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From RPA to AI Agent: Exploring a New Path for Financial Reconciliation Automation in SMEs

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Abstract: Financial reconciliation is a fundamental task in the financial management of small and medium-sized enterprises (SMEs), directly affecting accounting information quality and capital risk control. The traditional manual reconciliation model suffers from low efficiency and high rates of human error. RPA can automate standardized reconciliation processes, but is constrained by preset rules and struggles to autonomously handle diverse business exception scenarios, exhibiting clear application limitations. AI Agent, relying on perception, reasoning, and dynamic task planning capabilities, breaks through the capability boundaries of traditional automation tools and provides a new solution for the financial digital transformation of SMEs. This paper adopts conceptual analysis and comparative research methods to define the technical connotations of RPA and AI Agent, analyze the application bottlenecks of RPA in SME reconciliation scenarios, elucidate the internal logic of AI Agent reconstructing reconciliation business processes, and systematically review the various risks and constraints in the technology implementation process. The study argues that AI Agent does not replace accounting personnel, but rather constructs a new human-machine collaborative reconciliation model, providing theoretical reference for the financial automation construction of SMEs.

Keywords: Financial reconciliation; AI Agent; RPA; SMEs; Financial automation; Human-machine collaboration.

1. Introduction

1.1. Research Background

Financial reconciliation is a core foundational step in the accounting control system, the essence of which is the cross-verification of multi-source financial records to ensure conformity among accounts, documents, and physical assets. SMEs have weaker risk resistance and limited capital reserves; account errors can easily propagate to the cash flow level, making the reliability of reconciliation work significant for their operational sustainability. SMEs have complex business chains, with financial data scattered across multiple carriers such as online banking statements, value-added tax invoices, business ledgers, and accounting subsidiary ledgers. The data sources exhibit significant heterogeneity, and reconciliation work involves heavy workloads and complex causes of discrepancies.

Currently, a large number of SMEs in China still use manual reconciliation models, requiring accounting personnel to complete account matching, discrepancy identification, and cause investigation item by item. Manual operations not only consume substantial financial human resources but also are susceptible to interference from business peaks, personnel fatigue, and position changes, posing risks of accounting errors such as missed or incorrect verification. The quality of manual reconciliation is highly dependent on the professional competence and sense of responsibility of practitioners, with insufficient work standardization and weak internal control stability.

RPA (Robotic Process Automation), as a foundational tool for financial digitalization, has been gradually promoted in practice. This technology can simulate manual operations and automatically execute structured, rule-fixed financial operations, effectively reducing manual workload in standardized reconciliation scenarios. However, RPA's operating logic is highly dependent on pre-written scripts and can only handle pre-defined business situations. When non-preset business exceptions such as cross-period recognition, sales allowances, or red-letter reversals occur, the automated process is immediately interrupted, unable to independently complete discrepancy attribution, exhibiting significant capability boundaries.

With the iteration of large model technology, AI Agent, possessing autonomous perception, logical reasoning, task planning, and self-verification capabilities, is developing rapidly, opening new directions for financial process automation. Compared to RPA, which only executes fixed instructions, AI Agent can autonomously decompose business tasks, identify anomalous account items, and trace discrepancy causes in multi-source heterogeneous data environments, capable of adapting to the large number of non-standardized exception matters in reconciliation scenarios. This technical characteristic can specifically address the long-standing pain points in SME reconciliation operations.

1.2. Problem Statement and Research Significance

Can the application bottlenecks of RPA in SME reconciliation scenarios be resolved through AI Agent technology? What kind of reconstruction will AI Agent bring to traditional reconciliation business processes? What institutional, data, and security constraints will be faced during technology implementation? Clarifying these questions holds theoretical value and practical reference value for SMEs in selecting financial digitalization solutions adapted to their own resource endowments.

This paper adopts conceptual analysis and comparative research methods, requiring no enterprise empirical samples. The research first distinguishes the technical connotations and applicable boundaries of RPA and AI Agent, then analyzes the inherent limitations of RPA in SME reconciliation scenarios, explores the implementation path of AI Agent empowering financial reconciliation, identifies potential risks of

technology implementation, and provides ideas for the financial automation transformation of SMEs.

