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Research on Intelligent Audit System for Employee Expense Reimbursement Based on Agent Technology

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***Abstract*—Expense reimbursement auditing is a high-frequency task in corporate finance departments, requiring auditors to verify invoice authenticity, expense compliance, and approval process integrity across multiple dimensions. This work is repetitive and prone to errors due to auditor fatigue. This paper proposes an intelligent expense reimbursement audit assistant based on agent technology to automate preliminary auditing tasks. The intelligent agent integrates three core functional modules: invoice verification, standard compliance checking, and quota verification. It automatically identifies invoice information from reimbursement documents and validates authenticity through tax authority interfaces, cross-checks expenses such as meals and travel against corporate standards to detect overages, and verifies whether cumulative reimbursement amounts exceed departmental budgets. The system employs a rule engine architecture rather than complex machine learning algorithms, enabling finance personnel to maintain audit rules independently without continuous IT support. In practical application at a consulting firm, the system reduced document auditing time from an average of 15 minutes to 5 minutes per claim, improved anomaly detection rate by 40%, and significantly reduced manual audit costs and compliance risks. This paper elaborates on key implementation aspects, including audit rule base construction methods, common anomaly type identification logic, and human-machine collaborative audit process design, providing enterprises with a low-barrier, high-efficiency solution for financial digital transformation.**

***Index Terms*—Agent, Expense reimbursement, Intelligent audit, Rule engine, Financial automation**

I. Introduction

A. Research Background and Significance

With the continuous expansion of enterprise scale and increasing business activity frequency, employee expense reimbursement has become a critical component of corporate financial management. Large and medium-sized enterprises process thousands or even tens of thousands of reimbursement claims monthly, covering various expense categories including travel, entertainment, office supplies, and training costs. Under traditional manual audit modes, finance personnel must individually verify invoice information, check expense standards, and validate approval processes, resulting in enormous and highly repetitive workloads. The role of accountants has evolved significantly, with professionals now serving as digital innovators who must master new competencies in the age of automation [1]. In the wave of digital transformation, enterprises urgently need to leverage information technology to improve financial management efficiency, reduce labor costs, and ensure financial compliance.

In recent years, artificial intelligence technology has made significant advances in financial applications. Comprehensive literature reviews have documented the growing applications of AI in accounting and auditing [2], [3], revealing both opportunities and challenges in this rapidly evolving field. Agent technology, as an important branch of artificial intelligence, possesses characteristics such as autonomy, reactivity, proactivity, and social ability, enabling it to autonomously complete specific tasks in complex environments. Applying agent technology to expense reimbursement audit scenarios can construct an intelligent system capable of automatically perceiving document information, executing audit rules, and collaborating with finance personnel.

B. Challenges Faced by Expense Reimbursement Auditing

Current enterprise expense reimbursement auditing faces numerous challenges. High workload and repetitiveness constitute the most prominent issue. The data analytics journey in auditing has revealed complex interactions among auditors, managers, regulation, and technology [4]. Simultaneously, the rule system governing expense reimbursement exhibits complexity and dynamism, with different expense types having different standards and limits. Recent advances in autonomous and collaborative agentic AI systems demonstrate significant potential for enterprise applications requiring complex decision-making [5].

Invoice authenticity verification constitutes an important technical challenge. Fraudulent behaviors such as fake invoices and duplicate reimbursements occur periodically. The need

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for enhanced auditor data literacy has become increasingly critical, as auditors must develop competencies to effectively utilize data analytics tools and AI systems [6]. Furthermore, expense reimbursement auditing faces human-machine collaboration challenges. Research has demonstrated that AI is improving the audit process, with evidence showing enhanced efficiency and accuracy in various audit tasks [7]. Research indicates that auditors' reliance on AI systems varies significantly based on the complexity of estimates and the transparency of AI decision-making processes [8]. System maintainability is also an important consideration, particularly for small and medium-sized enterprises.

C. Application Value of Agent Technology

Agent technology provides new approaches to addressing these challenges. Agents possess goal orientation, enabling them to autonomously plan execution paths according to preset audit objectives. In expense reimbursement audit scenarios, agents can automatically identify claim types, invoke corresponding audit modules, execute rule checks, and ultimately provide audit conclusions. Rule engine-based agent architecture is particularly suitable for expense reimbursement audit scenarios. Rule engines explicitly express business logic in rule form, providing good interpretability that enables finance personnel to clearly understand the basis for each audit conclusion. Compared to black-box machine learning models, rule engine transparency helps build user trust in the system.

