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E2E Process Automation Leveraging Generative AI and IDP-Based Automation Agent: A Case Study on Corporate Expense Processing

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Abstract: This paper presents a case study of end-to-end (E2E) automation of corporate financial expense processing by combining generative AI (GenAI) and intelligent document processing (IDP) technologies with automation agents and shows the automation of intelligent tasks in a modern digital transformation environment. Although conventional RPA is effective in automating repetitive, rule-based, and simple tasks, it has limitations in handling unstructured data, responding to exceptions, and making complex decisions. In this study, we designed and implemented a four-step integration process, including automatic recognition of proofs such as receipts through OCR/IDP, item classification based on policy database, intelligent judgment support for exceptional situations through GenAI (LLMs), and human final decision and system learning (human-in-the-loop) through automation agents. As a result of the application to Company S, a large Korean company, quantitative effects such as reducing the processing time of branch receipt expenses by more than 80%, reducing error rates, and improving compliance rates were confirmed, as well as qualitative effects such as improving work accuracy and consistency, increasing employee satisfaction, and supporting data-based decision-making. In addition, the system learns from human judgment and continuously improves its ability to automatically handle exceptions, creating a virtuous cycle. This study empirically demonstrates that the organic combination of GenAI, IDP, and an automation agent overcomes the limitations of existing automation and is effective in realizing E2E automation of complex corporate tasks. In addition, it suggests the possibility of expansion to various business areas such as accounting, human resources, and purchasing in the future, as well as the development direction of AI-based hyperautomation.

Keywords: generative AI, IDP, automation agent, E2E automation, corporate expense processing

1. Introduction

The acceleration of digital transformation has led companies to expand their interest and investment in automating business processes to secure a competitive edge and achieve sustainable growth. In particular, the automation of repetitive and time-consuming office tasks is recognized as a key factor directly influencing productivity improvement and cost reduction. Initially, robotic process automation (RPA) was primarily used to automate rule-based repetitive tasks [1], but recent advancements in artificial intelligence (AI) technology, particularly generative AI (GenAI) and intelligent document processing (IDP), have overcome the limitations of RPA and opened possibilities for automating more complex and intelligent tasks. GenAI, which can create new content such as text, images, audio, and video based on extensive training data, has enabled users to easily utilize GenAI services [2, 3]. Specifically, GenAI chatbots have reached the level of analyzing human emotions and intentions to provide responses [4], and with the advent of large language models (LLMs), there have been significant improvements in automated conversation generation and translation [5]. However, GenAI can also generate responses that are in conflict with the latest information and may have a lower understanding of new problems or domains due to reliance on previously learned content [6]. To address this, solutions such as domain-specific fine-tuning of LLMs and using internal information to enhance reliability through methods such as RAG are being explored [7]. IDP goes beyond optical character recognition (OCR) by understanding the structure and context of documents to accurately extract and classify necessary information [8]. In addition, IDP is faster, cheaper, and more accurate than humans reading documents and inputting data [9]. These technological advancements are providing new opportunities for automating business processes in companies. Furthermore, the growth of the IDP market is driven by the increasing adoption of intelligent automation technologies to enhance productivity and efficiency across organizations. Core functions such as marketing, human resources, finance, and analytics are leveraging IDP software to automate tasks such as insight generation, document scanning, and candidate selection, thereby reducing workloads. This allows organizations to minimize repetitive and manual document processing tasks and focus on more strategic and value-added activities [10]. In particular, in corporate accounting tasks, GenAI contributes to improving efficiency and accuracy through automation and data analysis [11]. Among accounting tasks, financial expense processing is a representative repetitive business process that all organizations face. However, many companies still rely on inefficient methods such as manual processing and paper receipts for expense management. Manual expense management is prone to human errors and involves complex processes such as organizing paper receipts and filling out forms.

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The main reason for the delay in financial accounting tasks is the manual verification and review process for expense processing, which necessitates the introduction of automation to address this issue [9]. Many companies are actively seeking solutions to improve the efficiency of their expense processing to resolve such inefficiencies.

This study addresses these challenges by proposing an end-to-end (E2E) automation framework for corporate expense processing that integrates GenAI and OCR/IDP technologies with automation agents and by validating its effectiveness through a real-world case study. In doing so, it demonstrates the potential of hyperautomation, in which not only repetitive tasks but also exception cases requiring human judgment can be intelligently managed. The objectives of this study are to theoretically examine the concepts and contributions of these technologies, to analyze their application through an empirical case, and to compare pre- and post-adoption outcomes to assess their impact on enhancing corporate productivity and operational efficiency.

This paper is structured as follows. The introduction outlines the research background, objectives, and scope. The theoretical review examines the concepts and trends of GenAI, OCR/IDP, RPA, automation agents, and E2E automation, as well as the characteristics and limitations of corporate expense processing. The case study addresses issues in existing processes, the rationale and objectives of adopting an automation agent, and the four-stage implementation process. The effects analysis evaluates both quantitative and qualitative outcomes, identifies limitations, and suggests improvements. Finally, the conclusion summarizes the findings, highlights implications and contributions, and proposes directions for future research.

2. Literature Review

2.1. Generative AI

GenAI is a branch of AI that can generate new and original content by learning from existing data [2, 12]. It can generate data in various forms, such as text, images, audio, and video, and has shown remarkable progress in recent years with the development of deep learning technologies, especially the transformer architecture and LLMs [13]. GenAI is differentiated from analytical AI, which simply recognizes and classifies patterns, in that it produces creative outputs.

The core technology of GenAI is to learn the underlying patterns and structure of data based on large datasets [14]. For example, LLMs can learn from vast amounts of textual data to understand grammar, vocabulary, context, and even specific styles and can use it to generate new sentences, answer questions, summarize text, and more. These abilities have the potential to be utilized in a variety of ways in enterprises, including customer service chatbots, automated content marketing materials, and assistance with software code development. As a result, companies are looking for ways to utilize AI to automate various business processes, such as code writing, RAG-based search, and image processing, to increase productivity and efficiency [15].

In addition, by utilizing LLMs, it is possible to solve the problem that OCR has difficulty in misrecognizing characters, which is a limitation of systems that rely solely on OCR for document digitization [16].

In tasks with complex rules and exceptions, such as automating financial expense processing, which is the subject of this research, GenAI can play a role in determining user intent through natural language-based question and answer, understanding policy documents, and supporting appropriate judgment. For example, when account categorization for a new item is required, GenAI can recommend the most appropriate account based on existing data and policies or can help in determining whether the item complies with company policy. This opens up new possibilities for solving unstructured, context-dependent problems that traditional rule-based automation systems struggle to handle.

In terms of technology trends, GenAI is evolving to produce more sophisticated and human-like outputs as the size of the model increases and the quantity and quality of training data improve [13]. In addition, research on small language models (SLMs), which are specialized for specific domains or tasks, is ongoing, enabling the development of AI solutions that are optimized for specific industries or enterprise environments. In addition, just as humans acquire and understand information through various senses such as sight, hearing, and touch, multimodal AI systems can simultaneously process and understand various forms of data such as text, images, voice, and video [17]. These advances in multimodal AI have provided methodologies for implementing a multimodal LLM-based multiagent system (MAS) and effectively introducing AI technology into business processes. However, the utilization of GenAI involves ethical and technical challenges, such as the realism, bias, copyright issues, and possible misuse of generated content, and requires careful approach and continuous research [13].

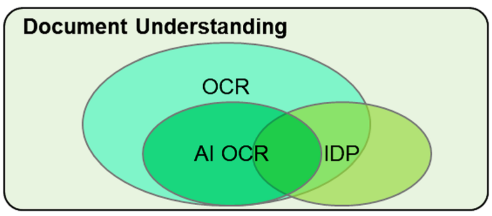
2.2. Document understanding technology

Document understanding is a technology that automatically extracts, classifies, and verifies text and data from various types of documents (paper, images, PDFs, etc.), converts them into digital data, and automates business processes. OCR and IDP play a key role in this process. Recently, it has been categorized into AI OCR, which adds AI capabilities to traditional OCR, and IDP, which enables IDP, as shown in Figure 1. IDP and OCR are complementary to each other. OCR provides the technical foundation for extracting text from document images, and IDP builds a comprehensive system that understands the meaning of documents based on OCR results, extracts necessary information, and utilizes it in business processes. Therefore, OCR plays a critical role in the data collection stage of IDP, and IDP implements the automation and intelligence of document processing by leveraging various AI technologies, including OCR.

2.2.1. Optical character recognition (OCR)

OCR is a method for extracting text from scanned documents and images [18]. CR is an OCR technology that first detects character areas in images or documents through the character detection stage and then performs the character recognition stage for those areas [19]. In general, the OCR process is divided into image preprocessing, text segmentation/localization, feature extraction, text recognition, and post-processing [20]. Through this, OCR technology can automatically extract text from images or scanned documents and convert it into editable digital data. Early OCR technologies primarily demonstrated high recognition rates for standardized fonts and clean background documents. However, due to factors such as diverse fonts, handwriting, complex layouts, and degraded image quality, their application in real-world work environments was limited. Nevertheless, with the recent advancements in AI, particularly deep learning-based image recognition technologies, the accuracy and scope of OCR have significantly improved [19]. The latest OCR engines support various languages and characters, providing relatively high-level text extraction performance even in low-resolution images or distorted documents.

Figure 1
Document understanding concept diagram



2.2.2. Intelligent document processing (IDP)

IDP is a concept that builds on this OCR technology and takes it a step further. Beyond simply extracting text, IDPs perform more intelligent document understanding and processing functions, such as automatically categorizing document types (e.g., invoices, contracts, and receipts), identifying specific fields within a document (e.g., vendor name, amount, date, and item) and extracting them into structured data, and validating the extracted information.