2. Relevant Concept Definition: RPA and AI Agent

2.1. RPA — Robotic Process Automation

RPA is an automated software technology that simulates human-machine interaction behavior based on preset scripts. Through solidified operating procedures, this technology automatically completes repetitive tasks such as data reading, information comparison, and file export, and can be externally attached to existing information systems without modifying the original financial software architecture.

In financial reconciliation scenarios, RPA can achieve fixed-process automation: automatically downloading bank statements, reading standardized ledger data, completing account comparison based on preset matching keys such as document numbers, amounts, and business dates, and outputting reconciliation result reports. In business scenarios with stable rules and unified data source formats, RPA can continuously execute repetitive operations, reducing simple human errors and improving basic verification efficiency.

RPA's application advantages are reflected in three aspects: first, lightweight deployment with low system modification investment and short implementation cycles; second, unified execution logic with traceable operation trajectories, facilitating internal control documentation; third, relatively controllable maintenance thresholds, suitable for market entities with limited resources. However, RPA technology has underlying constraints: this tool only executes established instructions, lacks business semantic understanding capability, and cannot autonomously handle business scenarios beyond script scope. Once data source formats or field specifications change, or business situations not pre-defined occur, the automated process becomes ineffective, requiring manual revision of rule scripts.

2.2. AI Agent — Artificial Intelligence Agent

AI Agent is an autonomous intelligent system built on large models, with core characteristics of environmental perception, autonomous task planning, logical reasoning, and iterative error correction. In open and uncertain business scenarios, the agent can receive external information, parse task objectives, decompose multi-level subtasks, invoke tools to complete execution, and dynamically adjust action plans based on execution feedback.

AI Agent contains four core capability modules: first, a multimodal perception module that supports parsing structured tables and unstructured text and document information; second, a business reasoning module that relies on business rules to identify data anomalies and determine the intrinsic causes of discrepancies; third, a task planning module that decomposes complex comprehensive tasks into ordered subtask sequences; fourth, a feedback error-correction module that verifies output result deviations and dynamically corrects analytical conclusions.

Applied to financial reconciliation scenarios, AI Agent breaks through fixed script constraints, can understand the core objectives of reconciliation business, and autonomously complete multi-source heterogeneous financial data parsing, account matching, and discrepancy classification. When facing non-conventional business such as cross-period transactions, sales allowances, and return red-letter reversals, AI Agent can rely on financial logic reasoning to generate discrepancy cause analysis rather than directly terminating the process. This capability of understanding, judgment, and dynamic adaptation meets the demand for accounting professional judgment in reconciliation business.

It should be clarified that RPA and AI Agent are not in a complete substitution relationship; the two have a relationship of technological evolution and functional complementarity. In practical scenarios, a combined architecture can be formed, with RPA undertaking stable standardized operations and AI Agent handling complex links requiring business reasoning. Clarifying the capability boundaries of the two helps SMEs select digitalization solutions based on their own resources and avoid blind technological investment.

2.3. Comparison of RPA and AI Agent in Financial Reconciliation Scenarios

Table 1. Capability Comparison of RPA and AI Agent in Financial Reconciliation Scenarios

Comparison Dimension	RPA	AI Agent
Operating Logic	Preset scripts, executing fixed rules	Autonomous reasoning, dynamic task planning
Data Adaptability	Only supports structured, format-fixed data	Compatible with structured and multi-source unstructured financial data
Exception Handling Mechanism	Only identifies preset exceptions; unknown exceptions trigger process interruption	Autonomously identifies and parses non-preset types of reconciliation discrepancies
Business Decision Capability	No autonomous business judgment, only mechanical instruction execution	Can conduct basic business reasoning and output discrepancy analysis conclusions
Human-Machine Collaboration Model	Machines complete standardized execution; exception matters handed to humans	AI undertakes basic verification work; financial personnel review high-risk matters

Although AI Agent possesses significant advantages over RPA in anomaly identification and unstructured data parsing, such technological capability advantages do not mean that it can be directly implemented on a large scale in enterprise financial reconciliation scenarios. From the current practice of financial digitalization in small and medium-sized enterprises, the deployment of AI Agent still faces multiple practical constraints. The first is the threshold of financial data governance. The prerequisite for AI Agent to parse multi-source unstructured materials such as invoices and bank receipts is that enterprises have completed the unification of basic data standards and the cleaning of historical dirty data. However, many SMEs have fragmented financial systems and inconsistent data calibers across different business modules; direct deployment of AI Agent will therefore produce numerous erroneous reasoning results. The second is explainability risk. Every operation of RPA has clear script logs, and financial and audit personnel can trace the source of each reconciliation operation. In contrast, discrepancy conclusions generated by AI Agent's autonomous reasoning are black-box outputs. Once a judgment deviation occurs in reconciliation, it is difficult to quickly locate the reasoning

process, which does not meet the compliance requirements for financial internal control and audit trails.

