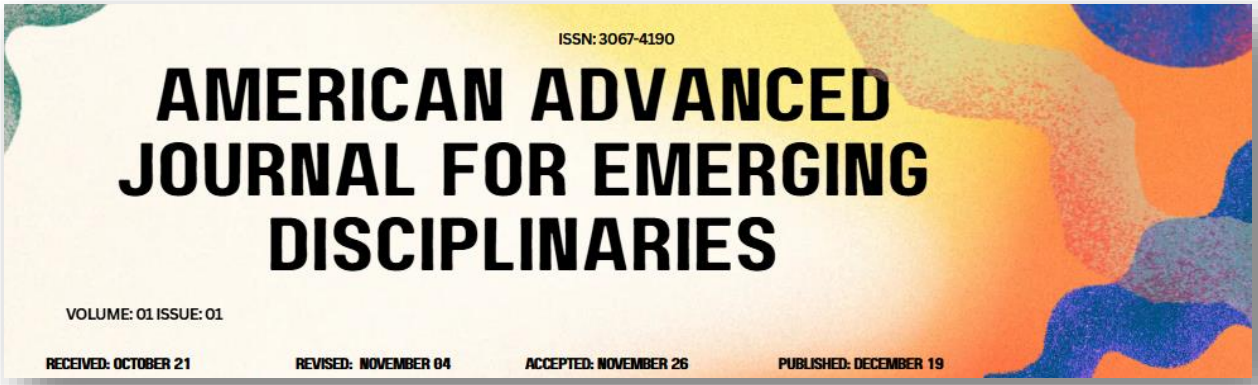

Secure Multi-Agent RAG for Enterprise Automation

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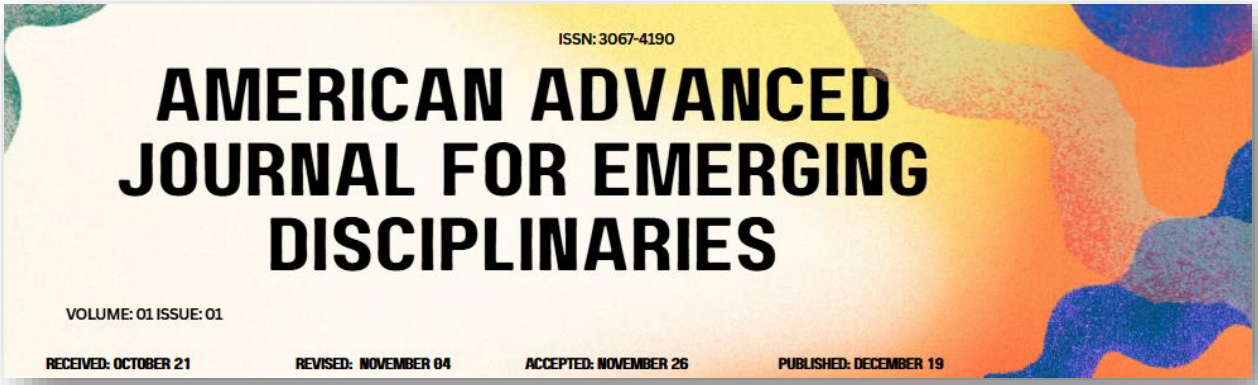
Abstract

Automating enterprise operations offers the promise of substantially increased agility and competitive advantage. However, enterprises are still constrained in their ability to leverage such innovations for many operations beyond routine transaction processing. Security and oversight requirements ordinarily preclude the deployment of advanced AI techniques in data-rich enterprise context. Recently proposed retrieval-augmented AI designs provide a means to address some of these limitations, enabling formal institutions to enforce policy and mitigate risk, even when operations require complex reasoning and data synthesis. Yet no formal framework for retrieval-augmented multi-agent systems exists. Such a framework is necessary to support comprehensive validation and evaluation of emerging systems while also guiding practical implementations. Providing such an underpinning costitutes the principal contribution of this work.

The contributions of this study formalize the design of retrieval-augmented multi-agent systems. A foundation architectural model is defined, linking agent modularity, open interfaces, and scalable operation to retrieval-augmented operation. Grounding the architecture for enterprise contexts supports a comprehensive theory of retrieval-augmented multi-agent systems. Security and governed operation are addressed via consideration of (1) agent role definitions; (2) data access and provenance management; (3) strategic behaviour, information source maintenance, and understandable queries. Together, these aspects provide the procedural scaffolding necessary for scientifically-grounded operational and performance evaluations, endorsing the continued development of novel retrieval-augmented multi-agent systems for enterprise automation.

Keywords: Enterprise Automation, Multi Agent, Retrieval Augmented, AI Systems, Agent Architecture, Data Retrieval, Knowledge Systems, Decision Making, Data Governance, Data Provenance, System Security, Risk Mitigation, Policy Enforcement, Scalable Systems, Modular Design, Open Interfaces, Information Access, Query Processing, System Evaluation, Intelligent Systems.

1. Introduction

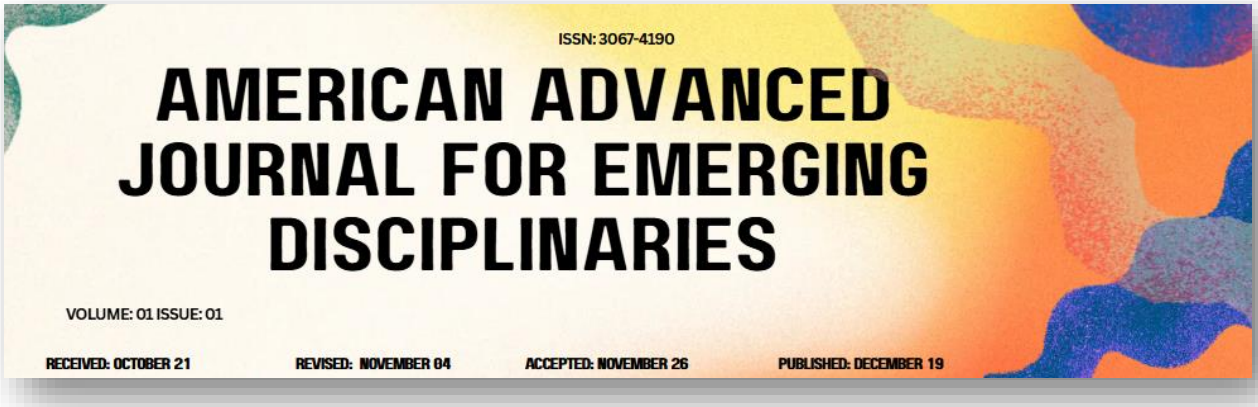


The automation of enterprise processes is increasingly supported by artificial intelligence (AI) systems. Serious concerns are, however, raised by the deployment of such solutions in security-critical infrastructures. There is a pressing need for new approaches that provide a more formalized and robust basis for enterprise automation. Recent research on retrieval-augmented AI models points in a promising direction. Methods and tools linking such AI systems to multi-agent systems (MASs) offer a powerful theoretical foundation. In the light of restrictions and expectations governing automation in enterprises, this theoretical groundwork helps identify opportunities for improvement. For instance, secure and governed automation conformed to the retrieval-augmented paradigm entails architectural specifications, guidance for performance assessment, a roadmap for practical adoption, and measures of alignment with security and compliance requirements.

Enterprise automation combines domain-specific processes, IT systems, and data sources, such that recurring tasks are executed with minimal or no user intervention. The processes can be automated using state-of-the-art AI models provided that explicit definitions, constraints, and domain knowledge are accessible. Such clear delineation is lacking in many business functions underpinning sales and marketing of services, products development, and operations. Significant parts of these critical areas must therefore remain dependent on manual execution or, more realistically, on limited support from conventional applications. Agents are software entities that play specific roles in automation enabled by AI. Dedicated technologies such as Robotic Process Automation (RPA) are designed for automation of simple and predictable tasks, where success can be easily predicted. AI Agents represent a broader, more generalizable approach based on Mult-Agent Systems (MASs).

2. Background

The retrieval-augmented multi-agent system concept connects two recent streams of AI research that share an explicit need for security, compliance, and governance within enterprise environments. The first stream concern research into enterprise automation in which business processes are automated using swarms of intelligent software agents with specialized roles. The second stream investigates how retrieval-augmented generation techniques can be applied to leverage publicly available, domain-specific data to improve the capabilities of AI systems. In either context, the retrieval components are implicit and none of the research contributors propose, analyze, evaluate, or discuss the implications of the security and governance constraints. Addressing these blind spots, this research thread investigates the security and



compliance requirements of retrieval-augmented enterprise automation systems with the aim of developing suitable evaluation methodologies and best practices guidelines.

The proposed work takes the form of a theoretical exploration that provides a foundation for future empirical work. Retention and governance concerns are integrated into the core architectural framework of retrieval-augmented multi-agent systems, and a theoretical description of enterprise environments introduces the security and compliance requirements that must be addressed when conducting a structured risk assessment within these domains.

2.1. Multi-Agent Systems in Enterprise Automation

Agent-based systems for online tasks—service provisioning, transport logistics, and food delivery—leverage public information and infrastructure. Given sufficient time, they return optimal solutions. Real-time requirements impose tighter timelines and, hence, necessitate alternative approaches supported by specialized knowledge. In the enterprise context, the set of requirements is more demanding—solutions must be reliable, secured, and compliant with privacy regulations. Such criteria shape how these knowledge retrieval facilities operate and how actors apply the retrieved information into task execution. Moreover, recent theoretical directions in intelligent information systems propose more robust replication schemes that further support security and privacy requirements.

To clarify, the primary objective is not to fulfil online tasks in a secure and compliant manner; rather, the focus is on devising secure and governed enterprise automation mechanisms, relying on a retrieval-augmented multi-agent system. In this respect, the concrete goals of the theoretical exposition concern specifying the core principles that direct the design of an enterprise system and formalizing the role of knowledge retrieval in supporting the automated execution of enterprise online tasks while enforcing security and compliance requirements.

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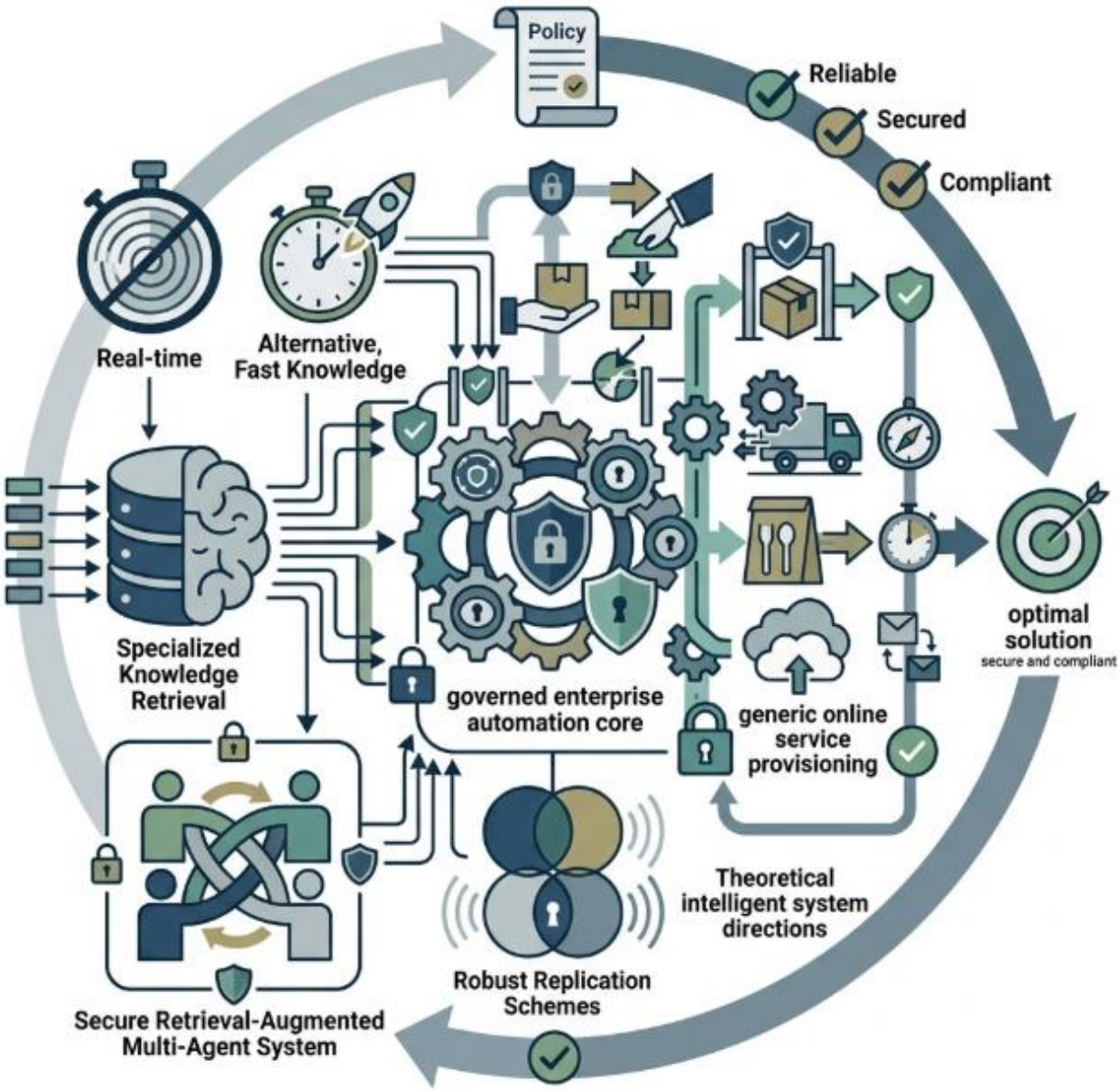