IDP solutions utilize a combination of various AI technologies, such as machine learning (ML), natural language processing (NLP), and computer vision, to accurately extract key information from unstructured or semi-structured documents and integrate it with enterprise systems (ERP, CRM, etc.) to automate subsequent business processes [8]. In particular, understanding document images [9] is a critical yet challenging task that requires complex capabilities such as text reading and comprehensive document comprehension [21]. However, recently, GenAI technologies have been integrated into IDP systems, where LLMs are used to understand document meanings and perform context-based data extraction and classification tasks. For example, when extracting information such as purchase items, amounts, and dates from receipt images, LLMs contribute to identifying accurate information by considering the context. In addition, LLMs are utilized in tasks such as automatically summarizing or classifying extracted data, enhancing the intelligence and efficiency of the IDP systems. IDP technology continues to evolve, and recently, it has been provided in the form of cloud-based services, which reduce initial implementation costs and increase scalability. Furthermore, "zero-shot" or "few-shot" learning techniques have been applied, enabling learning for specific document types with only a small number of sample documents, thereby providing flexibility to quickly respond to new types of documents [1, 22]. These technological advancements are playing a crucial role in expanding the scope of automation in document-intensive fields such as finance, accounting, law, and human resources.

The main comparison of OCR and IDP, as previously reviewed, is shown in Table 1.

In financial expense management tasks, OCR/IDP technology is used to perform automation. The receipts, invoices, and transaction statements submitted by employees are highly diverse in form and format and are mostly composed of unstructured data. Previously, financial personnel had to manually review these documents and input the necessary information into the system. However, with the introduction of IDP, this process can now be automated. For example, when a user uploads a corporate card receipt image to the system, the IDP solution automatically recognizes and extracts information such as the company name, business registration number, transaction date, supply amount, tax amount, total amount, approval number, and individual purchase item names, quantities, and unit prices from the image. In the automation agent case study of this research, IDP was utilized as the core technology in the first stage of the "document recognition" process, where it extracted text such as item names, amounts, and dates from receipt images and converted them into usable data. Notably, IDP's ability to go beyond simple OCR by understanding context and accurately classifying items significantly enhances the accuracy and efficiency of subsequent automation stages.

Table 1
Comparison of OCR and IDP

Item	OCR	IDP
Function	Read the text, digitize it, and convert it into a searchable format.	Read the text, understand its meaning using AI and NLP, and classify and analyze the data.
Subject matter	Structured data (fixed format)	Structured, semi-structured, and unstructured data can all be processed.
Technical components	Image enhancement, object detection, text recognition (OCR/ICR)	OCR + AI (NLP, ML), rule-based analysis
Main use cases	PDF conversion, digital archiving, search function	Loan application processing, customer due diligence (KYC), insurance claim automation
Contextual understanding ability	None	Presence (can understand context and extract additional information)
Automation potential	Limited (restricted to simple text extraction)	Advanced automation capabilities (including workflow triggers and decision support)

2.3. RPA and automation agent

RPA is a technology that algorithmizes simple and repetitive tasks to automate them through software, enabling them to be performed in place of humans [23]. It is also a method of automating tasks that users perform repeatedly and simply on computers by allowing software to execute them instead [24]. In this way, RPA is a technology that automates tasks, which means the automation of service tasks performed by humans [25]. In addition, RPA automation complements people by performing all or part of the functions previously performed by humans to achieve work goals [26]. RPA primarily mimics user interface (UI) interactions to operate existing applications (e.g., ERP, CRM, websites, and Excel), allowing for rapid automation without system changes, which is one of its advantages [1]. Initially, RPA was mainly applied to simple tasks based on clear rules and structured data, such as data entry, file transfer, email processing, and report generation. Through the introduction of RPA, companies could expect benefits such as improved work processing speed, reduced errors, cost savings, and employees' focus on high-value-added tasks [1].

However, traditional RPA has several limitations. First is the difficulty of handling unstructured data. It lacks the ability to understand and process various forms of unstructured data, such as images, natural language text, and scanned documents, making it difficult to apply to tasks involving such data. Second, it is rigid in handling exceptions. When an exception that deviates from the predefined rules occurs, RPA bots often stop working or make errors, requiring frequent human intervention. Third is the limitations of complex decision-making. It is difficult to implement complex decision-making logic that requires consideration of many variables or requires human judgment [1].

To overcome these limitations, the concept of intelligent automation or hyperautomation has emerged. The main technologies applied in hyperautomation include cognitive and execution technologies that recognize, execute, and make decisions regarding tasks and processes to be automated, enabling optimal automation [19]. Achieving hyperautomation requires providing services in a more automated manner to increase speed, reduce errors, and deliver them more consistently [27]. The goal is to expand the scope of automation and infuse intelligence by combining process automation technologies such as RPA with various technologies such as AI, ML, NLP, and IDP. Although traditional OCR systems can extract text from documents, they require separate systems for classifying document types or validating the extracted data. GenAI-supported OCR addresses these limitations by seamlessly integrating with IDP solutions, thereby establishing a unified pipeline for E2E document processing [28].

In the field of process automation, next-GenAI-based agents capable of executing complex tasks have emerged, with automation agents playing a crucial role [29]. Automation agents are no longer just simple task performers; they are intelligent software robots that can recognize more complex situations, analyze data, interact with users, and even improve their performance through learning by integrating AI technologies.

The essential functionalities required for E2E automation within major automation platforms are summarized in Table 2.

An automation agent acts as an interface and enabler for corporate finance staff to integrate IDP-extracted receipt information, database comparisons, and GenAI recommendations to make final decisions. In particular, it plays a key role in implementing a human-in-the-loop (HITL) mechanism that automatically reflects the finance staff's judgment (e.g., approving an account classification for a new item) into the system, allowing the system to learn and make decisions on its own when similar cases arise in the future. This creates a virtuous cycle where humans step in to handle exceptions and the system learns from the results, continuously improving the intelligence and adaptability of the automated system. This defines a new type of interaction between humans and ML algorithms, commonly referred to as HITL ML [30].

In the end, modern RPA is evolving beyond simple rule-based automation to collaborating with humans through automation agents combined with AI to flexibly respond to complex and dynamic work environments. This is essential for enabling E2E automation in areas of work where exceptions are common and human judgment is critical, such as processing a company's financial expenses.

2.4. E2E automation

E2E automation is the automation of a specific business process from start to finish without or with minimal human intervention. It aims to integrate multiple systems, departments, and different technology elements to manage and optimize the entire workflow in an integrated manner, rather than a piecemeal approach that automates individual tasks or specific parts. It is also recommended that a single E2E workflow is a process that starts and ends within a week or two because this is a reasonable turnaround time for the platform to monitor and manage. If it is too long, it may actually hinder automation management because the workflow needs to be monitored and managed as it progresses until it ends [19]. E2E automation is more than just replacing repetitive tasks; it is regarding supporting data-driven decision-making, flexibility to deal with exceptions, and ultimately maximizing business value [1].

Traditional task automation has primarily been carried out at the task level. For example, individual tasks such as data entry, report generation, and data synchronization between systems could be relatively easily automated using tools such as RPA. However, in reality, most corporate business processes are complex, involving multiple stages, various systems, and numerous stakeholders. In such an environment, fragmented automation has limitations in resolving bottlenecks in the entire process or achieving significant efficiency improvements. Instead, it often leads to new inefficiencies due to the disconnect between automated and manually processed parts.

E2E automation emerged as a concept to overcome these limitations, as shown in Table 3, which highlights its significance. In particular, with the advent of GenAI and LLMs, enterprises are leveraging technologies such as IDP and OCR to digitize documents. In the implementation of E2E solutions for document automation, advanced OCR technologies supported by LLMs play a crucial role in enhancing text recognition accuracy even from low-quality images [31].

This example of automating the "financial expense processing E2E process" with an automation agent illustrates the importance of E2E automation. The automation of the entire process of financial expense processing, from receipt attachment to information extraction through IDP, policy-based categorization, exception handling with AI Flow, and final review and system training with an automation agent, is organically connected and automated, effectively implementing complex scenarios that combine human judgment beyond the simple replacement of repetitive tasks. E2E automation plays a key role in helping organizations achieve true digital transformation and become more competitive.

2.5. An examination of corporate financial expense management tasks

The task of managing corporate financial expenses is a universal and essential administrative task that occurs in all organizations, regardless of their size or industry. It involves the process of reimbursing and paying expenses incurred by employees in relation to their work (e.g., transportation costs, meal expenses, purchase of supplies, and travel expenses) in accordance with the company's regulations and procedures. The task of managing expenses has the following key characteristics.

First, process various supporting documents: the most basic step in processing financial expenses is to collect and review the documents

Table 2
Comparison of automation agent platforms

Feature	Brity Automation[1]	UiPath	Power Automate
GenAI integration	Built-in AI Flow	Add-on via Azure OpenAI	Add-on via Azure
IDP support	Native module or external integration	Native (document understanding, IXP)	External via AI Builder
HITL	Full UI (Form, Agent)/DB loop	Partial (via Action Center)	Partial (via Approvals, AI Builder)
Policy-based classification	Built-in DB & AI combo	Requires custom logic	Built-in (AI Builder, Purview)
Feedback loop/learning update	Automatic DB/AI sync	Manual update	Limited (via AI Builder model retraining)
API modularity	Yes	Yes	Yes

[1] A hyperautomation solution for enterprise process automation utilizing AI technologies launched by SAMSUNG SDS.

Table 3
Benefits of E2E automation

Classification	Description
Enhanced process visibility and control	Monitor and manage work from start to finish to improve bottlenecks or inefficiencies and address compliance and risk management.
Maximizing operational efficiency	Increase productivity by minimizing manual work and seamlessly connecting data flows between multiple systems to reduce overall turnaround time and lower operational costs [1].
Data-driven decision support	Collect and analyze data generated throughout the process to enable decisions based on objective metrics.
Improve customer and employee experiences	Increased speed and accuracy of work increase customer satisfaction and free employees from repetitive, low-value tasks to focus on more creative, strategic work.
Achieving business agility and scalability	Build a flexible automation environment that can respond quickly to market changes or new business needs, and automated processes can be easily extended or adapted to other areas as needed.

that support the expenditure, such as receipts, tax invoices, transaction statements, and travel vouchers. These documents vary widely in form (paper and electronic), format, and type and level of information that they contain, especially receipts, which often contain a mixture of unstructured text and images.

Second, comply with internal regulations and policies: each company has its own regulations and policies regarding expense processing (e.g., allowable/unallowable items, limits, and account subject classification criteria). This goes beyond simply verifying the amount and includes determining whether the purpose and content of the expense are in line with the company's policies.