II. Related Work

A. Financial Audit Automation Technology

Financial audit automation represents an important direction for enterprise digital transformation. Early financial automation primarily focused on process automation technology applications, implementing automatic execution of repetitive tasks, but these solutions lacked intelligent decision-making capabilities. The application of AI-based decision-making in accounting and auditing raises important ethical challenges that must be carefully considered [9]. Recent advances in invoice detection and recognition systems based on deep learning have achieved significant breakthroughs, enabling accurate extraction of structured information from various invoice formats [10].

Research examining how financial executives respond to the use of AI in financial reporting and auditing reveals concerns about over-reliance on automated systems and potential loss of professional judgment [11]. Audit data analytics combined with machine learning has enabled full population testing, moving beyond traditional sampling-based approaches [12]. The changing landscape of accounting due to AI has created a paradigm shift that requires new frameworks and competencies [13]. A bibliometric analysis of big data and AI in accounting and auditing fields reveals rapidly growing research interest but also highlights gaps in practical implementation guidance [14].

B. AI-Based Decision-Making and Collaboration

Blockchain technology has emerged as a promising solution for advancing security, efficiency, and transparency in financial systems, including invoice verification [15]. A conceptual framework for auditing practices in the AI era has been proposed to help practitioners navigate these challenges [16], emphasizing the importance of maintaining human oversight, ensuring AI system transparency, and validating AI outputs.

Machine learning-enhanced text analytics has shown promise in efficient audit documentation review, demonstrating how AI can augment rather than replace human judgment [17]. The question of whether accountants should be afraid of AI has generated considerable debate [18]. While AI presents risks including job displacement concerns, it also offers significant opportunities for enhanced audit quality, reduced costs, and the ability to focus on higher-value analytical tasks.

While existing research has made substantial contributions, several gaps remain. Much of the literature focuses on advanced machine learning approaches that require significant technical expertise and data resources. There is limited guidance on practical implementation of intelligent audit systems that balance automation benefits with interpretability, maintainability, and ease of use. This paper addresses these gaps by proposing a practical agent-based intelligent audit system specifically designed for expense reimbursement scenarios.

III. System Design and Implementation

A. System Architecture

This paper's proposed intelligent expense reimbursement audit system adopts a layered architecture design, comprising four levels: data access layer, agent collaboration layer, rule engine layer, and user interaction layer. The data access layer obtains pending audit claim information from existing enterprise reimbursement systems, including invoice images, reimbursement amounts, expense types, and reimbursement personnel information. Studies investigating auditors' reliance on AI have found that control issues significantly affect trust and utilization patterns [19]. The agent collaboration layer is the system core, containing multiple function-specific agent modules, with each agent responsible for specific audit tasks, achieving collaborative work through message passing mechanisms.

The system adopts an event-driven architecture pattern. The impact of AI adoption on financial reporting quality has shown generally positive results when properly implemented [20]. When new reimbursement claims are submitted, the system triggers audit events, with the agent coordinator allocating tasks to various professional agents. Invoice verification agents, standard checking agents, and quota verification agents work in parallel, each completing assigned audit tasks before consolidating results to the decision agent. The decision agent provides final audit conclusions: automatic approval, requiring manual review, or rejection.

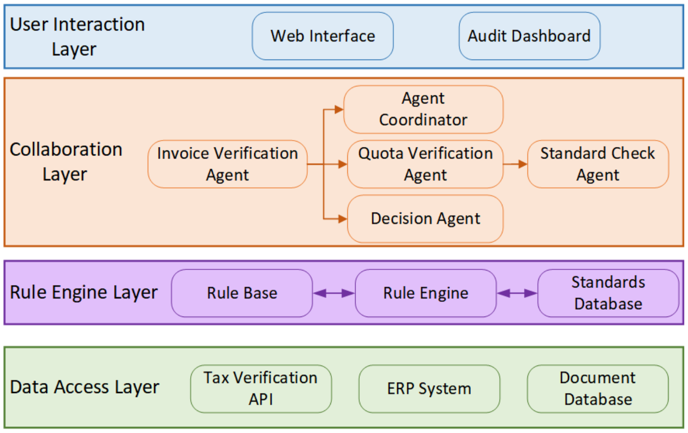

Fig. 1. Intelligent Audit of Expense Reimbursement System Architecture.

