
Design and Development of a Multi-Agent Artificial Intelligence-Based Financial Planner for Institutional Financial Management Optimization

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Keyword

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Abstract

Institutional financial management often faces optimization challenges due to limited understanding of influencing factors, difficulties in data integration, and the lack of human expertise. These constraints hinder the identification of opportunities, risk management, and sustainability. An adaptive and automated financial planning system is required. This study proposes the design of an Artificial Intelligence (AI)-based system for automated financial planning aligned with institutional standards. The system addresses these challenges by integrating financial needs analysis, standardized cost references, and automated budget summary preparation. Using a prototyping approach, the system employs AI agents to conduct in-depth analysis and produce comprehensive budgets. The proposed system leverages RAGflow, an open-source Retrieval-Augmented Generation (RAG) engine that uses deep document understanding to provide truthful question-answering from complex data.

1. Introduction

Institutional financial management often encounters challenges in achieving optimization [1]. A lack of deep understanding of various factors influencing financial performance, along with difficulties in integrating data from multiple sources, can hinder effective decision-making. This situation is further exacerbated by limited human resources with specialized expertise in financial analysis and strategic planning. Consequently, institutions often struggle to identify growth opportunities, proactively manage risks, and ensure long-term financial sustainability. Therefore, a more systematic and adaptive approach is required to manage institutional finances efficiently [2].

Sound financial planning requires strong knowledge and understanding of financial principles and the ability to apply them within the specific context of an institution [3]. Wise financial planning and the ability to manage institutional finances effectively are closely related to the level of financial knowledge and attitudes possessed by managers and stakeholders [4]. However, in practice, institutional financial planning is still largely dependent on manual processes and fragmented data sources, which can lead to errors and delays. Evidence from educational budgeting studies indicates that budget planning mechanisms are often implemented but not fully optimized, as seen in the mismatch between planned budgets and actual realizations in school financing contexts, where actual expenditures frequently fail to align with initial budget plans [5].

In addition, research on traditional budget processes highlights systemic inefficiencies, including time-consuming compilation, reliance on unsupported assumptions, and rigid annual planning cycles, which

hinder responsiveness and strategic alignment in financial decision-making [6]. These documented limitations of conventional budgeting illustrate why many institutions continue to experience inaccurate forecasts, suboptimal resource allocation, and prolonged operational timelines when preparing annual budgets.

Previous financial management systems mainly relied on rule-based mechanisms or single-agent AI decision support, which are limited in handling complex, heterogeneous, and evolving institutional financial data. Rule-based systems depend on predefined logic that is difficult to adapt to diverse financial scenarios, while single-agent approaches tend to process information linearly, restricting their ability to simultaneously interpret financial guidelines, activity requirements, and budget constraints. In contrast, a multi-agent AI approach enables task specialization, such as interpreting institutional regulations, analyzing activity-based financial needs, and validating budget compliance allowing parallel processing, adaptive reasoning, and more robust decision support. Moreover, existing financial planning tools rarely integrate intelligent document understanding with automated budget generation and validation based on institutional cost standards within a unified system. This gap indicates that a comprehensive AI-assisted financial planning solution that combines guideline interpretation, activity-based planning, and automated validation has not yet been sufficiently addressed in prior research, thereby positioning this study as a novel contribution to institutional financial management.

1.1 Accounting Information Systems

Accounting Information Systems (AIS) defines as an information system that integrates accounting functions and activities to produce relevant and reliable financial information for various stakeholders [7]. AIS encompasses the processes of collecting, processing, storing, and presenting accounting data into useful information for decision-making [8]. In the context of developing a Multi-Agent Artificial Intelligence (MAAI)-based Financial Planner for institutional financial management optimization, AIS theory becomes a critical foundation. The MAAI approach requires structured and accurate accounting data as input for decision-making algorithms, consistent with AIS principles in producing reliable financial information. Furthermore, AIS emphasizes the importance of integrating data from various sources, enabling agents in the MAAI system to access and process comprehensive information, resulting in financial planning recommendations that are more optimal and adaptive to institutional changes [9]. Therefore, the development of this Financial Planner focuses not only on artificial intelligence but also on ensuring that the quality of generated information aligns with fundamental AIS principles.