Third, frequent occurrence of exceptional situations: in financial expense processing, various exceptional situations can occur, for example, cases where the content of a receipt does not match the actual purchased item, where a new item does not clearly fall under the existing account classification criteria due to the introduction of a new item, or where there are typos or information omissions are common. For instance, when receipts that are classified as consumables include items such as coffee or snacks, such issues that cannot be resolved through simple automatic classification may frequently and continuously arise.

Fourth, multiple stakeholder involvement and approval processes: multiple stakeholders are involved in expense processing, including the expense applicant, department head, finance, and final approvers, and each step requires review and approval. Although this is intended to ensure transparency and accuracy, it can also slow down the process.

Fifth, data accuracy and audit trails are required: financial data are the basis for a company's accounting and tax filings. Therefore, they need to be highly accurate. In addition, all processes must be clearly recorded and traceable for future audits.

Owing to these characteristics, traditional manual-based financial expense processing requires significant time and effort and is prone to human errors. To address this, some companies attempted to introduce RPA to automate repetitive tasks such as data entry and information transfer between systems. However, traditional RPA faced challenges in achieving full automation of financial expense processing due to limitations such as those outlined in Table 4 [1].

In conclusion, the complexity, diversity, and frequent exceptions of corporate financial expense processing have made it difficult to implement effective E2E automation using simple automation technologies alone. To overcome these limitations, it is essential to accurately recognize receipts through OCR/IDP, support exception handling and judgment using intelligent technologies such as GenAI, and build a human–AI collaboration environment through automation agents.

The cases covered in this study integrate these technologies to present a new approach that goes beyond the limitations of conventional automation.

3. Proposed Methodology

This section presents the architecture, data flow, and integration of GenAI, OCR/IDP, and automation agents to realize E2E automation in corporate expense processing. The primary contribution of this study lies in proposing a framework that overcomes the limitations of conventional RPA by addressing unstructured data and exception handling through the integration of GenAI and IDP. Furthermore, the incorporation of an HITL mechanism via automation agents ensures that human judgment is embedded into the system, enabling continuous improvement of automation performance.

Table 4
Limitations of traditional RPA

Limit	Description
Limitations in the processing of unstructured evidence materials	Limitations in accurately recognizing and extracting necessary information from unstructured documents such as receipts [8].
Inability to respond to exceptional situations	Rule-based RPA struggles to handle unexpected situations that are not predefined [1].
Complexity in judgment and decision-making	The appropriateness of expense items, classification of account subjects, and review of policy violations require human cognitive judgment, making them difficult to automate.
Bottlenecks caused by partial automation	When only a portion of the entire process is automated, the lack of smooth integration between the automated and manual segments can lead to the emergence of new bottlenecks or affect the overall improvement in efficiency.

3.1. Technical approach and implementation method

In this section, we will describe in detail the technical approach and implementation of the E2E automation system for financial expense processing using an automation agent, as well as the integration plan for its key components. The financial expense processing automation based on an automation agent proceeds in four stages, as shown in Figure 2. The discussion focuses on the system architecture supporting this four-stage automation process; the core technologies such as GenAI, OCR/IDP, and the integration mechanism of automation agent; and the overall flow of data.

3.1.1. Overview of automation agent application

Currently, companies are moving beyond the automation of simple repetitive tasks to pursue flexible automation that considers exceptional situations, i.e., E2E automation combined with human judgment. However, building an automated environment that can flexibly incorporate human judgment in complex and diverse exceptional situations is a challenging task. To address this issue, this study applied Brity Automation, an automation-focused automation agent, to automate the financial expense processing tasks of a company, rather than directly developing a program source code.

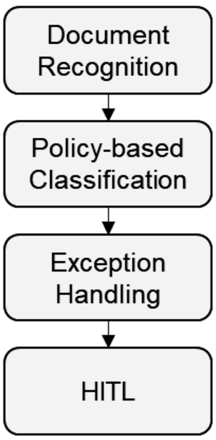
The main reasons for applying Brity Automation are as follows.

1) Increased demand for intelligent automation: beyond the limitations of simple RPA, there is a growing need for intelligent automation solutions that can implement complex E2E scenarios by leveraging GenAI, IDP, and business process automation (BPA).
2) Improving work efficiency and maximizing productivity: to alleviate the workload of financial personnel and enable them to focus on more valuable tasks, we aimed to address inefficiencies in financial expense processing, which accounted for an average of 1,448 cases per month and took more than 24 h to complete.
3) Enhancing support for partners and customers: it was necessary to create and provide use cases to help customers who had adopted RPA expand their automation areas and reduce trial and error for partners when applying the new features of Brity Automation.

The goals of financial expense automation using Brity Automation have been set as follows under this background.

1) Implementing E2E automation: from receipt submission to final processing and system learning, the entire financial expense process is integrated and automated.

Figure 2
Business automation process based on IDP and an automation agent



2) Exception handling intelligence: implement intelligent judgment support for new items and ambiguous cases through accurate information extraction using IDP and AI Flow[2] (LLM integration).
3) Establishing a human–AI collaboration environment: establish an HITL mechanism where finance managers review AI proposals and make final decisions through automation agent and the system learns from the results to continuously improve automation performance.
4) Flexibility and scalability: establish a foundation to respond flexibly to various exceptional situations and to expand the automation model to other business areas such as accounting, human resources, and procurement in the future.

In this paper, by automating the "financial expense processing" business process, which is a routine yet frequently involves exceptional situations, using Brity Automation, we aim to explore the extent to which the scope of automation can be expanded. Through this case study, we suggest that it holds significant importance in exploring the potential of intelligent automation.

3.1.2. Integration of main technologies used

The core of this system lies in the effective linkage of three major technologies: OCR/IDP, GenAI linkage using AI Flow, and automation agents. The linkage method of each technology is as follows.

1) Integration of OCR/IDP and workflow engine: when a user uploads a receipt, the workflow engine passes the image to the OCR/IDP module. The IDP module returns the extracted structured data to the workflow engine in JSON or XML format after image processing. These data are used as input for subsequent processing steps (policy-based classification, AI Flow calls, etc.). Brity Automation can integrate an external IDP solution through an API call or utilize the IDP function integrated within the platform.
2) Policy-based classification engine and AI flow integration with GenAI: when item information extracted through IDP is not clearly classified by the policy-based classification engine (not found in the whitelist/blacklist) or requires additional judgment, the workflow engine calls the AI Flow module. AI Flow sends the item information along with a predefined prompt (e.g., "Which account should this item be classified under according to the company's expense processing policy, and is it permissible? What is the basis for this?") to the GenAI model (LLM) API. The LLM generates a response based on its learned knowledge and provided company policy documents, which is then returned to the AI Flow module. During this process, the LLM may also utilize web search functionality to reference up-to-date information or external context.
3) Integration of AI flow (LLM interface) and automation agents: recommendations generated by AI Flow (LLM) regarding account compliance, policy alignment, and justification are presented to the finance team through the automation agent interface, along with other information (IDP extraction results and policy DB comparison results). On the basis of this information, the finance team makes the final decision, and if necessary, they can modify the recommendations or input additional details.
4) Integration of automation agents with backend systems (DB and orchestrator): the final decisions made by the finance team through the automation agent (approval, rejection, modified information, new learning data, etc.) are recorded and updated in relevant databases (policy DB, processing history DB, etc.) via the orchestrator. If the classification criteria for new items are finalized, they are

[2] Brity Automation's Langflow-based AI workflow builder lets you easily connect AI components like LLMs, data sources, and prompts to design complex applications.

reflected as whitelist/blacklist or AI model learning data, enhancing the system's intelligence. In addition, the final processing results are transmitted to ERP or accounting systems via APIs, enabling automatic subsequent accounting processes.

Such technological integration is implemented in a loosely coupled manner based on APIs, enabling independent upgrades or replacements of individual technical components and enhancing the overall flexibility of the system.

3.1.3. Data collection, processing, analysis, and reflection flow

The data flow in the E2E automation system for financial expense processing follows a cyclical lifecycle as follows.

1) Data collection:
   a. When users submit an expense request, they input related information (such as purpose of use and amount) along with the receipt image (unstructured data) into the system.
   b. The system collects uploaded receipt images as the primary input data.
2) Data processing:
   a. Stage process (IDP): the collected receipt images are sent to the OCR/IDP module, where they undergo text extraction and key field identification processes to be converted into structured data (item name, amount, date, etc.).
   b. Stage process (policy-based classification): the transformed structured data are compared with the database based on the policies of the predefined financial accounts set within the Brity Automation Orchestrator, and are initially automatically classified according to predefined rules (e.g., allow/block and account recommendations).
3) Data analysis and decision support:
   a. Stage process (AI flow): when an exception (unclassified item and ambiguous item) occurs in the first classification, the data are transferred to the AI Flow module. AI Flow uses GenAI (LLM) to comprehensively analyze company policy documents, past processing cases, and external web information when necessary to generate recommended accounts, policy compliance, and judgment grounds for the item.
4) User review and final decision:
   a. Stage (automation agent): the extraction results from the IDP, policy-based classification results, and analysis and recommendations from AI Flow are provided to the finance team through the automation agent interface. The finance team reviews these and makes a final decision to approve, reject, or modify.
5) Data reflection and system learning:
   a. The final decision of the finance officer is immediately reflected in the system. Approved expenses are transferred to the subsequent payment processing procedure, and related information can be integrated into the accounting system.
   b. Especially important is that the results of the responsible person's judgment (e.g., classification of new items and updated information) are fed back and stored as learning data for the policy database or AI model within the Brity Automation Orchestrator. Through this, the system continuously learns, improves its ability to automatically handle exceptions over time, and evolves in a direction that minimizes human intervention (self-learning & improvement).

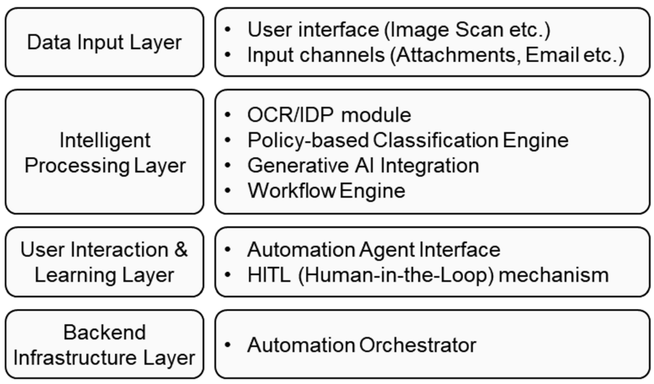
This circular flow of data is a key mechanism for enabling a learning automation system that goes beyond simple one-off automation, where the system continuously accumulates intelligence and improves performance. This improves system scalability and maintainability, facilitating integration with future business process changes.