B. Agent Core Module Design

The invoice verification agent is responsible for verifying authenticity and validity of invoices in reimbursement claims. This agent automatically identifies key invoice image information through OCR technology, including invoice codes, invoice numbers, issue dates, amounts, and seller tax numbers. Extracted invoice information is subsequently verified for authenticity through tax authority interfaces or blockchain-based verification systems. The system includes built-in invoice caching mechanisms to avoid repeated verification. Simultaneously, the invoice verification agent executes duplicate reimbursement detection, identifying multiple reimbursement attempts through comparing invoice numbers and image similarity.

Field evidence regarding challenges and opportunities for AI in auditing reveals complex technical, organizational, and human factors that must be addressed [21]. The standard checking agent is responsible for compliance checking of reimbursement amounts according to enterprise expense standards. This agent obtains applicable expense standards from the rule engine, determining corresponding limit standards based on factors such as reimbursement personnel rank, expense type, and location. The standard checking agent compares actual reimbursement amounts with standard limits, calculating excess amounts and ratios.

The quota verification agent is responsible for checking whether reimbursement amounts exceed departmental budgets or individual cumulative limits. This agent obtains departmental budget execution status from enterprise ERP systems, calculating budget balances after current reimbursement application approval.

C. Audit Rule Base Construction

The audit rule base is the system's knowledge foundation, containing enterprise expense standards, audit rules, and anomaly determination logic. The application of AI to financial statement audits presents both opportunities for enhanced efficiency and quality, as well as challenges related to professional standards and regulatory compliance [22]. The rule base adopts hierarchical categorization organization methods for easy management and maintenance. The rule base top level is divided into three major categories: basic rules, standard rules, and policy rules.

Basic rules define basic conditions that reimbursement claims must satisfy. Standard rules define limit standards and calculation methods for various expense types. Policy rules define special situation handling logic and human-machine collaboration trigger conditions. Table 1 shows the audit rule base classification system and typical rule examples.

Rule expression adopts "condition-action" patterns, with each rule comprising three parts: trigger conditions, rule content, and execution actions. The rule base establishment process includes four stages: rule collection, rule formalization, rule validation, and rule optimization.

D. Anomaly Identification Logic

Anomaly identification is a key function of intelligent audit systems. The system adopts multi-dimensional anomaly identification mechanisms, analyzing from multiple angles including invoice authenticity, expense rationality, and behavioral patterns. Research on AI-personalized learning paths demonstrates how AI can enhance competency development, with implications for training finance personnel [23]. The system defines anomaly score calculation methods for each anomaly category. Claim total anomaly scores are sums of individual anomaly scores:

$$S_{\text{total}} = w_1 \cdot S_{\text{invoice}} + w_2 \cdot S_{\text{standard}} + w_3 \cdot S_{\text{behavior}} \tag{1}$$

where S_{total} is the total anomaly score, and w_1, w_2, w_3 are corresponding weight coefficients. The system categorizes claims into three risk levels: low risk, medium risk, and high risk. Table 2 lists common anomaly types and their identification logic.

E. Human-Machine Collaborative Process

Human-machine collaboration is key to improving audit efficiency while ensuring audit quality. The system categorizes reimbursement claims into three processing paths: automatic approval, manual review, and automatic rejection. For low-risk claims, the system automatically approves audits without finance personnel intervention. For claims with moderate anomalies or requiring subjective judgment, the system transfers to manual review, providing detailed anomaly prompts and audit recommendations. The audit process design follows the principle of "machine priority, human backup." The efficiency improvement rate can be calculated as:

$$E = \frac{T_{\text{manual}} - T_{\text{auto}}}{T_{\text{manual}}} \times 100\% \tag{2}$$

The system provides audit monitoring dashboards, displaying audit progress, anomaly distribution, and manual review queues in real-time. This flexible human-machine collaboration mechanism ensures both audit automation rates and maintains necessary human supervision.

TABLE I
AUDIT RULE BASE CLASSIFICATION AND EXAMPLES

Rule Category	Rule Subtype	Rule Example	Trigger Condition	Execution Action
Basic Rules	Invoice Verification	Invoice must pass tax verification	All reimbursements with invoices	Call verification interface, reject if failed
Basic Rules	Information Integrity	Reimbursement must include complete approval signatures	All reimbursement claims	Check approval flow, reject if missing
Standard Rules	Travel-Accommodation	First-tier city accommodation not exceeding 500 yuan/night	Expense type = accommodation & city level = first-tier	Mark anomaly if exceeded
Standard Rules	Meal Limits	Regular staff meals not exceeding 100 yuan/day	Expense type = meals & rank = regular staff	Manual review if excess ratio > 20%
Standard Rules	Entertainment	Entertainment requires business description and counterparty info	Expense type = entertainment	Reject if description missing
Policy Rules	High-value	Single amounts exceeding 5000 yuan require director approval	Reimbursement amount > 5000	Check approver level
Policy Rules	Anomaly Patterns	Same employee reporting meals at limit ceiling for 3 consecutive days	Statistics of 7-day patterns	Mark suspicious, manual review