1.2 Multi-Agent Systems

Multi-Agent Systems (MAS) represent a distributed computing paradigm that models complex systems as collections of autonomous agents interacting to achieve collective or individual goals [10]. Each agent is capable of perceiving its environment, making decisions, and acting independently, while agent interactions often involving negotiation, coordination, and consensus are crucial for achieving optimal solutions [11], [12]. In the context of developing an AI-based Financial Planner for institutional financial management optimization, MAS theory provides a strong foundation. This approach enables modeling of various financial management aspects such as risk analysis, asset allocation, investment planning, and reporting as independent agents that interact. For example, a Risk Analysis Agent may interact with an Asset Allocation Agent to provide relevant risk information, while an Investment Planning Agent can coordinate with a Reporting Agent to ensure transparency and accuracy. By leveraging consensus and coordination principles central to MAS [13], this Financial Planner system can produce more adaptive, robust, and integrated recommendations compared to traditional approaches.

In this study, the accuracy evaluation involving three sample cases was conducted as an initial exploratory test to verify the functional interaction among agents and to ensure that the MAS-based architecture operated as intended. Although the number of test cases is limited, such pilot-scale testing is commonly applied in early-stage system development to validate conceptual feasibility and agent coordination logic prior to broader empirical evaluation.

2. Research Method

The prototyping model represents an iterative approach to system development characterized by building an initial functional model alongside an evolving information system design. This methodology is particularly well-suited for complex system development such as financial planners [14]. The rationale for using prototyping in this study lies in its ability to quickly generate and refine concepts, facilitating deeper understanding of user needs and system requirements [15]. The iterative nature of prototyping allows continuous feedback and adaptation, ensuring the final product aligns closely with intended functionalities and optimizes financial asset management in institutional contexts.

2.1 Needs Analysis

The "Needs Analysis" stage is a crucial foundation in the development of a Multi-Agent Artificial Intelligence-based Financial Planner for institutional financial management optimization. The main objective of this stage is to comprehensively identify and document user needs, including functional, non-functional, and specific operational requirements. The collected information serves as the basis for formulating accurate system specifications, ensuring that the developed Financial Planner truly meets the needs of the targeted financial institutions. The significant contribution of this stage lies in forming a deep understanding of challenges and opportunities in institutional financial management, which then guides the design and prototyping process, ensuring the relevance and effectiveness of the resulting solution.

2.2 Rapid Design

In the "Rapid Design" phase, this research aims to generate a visual representation and initial architecture of the Multi-Agent AI-based Financial Planner. This step utilizes rapid prototyping techniques to quickly communicate the system's core concepts, including agent interactions, data flow, and user interfaces. The main contribution of this stage is the creation of a well-defined framework that serves as the foundation for building a functional prototype. By accelerating the identification and validation of requirements, this phase significantly reduces the risk of later design errors and ensures the prototype effectively meets system requirements for institutional financial management optimization.

2.3 Prototype Development

In the "Prototype Development" stage, this research produces an initial functional representation of the Multi-Agent AI-based Financial Planner. The main objectives are to validate the core concepts, test agent interactions, and collect early feedback regarding system usability and effectiveness. The prototype serves as the basis for further iterations, allowing early identification and correction of key features, and ensuring alignment between the system and institutional financial management optimization needs. Overall, this stage lays a critical foundation for producing a suitable and effective Financial Planner.

2.4 Early User Evaluation

The "Early User Evaluation" stage is a critical step in validating the developed prototype. The main objective is to collect direct feedback from target users in this case, institutional financial management professionals regarding the prototype's usability, functionality, and user-friendliness. This feedback is systematically analyzed to identify areas requiring further improvement, ensuring the prototype effectively meets user needs and expectations. The evaluation results directly contribute to subsequent development iterations, enabling adjustments and feature optimization, thereby enhancing the relevance and effectiveness of the Multi-Agent AI-based Financial Planner in institutional financial management.

2.5 Prototype Refinement

The "Prototype Refinement" step is essential in this research process, aimed at identifying and addressing deficiencies or inconsistencies found during early user evaluations. Through this step, user feedback is directly used to modify and enhance the prototype, ensuring that implemented features truly meet user needs and expectations in the context of institutional financial management optimization. This process significantly contributes to improving the quality and relevance of the Multi-Agent AI-based Financial Planner and strengthens the foundation for effective system development aligned with the research objectives.