3.2. E2E proposal system architecture

The financial expense processing E2E automation system proposed in this study is based on the Brity Automation platform and is composed of multiple modules and technical elements integrated organically. The overall system architecture can be divided into four main layers: the data input layer, the intelligent processing layer, the user interaction and learning layer, and the backend infrastructure layer, as shown in Figure 3. Although the implementation was carried out using Brity Automation, the proposed architecture is platform-agnostic and can be deployed with any modern BPA system supporting RESTful API integration.

1) Data input layer:
   a. User interface: a web or mobile interface is provided for employees to upload receipt images (scanned or photographed) along with expense reports. This can be implemented through integration with Brity Automation's user portal or an existing groupware system.
   b. Support for multiple input channels: flexibility to collect evidence materials through various channels such as email attachments and direct capture via mobile apps.
2) Intelligent processing layer (IPL):
   a. OCR/IDP module: extracts text from uploaded receipt images and identifies key fields (business name, amount, date, items, etc.) to convert them into structured data. It integrates external or open-source IDP solutions in library form and enhances the accuracy of item classification through contextual understanding. In addition, enterprises implementing IDP must ensure compliance with data privacy regulations [32].
   b. Policy-based classification engine: performs primary automated classification based on item information extracted through the IDP, referencing a database (whitelist/blacklist/account policy information) built inside Brity Automation Orchestrator. This database reflects the company's expense processing rules and policies. This can be solved using prompts when using LLMs, which provide a detailed and personalized description of each agent's professional identity, including its profile, goals, and constraints [33].
   c. AI Flow module (GenAI integration): integrates with GenAI (LLM) to support intelligent judgment when exceptions (new items, ambiguous items, etc.) that are not handled by primary classification are encountered. This module leverages pre-trained company policy documents and external web search results to query the LLM and derive recommended accounts, policy compliance, and rationale for decisions. Users can also ask for

Figure 3
E2E automation system architecture



additional information or clarification through a natural language interface with the LLM.
   d. Workflow engine: a core function of the Brity Automation Orchestrator is that it defines the entire financial expense processing from data input to final handling and automates task flows, conditional branching, notifications, and more at each stage.
3) User interaction and learning layer:
   a. Automation agent interface: provides an integrated dashboard that allows financial officers to comprehensively review AI analysis results (IDP-extracted information, policy-based classification results, and AI Flow recommendations) and make final decisions. This interface must be intuitive and user-friendly, designed to present all necessary information at a glance.
   b. HITL mechanism: decisions made by finance personnel through the automation agent (e.g., confirming accounts for new items and adding similar terms) are not limited to one-time processing. Instead, they are automatically fed back and stored in the system's knowledge base (policy DB, AI model, etc.). Through this, the system continuously learns and becomes capable of making more accurate and autonomous judgments in the future when similar cases arise.
4) Backend infrastructure layer:
   a. Brity Automation Orchestrator: acts as the central control tower that manages, monitors, and executes the entire automation process. It performs functions such as workflow management, bot scheduling, database integration, API integration, security, and access control.
   b. Database: stores and manages policy information (whitelist/blacklist), processing history, learning data, user information, etc. In this case, the Brity Automation self-orchestrator database is used to ensure efficient maintenance and security.
   c. API gateway: provides an interface for safe and efficient data integration with external systems (ERP, accounting systems, groupware, etc.).

Such a hierarchical architecture enables organic integration and maintains the independence of each module, thereby enhancing the system's flexibility, scalability, and maintainability.

3.3. Contributions and innovations

Unlike conventional approaches that merely integrate RPA and IDP components, our proposed framework introduces a continuously improvable workflow architecture. This architecture is specifically designed to incorporate HITL feedback, thereby optimizing its adaptation to real-world exception handling patterns prevalent in finance operations.

The key contributions and innovations of the proposed framework are as follows:

1) Intelligent exception handling: the framework overcomes the limitations of traditional RPA by integrating IDPs and GenAI to handle unstructured data and complex exceptions.
2) Human–AI collaboration: the HITL mechanism builds a system that continuously learns from human judgment to improve itself.
3) Scalability: the API-based, loosely coupled architecture allows for flexible application to various domains, such as accounting, human resources, and procurement.
4) Practical applicability: the effectiveness of the framework has been empirically demonstrated through a real-world case study at Company S.

The following section presents a real-world implementation of the proposed system within Company S to empirically evaluate its effectiveness.

4. Experimental Results

To validate the effectiveness of the proposed E2E automation system, it was implemented and evaluated in the actual operational environment of Company S.

The subject of this study, Company S, is a major domestic corporation operating various business divisions and overseas branches, requiring the processing of a large number of corporate card receipts on a monthly basis. Expense management is a critical process for financial management and compliance with regulations at S, but the existing manual-based processing method was fraught with several issues. Therefore, this section aims to present the practical applicability and effectiveness of the proposed technology integration by detailing the problems of the existing process, the background and objectives of introducing an automation system, and the specific four-stage implementation process.

4.1. Business process analysis and design

Expense management is a representative administrative task experienced by nearly all office workers, involving the process of submitting a receipt after using a corporate card, followed by approval from the approver and the finance team, and finally being processed.

4.1.1. Analysis of existing business processes

The entire process involves complex procedures such as validating expense details, verifying account codes, and checking for prohibited items according to company policy. In particular, financial expense processing faced the following challenges and limitations.

First, the receipt review process exhibited a high dependence on manual work, requiring more than 24 h per month to process approximately 1,450 cases. Second, frequent exceptions such as item mismatches, newly introduced categories, and typographical errors necessitated direct intervention by financial staff. Third, reliance on manual data entry increased the likelihood of errors and omissions, making it difficult to ensure data accuracy. Fourth, conventional RPA solutions were limited to routine, repetitive tasks and proved inadequate for handling complex exceptions.

These challenges were adding to the workload of the finance department and hindering the overall efficiency of the company's operations. The need for a more intelligent E2E automation solution that could flexibly handle exceptions and effectively combine human judgment was urgent.

4.1.2. E2E automation process definition

The analysis of the existing work revealed that the E2E automation process to be introduced can be defined in the flow diagram shown in Figure 4.

When a user registers an expense receipt, the IDP automatically extracts the necessary information from the receipt. Subsequently, GenAI analyzes and verifies the expense details according to the company's policies, recommends the required items for system registration, and submits them. Finally, after the finance manager reviews and approves the submitted content, it is automatically registered in the ERP system.

4.1.3. E2E automation process design

The process begins when an individual card user registers a card usage receipt through the mobile app or the card expense management web screen. When processing personal expenses, the attached files are compared and verified against the input data and receipt content using RPA, IDP, and LLM to automate the manual verification process of the accounting department's account-specific responsible personnel. The entire workflow is shown in Figure 5.

Figure 4
Conceptual diagram of the E2E automation process

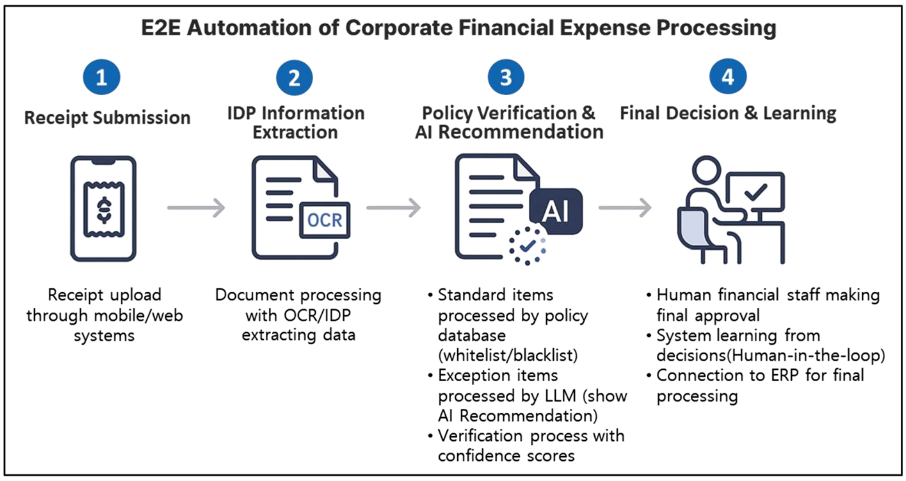
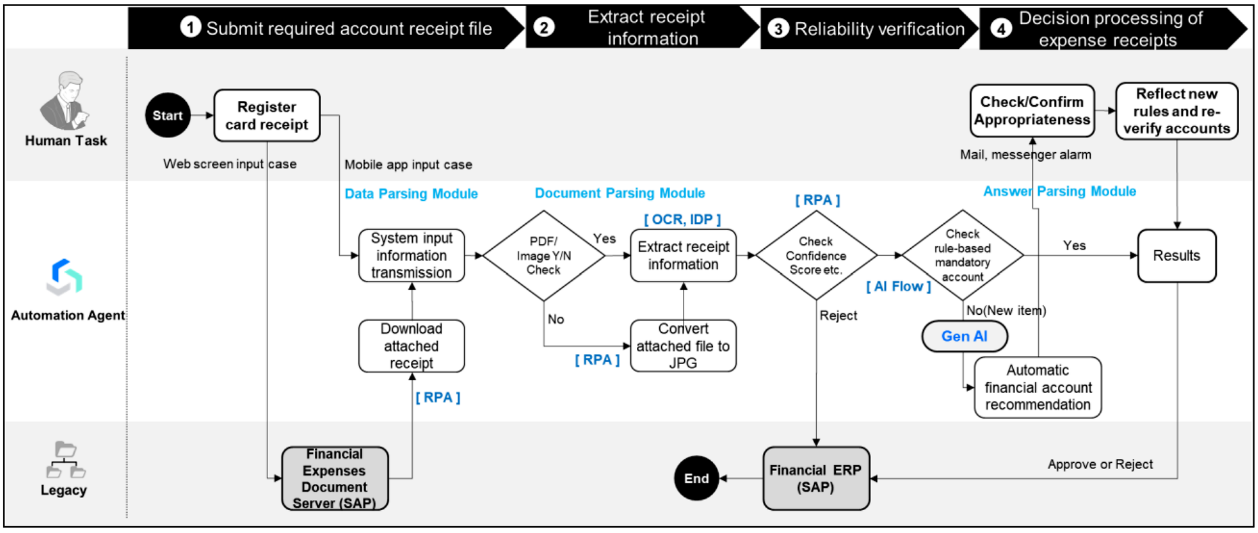


Figure 5
E2E expense processing workflow design



The entire processing consists of four stages, as detailed below.

