rate	3–5%	**0%**
Annual errors (line items)	104–156	**0**

TABLE II: Manual vs. Agentic AI Performance

III. Testing and Validation

The system underwent comprehensive testing across eleven test cases covering functional and non-functional require-ments. File reception via Google Drive Trigger (Test 1–2) and format detection for PDF, Excel, and PNG (Test 3–4) passed successfully. Line-item description extraction accuracy was validated against three sample invoices with 8–11 line items each (Test 5). Semantic matching and confidence score calculation (Test 6–7) correctly identified matches above and below the 75% threshold. Dashboard component rendering and real-time webhook updates (Test 8–9) displayed all required analytics elements. Heterogeneous format handling (Test 10) and execution time measurement (Test 11) confirmed sub-one-minute processing per invoice.

IV. Confidence Score Analysis

Semantic similarity scores ranged from 45.8% to 100%, reflecting the expected distribution of terminological discrep-ancies between supplier invoice descriptions and standardized ERP master data. High-confidence matches (e.g., “Apple1”

→ “Apple Juice 1L” at 100%) were automatically approved, while borderline cases (e.g., “WATAWALA TEA 400G X 30” at 67.76%) were correctly flagged for human review. This validates the 75% threshold as an effective decision boundary balancing automation coverage with accuracy assurance.

V. Dashboard Analytics

Fig. 4 presents the Invoice Match Dashboard providing stakeholders with real-time visibility into reconciliation per-formance. The dashboard displays match distribution via pie charts, confidence score distributions through horizontal bar charts, and detailed comparison tables showing extracted in-voice descriptions alongside matched master data entries with corresponding confidence levels and status indicators.

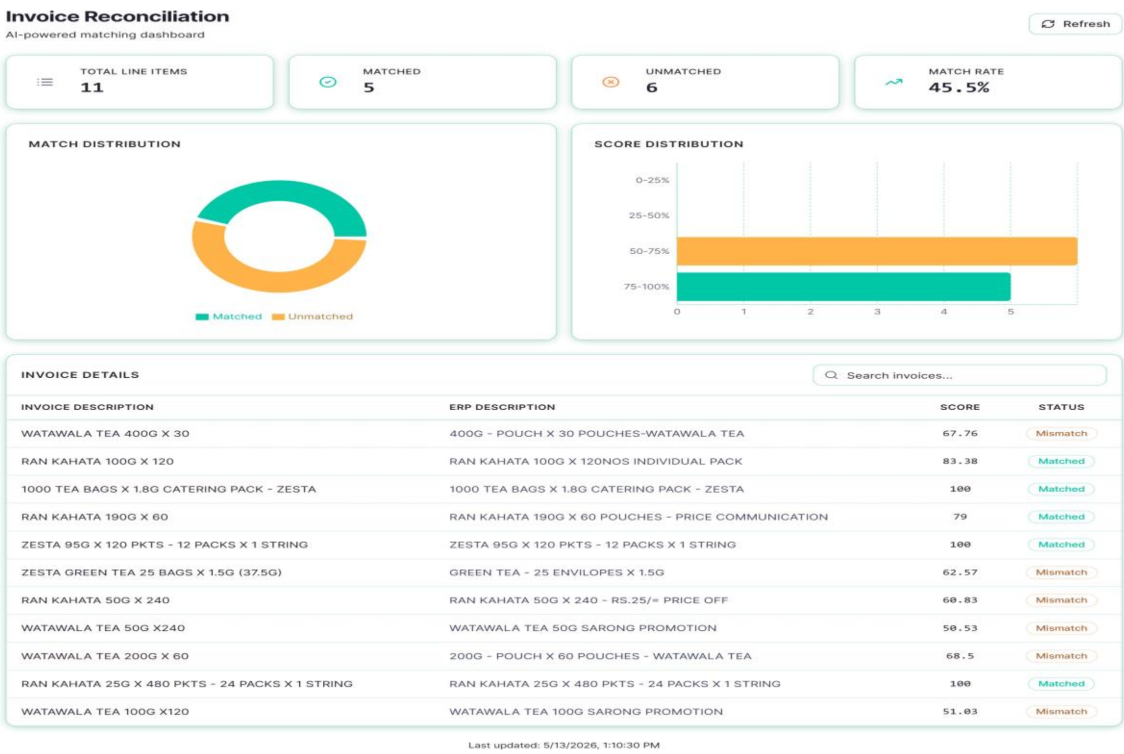

Fig. 4: Real-time analytics dashboard for invoice reconciliation monitoring.

VI. DISCUSSION

A. Key Findings

This research demonstrates that Agentic AI, orchestrated through n8n workflow automation with LLM-powered ex-traction and fuzzy semantic matching, achieves substantial efficiency and accuracy gains in invoice reconciliation. The 96% processing time reduction-from 225 minutes to 9 minutes weekly per distributor-translates to approximately 187 admin-istrative hours saved annually. This efficiency gain directly ad-dresses the scalability bottleneck identified in manual process-ing, where growing invoice volumes necessitate proportional staffing increases.

Hypothesis H1 is supported: the Agentic AI system pro-duced similarity scores consistently above the documented manual error threshold, with matched invoice line items achieving scores between 75% and 100%, confirming sig-nificant accuracy improvement over the 3–5% manual error rate [2]. Hypothesis H2 is also supported: the 75% confidence threshold accurately classified matching and non-matching in-voices across all three tested formats (PDF, Excel, PNG), with correctly flagged items enabling appropriate human oversight.

B. Business Impact

The elimination of manual data entry errors-previously 104–

156 erroneous line items annually per distributor-prevents downstream inventory discrepancies, payment disputes, and delivery failures. By stabilizing invoice processing timelines, the system directly contributes to improved OTIF performance, a critical metric in FMCG supply chain operations. The real-time XAI dashboard further enhances operational transparency, enabling stakeholders to make informed decisions based on visible confidence scores and match explanations.

C. Limitations and Future Work

The study scope is limited to invoice processing for Goods Receipt Note generation in mid-sized FMCG organizations, covering PDF, Excel, and image formats. Future work should address: (1) direct integration with ERP GRN posting sys-tems for fully automated workflows; (2) adaptive confidence thresholding based on supplier-specific historical patterns; (3) expansion to EDI, XML, and proprietary formats; (4) long-term evaluation of rare invoice template behavior; (5) simil-iarity match history could be used for selecting best responsive templates, detect fraud, detect anomalies, detect duplicates or for other predictive analytics and (5) implementation advance-ments such as adopting system to read multiple lanaguage invoices and chatbot integration for user query handling.

CONCLUSION

This research contributes a practical, empirically validated framework for Agentic AI in invoice reconciliation, demon-strating measurable improvements in efficiency, accuracy, and operational transparency. The confidence-based approach en-sures that automation benefits are realized without sacrificing human oversight for uncertain cases, aligning with respon-sible AI deployment principles in business-critical financial processes.

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