3. Results and Discussions

3.1 Results

This study aims to develop an adaptive and intelligent financial management system for complex institutions, addressing limitations often encountered in traditional financial planning approaches. The proposed system leverages RAGflow, an open-source Retrieval-Augmented Generation (RAG) engine that uses deep document understanding to provide truthful question-answering from complex data. By integrating this capability, the system can automatically extract, interpret, and manage institutional financial information from various sources, including unstructured documents such as financial guidelines, reports, and activity proposals.

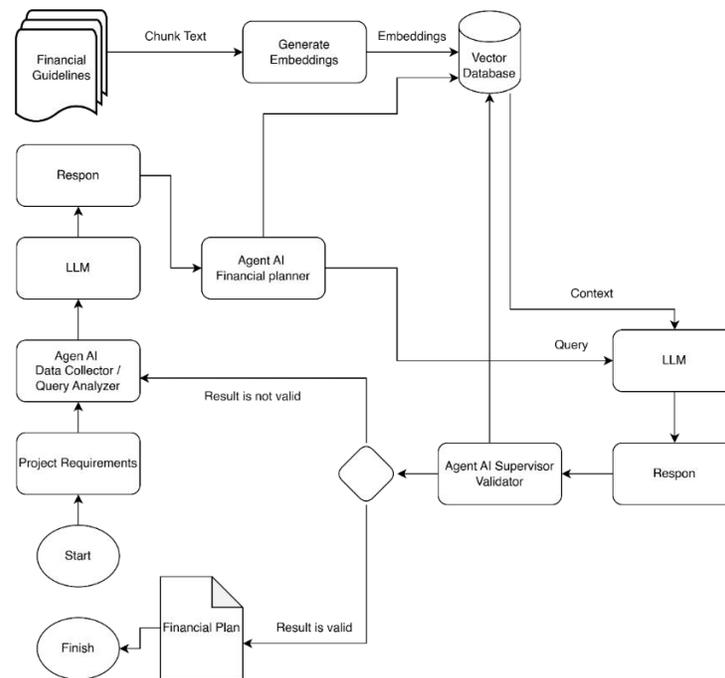


Figure 1. Flow Diagram of Financial Planner Multi Agent Artificial Intelligence

The system is composed of multiple specialized agents that operate collaboratively within a coordinated architecture. Each agent exhibits autonomous behavior, as it independently performs its designated task without continuous user intervention. The agents are also reactive, responding dynamically to user inputs such as activity descriptions or budget requests, and proactive, as they initiate validation and compliance checks automatically after a financial plan is generated. In addition, the agents demonstrate cognitive capabilities through contextual reasoning, enabling them to interpret natural language inputs, retrieve relevant regulatory information, and apply institutional cost standards during budget formulation.

The system development process follows an iterative design approach consisting of Needs Analysis, Rapid Design, Prototype Development, Early User Evaluation, and Prototype Refinement. The Needs Analysis stage identified key challenges in institutional financial management, including fragmented data sources, inconsistent application of financial standards, and high dependency on manual processes. The Rapid Design phase established the conceptual framework of the system, focusing on integrating intelligent document understanding and validation mechanisms.

During Prototype Development, RAGflow was configured and tested to ensure it could accurately interpret institutional financial guidelines and provide contextually appropriate financial recommendations. Feedback from Early User Evaluation helped refine the user interface, improve the accuracy of activity–cost matching,

and optimize the clarity of generated financial summaries. The final Prototype Refinement phase resulted in a system that is adaptive, responsive, and aligned with user needs.

The developed system integrates three essential capabilities that work seamlessly to support institutional financial planning.

3.1.1 Reading Institutional Financial Guidelines as Standardized References.

This feature enables the system to automatically read and interpret institutional financial guideline documents that define budget categories, cost limits, and allocation rules. Using RAGflow, the system builds a structured knowledge base from these documents through deep document understanding. The extracted information becomes the foundation for standardizing all financial planning processes, ensuring that the system consistently adheres to institutional regulations and minimizing the need for manual interpretation of complex financial documents.

