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Adaptive Agent-Based Business Automation Using Artificial Intelligence for Autonomous Task Coordination

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Abstract

This study aims to examine the potential of multimodal artificial intelligence (AI) for adaptive business-process automation and autonomous task coordination. It focuses on how different forms of workflow information can support the automated understanding of business activities. The study examines multimodal artificial intelligence performance in standard operating procedure generation and evaluates AI capability for workflow demonstration segmentation as a foundation for autonomous task coordination. The findings indicate that incorporating richer workflow information improves SOP-generation performance across the evaluated AI models. Combining textual intent with visual keyframes and action traces provides a more comprehensive representation of workflow activities and supports more effective procedural understanding. The workflow segmentation findings further demonstrate differences in model capability for identifying and organizing individual business-process activities. The results indicate that multimodal information can enhance AI-supported workflow understanding and provide useful capabilities for intelligent business-process automation. The study demonstrates that multimodal AI capabilities can provide an important foundation for adaptive agent-based business automation and autonomous task coordination. Integrating workflow objectives, procedural information, visual context, and interaction evidence may support future systems capable of more informed task planning and coordination. However, the findings are based on benchmark outcomes and do not represent independent experimental results from a newly implemented agent framework.

Keywords: Agentic artificial intelligence, Autonomous task coordination, Business automation, Multimodal artificial intelligence, Workflow automation

1. Introduction

Artificial intelligence (AI) is increasingly developing from systems that perform predefined analytical functions toward intelligent agents capable of reasoning, planning, decision-making, and action. This transition has contributed to the emergence of agentic AI, in which systems can pursue complex objectives with comparatively limited human intervention (Acharya *et al*., 2025). AI agents can combine information processing with autonomous decision-making, allowing them to respond to changing requirements rather than following only fixed instructions (Maharramova *et al*., 2025). The integration of machine intelligence with agent-based architectures has further expanded the potential for adaptive decision-making in complex environments (Saud and Rasool, 2025). Consequently, agentic AI represents an important technological direction for developing intelligent systems that can move beyond isolated predictions toward continuous goal-oriented activity.

The increasing complexity of organizational processes has encouraged interest in multi-agent AI**,** where multiple intelligent components cooperate to accomplish broader objectives. Multi-agent systems can distribute responsibilities among agents and coordinate their activities according to the requirements of a particular task or environment (Allmendinger *et al*., 2026). Such cooperation can be valuable in business settings; organizational processes frequently contain multiple activities that must be completed in a particular order. Research comparing agentic AI systems and AI agents emphasizes the importance of autonomy and cooperation when intelligent systems address complex objectives (Hanif *et al*., 2025). Enterprise architecture research has similarly examined multi-agent approaches for adaptive organizational design (Chen and Zhao, 2024). These developments provide a foundation for business automation architectures in which intelligent agents can support planning, coordination, monitoring, and execution.

Despite advances in intelligent automation, business workflows remain difficult to automate; operational processes can involve changing requirements, sequential dependencies, multiple resources, and interactions across digital environments (Kumar and Singh, 2026). Static automation mechanisms may perform well when processes remain unchanged but can become less effective when workflow conditions vary. AI-based decision-support research has consequently investigated dynamic workflow optimization to improve business operations under changing circumstances (Faldu, 2026). Adaptive enterprise approaches have also demonstrated how knowledge-based multi-agent systems can support the real-time management of organizational tasks and resources (Galuzin *et al*., 2022). Similar challenges have been examined in manufacturing, where multi-agent approaches have been used to address coordination and distributed process management (Pulikottil *et al*., 2021). These studies highlight the need for automation mechanisms that can interpret process requirements and adapt task organization accordingly.