TABLE II
COMMON ANOMALY TYPES AND IDENTIFICATION LOGIC

Anomaly Category	Anomaly Type	Identification Method	Score	Recommendation
Invoice Anomaly	Fake Invoice	Tax interface verification failed	100	Direct rejection
Invoice Anomaly	Duplicate Invoice	Invoice number or image similarity match	100	Direct rejection
Invoice Anomaly	Expired Invoice	Issue date exceeds 6 months from reimbursement date	30	Manual review
Expense Anomaly	Minor Excess	Exceeding limit by 10-20%	20	Auto-approve but mark
Expense Anomaly	Significant Excess	Exceeding limit by 20-50%	50	Manual review
Expense Anomaly	Severe Excess	Exceeding limit by over 50%	80	Recommend rejection
Behavioral Anomaly	High Frequency	More than 5 reimbursements in 7 days	15	Monitor attention
Behavioral Anomaly	Round Amounts	Multiple consecutive round hundreds or thousands	25	Manual review
Behavioral Anomaly	Concentrated	Sudden large volume after 3 months gap	20	Manual review
Quota Anomaly	Budget Overrun	Department budget balance negative	60	Manual review
Quota Anomaly	Near Limit	Cumulative reaches over 90% of limit	10	Reminder attention

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experimental Environment and Dataset

To validate the effectiveness of this paper's proposed intelligent expense reimbursement audit system, we conducted a three-month practical application test at a management consulting firm. The company has approximately 200 employees and processes 800-1000 reimbursement claims monthly. The experimental system was deployed in the company's internal private cloud environment, with hardware configuration of an 8-core CPU, 32GB memory server. The system was integrated with the company's existing OA office system and connected to the State Administration of Taxation's invoice verification interface.

The experimental dataset contains all reimbursement claims from October to December 2024, totaling 2,847 claims. The dataset includes 2,456 normal claims (86.3%) and 391 claims with various anomalies (13.7%). Anomalous claims include 73 with invoice issues (12 fake invoices, 28 duplicate reimbursements, 33 expired invoices), 242 with expense excesses (157 minor, 62 significant, 23 severe), and 76 with behavioral anomalies. We divided the dataset at a 7:3 ratio into training and testing sets.

B. System Performance Evaluation

System performance evaluation primarily proceeded from four dimensions: processing speed, accuracy, recall rate, and F1 score. The system's average processing time per reimbursement claim was 12 seconds. Compared to manual audit average processing time of 15 minutes, the system's processing speed improved approximately 75-fold. The system supports concurrent processing; in the test environment, it could simultaneously process 20 audit requests.

The system achieved an overall accuracy of 92.3% on the testing set. Invoice authenticity determination accuracy was 98.5%; expense standard checking accuracy was 94.7%; quota

TABLE III
EFFECT COMPARISON BEFORE AND AFTER SYSTEM APPLICATION

Evaluation Indicator	Before System	After System	Improvement
Average claim audit time	15 minutes	5 minutes (with manual review)	67%
Auto-approved claim ratio	0%	71.2%	—
Monthly manual audit hours	225 hours	75 hours	67%
Audit cycle	3-5 working days	Real-time to 2 days	60-80%
Anomalous claim identification	Approx. 60% (manual)	87.6% (system)	46%
Invoice verification coverage	Approx. 30% (spot check)	100% (full)	233%
Audit standard consistency	Medium	High	Significant
Monthly processed volume	900 claims	900 claims	0%
Finance personnel satisfaction	Average	Good	Improved
Employee satisfaction	Average	Better	Improved

verification accuracy was 96.1%. The system's anomalous claim identification recall rate reached 87.6%. Anomaly identification precision rate was 89.4%. Combining precision and recall rates, the system's F1 score was 88.5%.

The system's automated processing rate is an important indicator. In the testing set, low-risk claims accounted for 71.2%, all passing automatic audit without manual intervention. Medium-risk claims accounted for 21.5%, transferred to manual review. High-risk claims accounted for 7.3%. In actual operation, finance personnel only needed to process 28.8% of claims, with the remaining 71.2% automatically completed by the system.