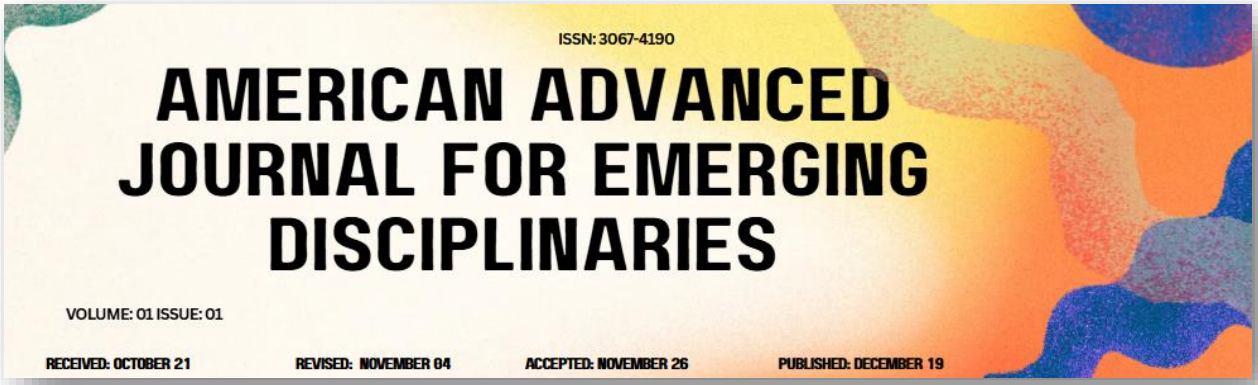


Fig 1: Governed Enterprise Automation: A Retrieval-Augmented Multi-Agent Framework for Secure, Real-Time Task Execution

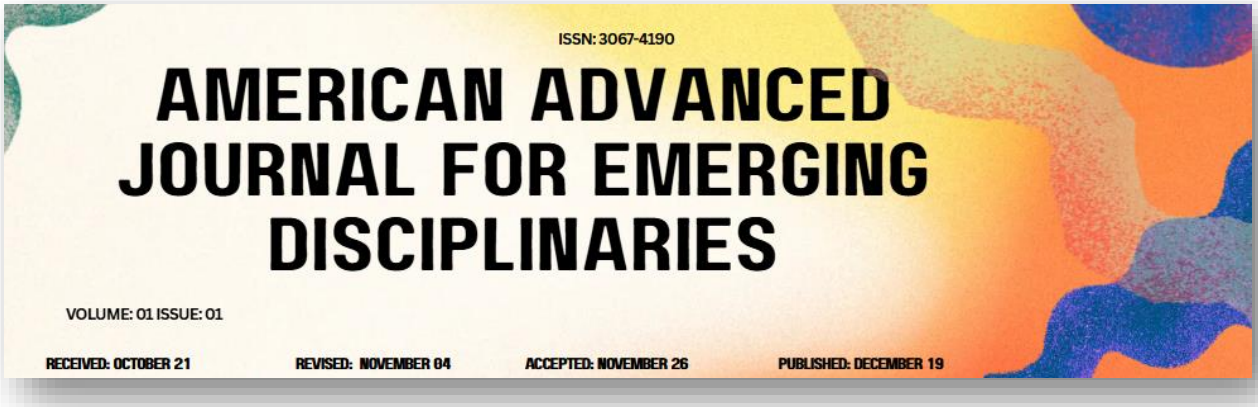
2.2. Retrieval-Augmented AI Paradigms

Most enterprise automation solutions are relatively self-contained. However, enterprise resources can also be exposed to outside agents to extend automation beyond narrow task boundaries or connect to business partners such as customers and suppliers. In these cases, both security and trust are critical factors. It is important to ensure that data access and use follows enterprise policies, any access requests can be audited internally and by external authorities, and that appropriate compliance standard requirements are satisfied at access time. Security also must take into account possible intrusion scenarios affecting the automation infrastructure. Failure of a single agent, whether due to equipment failure or malicious action, should not lead to failure of the entire automation system.

Retrieval-augmented AI paradigms enhance intelligence capabilities while reducing the necessary cognitive load of agents. Enterprise automation is all about lowering the required cognitive load for the execution of various operations by the enterprise, be it communication, hacks, or even managing complex problems during emergencies. While the main caveat in enterprise automation remains the scalability and enablement of skillsets of agents, retrieval-augmented AI solves it by acting as a full kit of end-to-end services. These paradigms allow the very complex tasks, such as generating a virtual customer at scale, to be handled but with the help of sophisticated AI agents that provide ability beyond the skillset of a single agent while lowering the load for the agent and covering every possible aspect of that request.

3. Methodology

The research design encompasses an extensive literature review supplemented with a multi-modal approach to integrating security and governance into enterprise processes and augmenting corporate knowledge bases using Retrieval-Augmented Generation (RAG). Primary research develops the foundational concepts of retrieval-augmented multi-agent systems (RAMAS) for secure and governed enterprise automation. Exemplifying industrial needs, practical considerations involved in addressing these concepts for enterprise-wide deployment and with support for retention, governance, and compliance represent crucial secondary explorations guiding applied research. Both strands affirm the ability of RAMAS to cope with



security concerns in processes performed by unconstrained agents, while also enabling Agent-Based Modelling and extreme risk assessment of compliance and enterprise-wide security.

Specific publications advance the examination of security by focusing on the economic dimension of an enterprise – its cash flow – or on external factors assessed through the resilience of industrial clusters and the businesses within them against adverse events. Other explorations employ noise analysis – an accepted methodology in failure prediction and control – to determine how compounds and mixtures of noise sources can be retained while still maintaining compliance with SLAs. Research systematises external assurance for standard compliance by developing methods for risk assessments using automated scoring techniques applicable to the potential impact on all enterprise processes resulting from the combined action of all the agents participating in a given process, whether as performing agents or as source of fail-over data.

3.1. Core Architectural Frameworks

A core architectural framework is presented to serve as the foundation of an agent-based system encompassing the security and governance constraints dictated by the need for trustworthy enterprise automation. The resulting layered architecture enables retrieval-augmented multi-agent systems, where the retrieval infrastructure accommodates enterprise considerations of security, latency, and freshness.

The architectural approach involves three key aspects. The first describes the agent roles and collaboration protocols, specifying the responsibilities of each agent type, their interrelations, the mutual trust required, and how they coordinate their tasks. The second considers the way in which agents access information from the underlying data infrastructure. Policies define which agent can obtain which information from which source, while auditing provides compliance with such policies. The third facet focuses on the indexes and caching mechanisms that facilitate efficient information retrieval, including data schemas, latency targets, freshness guarantees, and the construction of dynamic knowledge bases that integrate information from multiple sources, highlighting reliability aspects in terms of versioning and source credibility.

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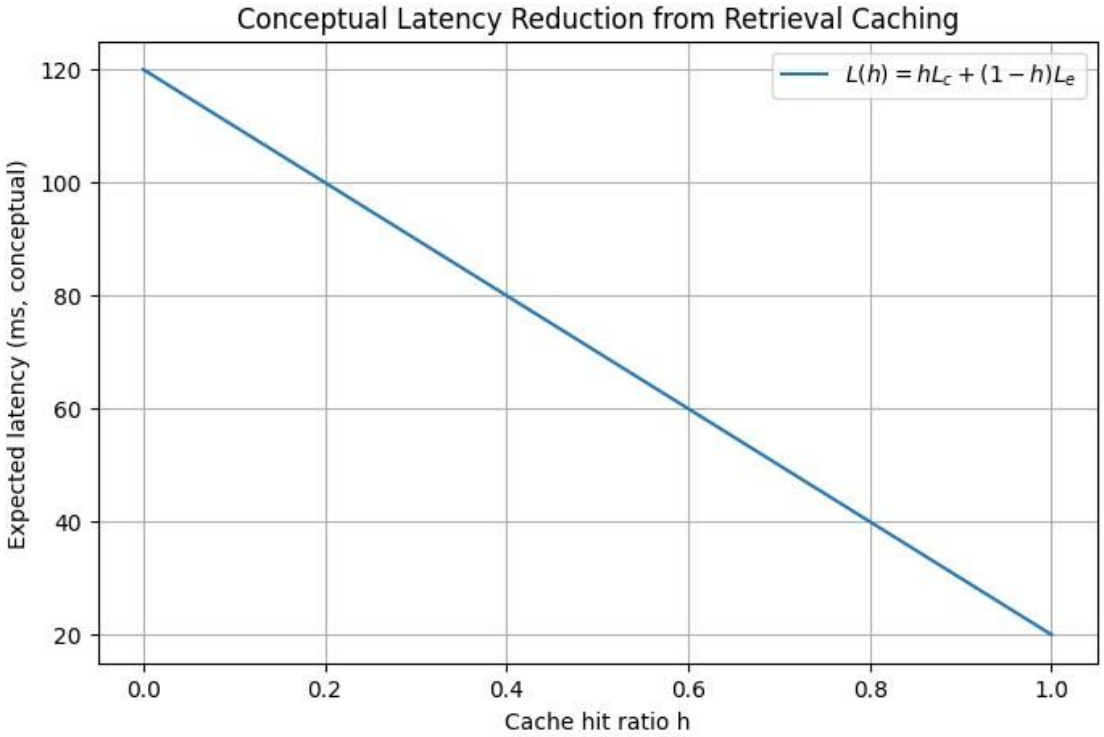
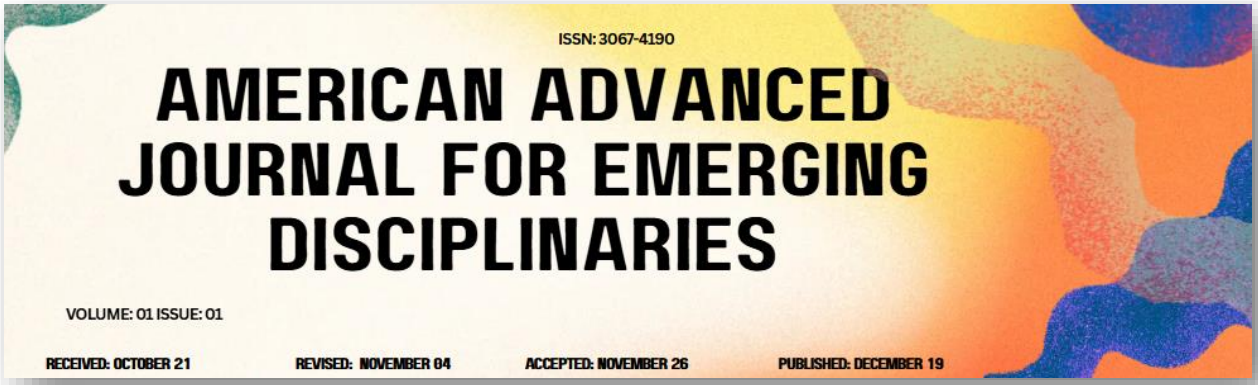


4. Objective of the Study

The construction of a multi-agent system enabling autonomous task execution in enterprise settings without human intervention remains elusive. When such systems are deployed within enterprises for automation, security, and governance considerations necessitate that the operations of the multi-agent system be transformed. These are typically hard-coded into interacting agents by choice, significantly impairing creative capabilities beyond what has been conceived by human authors. Retrieval-augmented generation systems address this limitation, but the exploitation of retrieval technology in a multi-agent context is neither widely theorized nor investigated. Hence, the objective of this study is to define the architectural principles and mechanisms underpinning retrieval-augmented application of multi-agent systems. The theory operates entirely within the AI-safety realm defined by these three aspects: data access, provenance management, and compliance control. By maintaining a no-authorship-flaw focus, these constraints enable real-world applications.