Autonomous decision-making represents a central requirement for advanced business automation; intelligent systems must determine appropriate actions rather than merely execute predetermined commands (Pulikottil *et al*., 2023). Recent research has examined the role of AI agents in business decision-making and their potential to support organizational activities through autonomous reasoning (Ghane *et al*., 2026). Multi-agent frameworks have also been proposed for enterprise digital transformation, emphasizing coordinated intelligence across organizational processes (Panigrahy, 2025). Business-oriented multi-agent infrastructures further address the need for flexible systems capable of supervising intelligent automation and supporting organizational expansion (Mokoena, 2026). In addition, autonomous agent systems have been examined in decentralized business environments, where coordination, governance, and decision-making are interconnected (Naseer *et al*., 2026). These developments indicate that effective autonomous task coordination requires both intelligent decision capabilities and mechanisms for organizing interdependent activities.

For autonomous task coordination to function effectively, an AI system must understand the workflow that precedes task execution. Textual descriptions can communicate an objective, but they may not fully represent the visual states, interaction sequences, and operational context associated with completing a process. Large language model-based approaches are increasingly being explored for multi-agent reasoning, planning, and execution, creating opportunities to connect language understanding with autonomous action (Janakiraman, 2026). Similarly, modular large language model agent architectures have been investigated for adaptive and process-aware execution (Skolik *et al*., 2026). Multi-agent robotic process automation provides another example of coordinating intelligent components around procedural activities (Micheal, 2025), while research on autonomous business decision systems emphasizes the growing role of coordinated AI models in organizational decision processes (Tayal *et al*., 2026). Cognitive agent-based computing has also demonstrated the broader relevance of agent-based approaches to complex adaptive computational and communication environments (Laghari and Niazi, 2016).

Although existing studies have substantially advanced agentic AI, multi-agent architectures, autonomous decision-making, and adaptive business automation, an important gap remains in connecting multimodal workflow understanding with autonomous business-process coordination. Existing research frequently focuses on agent architecture, decision-making, or task execution, while comparatively less attention is given to systematically evaluating how different forms of workflow information contribute to the capabilities required before autonomous coordination can occur. In particular, an intelligent system must be able to understand task intentions, reconstruct procedural knowledge, recognize workflow boundaries, and interpret visual and interaction information. A benchmark-based examination of these capabilities can therefore provide useful evidence for designing future adaptive agent-based business automation systems.

The objective of this study is to examine the effectiveness of multimodal artificial intelligence in understanding business workflows and generating standard operating procedures (SOPs) using different forms of workflow information. The ability of AI models to identify workflow segments and support autonomous task coordination by comparing benchmark performance across different multimodal input configurations.

2. Materials and Methods

2.1 Research Design

This study follows a benchmark-based research design to investigate artificial intelligence applications in automated business-process understanding and task coordination. The benchmark was selected since it combines textual, visual, and interaction-based information within individual workflows. Such a structure allows different aspects of automated process understanding to be examined systematically. The analysis concentrates on standard operating procedure generation and workflow demonstration segmentation, as these tasks provide measurable evidence of how artificial intelligence can interpret business activities and organize information required for subsequent autonomous task coordination.

2.2 Data Structure

The study uses the WONDERBREAD benchmark as its primary data source. The dataset contains 2,928 human demonstrations representing 598 workflows and includes information collected from four web-based environments. Each demonstration provides multiple forms of workflow information, including the intended task, recorded process activity, interaction traces, visual keyframes, and corresponding standard operating procedures. The benchmark also contains a quality-controlled Gold subset comprising 724 demonstrations associated with 162 workflows. On average, a workflow contains approximately 4.9 demonstrations, 7.8 process steps, and 37.2 seconds of activity. These characteristics provide a structured basis for examining multimodal artificial intelligence performance in business-process automation.

2.3 Multimodal Information Representation

Workflow information is represented through several complementary modalities to capture both the purpose and execution of a business activity. The textual intent describes the objective that a user seeks to accomplish, while the standard operating procedure represents the expected sequence of activities. Visual keyframes provide information about interface conditions and screen states observed during task execution. Action traces additionally record user interactions performed throughout the workflow. The study considers these information types individually and in combination when examining benchmark performance. This multimodal representation is important autonomous business automation requires more than understanding task descriptions; it also requires recognition of the operational context and actions associated with completing each workflow.