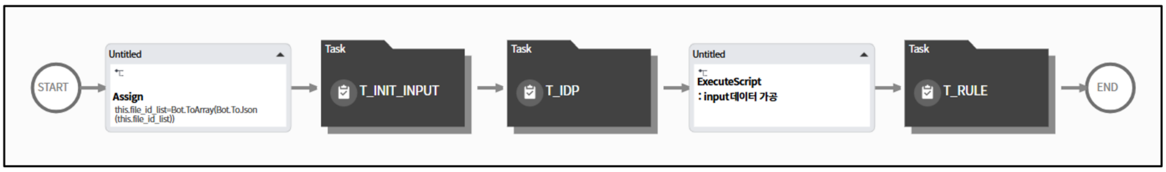
1) Mandatory account receipt file transmission: the card user registers the usage receipt, and the expense processing system sends the approved data (description, account, and attachment) to Brity Automation.
2) IDP receipt information extraction: Brity Automation extracts information from the receipt attached to the received approval data. At this time, file formats other than PDF and images are converted to JPG.
3) Reliability verification: if the confidence score of the extracted mandatory items is below 50, the receipt is considered defective, and a notification is sent to the user. For payment data where the selected account is a routine expense, it is determined whether the detailed items extracted by IDP are appropriate for the description and account using LLM.
4) Approval decision: if the final results, account details, and attachments are appropriate, they are approved and sent to SAP. If not, they are rejected and sent to SAP. In addition, on the basis of the results processed by Brity Automation, the SAP approval process is automatically progressed (approval or rejection).

To ensure interpretability, the "Answer Parsing Module" returns each LLM response with a justification string that includes the reasoning process and references to applicable company policy. This supports human decision-making by increasing transparency in the automation process. Instead of post-hoc explainability methods, this system relies on an HITL workflow where human feedback directly validates and corrects LLM outputs, offering operational explainability.

4.2. Implementation workflow

The workflow for automating financial expense processing using automation agents was implemented through the four-step process depicted in Figure 2. In addition, as shown in Figure 6 implemented in the actual automation agent design tool, the system receives user input through the form UI, recognizes documents using the IDP/OCR module (T_IDP), and then delivers the results through the form UI

Figure 6
Integration of each module with the automation agent



after processing through the policy-based classification and exception application (T_RULE) process.

4.2.1. Step 1: document recognition

The first step in automation is to accurately extract the required information from the receipt image uploaded by the user using the IDP module. To achieve this, Brity Automation leverages IDP technology.

When users submit their card usage records, they can attach a receipt image. On a mobile app, the receipt can be automatically captured and attached, or on a PC screen, as shown in Figure 7, a receipt image can be attached. At this time, the service can choose between OCR or IDP modules, and the document type can utilize pre-trained receipt types to check or modify the data extracted in advance.

When using a corporate card, notifications are delivered to the user through a messenger app, as shown in Figure 8. The image displays the usage receipt, and the notification message instructs the user to submit an expense reimbursement approval for the card usage. Upon reviewing the content, it can be confirmed that a payment of 9,000 won was made at"팝스토어잠실향군타워점 (Popstore Jamsil Hyanggun Tower Jeom)" on March 25, 2025.

At this point, the IDP solution analyzes the image and extracts key text information such as item name, amount, and transaction date. Unlike traditional OCR technology, using IDP technology allows for understanding the context and accurately classifying items, demonstrating the intelligent information processing capabilities of IDP beyond simple text extraction. The extracted data are transformed into a user-friendly format (such as HTML or Markdown) as shown in Figure 9 and utilized in subsequent processing steps. In addition, this process is implemented in Brity Automation to easily integrate 3rd party IDP using a drag-&-drop method, thereby enhancing user convenience.

4.2.2. Step 2: policy-based classification

When data are successfully extracted from a receipt through IDP, the task involves using Brity Automation's "Data Service/Database" feature to determine whether the extracted item is allowed or prohibited according to the company's policy.

To achieve this, Brity Automation builds its own database within the orchestrator, as shown in Figure 10, and pre-sets the types of authorized goods and product information for each account in an allowed item list (whitelist) and prohibited items in a list (blacklist).

For example, a whitelist might list common food and beverage items, and a blacklist might list inappropriate items that are less work-related, such as gold rings or gift certificates. In addition, depending on your company's policies, accounts such as office supplies may only be allowed for consumables.

The system performs automatic filtering by comparing the extracted receipt data with the database as shown in Figure 11. This process is stored in Brity Automation's own database, not in an external one, providing efficient maintenance and security.

4.2.3. Step 3: handling exceptional situations

Recognizing documents through IDP and initial classification based on policies alone is insufficient to address all situations. In particular, exceptions occur in cases of new items not registered in the existing database or items with ambiguous classification criteria. This was confirmed through a purchase case of a beverage called "심플리블랙(Simply Black)." When the item is a new entry not listed in the whitelist or blacklist, Brity Automation's AI Flow function is activated. AI Flow, as shown in Figure 12, queries an LLM based on the company's expense policy document to determine whether the item complies with company policy and which account should be used for

Figure 7
Receipt attachment screen

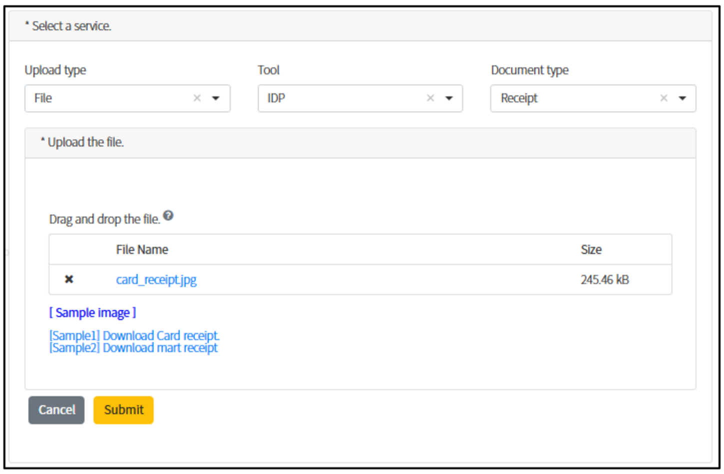


Figure 8
Receipt and corporate card usage notification

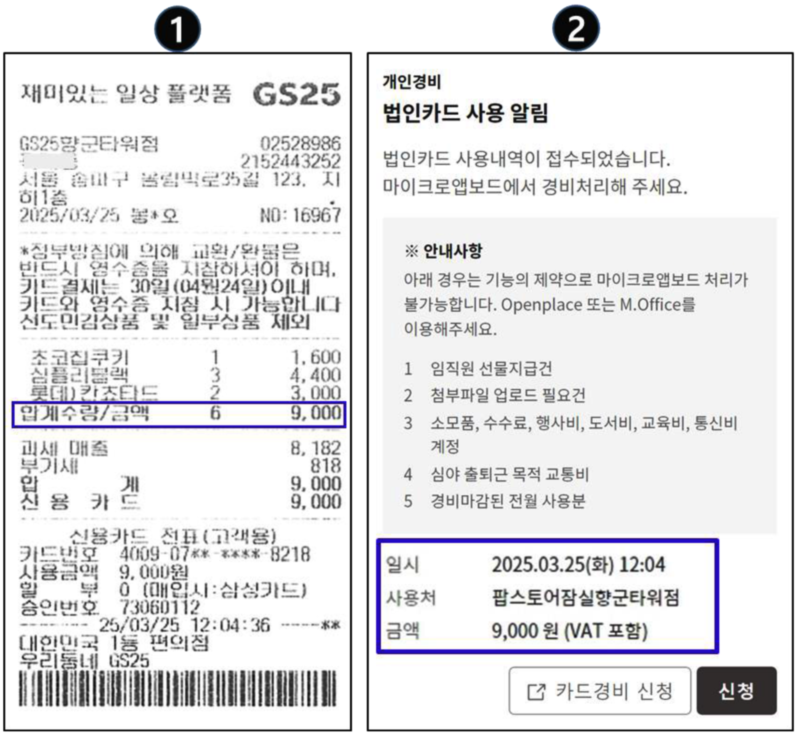
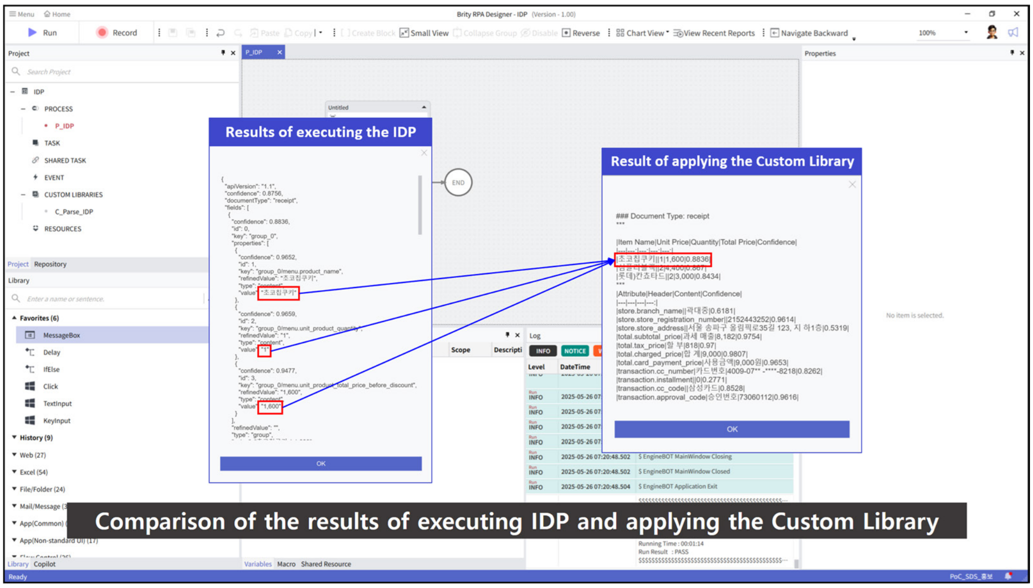


Figure 9
IDP module design by Brity Automation



processing. For example, by asking, "Which account should Simply Black be processed under?" GenAI reviews the policy document and item classification criteria, as shown in Figure 13, and provides a recommended account along with the reasoning based on the results. In this case, AI identifies a similar item called "Simply Smooth Black" and recommends classifying it under a catering-related account. The role of AI is to support decision-making as a reference tool, and the final decision is made by a human.