Enterprise automation has evolved through the introduction and deployment of information technologies toward a full brain-integration automation, supporting business operations with immediate execution of commands without human intervention. Today, this brain is embodied by the concept of a multi-agent system interacting in an enterprise for task execution. Yet, the more tasks a multi-agent system performs, the more the practical autonomy of the multi-agent system declines, as the different actions and executions are frequently hard-coded in the different interacting agents. Hence, human authors limit the creative capacity of the multi-agent system. Recently, this aspect has been tackled with the concept of retrieval-augmented generation, where the results generated by a generative model are enriched with external knowledge.

Equation 1: Data-flow equations

1.1 Source → Cache → Dynamic Knowledge Base → Agent Output

Sources → Cache / Index → Dynamic KB → Agent Decision / Output

Let:

- $x_j(t)$: raw information from source j at time t
- $c_j(t)$: cached representation of source j
- $k_j(t)$: curated / integrated knowledge-base entry
- $y_i(t)$: output of agent i

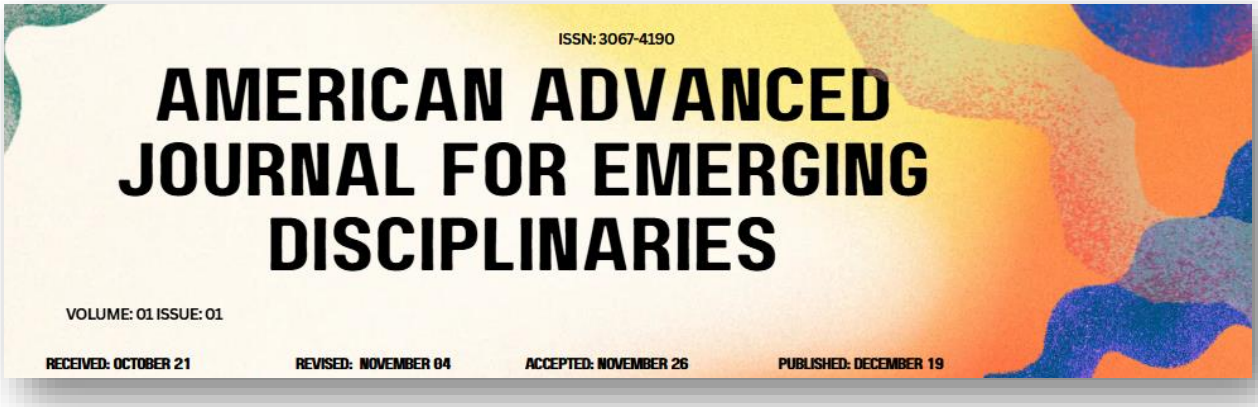
Step 1: Cache refresh rule

If source j is refreshed at time t, cache content becomes source content:

$$c_j(t) = x_j(t).$$

If not refreshed, cached content remains prior content:

$$c_j(t) = c_j(t - \Delta t).$$



This can be written compactly with a refresh indicator $u_j(t) \in \{0,1\}$:

$$c_j(t) = u_j(t)x_j(t) + \big(1 - u_j(t)\big)\, c_j(t - \Delta t).$$

Step 2: Knowledge-base integration

The dynamic knowledge base integrates cached items:

$$k(t) = \mathcal{I}\big(c_1(t), c_2(t), \dots, c_m(t)\big),$$

where $\mathcal{I}$ is the integration/fusion operator.

Step 3: Agent retrieval and decision

Agent i receives retrieved context $r_i(t)$:

$$r_i(t) = \mathcal{R}_i\big(k(t), q_i(t)\big),$$

where $q_i(t)$ is the query.

Its output is then:

$$y_i(t) = \mathcal{G}_i\big(r_i(t), z_i(t)\big),$$

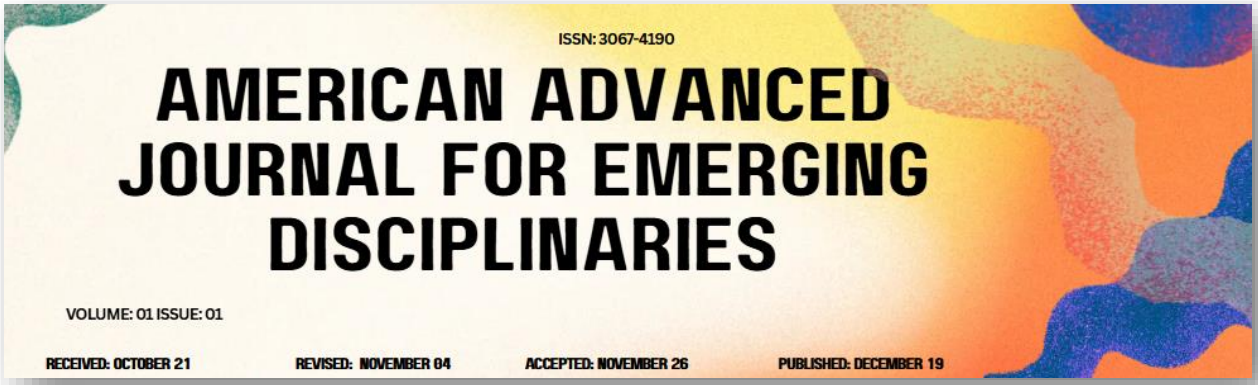
where $z_i(t)$ is local state / task context.

Final pipeline formula

$$y_i(t) = \mathcal{G}_i\left(\mathcal{R}_i\left(\mathcal{I}\big(c_1(t), \dots, c_m(t)\big), q_i(t)\right), z_i(t)\right).$$

4.1. Research Aims and Intended Contributions

Secure and governed environments impede enterprise automation by limiting access to mission data and rules while introducing trust boundaries. Knowledge retrieval approaches securely and efficiently provide missing information. A retrieval-augmented multi-agent architecture applies these principles, distributing cooperation among functionally heterogeneous agents and ensuring security, compliance, and execution speed. The research synthesises a



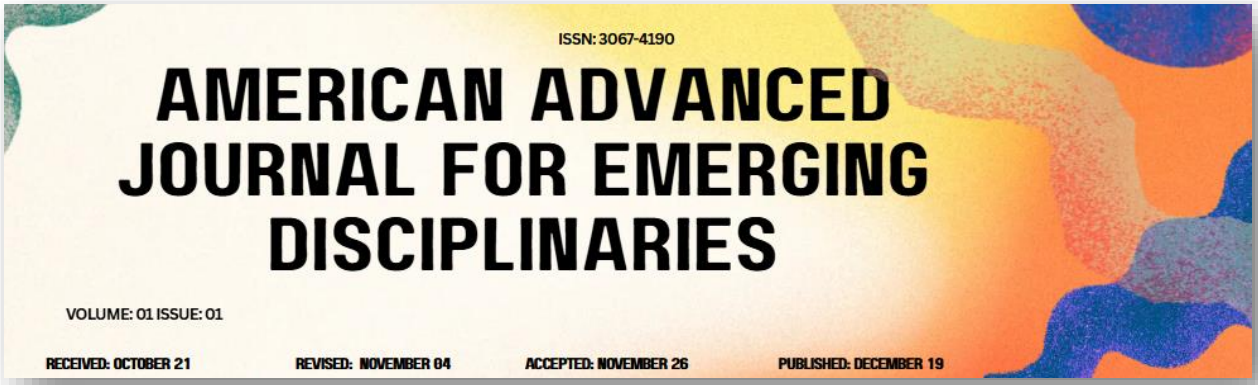
theoretical framework for such systems and explicitly specifies security, governance, and retrieval considerations.

When secure or governed enterprise automation becomes possible, alternative solutions reduce execution speed, bypass formal execution or control, or ignore compliance and security concerns. An added layer of retrieval-augmented multi-agent cooperation satisfies the main objectives, with agents focusing on their knowledge domain and acting independently and in parallel. Communication bandwidth becomes irrelevant. Providing the knowledge needed for each task, even if large late-bound datasets stored and indexed in the enterprise are partially out-of-date or inaccurate, allows high task-completion speed. The delays introduced by respecting policy requirements become negligible.

5. Research Summary

The paper articulates a theoretical foundation for retrieval-augmented multi-agent systems and analyses how the proposed ideas can assist enterprise automation while taking security and governance requirements into account. Enterprise automation holds the promise of increasing operational efficiency, decreasing costs, and enabling easier accomplishment of repetitive tasks. However, the adoption of these solutions has been limited by the difficulty of integrating the different existing systems, the inability of the resulting orchestrations to react to unexpected situations, and the challenges that accessing all services in a secure and governed way entails. Retrieval-augmented multi-agent systems are a new approach to multi-agent systems that attempts to combine heterogeneous agent systems, optimization in the form of AI planning, and sophisticated knowledge retrieval and integration mechanisms.

Key ideas from the architectural foundations for retrieval-augmented multi-agent systems are mapped to how enterprise automation can benefit from supporting security and governance requirements. Modularity, interoperability, and scalability are discussed, together with mechanisms for knowledge indexing, caching, provenance management, and dynamic quality assessment. The treatment of agent roles and collaboration protocols, data access and provenance tracking, and interaction patterns further clarify how retrieval-augmented multi-agent systems can contribute to enterprise automation under security and governance constraints. Together, these elements showcase the potential of retrieval-augmented multi-agent systems within the context of security- and governance-aware enterprise automation.



5.1. Theoretical Framework for Retrieval-Augmented Multi-Agent Systems

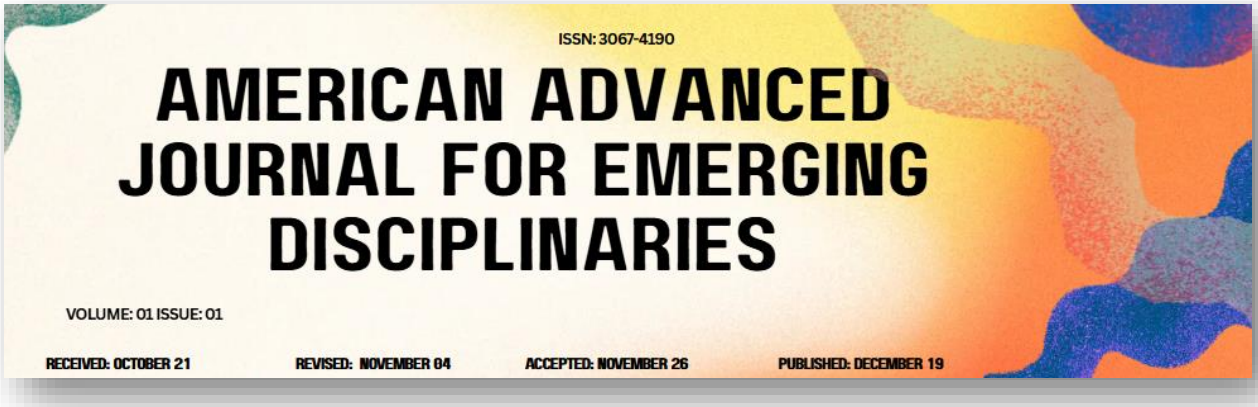
Most theoretical framing relies heavily on the notions of modularity, interoperability, and platform independence, while considering the extensive use of retrieval-augmented Large Language Models as a key development for overcoming some intrinsic limitations of self-contained artificial intelligence systems. Specific elements such as knowledge retrieval, user interface design, and learning have emerged as increasingly important research topics. These must be present in any multi-agent setup but are also relevant in self-contained systems.