Such implementation constraints determine that accounting digital transformation is not a simple "technology replacement," nor is it a matter of directly eliminating RPA with AI Agent, but rather of forming a layered automation architecture: mature, stable, and rule-fixed reconciliation processes continue to be handled by RPA; complex scenarios involving unstructured documents and unknown discrepancy identification are assigned to AI Agent for preliminary parsing; and financial personnel ultimately complete risk review. This layered model also imposes new requirements on the capabilities of accounting positions. Accounting personnel must not only master basic accounting and bookkeeping but also possess the digital literacy to understand the logic of automated processes and verify AI output results. This is also a core proposition that talent cultivation in higher vocational Big Data Accounting programs needs to address.

3. Application Bottlenecks of RPA in SME Financial Reconciliation

Although RPA provides a foundational solution for financial automation, constrained by its underlying technical logic, this tool has multiple structural constraints in SME reconciliation scenarios, constituting bottlenecks in technology application and highlighting the application space for AI Agent.

3.1. High Maintenance Costs of RPA in Processing Heterogeneous Data

SME financial data sources naturally possess multi-source heterogeneous characteristics. Records of the same economic transaction are scattered across carriers such as online banking statements, electronic invoices, Excel business ledgers, and financial software subsidiary ledgers, with various data lacking unified specifications in field names, text conventions, file formats, and coding systems. For example, the same counterparty customer name may appear in abbreviated and full forms across different tables, and summary text expressions for similar businesses are inconsistent.

RPA has strong dependence on data source formats, requiring separate development of parsing scripts and matching rules for each type of independent data source. Once an enterprise changes its online banking export template, adjusts ledger fields, or adds new business document types, the original scripts need to be re-debugged and modified. SMEs have weak informatization foundations, and financial document templates change relatively frequently. Continuous script maintenance will generate high time and labor costs, weakening the long-term economic viability of automation solutions.

3.2. Insufficient Capability of RPA in Handling Business Exceptions

The core difficulty of reconciliation business is not standardized account matching, but the identification and attribution of various non-conventional exception matters. The causes of reconciliation discrepancies are diverse, covering bank outstanding items, sales discounts and allowances, return red-letter reversals, cross-period revenue recognition, manual entry errors, and other types, with multiple causes potentially overlapping in practice.

RPA can only identify discrepancy types pre-defined within scripts. For new business discrepancies not included in the rule base, RPA cannot autonomously assess business reasonableness, only marking records as anomalies and terminating the process, with subsequent discrepancy investigation still requiring manual completion by accounting personnel. RPA only simplifies basic matching operations and cannot address the most labor-intensive anomaly analysis link in reconciliation business, with automation marginal benefits significantly compressed. For SMEs with flexible business models and frequent exception matters, this deficiency limits RPA's application value.

3.3. RPA Lacks Autonomous Attribution and Iterative Learning Capabilities

From the perspective of system function positioning, RPA is an execution-layer tool without business decision-making capability. RPA can only complete account comparison operations and cannot conduct risk grading, cause classification, and business interpretation for discrepancy matters. The core value of reconciliation business lies in distinguishing timing-related normal discrepancies, business errors, and internal control deficiencies — a link requiring business judgment that RPA cannot achieve. Therefore, the "last mile" of the reconciliation process is highly dependent on manual intervention, making it difficult to construct a complete closed loop from data collection, automatic matching, discrepancy analysis, to risk alerts.

Simultaneously, RPA does not possess continuous learning capability and cannot accumulate business experience or iterate matching rules based on historical reconciliation cases. For recurring similar discrepancies, RPA continuously repeats fixed operations without autonomously optimizing processing logic, making it difficult to continuously improve reconciliation efficiency through business accumulation, creating a gap with SMEs' goals of leveraging digitalization to enhance financial management quality.