4. HONORARIUM PEGAWAI TIDAK TETAP (PTT) - NON PNS			
NO.	URAIAN	SATUAN	BESARAN
(1)	(2)	(3)	(4)
1.	Tenaga Kesehatan		
	a. Dokter	Orang/Bulan	Rp3.500.000
	b. Paramedis (S1)	Orang/Bulan	Rp2.750.000
	c. Paramedis (D3)	Orang/Bulan	Rp2.500.000
2.	Tenaga Kependidikan		
	a. Tenaga Pemrograman(S1)/Tenaga Jaringan Internet (S1)/Staf TPP (S1)/Auditor SPI (S1)/Tim Teknis (S1)/Laboran (S1)	Orang/Bulan	Rp3.000.000
	b. Tenaga Administrasi (S1)	Orang/Bulan	Rp2.600.000
	c. Tenaga Administrasi dan Teknisi (D3)	Orang/Bulan	Rp2.350.000
	d. Tenaga Administrasi dan Teknisi (SMA/SMK)	Orang/Bulan	Rp2.200.000
	e. Tenaga parkir, kebersihan, taman, pengemudi/sopir, juru masak, pramu kantor, dan satuan pengamanan	Orang/Bulan	Rp2.100.000
	f. Pengemudi/sopir Rektor	Orang/Bulan	Rp2.600.000
	g. Pengemudi/sopir Wakil Rektor	Orang/Bulan	Rp2.500.000
	h. Komandan Regu Satuan Pengamanan	Orang/Bulan	Rp2.250.000
Penjelasan: Penggangkatan tenaga melalui Keputusan Rektor.			

Figure 2. Sample of scanned financial documents

8. HONORARIUM KEGIATAN PUSAT LAYANAN FENYANDANG BERKEBUTUHAN KHUSUS | NO. | URAIAN | SATUAN | BESARAN |

(1)	(2)	(3)	(4)
1.	Honorarium Penejemah Bahasa Isyarat	Orang /Kegiatan	Rp500.000
2.	Transport Mahasiswa Pendamping	Mahasiswa	Rp100.000
3.	Transport Penerjemah Bahasa Isyarat	Orang/ Kegiatan	Rp150.000
4.	Bantuan pejalanan Pendamping Narasumber Disabilitas		
	a. Dalam Kota	Orang/ Kegiatan	Rp150.000
	b. Luar Kota	Orang/ Kegiatan	Rp500.000

Penjelasan: - a. Honorarium Penerjemah Bahasa Isyarat diberikan kepada pegawai UM melalui mekanisme insentif kineija a tau seseorang dari luar UM yang diberi tugas untuk menejemahkan materi yang disampaikan narasumber dengan bahasa isyarat. - b. Biaya pejalanan Pendamping Narasumber Disabilitas diberikan kepada seseorang dari luar UM yang diberi tugas mendampingi Narasumber Disabilitas berdasarkan surat perintah pejabat yang berwenang. - c. Biaya pejalanan Pendamping Narasumber Disabilitas meliputi biaya akomodasi dan tiket.

9. SATUAN BIAYA KEGIATAN KULIAH KERJA NYATA (KKN) | NO. | URAIAN | SATUAN | BESARAN |

(1)	(2)	(3)	(4)
1.	Kuliah Kerja Nyata (KKN) Reguler		
	a. Bantuan dana program	Mahasiswa	Rp100.000
	b. Bantuan uang harian dan transport mahasiswa penempatan di luar Jawa	OK	Rp1.500.000
	c. Bantuan uang harian dan transport mahasiswa penempatan di luar negeri	OK	Rp3.000.000
	d. Bantuan konsumsi	Mahasiswa	Rp15.000
	e. Honorarium Kesbang Linmas	OK	Rp250.000
	f. Honorarium Camat	OK	Rp500.000
	g. Honorarium Kepala Desa	OK	Rp500.000
	h. Honorarium Panitia Desa	OK	Rp250.000
	i. Seragam Mahasiswa (Kaos)	Stel	Rp100.000
	i- Sera		

Total 11 < 1 2 > 10 / page Go to Page

Figure 3. Sample of processed documents (extracted information)