Figure 14 presents a segment of a policy code that filters itemized contents from card payment receipts at the prompt level in accordance with predefined policies. The filtered information is then re-queried to an LLM, and the results are compared with the model's recommendations.

4.2.4. Step 4: HITL phase

The final decision on the content proposed by AI is the responsibility of the financial officer, which is the step of automatically reflecting the

Figure 10
Policy-based database configuration

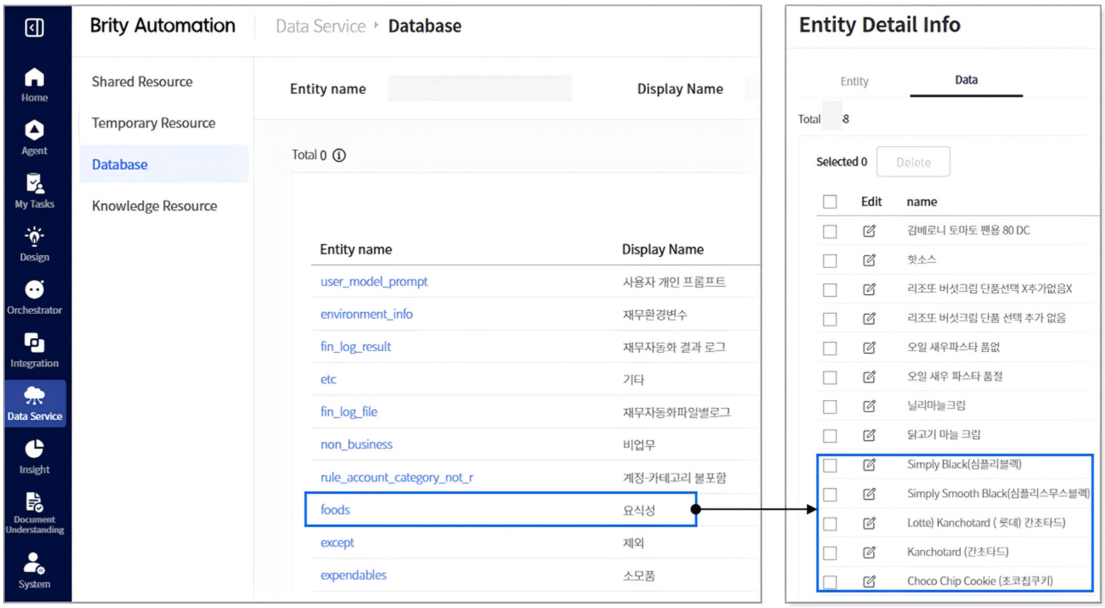
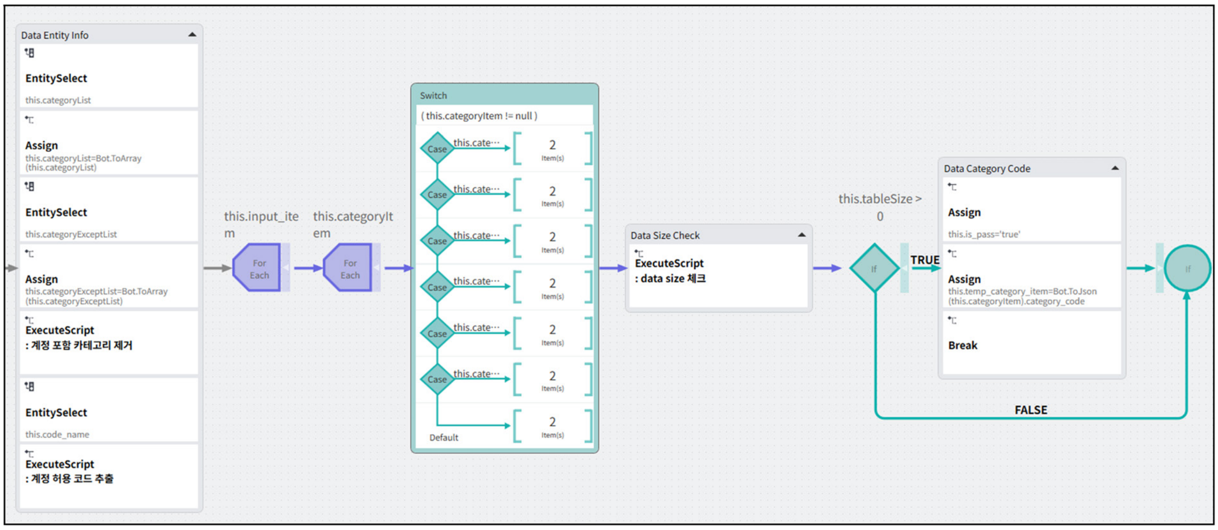


Figure 11
Database utilization linked design in Brity Automation designer



user's judgment in the system. Brity Automation's messenger channel agent provides an interface and execution environment to support the financial officer in making such final decisions effectively.

Figure 15(a) is the financial manager's messenger channel agent screen. Through this agent, it is possible to perform question-and-answer using RAG and execute RPA. Here, I can check and proceed with the task assigned to me, which is to confirm the card expense application agreement.

The responsible party can comprehensively view the receipt image extracted by the GenAI through IDP, the comparison results with the existing database (whitelist/blacklist), and the content recommended by the AI Flow through LLM (account, policy compliance, basis, etc.) through the messenger channel agent screen using the form UI, as shown in Figure 15(b). On this screen, the finance manager can either accept the GenAI's proposal as is or, as needed, modify the item name or add similar words to improve the system's knowledge base.

The most critical feature is that when a financial officer reviews and approves recommendation data for a new item, as shown in Figure 16, the decision does not only affect the current case but is automatically reflected in the database within the Brity Automation Orchestrator, as shown in Figure 17. This allows the system to autonomously perform the correct processing based on past learned judgments when similar items or situations occur in the future. For example, if "Simply Black" is identified as a coffee beverage and classified under a food and beverage account, this information is registered in the system, enabling automatic processing the next time

Figure 12
Design of receipt item classification using AI flow

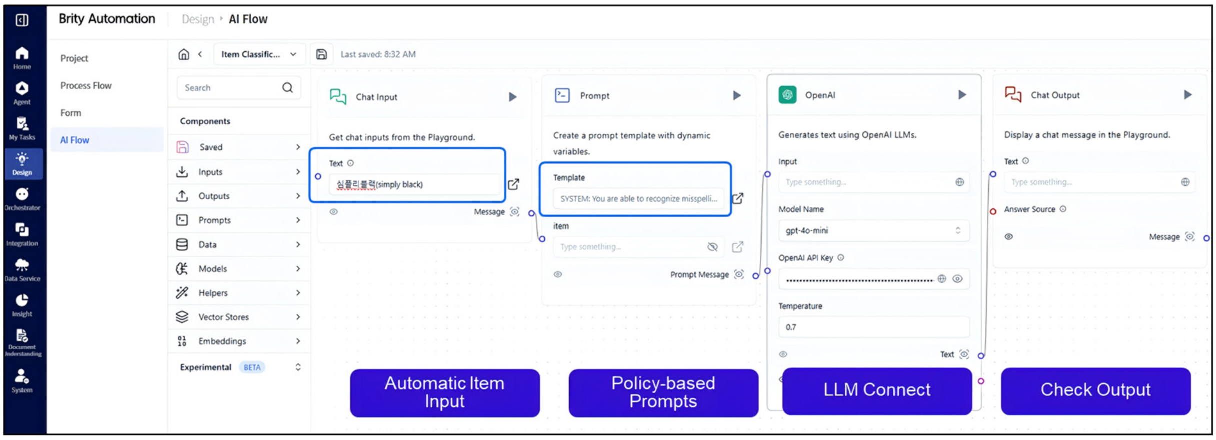
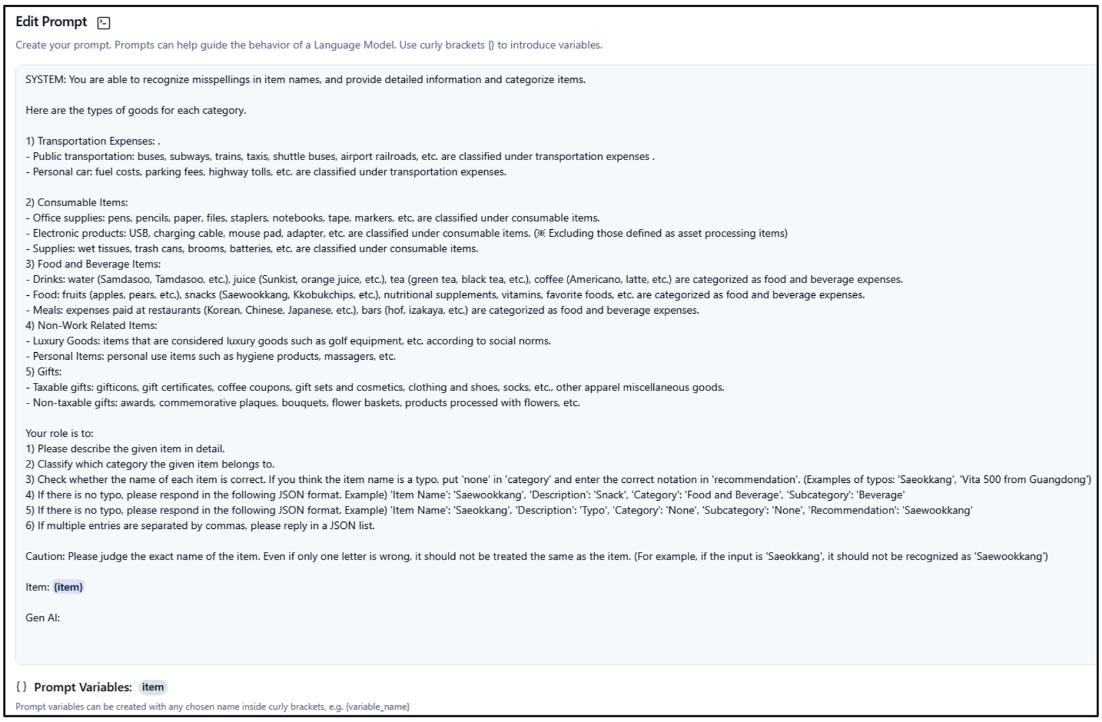


Figure 13
Policy-based prompts



the same item occurs. In addition, by storing similar words together, the system can flexibly respond to spelling errors or subtle differences in brand names. As shown in Figure 18, by automatically incorporating user judgments, the automation agent effectively integrates human intellectual judgment into the system and serves as a key component of the HITL mechanism, gradually enhancing the intelligence of the automation system through continuous learning.