3.4. RPA Implementation Constrained by Composite Talent Supply

Although RPA is classified as a low-code tool, script development, rule iteration, and troubleshooting all require users to simultaneously master RPA technology and accounting business knowledge. SMEs generally lack cross-disciplinary composite talents and mostly require external service providers for technical support. Once external technical support terminates, already-deployed automation processes become difficult to maintain continuously. Talent resource constraints further limit the long-term implementation of RPA in SME scenarios, also demonstrating that merely introducing technical tools cannot independently complete financial digitalization transformation.

4. Transformation Path of AI Agent-Driven Financial Reconciliation

Compared to RPA's fixed script-driven execution model, AI Agent is task-objective-oriented, relying on perception, reasoning, and dynamic planning capabilities to reshape the business logic of financial reconciliation and construct a new human-machine collaborative reconciliation paradigm. This paradigm does not involve intelligent systems completely taking over all reconciliation work, but rather hierarchically

reconstructing business processes: repetitive, low-risk basic tasks such as data collection, account comparison, and preliminary discrepancy classification are assigned to AI Agent, while accounting personnel focus on high-value judgment links such as risk screening, business characterization, and major error review, achieving reallocation of financial resources. The complete intelligent reconciliation process can be divided into four progressive stages.

4.1. Autonomous Collection and Standardized Preprocessing of Multi-Source Heterogeneous Financial Data

SME financial data is scattered across independent business systems and document carriers, and non-uniform data formats are the primary obstacle to automation implementation. Traditional RPA requires separate configuration of parsing scripts for each type of file, whereas AI Agent possesses multimodal information parsing capability and can autonomously read heterogeneous data sources such as online banking export statements, electronic invoice PDF files, Excel business ledgers, and financial software subsidiary ledgers. The agent can automatically identify document structures, extract key fields such as transaction dates, counterparty entities, transaction amounts, business summaries, and voucher numbers, complete data cleaning, deduplication, and format unification, and transform unstructured document information into structured datasets available for comparison.

In the preprocessing stage, AI Agent can automatically identify dirty data, flag data quality defects such as missing fields, amount logic contradictions, and non-standard entity names, and generate data quality reports for feedback to financial personnel for pre-correction. This stage breaks away from RPA's strong dependence on fixed templates. When enterprise ledger formats and document styles undergo minor changes, the agent does not require manual script rewriting, relying on semantic understanding capability to adaptively parse documents, significantly reducing automation system maintenance costs and adapting to the realistically flexible and variable financial documents of SMEs.

4.2. Intelligent Account Matching and Discrepancy Flagging

After completing data preprocessing, AI Agent initiates multi-dimensional account matching work. Unlike RPA, which relies only on single fixed fields such as document numbers and amounts for matching, AI Agent can conduct flexible matching combined with business semantics. For example, when counterparty customer names have inconsistent abbreviations and full names, the agent identifies through semantic similarity to complete account association of the same entity; for businesses with discounts or installment settlements, it can perform combined matching of multiple records according to business logic, rather than being limited to hard comparison of single-amount exact matches.

After matching is completed, the system automatically classifies account records into three categories: fully matched account items, pending-verification account items with amount or time discrepancies, and unmatched isolated account items. AI Agent flags all unmatched entries, retaining original document traceability links to preserve audit trails for subsequent discrepancy analysis. This stage releases accounting personnel from item-by-item comparison of tens of thousands of records, substantially reducing time investment in basic verification.

4.3. Autonomous Attribution and Risk Grading of Reconciliation Discrepancies

Discrepancy attribution is the core difficulty that traditional RPA cannot effectively resolve, and also the most core advantage of AI Agent compared to traditional automation tools. For flagged discrepancy entries, AI Agent relies on built-in accounting business rules, combines document context information to conduct logical reasoning, and automatically distinguishes discrepancy types: bank outstanding items, sales allowances and cash discounts, red-letter invoice reversals, cross-period recognition business, entry errors, etc.