3.1.2 Generating Financial Planning Based on Activity Needs Interpretation.

Once the institutional standards have been established, the system analyzes input data related to proposed institutional activities. Through semantic reasoning, RAGflow interprets textual descriptions—such as objectives, scope, and resource requirements—and connects them to relevant cost categories and allowable budget items from the guideline knowledge base. The output is a draft financial plan that includes itemized cost estimations, budget structure, and recommendations aligned with institutional financial policies. The system automatically produces financial documents in Indonesian, as institutional reporting standards in Indonesia require the use of Bahasa Indonesia as the official language in administrative and financial documentation. This process significantly accelerates budget preparation while maintaining accuracy and compliance.

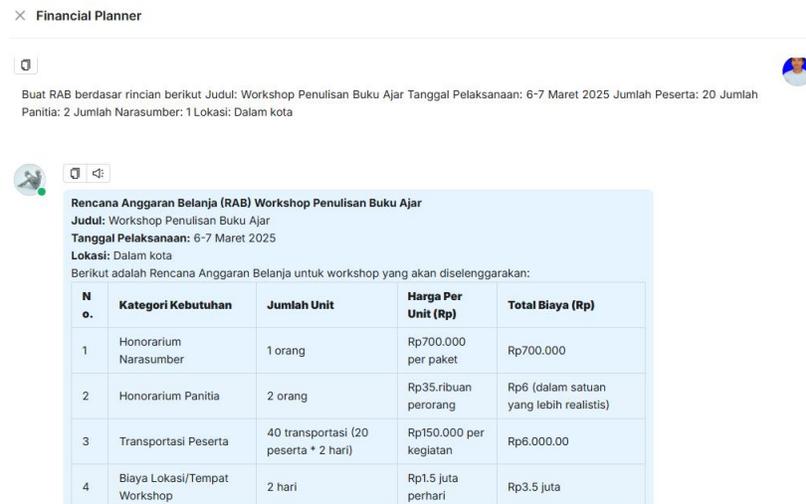


Figure 4. System generating a draft of financial plan based on user criteria

3.1.3 Revalidating Financial Plans According to Institutional Cost Standards.

After generating a financial plan, the system performs an automated revalidation process to ensure consistency and compliance with institutional cost standards. The validation mechanism detects potential deviations such as over-budget allocations or unrecognized cost items and provides structured feedback for adjustment. By enforcing standard-based revalidation, the system improves transparency and accountability, reducing the likelihood of errors or rejections during institutional financial review.



Figure 5. System validating the earlier results of financial plan

Through these integrated features, the developed prototype demonstrates the effectiveness of AI-based automation in supporting institutional financial planning. The system not only enhances accuracy and efficiency in financial document processing but also ensures strong alignment with institutional cost standards and financial policies. Evaluation results indicate that the system can serve as a foundation for broader implementation of AI-assisted financial management solutions in higher education and other complex institutional environments.

To evaluate the effectiveness of the proposed Multi-Agent AI-based financial planner system, a series of tests were conducted to measure its accuracy, functionality, and alignment with institutional financial standards. The testing involved simulated financial documents, planning scenarios, and validation processes that reflect real institutional practices. The results are summarized in the following table:

Table 1. System Testing Results Summary

No	Testing Aspect	Result	Performance Score (%)	Identified Error Causes
1	Financial Guidelines Interpretation Accuracy	Inconsistent data extraction across document types	47.5%	Variations in document structure, implicit regulatory clauses, and inconsistent terminology across guideline sections
2	Semantic Understanding of Activity Descriptions	Accurate mapping between activity needs and cost categories	90.0%	Minor ambiguity only when activity descriptions lacked quantitative detail
3	Financial Plan Generation Efficiency	Significant reduction in preparation time compared to manual process	83.3% faster	Iterative clarification required for non-standard activity descriptions
4	Validation Against Institutional Standards	High consistency with institutional spending limits	93.3%	Errors occurred mainly in conditional or exception-based regulations
5	Error Detection and Feedback Clarity	Low precision in anomaly identification and vague feedback messages	45.0%	Limited anomaly classification logic and lack of explanatory feedback generation