Consequently, a retrieval-augmented multi-agent system can be defined as a system enabling a group of agents equipped with a large array of specialized skills and models, making dedicated decisions for a specific topic and capable of task execution and coordination, but without the need of executing always-on agents. Multi-modal action is another essential aspect, as agents are designed to work as a team, supporting both execution and supervision roles, according to the application and the working context. Agents can have specific tasks, such as gathering information, configuring monitoring visualizations, and executing plans, or more general roles, such as acting as knowledge portals facing external agents or end users. Having trustworthy agents, augmented with specialized models capable of risk assessment, interaction with humans and other systems through negotiation, and an expert role in both production and supervision, enables a highly secure working environment.

6. Theoretical Foundations of Retrieval-Augmented Multi-Agent Systems

Architectural principles dictate that retrieval-augmented multi-agent systems be modularly structured, allow for the concurrent operation of multiple independent instances, and support heterogeneous components and external resources, such as algorithms, subsystems, source systems, controllers, and supervisory systems. These properties improve fault-tolerance and allow for distribution across localized infrastructures, avoiding higher latency, lower responsiveness, and increased potential failure of geographically distant infrastructures. Modularity enables straightforward replacement of MAC layers, within separate clusters, as MAC-specific solutions, e.g. for legal negotiations, emerge without hindering maintenance or replacement of other components.

Multi-Agent Systems can communicate and negotiate with each other using a message broker layer or brokered Topic Messaging. The communication broker has the autonomy to



decide which agent should react to each request instead of agents directly addressing each other. This further reduces latency and improves overall response time since geographically closer agents are chosen to fulfill requests. Security and trust relationships can also be handled at the message broker itself. Communication topics and structures can be built in such a way that each agent subscribes only to the topics it is interested in, thus filtering out messages that are not relevant. It can also publish these messages back into the broker for other agents that would need that information.

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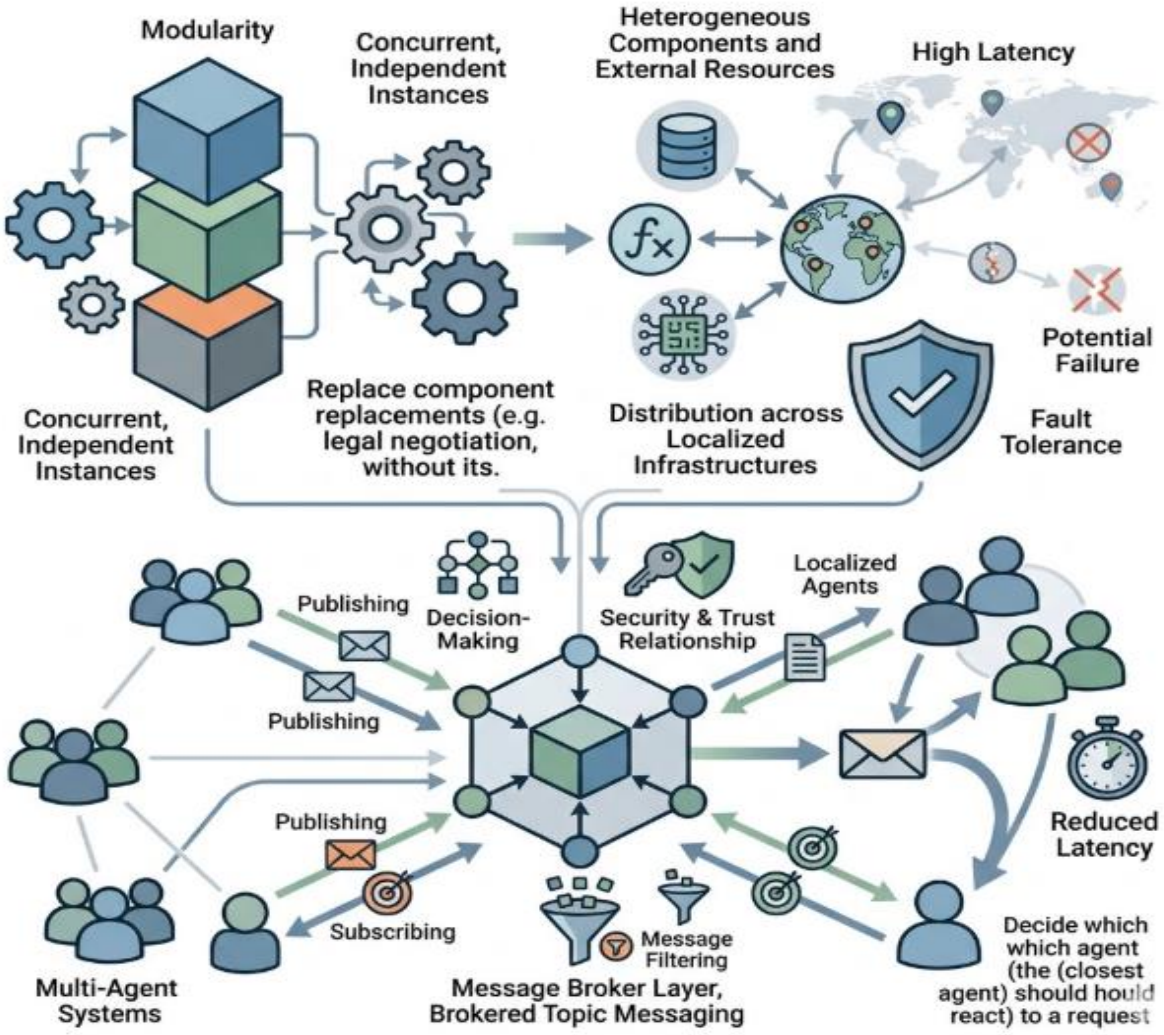
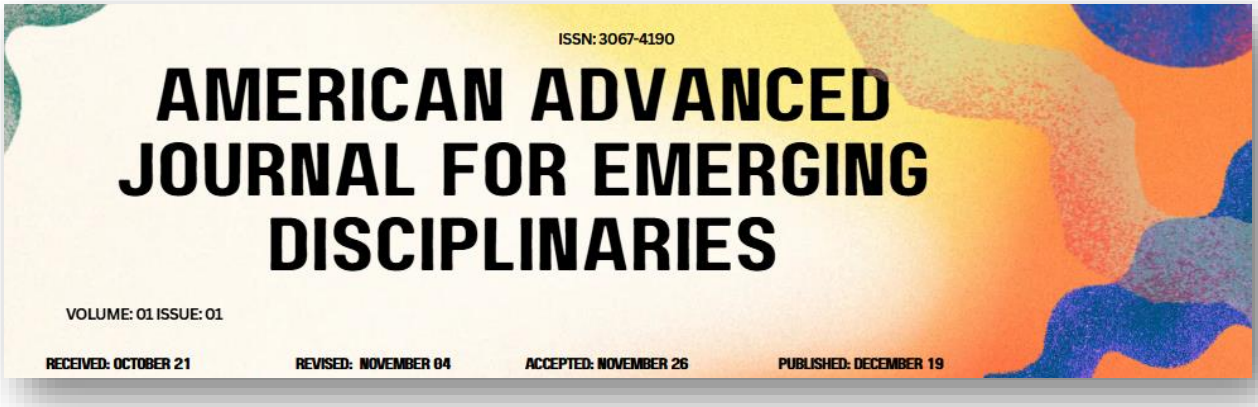


Fig 2: A Modularity-First Architecture for Low-Latency, Fault-Tolerant, Retrieval-Augmented Multi-Agent Systems (RA-MAS) with Broker-Mediated Interoperability

6.1. Architectural Principles



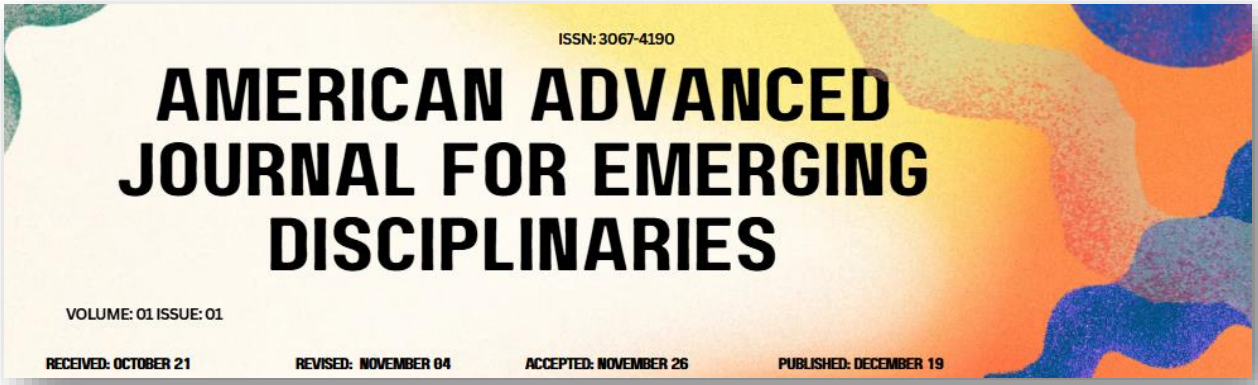
Modularity, interoperability, and scalability are key properties of retrieval-augmented multi-agent systems. A modular structure encourages the extensive use of off-the-shelf components, which simplifies customisation and enables the development of a multi-agent marketplace. Interoperability allows components to work together with minimal engineering effort, hence facilitating the use of different components, applications, tools, and protocols. It also enables the sharing of information and the creation of synergies across different enterprise applications. Scalability allows the service capacity to extend beyond the physical limitations of dedicated installations.

The absence of a global data repository motivates a modular architecture based on distributed knowledge sources and agents indexed by domain and knowledge type. Indexing and caching approaches manage the knowledge retrieval process. A combination of temporal and session-based caching is used to keep the cached information fresh. A highly available architecture is realised through a combination of a master-slave structure and a peer-to-peer network. A task-allocation mechanism allocates tasks based on agent priorities and estimated completion times.

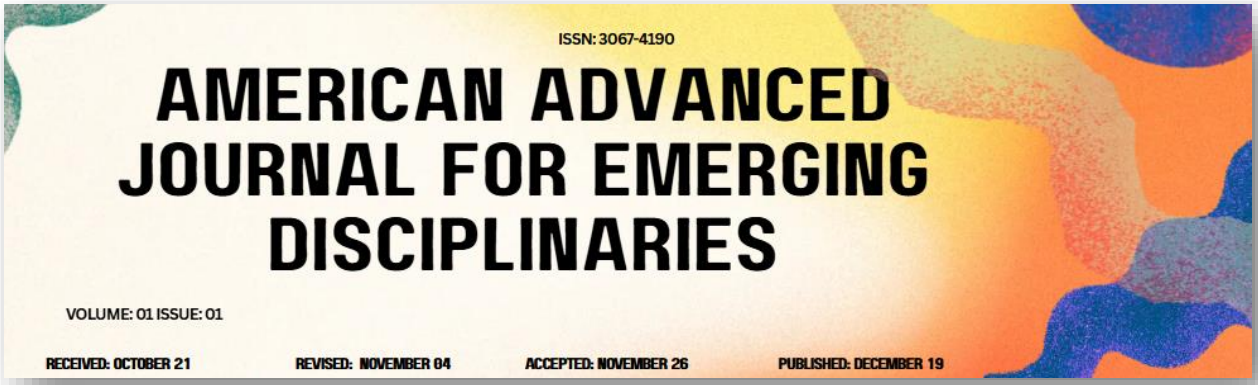
6.2. Knowledge Retrieval and Integration Mechanisms

Indexing structures for enterprise-specific knowledge repositories must support efficient querying, responsive operation, and rapid adaptation to changes. Provenance information remains essential for security and governance requirements. A pivotal feature of the retrieval process is the integration of results received from various sources. Guarantees are needed that fused data remain logically consistent and fused responses derived from suppliers of differing reliability are appropriately weighted.

Retrieval of relevant information from data caches and dynamic knowledge bases must occur in response to question-answering and decision-support requests. For every specific type of query or request, parameters must indicate desirable response characteristics, such as the maximum permissible latency, the degree of freshness, and the level of reliability required for the answer to the query or question. Control measures on the freshness of cached answers and continuously updating dynamic knowledge bases must align with ongoing response time requirements and resource availability.