On the basis of identifying discrepancy types, the agent further conducts risk grading management. For conventional, low-risk temporary discrepancies such as bank settlement time differences, the system automatically generates standardized explanations; for discrepancy matters with large amounts, abnormal business logic, or long-term outstanding balances, they are flagged as high-risk entries and prioritized for push to financial personnel for review. Simultaneously, AI Agent can generate complete discrepancy analysis working papers, listing original document evidence, reasoning logic, and preliminary conclusions, forming traceable working documents. It should be emphasized that the agent's output conclusions are only reference judgments and do not constitute final accounting determinations; all high-risk matters must undergo manual review and confirmation by financial personnel.

4.4. Human-Machine Collaborative Review and Reconciliation Report Output

After AI Agent completes the aforementioned processing, it generates complete reconciliation reports, discrepancy lists, and risk ledgers, entering the human-machine collaborative review stage. Accounting personnel need not verify all accounts, but only conduct manual professional judgment on system-flagged high-risk matters and agent-flagged doubtful entries, verify business authenticity, and confirm discrepancy handling plans. After review is completed, personnel feed final processing results back to AI Agent, forming a closed-loop feedback. The agent can accumulate this business case and optimize identification logic for subsequent similar businesses, achieving continuous iteration.

Throughout the entire process, AI Agent undertakes transactional work such as data processing, basic matching, and preliminary discrepancy screening; financial personnel retain final review authority, accounting characterization authority, and risk disposal authority. The human-machine collaboration model fully leverages the computational advantages of intelligent systems and the professional judgment advantages of accounting personnel, improving reconciliation efficiency while controlling risks. For SMEs with limited digitalization budgets and incomplete information systems, the lightweight deployment AI Agent solution does not require large-scale replacement of existing financial software and can achieve intelligent upgrading of reconciliation processes with lower investment.

5. Practical Obstacles to AI Agent Implementation in SME Financial Reconciliation Scenarios

Although AI Agent has significant technical advantages in reconciliation scenarios, constrained by multiple factors including the technology itself, enterprise data foundations, internal control rules, personnel capabilities, and information security, the technology still faces a series of practical constraints in SME implementation, and it cannot be simply assumed that agents can rapidly achieve large-scale application.

5.1. Accounting Judgment Distortion Risk from Large Model Hallucinations

AI Agent relies on large language models to achieve semantic understanding and logical reasoning, inherently possessing hallucination problems. In financial business scenarios, hallucinations manifest as the agent generating erroneous interpretations of document content and business transaction backgrounds, fabricating non-existent business logic, and generating discrepancy conclusions that do not conform to accounting standards. Financial information possesses extreme rigor; once the agent outputs erroneous attribution conclusions, if accounting personnel do not carefully review, it can easily cause accounting record errors, affect account-physical conformity, and even trigger derivative risks such as internal control failure and tax filing deviations.

The particularity of this risk lies in the fact that hallucinated output text is often logically coherent and not easy to directly identify as true or false. Therefore, in practical application, a rigid review mechanism must be established, clarifying that AI output content is only for auxiliary reference and cannot be directly used as the basis for accounting records. Enterprises need to delineate usage boundaries and strictly prohibit AI Agent from independently completing accounting determinations, thereby mitigating accounting error risks brought by hallucinations.

5.2. SME Basic Data Quality Shortcomings Constraining Intelligent Analysis Effectiveness

The analysis quality of AI Agent is highly dependent on the reliability of original input data. Currently, a large number of SMEs have insufficient financial standardization, with common phenomena such as missing business document information, brief summary records, non-standard counterparty entity names, and incomplete business attachment retention. Dirty data and incomplete data directly interfere with the agent's parsing and reasoning processes, causing matching errors, discrepancy misjudgments, and other problems.

Unlike large enterprises that possess mature data governance systems, SMEs lack dedicated data governance manpower and funding investment, and historically non-standard financial data is difficult to clean up at once. Weak data foundations constitute a prerequisite constraint for technology implementation. Even if high-performance AI Agent is introduced, if the underlying data source quality cannot be guaranteed, the effectiveness of intelligent reconciliation will be greatly reduced. SMEs advancing intelligent reconciliation construction should not only focus on introducing technical tools but also simultaneously improve financial document management specifications and consolidate data foundations.