2.4 SOP Generation Procedure

Standard operating procedure generation is examined as a structured workflow-documentation task. In this setting, an artificial intelligence model receives information describing a business activity and produces an ordered sequence of procedural steps. Three information configurations are considered: workflow intent alone, intent combined with visual keyframes, and intent combined with keyframes and action traces. The resulting procedures are compared with reference SOPs associated with the corresponding workflow demonstrations. Performance is assessed using precision, recall, F1-score, and average generated steps. These measures collectively indicate whether the generated procedures contain relevant activities, capture the required workflow operations, and maintain an appropriate level of procedural detail without introducing excessive or unsupported actions.

2.5 Workflow Demonstration Segmentation

Workflow demonstration segmentation examines the ability of an artificial intelligence model to separate continuous business-process demonstrations into their corresponding workflow units. The task requires the model to determine which portions of a sequence belong to individual activities and to identify appropriate workflow boundaries. Different information configurations are examined by providing workflow intent alone or supplementing it with SOP information and visual keyframes. The benchmark evaluates segmentation quality using the Adjusted Rand Index and V-measure. The two measures provide complementary information concerning agreement between predicted and reference workflow assignments. Accurate segmentation is important for autonomous task coordination; individual processes must first be identified correctly before they can be independently managed or assigned.

2.6 Evaluation Framework and Comparative Analysis

The evaluation compares the benchmark results reported for GPT-4, Claude 3 Sonnet, and Gemini Pro 1 across the available multimodal configurations. SOP generation is assessed using precision, recall, F1-score, and average step count, whereas workflow segmentation is evaluated through Adjusted Rand Index and V-measure. The analysis examines how performance changes when additional visual and interaction information is incorporated into the model input. Higher metric values indicate stronger agreement with the corresponding reference outputs for the evaluated task.

3. Results

3.1 Dataset and Characteristics

The WONDERBREAD benchmark provides a broad foundation for examining AI-supported business-process automation. It contains 2,928 human demonstrations covering 598 workflows, including 724 Gold demonstrations across 162 Gold workflows. The benchmark evaluates six business-process-management tasks and represents four websites. Each workflow contains an average of 4.9 demonstrations, with approximately 7.8 steps and a mean duration of 37.2 seconds. These characteristics indicate that the benchmark captures diverse workflow activities while providing sufficient structured information for evaluating automated process understanding, task coordination, and workflow execution in business environments.

Table 1. Characteristics of the WONDERBREAD business-process benchmark

Dataset characteristic	Value
Total human demonstrations	2,928
Total workflows	598
Gold demonstrations	724
Gold workflows	162
BPM evaluation tasks	6
Average demonstrations per workflow	4.9
Average workflow steps	7.8
Average workflow duration	37.2 s
Websites represented	4

Source: *Wornow et al., WONDERBREAD, NeurIPS 2024.*

3.2 SOP Generation Performance

The benchmark results show that adding richer workflow information improves SOP generation across all evaluated models. GPT-4 records the strongest performance, increasing its F1-score from 0.49 with intent alone to 0.82 when keyframes and action traces are included, as shown in Table 2. Claude 3 Sonnet follows a similar pattern, reaching 0.76, while Gemini Pro 1 achieves 0.58 under the same configuration. The results also show that recall generally exceeds precision, suggesting that models may include plausible steps that were not actually performed. Overall, combining textual intent with visual and action-based evidence provides a more complete representation of workflow execution.