Through the above four-stage automation process, Brity Automation completes the E2E automation of the financial expense processing tasks. From the initial stage where users submit receipts, through information extraction using IDP, policy-based automatic classification, intelligent exception handling support using AI Flow, and final review by financial personnel through automation agent, and up to system learning, the entire task process for each step is integrated and executed organically within the process flow function of the Brity Automation Orchestrator, as shown in Figure 19.

The moment of human intervention occurs only once, but that decision enables hundreds of automated processes, suggesting that human intellectual judgment can be effectively integrated into the system, achieving sustained automation efficiency without repeated interventions. This can be considered a significant advancement overcoming the limitations of existing RPA because it goes beyond the automation of simple repetitive tasks and extends to the automation of even “complex processes requiring human intervention.”

Figure 14
Example code for policy comparison recommendation

```
var product_list = [];
var suggestion_list = [];

// Define a redefined push function that takes value, list, and list2 as parameters.
function redefine_push(value, list, list2) {
    var product = "";

    // Check if the "recommand" property exists in the value object.
    if ("recommand" in value) {
        // Store the value of the "recommand" property in the suggestion variable.
        var suggestion = value["recommand"];
        product = suggestion;
        list2.push(suggestion);
    }
    return product;
}

// Check if conformance is an object.
if (typeof conformance === 'object') {
    // Append the length of the conformance array to the category string.
    this.category += "L:" + conformance.length + "\n";

    if (conformance.length > 0) {
        // Call the redefine_push function to process each element of the conformance array
        // and add the result to the suggestion_list.
        suggestion_list.push(redefine_push(conformance, this.redefine_list, product_list));
    }
}
```

4.2.5. Compliance with data privacy and security regulations

Given the sensitive nature of financial and personal information, this system is meticulously designed to ensure strict adherence to data privacy regulations. Personally identifiable information, such as names and credit card numbers, undergoes masking prior to AI processing. During the HITL review phase, access to original, unmasked data is restricted based on role-based access controls. Furthermore, internal controls and comprehensive audit logs are maintained to ensure full compliance with both the General Data Protection Regulation (GDPR) and South Korea's Personal Information Protection Act (PIPA).

4.3. Evaluation results

This section analyzes the effects of the introduction of the financial expense processing E2E automation system of GenAI and OCR/IDP-based automation agent system using Brity Automation, divided into quantitative and qualitative aspects, including an integrated analysis of their operational efficiency and organizational benefits. In addition, the limitations that may occur during the implementation process and future improvement plans to overcome them and further develop the system are presented.

4.3.1. Quantitative effects

The pilot implementation of the automation system was conducted over a one-month period, targeting 1,448 paper receipts (image files such as PNG and JPG). Its performance was evaluated using confusion matrices and key metrics, with the results presented in Tables 5 and 6.

To evaluate the robustness of the observed results, 95% confidence intervals were computed using 1,448 expense receipt entries collected during the evaluation phase. The proposed E2E system showed a classification accuracy of 83.3% (95% CI: 80.2%–86.4%) and a false negative rate of 16.7% (95% CI: 14.0%–19.6%), indicating statistical significance in performance improvements compared to the baseline. Among the test cases, false negative cases (FN = 242, approximately 16.7% of the total) indicated instances where the system failed to recommend a valid account or provided an incorrect suggestion. The most common types of exceptions included the following:

1) Inability to extract items due to the narrow character spacing in the receipt's item list.
2) Misclassification of consumable accounts or food-related items (e.g., "Blueberry Smoothie" keyboard).
3) OCR misreading errors from low-resolution or distorted images.

Most of these exceptions were mitigated through human feedback, and their frequency progressively decreased as the system learned over time during operation.

An F1 score of 0.90 indicates that the model is performing well in both precision and recall, demonstrating a well-balanced trade-off between the two. This balance reflects a model that prioritizes both the accuracy of positive predictions and minimizing false negatives.

In addition, the expected quantitative effects based on general intelligent automation adoption cases are as follows:

1) Significantly reduced processing time: company S's previous manual financial expense processing took more than 24 h for an average of 1,448 cases per month. Automatic information extraction through IDP, automatic categorization based on policies, support for judging exceptional situations through AI Flow, and an increase in the percentage of automated processing by the automation agent based on what it has learned have dramatically reduced the overall processing time. Processing time per case was reduced from minutes to tens of seconds, resulting in a monthly time savings of more than 80% to 90%. This frees up time for finance staff to focus on more analytical and strategic work, away from repetitive tasks.

Figure 15
Messenger channel agent screen: (a) the messenger home screen where an alarm is displayed when a financial manager receives a request for agreement; (b) new item addition confirmation screen

(a) (b)