5.3. Information Security and Privacy Risks of Sensitive Financial Data

Reconciliation datasets contain highly sensitive commercial financial data such as enterprise bank capital flows, revenue conditions, and counterparty customer information. Currently, most AI Agent services rely on cloud-based large model interfaces for data parsing, and the process of uploading financial materials to external servers poses security risks of data leakage, third-party capture, and unauthorized data reuse. Once enterprise financial data is leaked, it directly harms enterprise commercial interests.

From the perspective of internal control and auditing, attention must also be paid to data access permissions and operation log retention. The entire process of the agent processing financial data must completely record operation trajectories to meet regulatory requirements for traceability of accounting materials and audit trails. SME information security management systems are generally incomplete, lacking data security control processes for AI tools. Directly connecting to external intelligent services will add information security control pressure.

5.4. Structural Shortcomings in Digital Literacy of Accounting Practitioners

The application of AI Agent imposes new requirements on the capability structure of SME financial personnel. Financial personnel must not only master traditional accounting knowledge but also understand the capability boundaries of AI tools, be able to verify the reasonableness of agent output conclusions, and identify AI hallucinations and erroneous judgments. At present, many SME accounting personnel have long been accustomed to traditional manual reconciliation models and have insufficient understanding of artificial intelligence and intelligent financial tools, exhibiting two extreme mindsets: some personnel overly trust AI output results and weaken manual review; others have resistance to new technologies and are unwilling to adapt to human-machine collaborative work models.

Talent shortcomings not only limit the implementation and use of AI Agent but also affect subsequent system maintenance and optimization. Enterprises need to provide supporting digital financial capability training to help financial personnel establish human-machine collaborative thinking, clarify the core review responsibility of humans in intelligent financial processes, and complete role transformation: from account verification operators to financial risk control personnel.

5.5. Cost Input and Input-Output Benefit Constraints

Compared to purely manual reconciliation, AI Agent deployment, interface calls, continuous debugging, and maintenance generate ongoing costs. Although lightweight agent solutions require lower investment than large-scale integrated business-finance platforms, for SMEs with thin profit margins and tight cash flows, input-output ratios still require prudent evaluation. In addition to direct technical service fees, there are hidden costs including preliminary data standardization, personnel training, and internal control process revision and other supporting investments.

Some SMEs find it difficult to quantify the benefits brought by intelligent reconciliation and cannot intuitively measure the economic value of labor savings and error reduction, resulting in insufficient investment willingness among enterprise management. Therefore, AI Agent promotion among SMEs requires prioritizing low-cost lightweight solutions, controlling supporting investments, and progressing implementation gradually to avoid operational pressure from one-time large technology investments.

6. Conclusion

RPA, as the first-generation tool of financial automation, successfully achieved automated processing of standardized reconciliation business, to a certain extent alleviating the repetitive work burden of SME financial personnel. However, constrained by the underlying operating logic of preset scripts, RPA cannot autonomously handle diverse business exception matters and has an insurmountable capability ceiling in discrepancy attribution and flexible matching scenarios, with automation value limited to simple matching links. AI Agent, with technical characteristics of multi-source data perception, business logic reasoning, and dynamic task planning, breaks through RPA's inherent constraints, can autonomously parse heterogeneous financial documents, identify reconciliation discrepancies, and conduct preliminary attribution, constructing a new human-machine collaborative intelligent reconciliation model and providing a new implementation path for SME financial reconciliation automation transformation.

Simultaneously, the application boundaries of AI Agent should be viewed rationally. This technology is not a universal solution; multiple practical obstacles including large model hallucinations, enterprise data quality deficiencies, financial information security, personnel digital literacy, and cost constraints limit large-scale implementation at the current stage. AI Agent's positioning is as an auxiliary tool for accounting personnel, not a substitute for accounting positions. SMEs advancing financial intelligent construction should not blindly pursue fully automated unmanned processes but should adopt a gradual transformation strategy: relying on AI Agent to undertake low-risk transactional work such as data collection, account comparison, and preliminary discrepancy screening, with financial personnel firmly grasping core links such as business review, risk assessment, and accounting determination, releasing digitalization efficiency while controlling risks.

From the perspective of technological evolution, RPA and AI Agent are not in a complete substitution relationship; the two can form a complementary architecture. RPA stably executes highly standardized operations, AI Agent handles complex exception scenarios requiring business reasoning, and the integration of the two will become an important development direction for financial automation of small and medium-sized market entities.

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