Table 2. SOP-generation performance of multimodal foundation models

Model	Input information	Precision	Recall	F1-score	Average steps
GPT-4	Intent	0.48	0.59	0.49	13.10
GPT-4	Intent + Keyframes	0.69	0.79	0.71	10.32
GPT-4	Intent + Keyframes + Trace	0.80	0.88	0.82	10.26
Claude 3 Sonnet	Intent	0.53	0.54	0.50	11.34
Claude 3 Sonnet	Intent + Keyframes	0.67	0.78	0.70	11.35
Claude 3 Sonnet	Intent + Keyframes + Trace	0.72	0.85	0.76	10.94
Gemini Pro 1	Intent	0.40	0.36	0.34	7.31
Gemini Pro 1	Intent + Keyframes	0.48	0.51	0.46	11.28
Gemini Pro 1	Intent + Keyframes + Trace	0.58	0.63	0.58	11.09
Ground truth	—	1.00	1.00	1.00	8.40

Source: *Wornow et al., "WONDERBREAD: A Benchmark for Evaluating Multimodal Foundation Models on Business Process Management Tasks,"* Advances in Neural Information Processing Systems 37*, 2024, DOI: 10.52202/079017-3682. Dataset: WONDERBREAD, Zenodo DOI 10.5281/zenodo.14094162.*

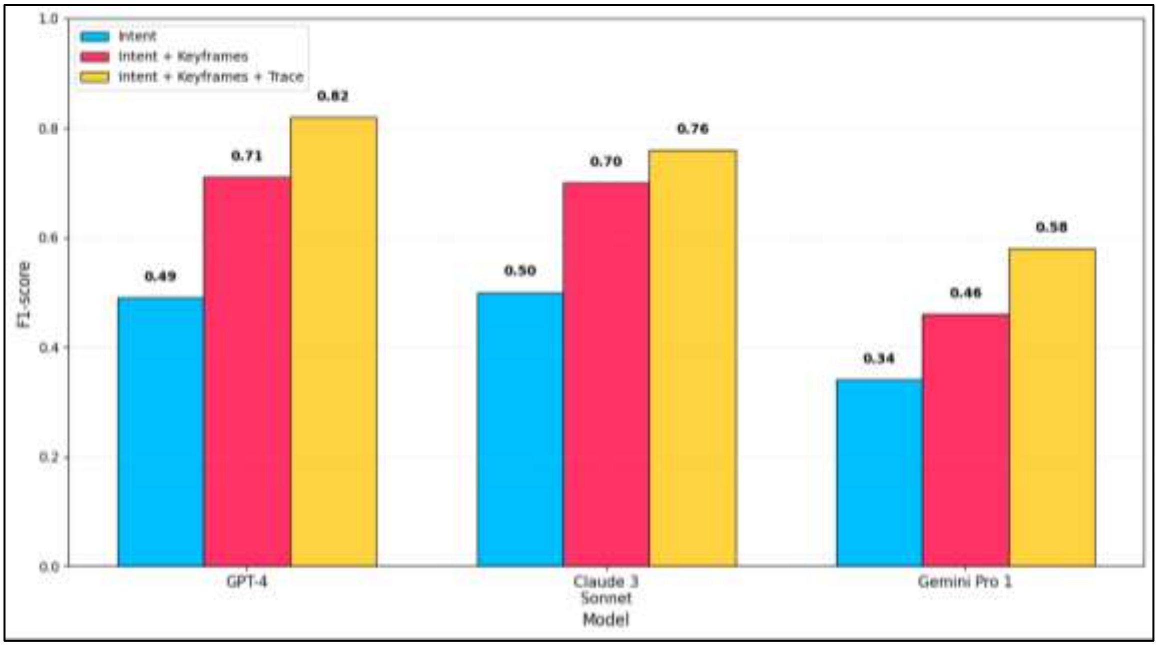

Figure 2. SOP Generation Performance of Multimodal Foundation Models

The WONDERBREAD benchmark results for SOP generation across GPT-4, Claude 3 Sonnet, and Gemini Pro 1. The results show that providing additional workflow information consistently improves F1-score for all three models, as shown in Figure 2. GPT-4 achieves the highest F1-score of 0.82 when intent, keyframes, and action traces are jointly provided, compared with 0.49 using intent alone. Claude 3 Sonnet improves from 0.50 to 0.76, while Gemini Pro 1 increases from 0.34 to 0.58 under the same progression. These findings indicate that combining textual intent with visual and action-level information can substantially improve automated SOP generation.