C. Audit Efficiency Comparison

To quantify the system's effect on improving audit efficiency, we compared audit workload and audit time before and after system implementation. Before system implementation, the company had 3 full-time finance personnel responsible for reimbursement audit work. Average audit time was approximately 15 minutes per claim. Based on 900 monthly claims, three finance personnel invested total monthly work hours of approximately 225 hours in reimbursement auditing.

After system implementation, audit efficiency significantly improved. For medium-risk claims marked by the system, manual review averaged approximately 5 minutes. For high-risk claims, manual re-review averaged approximately 8 minutes. Comprehensive calculation showed monthly manual audit total work hours after system implementation were approximately 75 hours, reduced by 150 hours compared to before, with workload decreased by approximately 67%.

Audit timeliness also showed marked improvement. Before system implementation, reimbursement claims typically required 3-5 working days for audit completion. After system implementation, automatically approved claims completed audits in real-time, with employees receiving audit results within seconds. Claims requiring manual review had average audit cycles shortened to 1-2 working days. Table 3 provides detailed comparison of various efficiency indicators.

D. Anomaly Identification Accuracy

Anomaly identification is one of the intelligent audit system's core values. In the test dataset, the system identified 115 anomalous claims, including 103 true anomalies and 12 false positives, with a false positive rate of 10.4%. Through rule optimization, the false positive rate in actual operation gradually decreased to approximately 7%.

More importantly, the system discovered multiple anomalies potentially overlooked in manual auditing. In comparative experiments, manual auditing identified 70 anomalous claims, while actually annotated anomalous claims totaled 117, with manual audit omission rate reaching 40%. Among the 103 anomalies identified by the system, 47 were initially overlooked by manual auditing. This indicates the system has obvious advantages in anomaly identification comprehensiveness and consistency.

Invoice authenticity identification accuracy was highest at 98.5%. Duplicate invoice identification accuracy was 96.4%. Expense excess identification accuracy was 94.7%. Behavioral pattern anomaly identification had accuracy of 81.3%. Through continuous rule optimization and anomaly case accumulation, behavioral anomaly identification effectiveness is gradually improving.

E. Practical Application Cases

Through specific application cases, the system's practical effects can be intuitively demonstrated. In duplicate reimbursement identification, an employee submitted a meal expense reimbursement of 385 yuan on October 15. On November 20, the same employee resubmitted the identical invoice. The system detected the duplicate invoice number during verification and automatically rejected the claim. In expense standard checking, a department manager's accommodation fee of 600 yuan per night exceeded the mandated 500 yuan standard. The system identified the excess and marked it as medium risk. Finance personnel discovered the business trip coincided with a local exhibition period causing hotel price increases, subsequently approving the reimbursement while adding special rules to prevent similar misjudgments. In behavioral anomaly identification, the system flagged an employee who submitted 5 meal expense reimbursements over 5 consecutive days, each approaching the limit and concentrated at month-end. Finance verification confirmed all claims corresponded to actual business trips with genuine invoices. Although ultimately determined as normal, the system's warning mechanism effectively prompted attention to potentially irregular reimbursement patterns, demonstrating its value in proactive risk management.

V. Conclusion

This paper proposes an intelligent expense reimbursement audit system based on agent technology to address challenges in enterprise auditing including low efficiency, complex rules, and difficult anomaly identification. The system adopts a multi-agent collaborative architecture, decomposing audit tasks into three independent modules: invoice verification, standard checking, and quota verification, with rule engines as core reasoning mechanisms. Practical application demonstrates significant improvements: audit time decreased from 15 minutes to 5 minutes (67% efficiency gain), anomalous claim identification increased from 60% to 87.6%, and 71.2% of claims achieved automatic approval. Key system advantages include moderate technical barriers enabling rapid deployment, strong interpretability with traceable audit conclusions, and good maintainability through configuration interfaces. The agent technology implementation achieves modular design and parallel processing, while the human-machine collaboration mechanism effectively leverages respective strengths of automation and human expertise.

Despite promising results, several limitations warrant further research. The system demonstrates limited capabilities in handling complex scenarios, with relatively low accuracy in behavioral anomaly identification and weak cross-claim association analysis. Future work should focus on introducing machine learning techniques to enhance intelligence levels and adaptive capabilities, strengthening fraud detection through graph databases for cross-claim pattern analysis, and exploring blockchain technology to address invoice verification constraints from external interface dependencies. Additionally, extending intelligent automation to broader financial processes and addressing ethical challenges regarding accountability frameworks and appropriate boundaries between human judgment and machine automation become increasingly important as systems assume greater audit responsibilities. With continuous advancement of artificial intelligence and deepening enterprise digital transformation, this research provides a practical foundation for intelligent financial management systems.

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