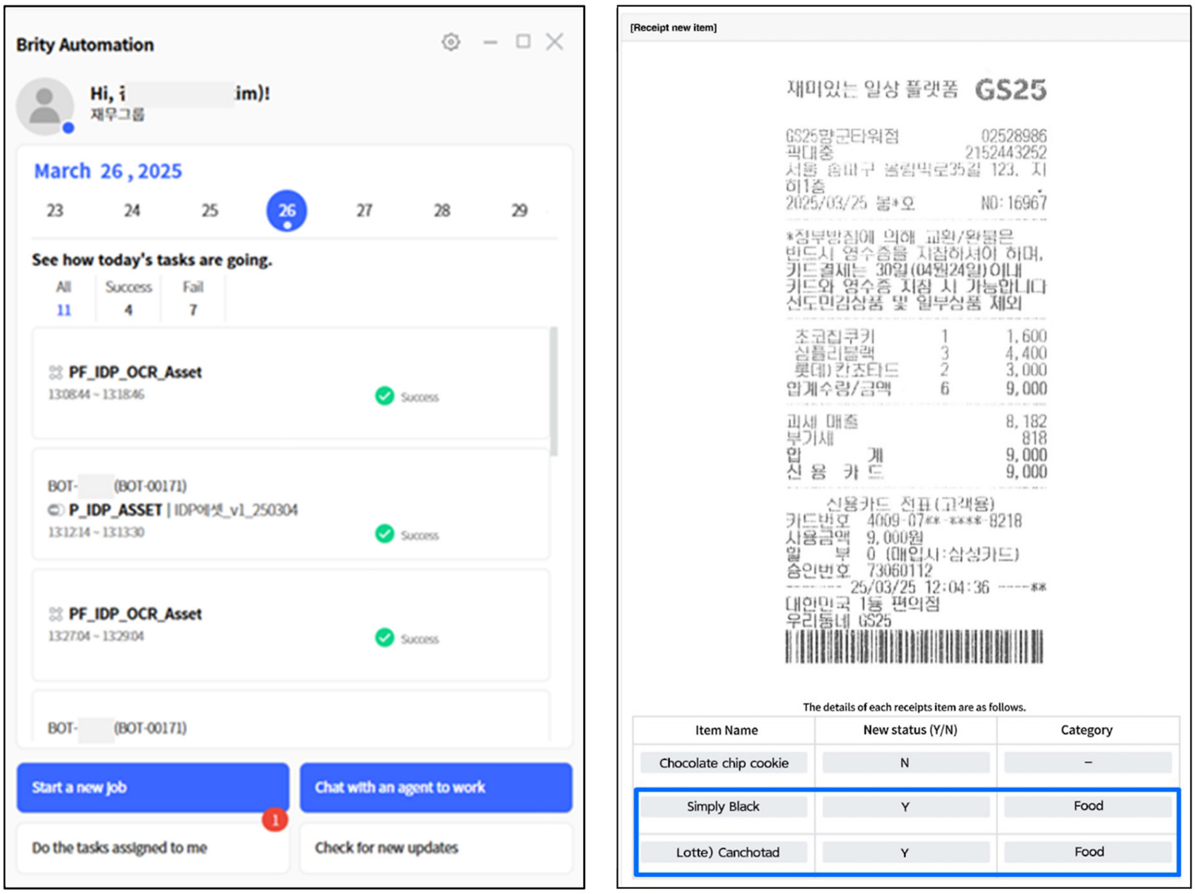


Figure 16
New item recommendation and data recommendation screen

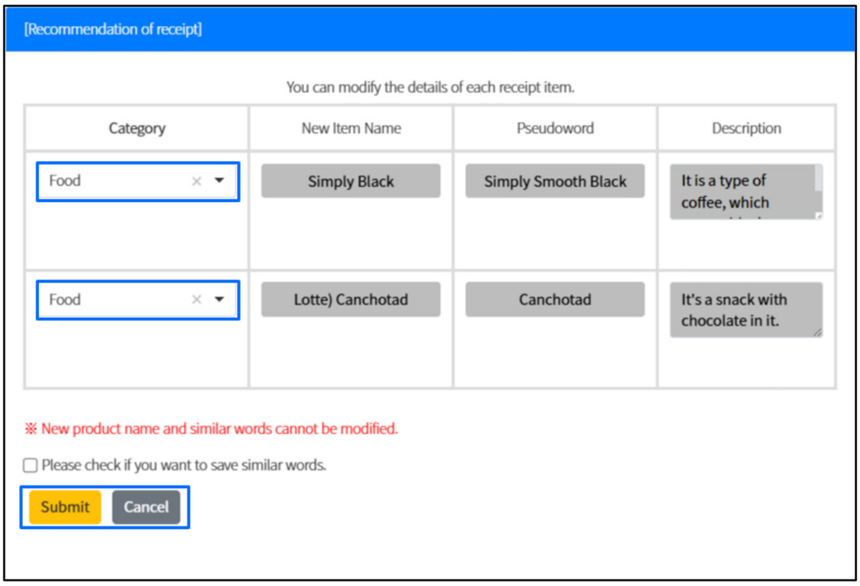


Figure 17
New item recommendation and data approval screen

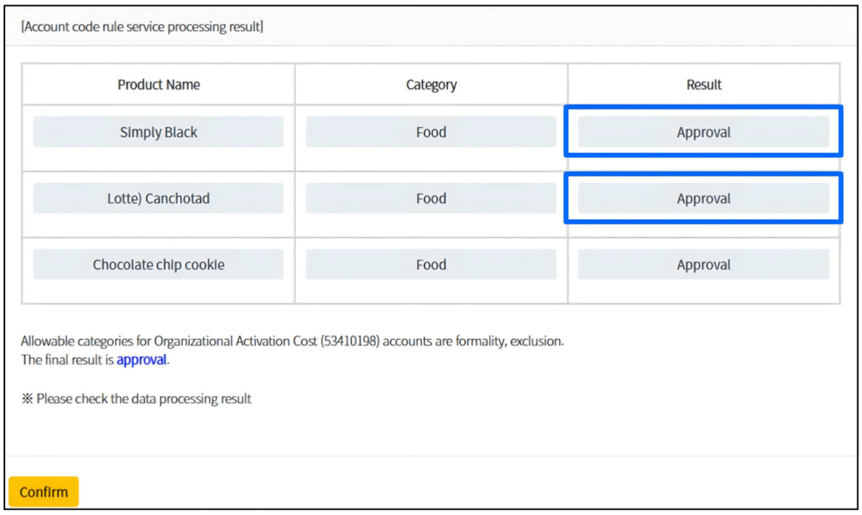


Figure 18
HITL process

2) Reduced operational costs: faster turnaround times translate into lower labor costs. Reducing the number of man-hours spent on certain tasks or enabling the same number of people to do more work translates into real cost savings. It also reduces overhead costs, such as manual error correction and paper document management.
3) Increased capacity and scalability: automated systems can operate 24 h a day, 7 days a week, 365 days a year, giving you the flexibility to handle increased workloads. It effectively distributes the workload of expense processing, which is especially concentrated at the end of the month or the end of the year, and provides scalability to respond to the increase in workload as the company grows without additional manpower.
4) Reduce error rates: accurate data extraction and system-based validation processes through IDPs can significantly reduce human errors (typos, omissions, etc.) that can occur during manual entry. This increases the accuracy of data, improving the reliability of financial reporting and reducing the time and cost of error correction.
5) Improved compliance: the system's built-in policy database and AI-powered validation logic ensure that all expense processing is conducted consistently and in accordance with pre-defined company regulations and policies. This leads to stronger internal controls and easier audit responses.

4.3.2. Qualitative effects

In addition to quantitative metrics, adopting E2E automation has a number of qualitative effects that positively affect organizational culture and ways of working.

Automation enhances the accuracy and consistency of tasks by minimizing subjective variation and enabling AI to progressively improve its handling of complex exceptions through continuous learning. Employees are relieved from repetitive tasks and can instead focus on reviewing analyses and making final decisions, thereby increasing job satisfaction and engagement, and the value and impact

Figure 19
Human task and overall workflow integration process flow

of their limited interventions are amplified. Furthermore, the data accumulated throughout the automation process provide valuable insights for decision-making, including expenditure pattern analysis, budget management, and internal control. Finally, AI Flow and automation agents facilitate rapid adaptation to new expense categories

Table 5
Confusion matrix validation target

Classification	Normal	Error		
Verification target	TP (agreement/agreement)	TN (rejected/rejected)	FP (rejected/approval)	FN (agreement/rejection)
1,448 items	1,073	133	0	242

Table 6
Quantitative evaluation metrics

Performance metrics	Calculation formula	Result
Accuracy	$(TN + TP)/(TN + FN + FP + TP) = (133 + 1{,}073)/(133 + 242 + 0 + 1{,}073)$	0.83
Precision	$TP/(TP + FP) = 1{,}073/(1{,}073 + 0)$	1
Recall	$TP/(TP + FN) = 1{,}073/(1{,}073 + 242)$	0.82
F1 score	2/((1/Precision) + (1/Recall)) = 2/(1/1 + 1/0.82)	0.90

or policy changes, allowing organizations to respond flexibly to evolving business environments and regulatory requirements.

4.3.3. Integrated impact analysis

The synergy of quantitative and qualitative effects shows the transformational potential of the E2E automation system. Quantitatively, an F1 score of 0.90 indicates high reliability and demonstrates time and cost savings. Qualitatively, it created an efficient, accurate, and employee-centered work environment. These results have streamlined cost processing, reduced operational bottlenecks, and enhanced regulatory compliance, resulting in a sustainable competitive advantage for Company S. The HITL mechanism created a virtuous cycle where human judgment enhanced system intelligence, reducing future manual intervention.

4.3.4. Limitations and future enhancements

The adoption of GenAI and OCR/IDP-based automation agents can enhance organizational efficiency. However, several limitations arise during implementation. The initial setup often entails high costs and extended time requirements, which can be mitigated through the use of cloud-based SaaS, phased deployment, and pre-trained models. Performance heavily depends on the availability of high-quality training data, necessitating data augmentation and continuous learning supported by HITL mechanisms. The black-box nature of GenAI poses challenges to reliability and explainability, which can be addressed by providing decision rationales, integrating policy frameworks, and adopting XAI technologies. Insufficient technological acceptance among employees requires complementary strategies such as training, UI improvements, and participatory system design. Because corporate expense data involve sensitive information, robust technical and managerial security measures—such as encryption, access control, and regular audits—are essential. Furthermore, as this study is based on short-term data, broader and longer-term analyses are needed to strengthen generalizability. Finally, given the evolving nature of policies and operational environments, long-term success requires flexible system architectures, systematic version control, and self-learning-based maintenance mechanisms.

By being aware of these limitations in advance and preparing appropriate improvement measures, companies can increase the likelihood of successfully introducing intelligent automation systems and maximize their effectiveness.

5. Discussion and Conclusion

5.1. Summary and conclusion

This study proposes and evaluates an E2E automation framework for corporate expense processing, built on an automation agent that integrates GenAI, OCR/IDP technologies, and an HITL mechanism. The proposed system was deployed in a real-world financial environment and evaluated using 1,448 receipt entries collected over the course of one month. The conclusions drawn from the study are as follows.

First, the existing financial expense processing task had various problems in implementing automation, such as high manual dependence, frequent exceptions, and difficulties in securing data accuracy, and simple RPA alone was not enough to solve these complexities. To overcome these challenges, we found that accurate document recognition through IDPs, intelligent exception handling and judgment support using GenAI, and the introduction of automation agents that collaborate between humans and AI were essential.

Second, through the analysis of the Brity Automation case, we demonstrated that the four-step approach of “document recognition” using IDP, “policy-based classification” based on database, “exception AI query” through AI Flow (LLM integration), and “automatic reflection of user judgment into the system” through automation agent can effectively implement E2E automation of financial expense processing. In particular, the HITL mechanism, in which the system learns the final human judgment and continuously improves the automation performance, is a key element of intelligent automation.

Third, the proposed automation system was found to yield both quantitative benefits—such as reduced processing time, lower operational costs, and fewer errors—and qualitative improvements, including enhanced task accuracy and more consistent support for data-driven decision-making. These outcomes indicate the system’s potential to support overall operational efficiency and strategic responsiveness in organizational settings.

Fourth, we recognized that there are limitations and challenges in the process of introducing intelligent automation systems, such as initial deployment costs, securing data quality, explainability of AI models, change management, and security, and emphasized the importance of preparing appropriate improvement measures.

In conclusion, the organic combination of GenAI, OCR/IDP, database, and automation agents enables successful E2E automation, even in complex and exception-prone business areas such as financial expense processing, and has the potential to fundamentally transform the way organizations operate beyond simple task replacement. The Brity Automation case provides important empirical evidence of how such technology integration can lead to real business value.

5.2. Implications, contributions, and future research directions

This study has the following implications and contributions.

From an academic perspective, first, this study presents a concrete framework and practical case studies on how cutting-edge AI technologies, such as GenAI, can be integrated with traditional RPA and IDP to automate complex enterprise business processes. Second, by emphasizing the importance and implementation strategies of effective human–AI collaboration models (HITL) in the E2E automation process, it contributes to the field of intelligent automation research.

Practical implications include the following: first, providing a practical introduction strategy, technical configuration plan, expected effects, and potential challenges for companies considering financial expense processing automation. Second, through case analysis based on actual solutions such as Brity Automation, it offers specific information that companies reviewing the construction or introduction of similar systems can use for benchmarking. Furthermore, this framework is broadly applicable to any enterprise automation environment that supports RESTful or event-driven APIs. Third, it demonstrates the possibility of expanding the scope of automation beyond simple repetitive tasks to areas requiring human judgment, thereby presenting the potential for the spread of intelligent automation to other business domains.

This study demonstrated the feasibility of E2E automation in financial expense processing by integrating GenAI and OCR/IDP technologies with Brity Automation. Future research may extend in several directions: expanding applications to diverse industries and unstructured document-intensive tasks, enhancing domain-specific learning and transparency through explainable AI, and leveraging process mining to analyze and optimize automation effectiveness. Furthermore, it is essential to address the socio-ethical implications of intelligent automation—such as workforce transformation, data privacy, and algorithmic bias—through institutional and policy measures. Ensuring safety and accountability through HITL verification and audit traceability is also critical. Finally, advancing toward multimodal AI capable of processing voice, video, and other heterogeneous data will further increase the effectiveness of intelligent automation, contributing significantly to corporate digital transformation and sustainable innovation.

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An earlier version of this work was made available as a preprint [34].

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Cheonsu Jeong: Conceptualization, Supervision, Writing – original draft. **Seongmin Sim:** Software, Writing – review & editing. **Hyoyoung Cho:** Software, Writing – review & editing. **Sungsu Kim:** Software, Writing – review & editing. **Byounggwan Shin:** Software, Writing – review & editing.

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