3.3 Workflow Demonstration Segmentation

The workflow segmentation results indicate that GPT-4 consistently provides stronger performance than Gemini Pro 1 across the evaluated input settings. For GPT-4, the Adjusted Rand Index increases from 0.80 with intent alone to 0.85 when SOP information is added, while the V-measure rises from 0.86 to 0.87 as shown in Table 3. Incorporating keyframes maintains the Adjusted Rand Index at 0.85 and further improves the V-measure to 0.88. Gemini Pro 1 records lower scores, with its best V-measure reaching 0.69 using intent alone. These findings demonstrate differences in the models' ability to identify and organize workflow segments accurately.

Table 3. Workflow-segmentation performance

Model	Input information	Adjusted Rand Index	V-measure
GPT-4	Intent	0.80	0.86
GPT-4	Intent + SOP	0.85	0.87
GPT-4	Intent + SOP + Keyframes	0.85	0.88
Gemini Pro 1	Intent	0.58	0.69
Gemini Pro 1	Intent + SOP	0.53	0.65
Gemini Pro 1	Intent + SOP + Keyframes	0.55	0.66

Source: *Wornow et al., "WONDERBREAD: A Benchmark for Evaluating Multimodal Foundation Models on Business Process Management Tasks," Advances in Neural Information Processing Systems 37, 2024, DOI: 10.52202/079017-3682. Dataset: WONDERBREAD, Zenodo DOI 10.5281/zenodo.14094162.*