3.2 Discussion

The findings of this study demonstrate a clear relationship between the theoretical foundations of Multi-Agent Systems (MAS) and the observed system performance, particularly highlighting the critical role of agent architecture when combined with appropriate preprocessing mechanisms in handling institutional document complexity. The relatively low score in Financial Guidelines Interpretation Accuracy (47.5%) reflects challenges commonly reported in prior studies on unstructured financial document processing, where heterogeneous formats, complex tables, and multi-layered regulatory rules constrain agent performance in the absence of robust normalization and multimodal pipelines. Consequently, improvements in preprocessing strategies, such as high-quality OCR, table normalization, and domain-adapted RAG pipelines are likely to significantly enhance guideline interpretation accuracy [16].

In contrast, the strong performance in Semantic Understanding of Activity Descriptions (90.0%) aligns well with MAS theory, particularly the principle of task specialization. The agent dedicated to semantic interpretation was able to effectively extract contextual meaning from activity descriptions and map them to appropriate financial categories. This finding supports existing literature indicating that responsibility distribution and domain-adapted embedding representations substantially improve semantic reasoning

performance in RAG-based financial systems. Therefore, designing agents with strong task specialization proves effective in domains requiring deep contextual interpretation [17].

The significant improvement in Financial Plan Generation Efficiency, where the system generated financial drafts more than eight times faster than manual processes, further illustrates the practical advantages of autonomous agents and parallel processing within MAS architectures. This outcome is consistent with broader findings on the contribution of AI to operational efficiency and accountability in institutional financial management, particularly when routine tasks are automated and integrated with validation mechanisms. As such, MAS architectures that combine agent autonomy with coordinated parallel execution can substantially reduce human administrative workload [18].

Similarly, the high score achieved in Validation Against Institutional Standards (93.3%) demonstrates the effectiveness of reactive and rule-aware agents in enforcing compliance. The validation agent's ability to automatically cross-check budget proposals against institutional cost standards reflects core MAS principles of responsiveness and inter-agent coordination. This result also aligns with studies emphasizing the importance of transparency and explainability in automated validation systems to increase stakeholder trust. Accordingly, strengthening explainable AI components within validation agents may further improve user acceptance of automated compliance outcomes [19].

However, the lower performance observed in Error Detection and Feedback Clarity (45.0%) reveals limitations in the system's current cognitive feedback mechanisms. While agents successfully detected major deviations, the limited depth and clarity of explanatory feedback reduced its practical usefulness for end users. This finding is consistent with systematic reviews of explainable AI, which highlight that decision transparency remains a critical yet underdeveloped component in many financial AI applications. Therefore, future system enhancements should focus on improving inter-agent communication protocols and developing structured, actionable explanation modules for human users [16], [19].

From a practical perspective, these findings have important implications for higher education institutions. For academic staff, the system can reduce administrative burdens associated with budgeting academic activities, allowing greater focus on teaching and research planning. In terms of institutional governance, automated validation and standardization mechanisms enhance transparency, accountability, and consistency in financial decision-making. For financial management units, the MAS-based system offers a scalable solution to improve efficiency, minimize human error, and ensure regulatory alignment, particularly in environments characterized by limited financial expertise or high administrative workloads. These implications are consistent with prior studies on AI-driven financial transformation at the organizational level [20].

Overall, this discussion confirms that integrating MAS theory with RAG-based and multimodal document understanding provides both theoretical and practical value for institutional financial planning. While certain limitations remain, particularly in complex document interpretation and feedback clarity, the results validate the suitability of a multi-agent AI approach for institutional financial contexts and clearly identify future development pathways. These include enhancing document preprocessing and normalization, strengthening explainable feedback mechanisms, and refining domain-specific RAG pipelines supported by continuous multimodal benchmarking [16], [17], [21].

4. Conclusions

This study aimed to design and evaluate a RAG-based financial management system capable of supporting institutional budgeting through automated guideline interpretation, activity-based financial planning, and validation against institutional cost standards. Built upon Ragflow, an open-source Retrieval-Augmented Generation (RAG) engine that uses deep document understanding to provide truthful question-answering from complex data the proposed system successfully integrates these three core functions into a unified multi-agent architecture. By combining natural language processing and retrieval-based reasoning, the system addresses key challenges in institutional financial planning, including human error, inconsistency in

standard application, and high dependence on manual processes. Studies indicate that AI-driven systems can enhance accuracy, efficiency, and consistency in decision support environments, even when applied to different operational domains.