Symbol	Meaning	Domain
i	Agent index	$1, \dots, n$
j	Source index	$1, \dots, m$
k	Task index	$1, \dots, K$
h	Cache hit ratio	$[0,1]$
L_c	Cache-hit latency	> 0
L_e	External retrieval latency	> 0
L	Expected retrieval latency	> 0
a	Data age	≥ 0
$F(a)$	Freshness score	$[0,1]$
λ	Freshness decay constant	> 0
r_j	Reliability / credibility of source j	$[0,1]$
x_j	Value returned by source j	task dependent
$\hat{x}$	Fused estimate	task dependent
t_i	Trust score of agent i	$[0,1]$
p_k	Task priority	normalized $[0,1]$
d_k	Deadline for task k	> 0
e_{ik}	Estimated completion time of agent i on task k	> 0
a_i	Availability of agent i	$[0,1]$
s_{ik}	Composite assignment score	$\mathbb{R}$
q	Query	symbolic
$\pi(q,i)$	Policy decision for agent i on query q	$\{0,1\}$
P	Number of policy-compliant operations	integer
N	Total operations	integer
S_{impl}	Implementation Security	$[0,1]$



Symbol	Meaning	Domain
D_{ctrl}	Operation Data Control	[0,1]
ϕ	Operation Control Factor	> 0
R_k	Risk score of task k	[0,1]
C	Total cost	≥ 0
p_f	Failure probability of one agent	[0,1]
b	Number of backups	integer

7. System Architecture for Secure Enterprise Automation

In agent-based enterprise automation, the heterogeneity of task execution and the security and governance requirements characteristic of these environments demand a unifying conceptual framework connecting the agents, orchestration logic, and addressed tasks. Trust in the behavior of agents, whether internally or externally, not only affects the nature of collaboration protocols but also implies additional requirements for data sharing, access control, and infrastructure usage.

A complete agent architecture framework for enterprise automation has a distinct target: make the retrieval properties evident, allowing non-expert stakeholders to determine whether the intended objectives have been satisfied. Data security, compliance with governance and regulatory requirements, risk mitigation, and SLA satisfaction are all fulfillment criteria for an efficient enterprise automation solution, establishing the practical validation of the usefulness of the scientific contribution. The subsequent analysis focuses first on the allocation and negotiation phases, then on the data access and caching processes, and finally on how knowledge retrieval shapes internal interactions. Ideally, these aspects should be studied jointly; however, the current decomposition facilitates practical reasoning and thus seeks to show how the different parts of the system support its operation without focusing exclusively on security or efficiency.

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Equation 2: Query latency, caching, and freshness

2.1 Expected latency under cache hits and misses

Let:

- h: probability of cache hit
- L_c: latency if cache hit occurs
- L_e: latency if cache miss causes external retrieval

There are only two mutually exclusive cases:

1. Hit occurs with probability h, latency L_c
2. Miss occurs with probability $1 - h$, latency L_e

By expectation:

$$L = hL_c + (1 - h)L_e.$$

Simplify

$$L = L_e - h(L_e - L_c).$$

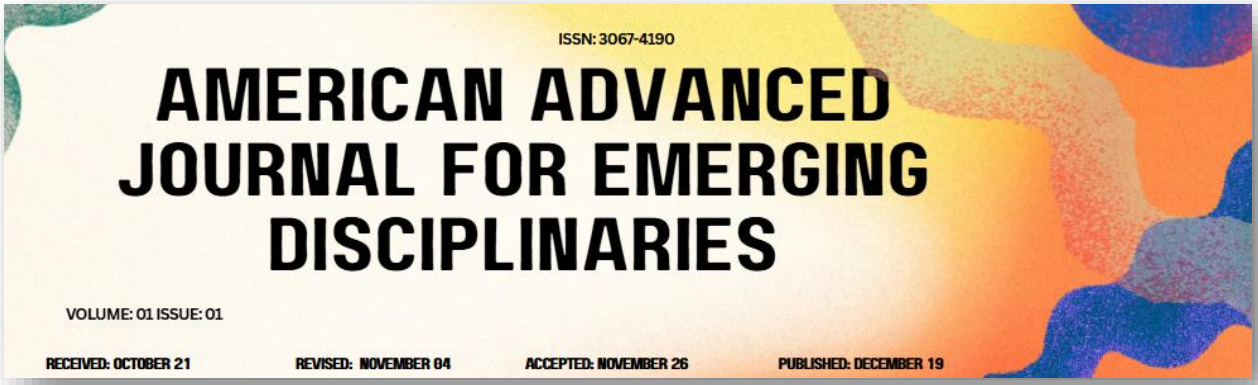
2.2 Freshness as a function of age

Let:

- a: age of the cached item
- $F(a)$: freshness score
- $\lambda > 0$: decay rate

Reasonable constraints from the paper:

1. Maximum freshness at age zero: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$F(0) = 1$

2. Freshness decreases as age increases:

$\frac{dF}{da} < 0$

3. Decay rate proportional to current freshness:

$\frac{dF}{da} = -\lambda F$

Solve:

$$\frac{dF}{F} = -\lambda\, da$$

Integrate:

$\int \frac{1}{F}\, dF = -\lambda \int da \ \ln F = -\lambda a + C$

Apply $F(0) = 1$:

$$\ln 1 = C = 0$$

Hence:

$$F(a) = e^{-\lambda a}.$$

7.1. Agent Roles and Collaboration Protocols

Multi-agent systems rely on agents' concurrent operation to achieve their respective goals and satisfy their requirements. Agent collaboration arises naturally when their goals are complementary. This section defines potential agent roles in cloud service environments, including requirements that give rise to collaborations, protocols for role assignment, simplicity, and management of prerequisites. Security and efficiency considerations influence trust assignment to potential peers and dictate failure-handling strategies.

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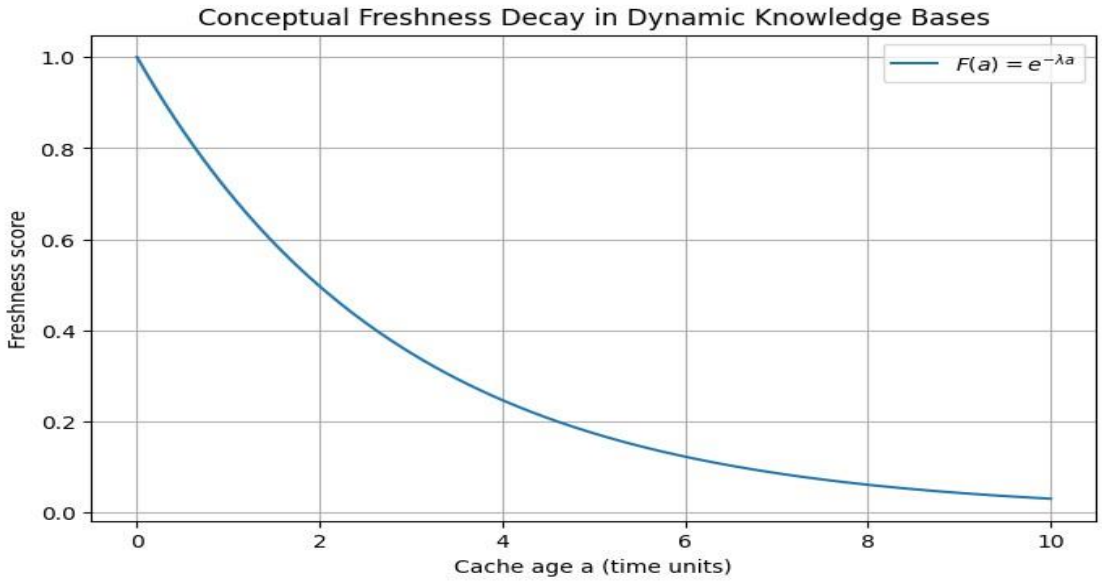
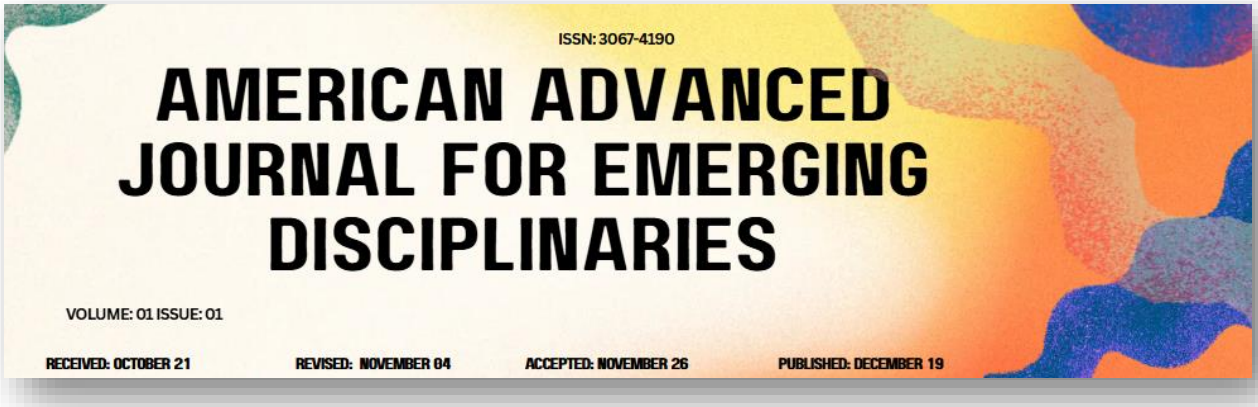
Public clouds present several forms of risk that require proactive management, including the processing of sensitive data by untrusted parties, service denials, implementation errors in programming module, and data unavailability because of performance bottlenecks, sudden usage surges, or different usage patterns by the cloud system. The task assignment mechanism can therefore assign sensitive-data-processing tasks only to trustworthy agents and prioritize such agents in SLA-sensitive task allocations. Furthermore, recovery from task failure is simplified because the trust module indicates potential fallback agents.



7.2. Data Access, Provenance, and Access Control

The interaction patterns of retrieval-augmented multi-agent systems address enterprise security and governance concerns by formalizing the provenance of data shared among agents and restricting data access according a well-defined policy that is enforced by a specialized module. Every agent in the system has the capability of producing or consuming information. Furthermore, agents can parallelize an information consumption task across multiple sources that provide diverse perspectives over a topic area such as software libraries or machine learning models. Fulfilling the latter requires trust between the agents, which is represented in the system by a trust score. Whenever an agent needs to consume information, its trust profile is the basis to



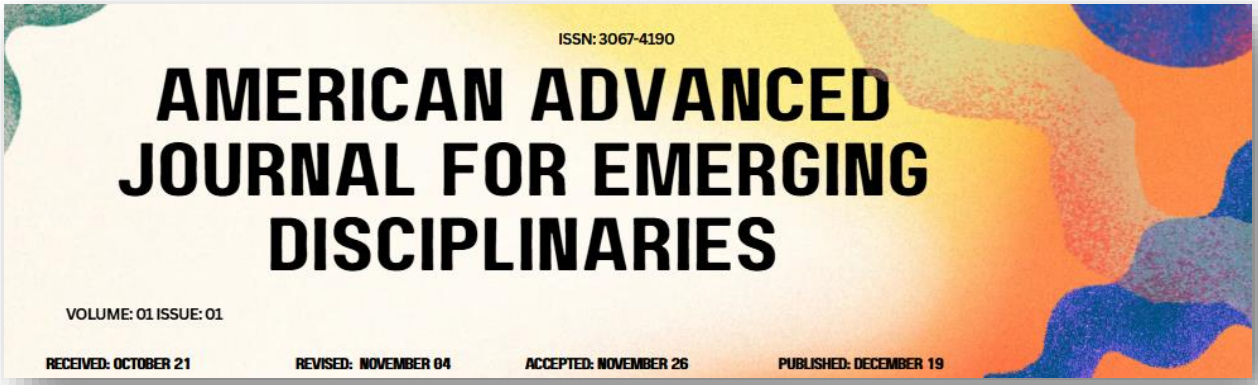
determine which agents to query. A negotiation process enables agents to distribute the computing load imposed by time-consuming tasks, and task allocation considers the trust scores as additional priority criteria. Coordination protocols have been formulated to integrate task outputs produced by independent agents while effectively handling task failures or missed deadlines.