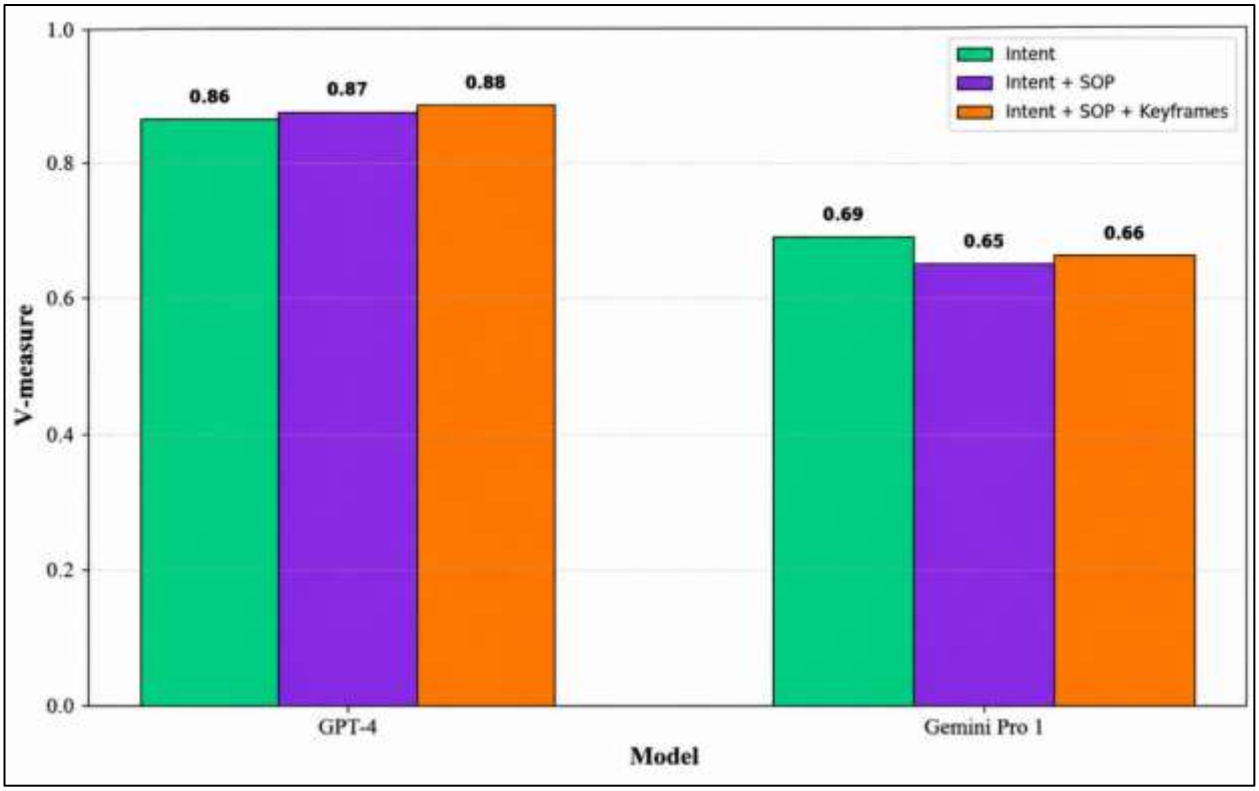

Figure 3. Workflow Demonstration Segmentation Performance

The V-measure obtained by GPT-4 and Gemini Pro 1 under three workflow-information settings. GPT-4 achieves scores of 0.86, 0.87, and 0.88 when provided with intent, intent plus SOP, and intent plus SOP plus keyframes, respectively, as shown in Figure 3. Gemini Pro 1 records 0.69, 0.65, and 0.66 under the same settings. Thus, GPT-4 maintains higher segmentation performance across all configurations, while the addition of workflow information produces only modest changes in both models. The highest observed value is 0.88 for GPT-4, indicating stronger consistency in assigning related workflow demonstrations to the correct segments.

4. Discussion

The findings provide useful evidence about the capabilities required for intelligent business-process automation. The benchmark demonstrates that workflow understanding becomes stronger when an AI model receives information from multiple sources rather than relying only on a textual description. In the SOP-generation task, performance improves as additional workflow information is introduced, indicating that business activities cannot always be adequately represented through task intent alone. The segmentation results similarly show that models can identify workflow relationships with considerable consistency, although performance varies across models and input configurations. These observations suggest that effective autonomous automation depends on the quality and completeness of the information available to the intelligent system.

The SOP-generation findings demonstrate the value of combining textual, visual, and interaction-based information. GPT-4 shows the strongest improvement when keyframes and action traces are added to workflow intent, while Claude 3 Sonnet and Gemini Pro 1 demonstrate similar improvements across the progressively richer configurations. This pattern indicates that visual and action information can provide contextual details that may not be explicitly represented in a task description. The reduction in average generated steps for some configurations also suggests that additional workflow evidence can help models produce procedures that are more closely aligned with actual process execution. For business automation, this capability is important because reliable procedural knowledge can provide a foundation for task planning and subsequent agent execution.

The segmentation findings provide complementary evidence concerning automated workflow organization. GPT-4 maintains stronger performance than Gemini Pro 1 across all evaluated configurations, with its V-measure reaching the highest observed value when intent, SOP information, and keyframes are combined. The results indicate that workflow descriptions and visual information can assist models in recognizing relationships between demonstrations. However, the relatively modest changes produced by additional information in some configurations suggest that multimodal input does not automatically guarantee substantial improvements for every model. This variation highlights the importance of evaluating individual model capabilities rather than assuming that additional information will produce uniform gains across different AI systems.

The findings have direct implications for the design of adaptive agent-based business automation systems. An autonomous agent requires a sufficiently detailed representation of the task environment before it can make reliable decisions or execute actions. The benchmark results suggest that combining task intent with procedural, visual, and interaction information can provide a richer representation of business activities. Within an agent-based architecture, these information sources could support different stages of automation, including task interpretation, planning, state recognition, and action selection. However, the present study does not experimentally implement such an architecture. Therefore, the findings should be interpreted as evidence concerning capabilities that may support adaptive agent systems rather than as direct validation of a newly developed autonomous agent framework.