The evaluation results provide clear validation that the primary research objectives have been largely achieved. The objective of generating structured financial plans based on interpreted activity needs was met, as evidenced by strong performance in financial plan generation efficiency and semantic understanding, with accuracy and efficiency scores exceeding 80%. Similarly, the objective of ensuring compliance with institutional financial standards was fulfilled through the validation mechanism, which achieved a high consistency score (93.3%), demonstrating the system's capability to automatically enforce institutional spending rules and policy constraints. These findings are consistent with prior studies highlighting the effectiveness of AI-driven systems in enhancing accuracy, efficiency, and compliance in financial planning and reporting processes.

However, the objective of fully reliable guideline interpretation across diverse document formats has not yet been completely achieved. The lower performance in financial guideline interpretation accuracy (47.8%) and adaptability to policy changes (43.5%) indicates that the system still encounters limitations when processing complex, heterogeneous, or evolving regulatory documents. This limitation reflects challenges commonly reported in RAG-based document processing and compliance-oriented AI systems, particularly when dealing with implicit rules, unstructured layouts, and frequent policy updates. These findings suggest that while the system meets its functional objectives at the planning and validation levels, further refinement is required to strengthen document comprehension robustness.

Overall, the results confirm that the proposed RAG-based multi-agent approach offers a viable and effective solution for institutional financial management, particularly in automating budget preparation and ensuring consistency with established standards. This contribution aligns with broader research on the role of AI in strengthening financial governance, transparency, and accountability within public and educational institutions. Future work will focus on enhancing document understanding mechanisms, improving adaptability to regulatory changes, and integrating real-time policy synchronization to fully realize the system's intended objectives and support more resilient, context-aware institutional financial management.

5. References

- [1] C. Tian, 'Research on Financial Management Issues and Countermeasures in Chinese Higher Education Institutions', *Proceedings of Business and Economic Studies*, vol. 7, no. 4, Art. no. 4, Aug. 2024, doi: 10.26689/pbes.v7i4.7697.
- [2] H. Hong, 'Optimization Design of Financial Shared Services Based on Improved Algorithms and Artificial Intelligence', in *2024 3rd International Conference on Data Analytics, Computing and Artificial Intelligence (ICDACAI)*, Oct. 2024, pp. 552–556. doi: 10.1109/ICDACAI65086.2024.00106.
- [3] I. E. Nikulina, E. A. Ershova, A. A. Tarabanovsky, and A. A. Zemtsov, 'Finance Planning In The University Using Information Methodology "Aris"', presented at the Information Technologies in Science, Management, Social Sphere and Medicine, Atlantis Press, May 2016, pp. 105–110. doi: 10.2991/itsmssm-16.2016.22.
- [4] N. K. D. S. Rahayu and M. A. Meitriana, 'Pengaruh Literasi Keuangan dan Sikap Keuangan Terhadap Perilaku Pengelolaan Keuangan Mahasiswa Prodi Pendidikan Ekonomi Undiksha', *Ekuitas: Jurnal Pendidikan Ekonomi*, vol. 11, no. 2, Art. no. 2, 2023, doi: 10.23887/ekuitas.v11i2.65999.
- [5] I. Irmawati and S. Aprilia, 'Ketidaksesuaian Realisasi Belanja Pemeliharaan Dengan Rencana Anggaran Menjadi Permasalahan Pembiayaan Di Sekolah', *Jurnal Penelitian Pendidikan*, vol. 24, no. 2, pp. 221–226, Aug. 2024, doi: 10.17509/jpp.v24i2.73372.