Three main challenges arise when developing the patterns that orchestrate information data production and consumption between agents. Agents must be able to produce information and share it with other agents. Provenance information is necessary to distinguish the origins of the data available for different agents eventually consuming it. Information access policies must be established to guarantee that only users authorized with a specific role can access or leverage the information. With these procedures formalized during the design of the interaction patterns, production and consumption of data can be achieved while ensuring the security and governance conditions.

8. Retrieval Strategies for Enterprise Contexts

Enterprise AI systems are often deployed to carry out seldom-executed tasks that are crucial for business operations: risk assessment, compliance verification, supplier credibility checks, security testing, and so on. Besides being seldom executed, these tasks must satisfy stringent latency requirements and data freshness requirements that vary across queries. For instance, a Hotmail customer may be the target of a phishing attack with a forgery message containing a malicious URL that redirects the user to the profile page of the phishing site. Since internet users are constantly receiving e-mails, the latent period of the phishing service on the Internet may extend for very few minutes. Thus, the time taken for phishing site detection is one critical factor affecting the detection probability. Phishing site detection will succeed at a particular rate if the detection time is much smaller than the latent period of such sites. Therefore, for the task of phishing site detection, the freshness of the knowledge is crictcal. In contrast, the detection of bank fraud requires the knowledge sources to be accurate. Caching erroneous data during detection will lead to severe losses.

Due to the above characteristics, the knowledge-base used by the system should be dynamically built by periodically updating the data using the best possible sources. Since the sources may not provide correct information with a very high probability, the information from



different sources is also not equally reliable, and it changes over time, the issues of reliability and versioning must also be addressed when building such a dynamic knowledge base.

8.1. Indexing, Caching, and Query Processing

Analysis and processing of enterprise data in a timely manner is a requirement emphasized by all large organizations. In information retrieval, latency corresponds to how long it takes to return the result set of a query. Freshness is related to how new the information is and is indicated by the time elapsed from the most recent version of the data stored in the source system. As the freshness of the response is reduced, the size or number of items considered for processing increases. Therefore, three aspects must be specified to ensure an adequate trade-off among these three factors. First, the information schema must be defined, including the type of RDF properties that will be retained in the cache. Second, the storage size allocated for cached information must be established, specifying the maximum cache size in bytes or the maximum number of records. Third, the information-aging model must be defined. The information must be dynamically indexed at the start or end of the process, depending on the freshness requirements, available resources, and number of accessible sources. Freshness guarantees must take precedence over availability or other aspects in a way that aligns with the service-level agreement defined for a cache query.

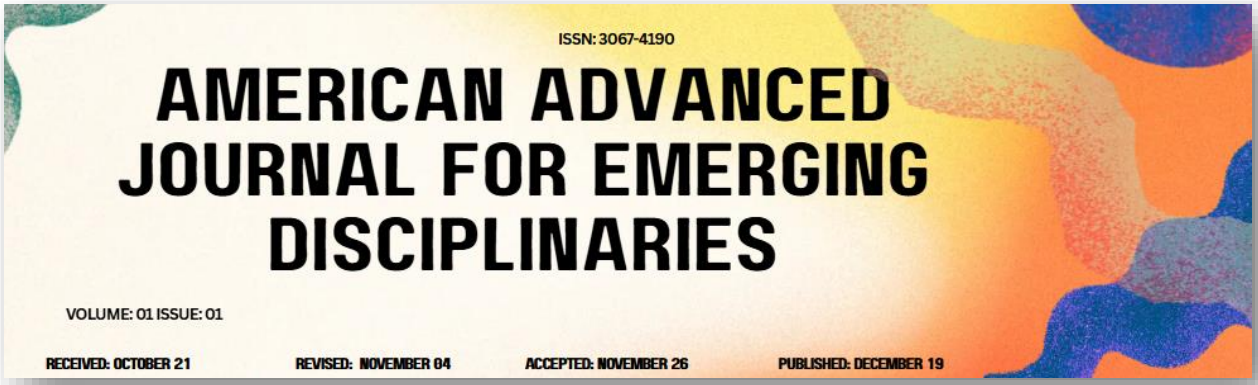
When the caching system cannot respond to a query, the latency can no longer be defined on a per-query basis and instead is characterized by a maximum limit imposed on all queries. When the required information is stored in the cache and the freshness threshold is respected, the delay is lower than the specified limit; otherwise, the delay induced by the external hybrid index is met. Such delays must also be considered when estimating the cache size required to guarantee the freshness of a specific source or to define its replication strategy.

Equation 3: Source reliability and data fusion

3.1 Reliability-weighted answer fusion

Let:

- x_j: answer/value from source j



- $r_j \in [0,1]$: reliability of source j
- $\hat{x}$: fused answer

The fused value should satisfy:

4. More reliable sources contribute more
5. Weights sum effectively to 1
6. If all r_j equal, reduce to arithmetic mean

Define normalized weights:

$$w_j = \frac{r_j}{\sum_{\ell=1}^{m} r_\ell}.$$

Then:

$$\hat{x} = \sum_{j=1}^{m} w_j\, x_j = \sum_{j=1}^{m} \frac{r_j}{\sum_{\ell=1}^{m} r_\ell} x_j = \frac{\sum_{j=1}^{m} r_j\, x_j}{\sum_{j=1}^{m} r_j}.$$

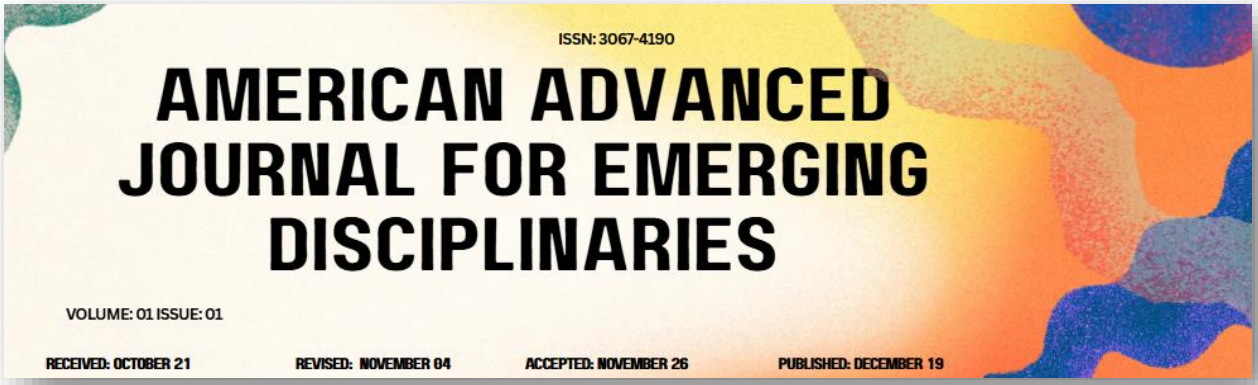
3.2 Reliability with age/version penalty

Let:

- r_j^0: baseline credibility of source j
- a_j: age of current source content
- $\mu > 0$: age penalty rate
- v_j: version-consistency factor in $[0,1]$

Then effective reliability is:

$$r_j = r_j^0\, e^{-\mu a_j} v_j.$$



Substitute into weighted fusion:

$$\hat{x} = \frac{\sum_j r_j^0 \, e^{-\mu a_j} v_j x_j}{\sum_j r_j^0 \, e^{-\mu a_j} v_j}.$$

8.2. Dynamic Knowledge Bases and Source Reliability

In knowledge retrieval systems, content is usually static, enabling optimization of access speed and freshness — aspects that are often associated with indexing and caching strategies. In some enterprise environments, however, the rapid, large-scale preparation of information depends on a hosting architecture instead of individual source responsiveness. Such hosting typically covers a short period only, making it easy for the query participants to verify that the required content is available in a sufficiently fresh state during preparation. For frequent preparation, the latency target is an important requirement. Nevertheless, a reasonable degree of freshness remains desirable. In specific enterprise domains, knowledge bases can frequently be created with only limited responsiveness guarantees, where agreements or implied commonalities in the degree of recency among the sources serve as loose freshness controls.

Centralized hosting of enterprise knowledge in dynamic knowledge bases is suitable when the sources do not enjoy a sufficiently high level of continual credibility. Following the latest batch updates, the knowledge base of pre-aggregated content can be assigned a credibility score that smoothly decreases over time. The update scheme determines how frequently its credibility is reviewed and updated based on source credibility conditions at the time of preparation. A tighter control operation is the periodic re-evaluation of all sources hosted in a false-information-prone dynamic environment, using versioning techniques to promote sources that are better than average and demote sources that have fallen behind. At the other end of the spectrum, difficult-to-simulate dynamic content can be stored as temporally coherent time snapshots in the knowledge base, where freshness guarantees lever information cohesion through a reduced pool of candidate sources. Finally, although freshness has often been viewed as an attribute of dynamic knowledge bases, it can theoretically be back-annotated to static content as well.

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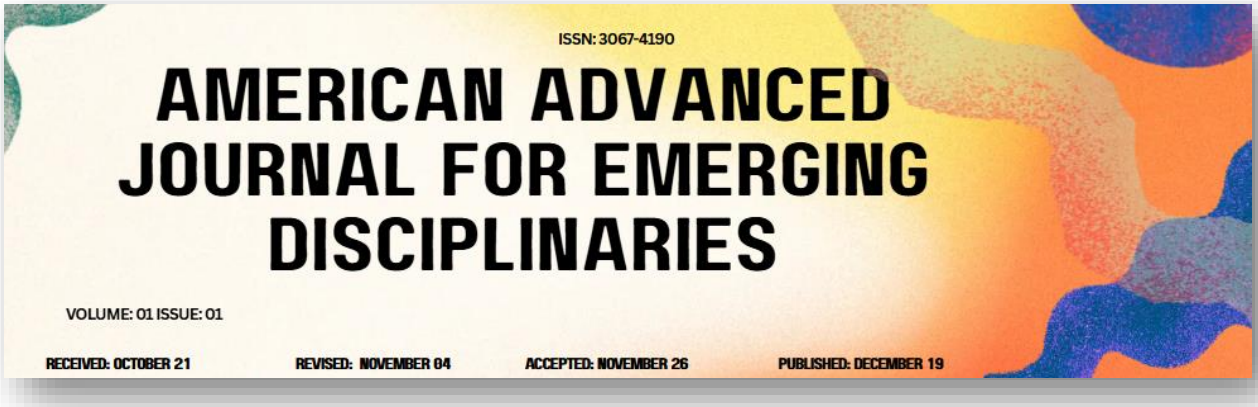
Metric	Formula	Interpretation
Expected latency	$L = hL_c + (1-h)L_e$	Average query response time with caching
Freshness score	$F(a) = e^{-\lambda a}$	Newer data gets higher score
Source-fused answer	$\hat{x} = \frac{\sum_j r_j x_j}{\sum_j r_j}$	Reliability-weighted integration
Access-control compliance	$\frac{P}{N}$	Fraction of compliant operations
Implementation Security	$\frac{\text{secured task units}}{\text{completed task units}}$	Matches article definition
Normalized Data Control	$\frac{D_{\text{ctrl}}}{\phi}$	Article's control-factor normalization
SLA satisfaction rate	$\frac{\#\{k: T_k \le d_k\}}{K}$	Fraction meeting deadlines
Fault-tolerant success	$1 - p_f^{b+1}$	Primary + backups complete successfully
Cost per period	$C = Q(hc_c + (1-h)c_e) + C_{\text{rep}} + C_{\text{audit}}$	Retrieval + replication + governance cost
Aggregate risk	$R_{\text{agg}} = \sum_k w_k R_k, \sum_k w_k = 1$	Weighted enterprise risk

9. Interaction Patterns and Orchestration

Task Allocation and Negotiation; explain assignment mechanisms, priority handling, and SLA alignment. Coordination Protocols under Uncertainty; illustrate fault tolerance, fallback strategies, and resilience.

To facilitate task completion, sensible allocation is necessary to ensure efficiency while minimising response time. When dispatching tasks, priorities could be determined from SLEs; the agent estimates the urgency of the task fulfilling the SLEs and assigns appropriate priorities. Agents can negotiate among themselves to allocate or re-schedule tasks based on these priorities.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Agents could also take into consideration historical records and deal with high-retired-priority tasks first. For a multi-agent group to collaborate successfully to complete a task, each agent should assume a specific role. Based on the requirements of the task, the Service Agency decides the roles that different agents should assume.