Accurate workflow identification is particularly important when multiple business activities must be coordinated. The segmentation results indicate that AI models can distinguish workflow units with measurable consistency, providing a potential foundation for separating complex processes into manageable tasks. When combined with SOP-generation capabilities, workflow segmentation could support a broader coordination process in which an intelligent system first identifies the objective, determines the relevant workflow, develops procedural knowledge, and subsequently assigns or executes appropriate actions. Such a process could reduce dependence on rigid automation rules. Autonomous coordination also requires reliable state monitoring, error handling, decision control, and mechanisms for human intervention, which are outside the direct scope of the present benchmark analysis.

The findings are consistent with earlier research emphasizing coordination as a central requirement of intelligent agent-based automation. Terán *et al*. (2017) examined multi-agent coordination mechanisms in industrial automation and demonstrated the importance of coordination strategies for managing distributed automated activities. Similarly, agent-based analysis of task automation has highlighted the interaction between automation and changes in work activities and worker adjustment (Upreti and Sridhar, 2022). More recent research has considered agentic business-process management from a governance perspective, emphasizing that autonomous agents operating within business processes require appropriate management and oversight (Vu *et al*., 2025). The present findings complement these perspectives by showing the importance of workflow information for the understanding stage that can precede autonomous coordination. The results also align with research describing complex adaptive systems as evolving from individual adaptive agents toward broader intelligent societies (Zhou *et al*., 2024). Furthermore, the observed potential for AI systems to handle increasingly complex activities is consistent with the growing discussion surrounding autonomous AI agents for complex task automation (Zuo, 2025).

From a practical perspective, the findings indicate that organizations seeking intelligent workflow automation should consider integrating multiple sources of process information rather than depending exclusively on textual task descriptions. Visual states, interaction histories, and procedural knowledge can provide complementary information for understanding business activities. Theoretically, the study supports a view of autonomous business automation as a sequence of interconnected capabilities rather than a single AI function. Workflow understanding, procedural representation, segmentation, planning, and coordination can be regarded as complementary components within a broader intelligent automation architecture.

Several limitations should be considered when interpreting the findings. These limitations restrict the extent to which the findings can be generalized to fully operational business environments.

Future research should extend the benchmark-based analysis toward the implementation and experimental evaluation of an adaptive agent-based automation architecture. Such work could integrate workflow understanding, task planning, agent communication, execution monitoring, and human oversight within a unified system. Experiments using additional business domains and real organizational workflows could further examine generalizability. Future studies should also evaluate reliability, execution accuracy, adaptation to workflow changes, response to unexpected events, computational cost, and the effectiveness of human intervention. These directions would enable stronger empirical validation of whether the capabilities identified in the present analysis can be transformed into reliable autonomous task-coordination systems.

5. Conclusion

This study examined the role of multimodal artificial intelligence in supporting adaptive business-process automation and autonomous task coordination. The analysis used the WONDERBREAD benchmark to investigate workflow understanding through SOP generation and workflow demonstration segmentation. The findings indicate that incorporating textual intent with visual keyframes and action traces can improve SOP-generation performance across the evaluated models. GPT-4 achieved the strongest reported F1-score when richer workflow information was provided. Workflow segmentation results also showed that GPT-4 consistently outperformed Gemini Pro 1 across the examined configurations. The study provides benchmark-based evidence that multimodal workflow information can strengthen AI-supported process understanding. These capabilities can serve as important building blocks for intelligent systems designed to interpret business activities and transform workflow information into structured procedural knowledge. The findings suggest that reliable workflow understanding and segmentation can provide a foundation for future agent-based systems that coordinate business tasks. Combining task objectives, procedural information, visual context, and interaction histories may enable more informed task planning and execution. The study demonstrates the relevance of multimodal AI capabilities to adaptive business automation. However, the findings represent benchmark outcomes rather than independent evaluation of a newly implemented agent framework. Future empirical implementation is therefore required to validate autonomous task coordination in real-world business environments.

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