- [6] R. Ramlall and S. Grobbelaar, 'Deficiencies in the traditional budgeting process cause the negative behaviour of budgetary slacking', *South African Journal of Business Management*, vol. 55, no. 1, p. 12, Jun. 2024, doi: 10.4102/sajbm.v55i1.4348.
- [7] J. Febriantoko, *Sistem Informasi Akuntansi*. 2024.
- [8] F. Zamzami, N. D. Nusa, and I. A. Faiz, *Sistem Informasi Akuntansi*. UGM PRESS, 2021.
- [9] F. B. Limba and S. G. Sapulette, *SISTEM INFORMASI AKUNTANSI*. CV WIDINA MEDIA UTAMA, 2023. Accessed: Jun. 29, 2025. [Online]. Available: <https://repository.penerbitwidina.com/publications/564573/>
- [10] A. Amirkhani and A. H. Barshooi, 'Consensus in multi-agent systems: a review', *Artif Intell Rev*, vol. 55, no. 5, pp. 3897–3935, Jun. 2022, doi: 10.1007/s10462-021-10097-x.
- [11] R. Calegari, G. Ciatto, V. Mascardi, and A. Omicini, 'Logic-based technologies for multi-agent systems: a systematic literature review', *Auton Agent Multi-Agent Syst*, vol. 35, no. 1, p. 1, Oct. 2020, doi: 10.1007/s10458-020-09478-3.
- [12] R. C. Cardoso and A. Ferrando, 'A Review of Agent-Based Programming for Multi-Agent Systems', *Computers*, vol. 10, no. 2, Art. no. 2, Feb. 2021, doi: 10.3390/computers10020016.
- [13] J. Palanca, A. Terrasa, V. Julian, and C. Carrascosa, 'SPADE 3: Supporting the New Generation of Multi-Agent Systems', *IEEE Access*, vol. 8, pp. 182537–182549, 2020, doi: 10.1109/ACCESS.2020.3027357.
- [14] J. D. Naumann and A. M. Jenkins, 'Prototyping: The New Paradigm for Systems Development', *MIS Quarterly*, vol. 6, no. 3, pp. 29–44, 1982, doi: 10.2307/248654.
- [15] R. Budde, K. Kautz, K. Kuhlenskamp, and H. Züllighoven, *Prototyping: An Approach to Evolutionary System Development*. Springer Science & Business Media, 2012.
- [16] S. Cho, J. Moon, J. Bae, J. Kang, and S. Lee, 'A Framework for Understanding Unstructured Financial Documents Using RPA and Multimodal Approach', *Electronics*, vol. 12, no. 4, p. 939, Jan. 2023, doi: 10.3390/electronics12040939.
- [17] S. Kim, H. Song, H. Seo, and H. Kim, 'Optimizing Retrieval Strategies for Financial Question Answering Documents in Retrieval-Augmented Generation Systems', Mar. 19, 2025, *arXiv*: arXiv:2503.15191. doi: 10.48550/arXiv.2503.15191.
- [18] C. Aldemir and T. Uçma Uysal, 'Artificial Intelligence for Financial Accountability and Governance in the Public Sector: Strategic Opportunities and Challenges', *Administrative Sciences*, vol. 15, no. 2, p. 58, Feb. 2025, doi: 10.3390/admsci15020058.
- [19] N. Ammar and A. Shaban-Nejad, 'Explainable artificial intelligence recommendation system by leveraging the semantics of adverse childhood experiences: Proof-of-concept prototype development', *JMIR Medical Informatics*, vol. 8, no. 11, 2020, doi: 10.2196/18752.
- [20] A. Roy, J. Ara, S. Ghodke, and J. Akter, 'Artificial Intelligence in Corporate Financial Strategy: Transforming Long-Term Investment and Capital Budgeting Decisions', *Journal of Economics, Finance and Accounting Studies*, vol. 7, no. 5, pp. 50–59, Sep. 2025, doi: 10.32996/jefas.2025.7.5.6.
- [21] S. Zhao, Z. Jin, S. Li, and J. Gao, 'FinRAGBench-V: A Benchmark for Multimodal RAG with Visual Citation in the Financial Domain', Sep. 09, 2025, *arXiv*: arXiv:2505.17471. doi: 10.48550/arXiv.2505.17471.

- [22] K. B. P. Y. Perkasa and F. E. Purwiantono, 'Sistem Rekomendasi Jurusan Menggunakan Algoritma Naïve Bayes Gaussian Berbasis Web', *J-INTECH*, vol. 11, no. 2, pp. 361–370, Dec. 2023, doi: 10.32664/j-intech.v11i2.1090.