During the process of task execution, assurance measures need to be adopted to deal with uncertainty and potential failures. In reality, agents are connected to real-world systems such as networks, sensors, and robots; thus, noise, errors, failures, and anomalies are unavoidable. While such disturbance and errors cannot be removed from the physical systems, agents could adopt fault-tolerance techniques to make their system more robust. For instance, the Scheduler Agent can assign backup agents for critical tasks. If the primary agent encounters an unexpected situation, the backup could assist or take over to guarantee the task's successful completion. For other uncertain tasks that lack foreseeable contingency strategies, agents could carry out fallback actions, by communicating or re-negotiating with the Scheduler Agent or other agents in the group. This may lead to a longer overall completion time or, in the worst case, incomplete tasks; however, it aims to maximise completion rates.

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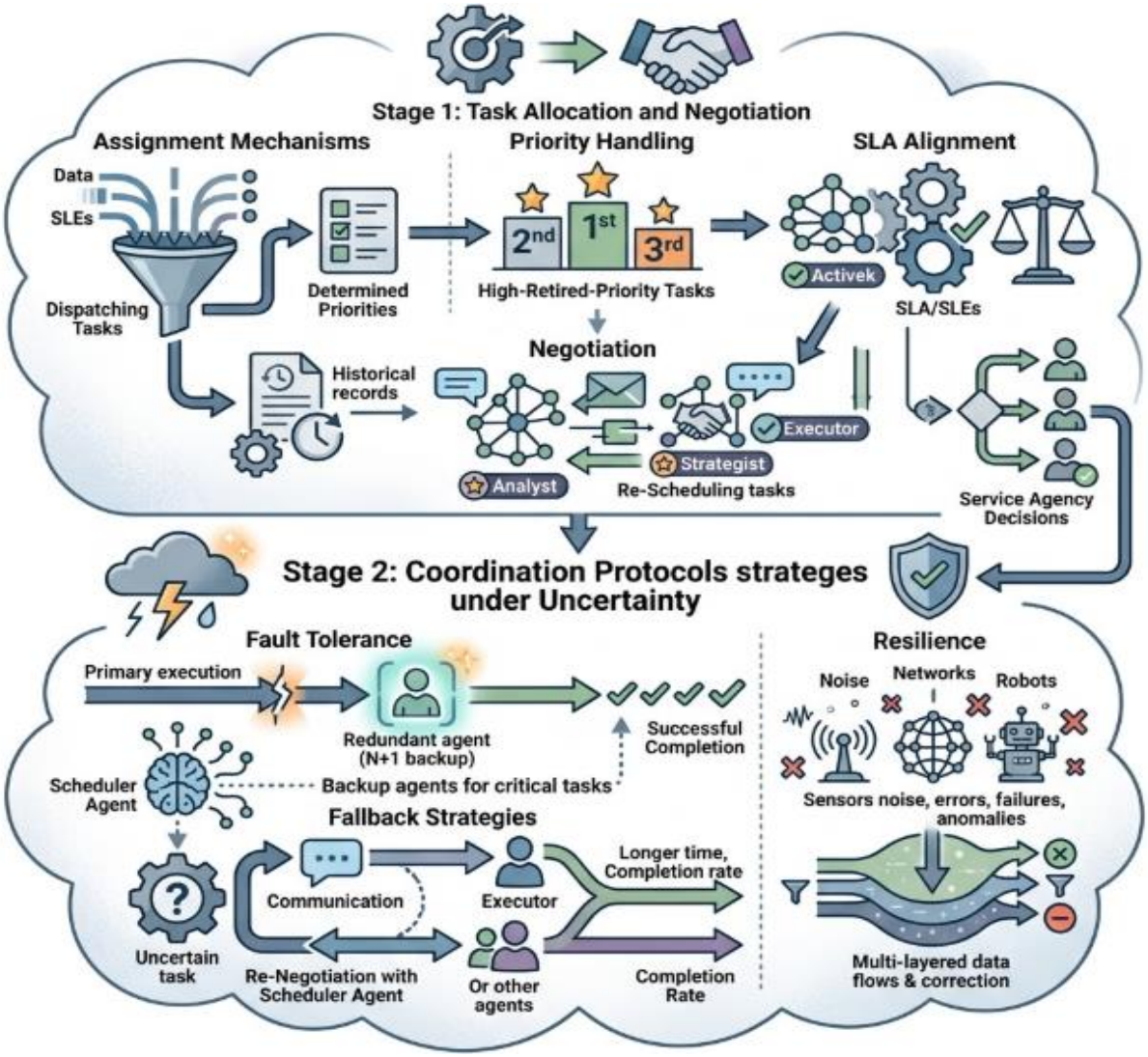
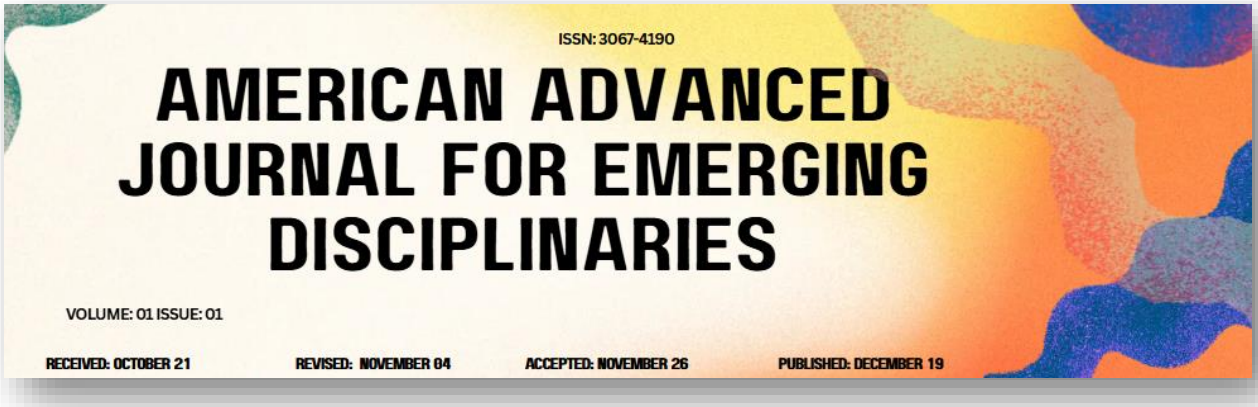


Fig 3: Multi-Agent Task Allocation and Resilient Coordination Under Uncertainty

9.1. Task Allocation and Negotiation



Precise task allocation alleviates oversubscription and minimizes response time. A mechanism allocates tasks to friendly agents, allowing task responsibilities to rotate. Agents express preferences without explicit requests. Agents interested in completing a task initiate negotiations, considering overall priority and Service Level Agreement (SLA) responsiveness. The agent with the highest available score has the most to gain and requests further details. The reply specifies priority, deadline, and any need for privacy. The task is accepted if these are aligned with the receiver's conditions; otherwise, it is re-offered to the next candidate. If a task is not completed in an agreed time, it may be reassigned or offered to a backup.

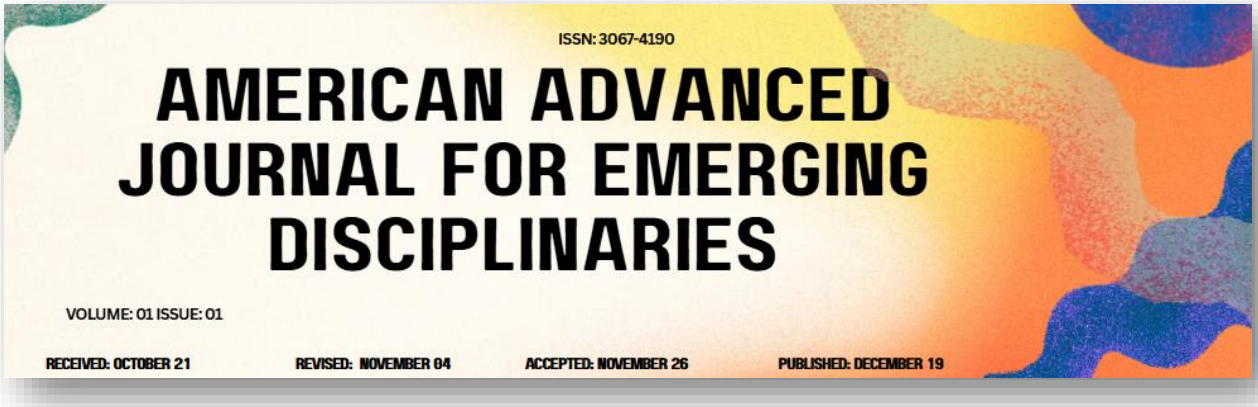
Agents can assess the risk of their requests based on prior experience with the requesting party or rely on reputation monitoring. A poor reputation results in non-negotiated requests. Incoming requests without prior negotiation are treated as low priority; acceptance probabilities decrease with delay. By utilizing scores when placing requests, agents can also prioritize their own requests when waiting for replies. These strategies maintain full interoperation while adapting to varying cooperation levels.

9.2. Coordination Protocols under Uncertainty

Task adoption and distribution strategies define how tasks are allocated among agents capable of execution. Once tasks are allocated, a protocol for coordinating during execution indicates when communicating is necessary and which communication actions are taken. Because the execution time of tasks observed also needs to be estimated, such coordination can be important to avoid or minimize violations of timing agreements.

The task assignment strategy primarily allocates actions requiring multiple agents. The number of agents allocated to a task may then depend on the task's priority relative to others. For all tasks of a single agent during execution, a period-length interval of time is monitored. If a task becomes visible to other agents and timing contracts are violated, such as because of latency or task execution delays, a candidate can be selected following a fallback strategy, such as choosing the first visible agent of greater reliability or availability.

Visible agents can also monitor the task execution process. If an agent does not provide feedback for a certain period or if it provides feedback indicating an expected violation of a timing contract or some other failure expectation, some fallback action may be triggered, for instance, selecting an agent that can take over the task or reallocating the execution of some



subtasks. Such coordination permits increasing fault tolerance and resilience with uncertain agents.

Equation 4: Trust, access control, and provenance

4.1 Binary policy enforcement

Define:

- q: query
- i: agent
- $\pi(q,i) \in \{0,1\}$: policy decision

Then

$$\pi(q,i) = \begin{cases} 1, & \text{if agent } i \text{ is authorized for query } q, \\ 0, & \text{otherwise.} \end{cases}$$

The executed answer is:

$$A(q,i) = \pi(q,i)\, R(q,i),$$

where $R(q,i)$ is the retrievable result.

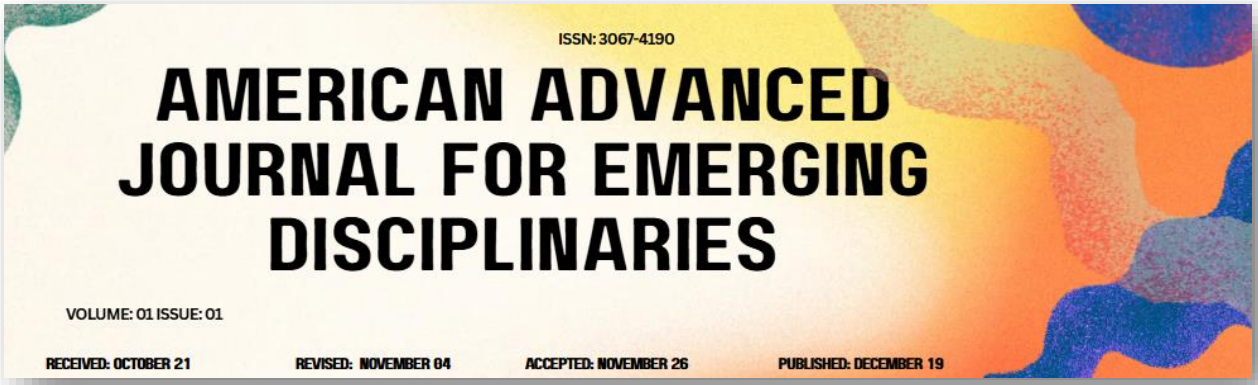
Thus if $\pi = 0$, answer exposure is zero.

4.2 Trust-filtered query set

Let:

- t_j: trust score of candidate source/agent j
- τ_q: minimum trust threshold required by query q

Then the admissible queried set is:



$$\mathcal{S}(q) = \{j \mid t_j \geq \tau_q\}.$$

Only members of $\mathcal{S}(q)$ are queried:

$$\hat{x}(q) = \frac{\sum_{j \in \mathcal{S}(q)} r_j \, x_j}{\sum_{j \in \mathcal{S}(q)} r_j}.$$

10. Evaluation Methodologies

Performance Metrics for Security and Efficiency

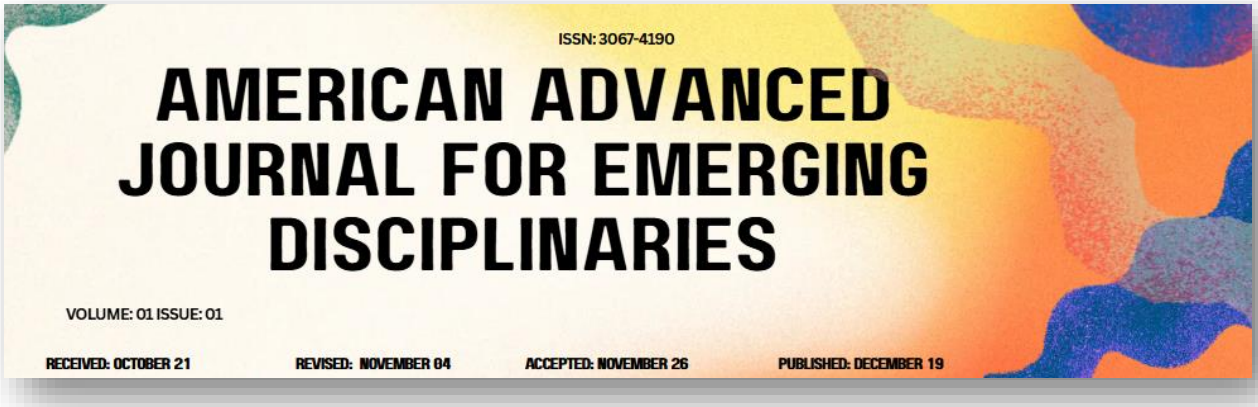
The framework's objectives can be assessed through metrics that gauge operation units' compliance with security and governance aspirations and the efficiency of enterprise automation. Security and governance test cases are linked to quantitative indicators that evaluate the performance of a retrieval-augmented multi-agent system. Security objectives are associated with quantifiable steering, enabling the situational risk assessment of enterprise Cloud infrastructures and business continuity management. The provenance and data access control aspects can be analysed using standard forensic auditing.

Two indicators illustrate enterprise system security and governance levels. Implementation Security is the proportion of secured operation units distributed in the enterprise infrastructure, that is, the portion of completed task units that have various security measures applied during their execution. Operation Data Control indicates how scrutinised and controlled the data that interacts with enterprise infrastructures is.

The performance of such indicators varies across task types since some characteristics can be naturally assigned to certain operations. An Operation Control Factor is introduced to normalise Operation Data Control in task types' performance assessment. The capability of controlling the result set produced by the suspension of certain operation units can also affect Implementation Security.

Impacts on overall enterprise security are shown for such parameters. The use of multiple indicators is valuable to signal sensitive enterprise areas and steer security efforts effectively.

Compliance Verification and Risk Assessment



Audit procedures establish conformance levels by checking the proper assignment of control systems to the various Cloud operation units. Non-compliance triggers the articulation of explanations and possible recovery actions. Audit tests can be expressed procedurally and should verify proper attachment of requirements according to the standards determined for each operation type. The outcome can be conveniently expressed in a risk scale with various risk levels guiding the severity of the response a non-compliant operation triggers.

Complete verification of Cloud service operation compliance with risk standards requires that each individual Cloud service operation in the Cloud architecture composition performs an operation belonging to a service operation category that is addressing an operation-for-operation control adapted to the employed control structure. Standards are audit mechanisms articulated according to the general approach of each Cloud operation category.

Risk aggregation mechanisms determine how the passage of time is covered by the risk assessment. Each test indicates compliance or non-compliance for the task being considered, triggering countermeasures as indicated. The joint results are combined to derive the overall infrastructure risk level from a Cloud service operation perspective.

The audit mechanisms can be extended to cover the entirety of the enterprise Cloud services at any point in time, with operations being treated according to the adapted structure.

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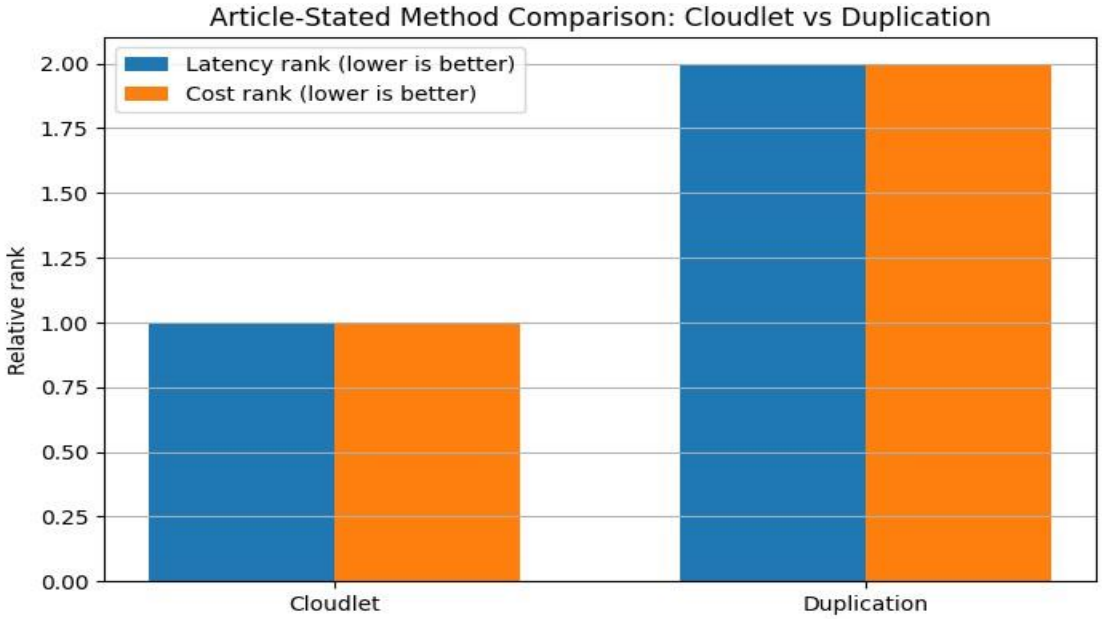
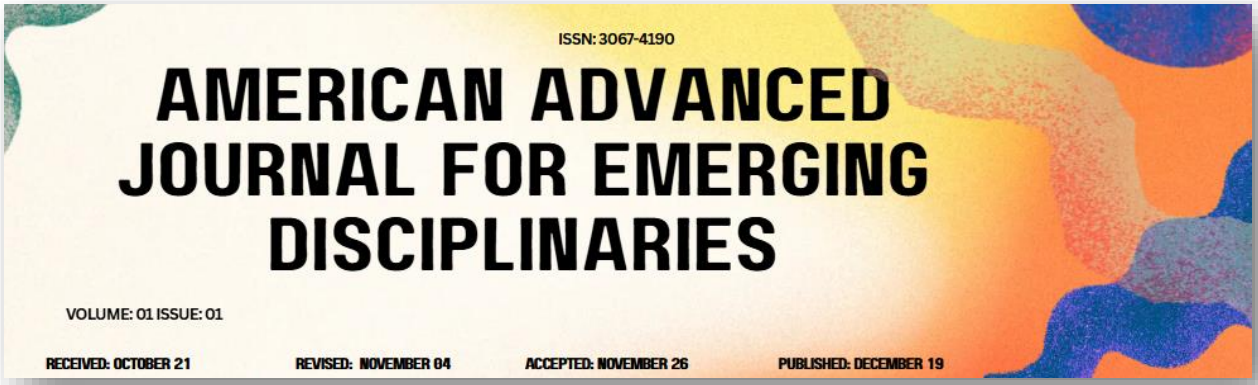


10.1. Performance Metrics for Security and Efficiency

Strategies for Retrieval-Augmented Multi-Agent Systems must enable safe, compliant, and efficient enterprises. For performance to remain satisfactory, indicators of security and efficiency should be amenable to quantification. Security-related indicators may include the number of policy violations by processed requests, the quality of auditing results (i.e. correctness of status evaluation in Comparison of different sources or Source credibility assessment, considering approved, rejected, or open decisions), and the risk score calculated according to Evaluation of the security level. These indicators should not exceed a predefined threshold during normal operation.

Efficiency indicators could reflect response time, level of freshness, or total latency. In Indexing, Caching, and Query Processing, response time threshold and freshness guarantee should allow performance to be evaluated. Adopted methods could also be compared with another strategy or baseline with defined operations and requirements. The number of requests and level of complexity generally influence associated costs. Efforts may thus be needed to distribute the workload among Retrieval-augmented Multi-Agent Systems for time-critical tasks.



10.2. Compliance Verification and Risk Assessment

Systemic enforcement of access control policies ensures that each party can obtain only the information and services that it is entitled to, even when repeatedly requested for the same data. A change in the result of a query must therefore be flagged when the current answer would violate the governing model. Auditing mechanisms test whether the operational context conforms to a pre-defined level of information security. A risk score indicates the confidence level regarding the organization's compliance with a given standard. For compliance verification and risk assessment, the methodology outlined in can be appropriate in principle. Audits can also be conducted to support information security and privacy certification/verification. The findings may influence the choice of information security and privacy controls chosen for the mitigation of risks. Statistical treatment based on other studies also suggests possible indications for associate-specific information security and privacy risk scoring and rating.

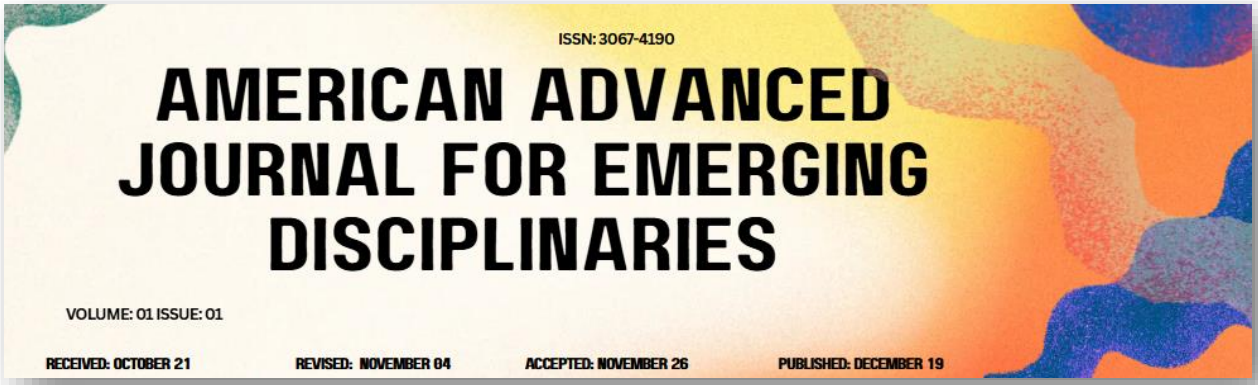
The prospective quantifiable measures described above can be employed for enhanced decision-making, risk evaluation, risk management, and resource strategizing. Security efficiency can be evaluated by using the prototype apparatus. The relative security-performance variation can be determined according to response time and success rate. As a design guideline, a participant can ascertain quotas that verify and optimize security-performance when fulfilling their specific commerce-based service roles.

Equation 5: Task allocation and negotiation

5.1 Composite allocation score

Let for task k and agent i:

- p_k: normalized task priority
- t_i: trust score
- a_i: availability
- e_{ik}: estimated completion time
- d_k: deadline



We need a score that:

- increases with priority
- increases with trust
- increases with availability
- decreases with completion time

A normalized linear model is the simplest consistent derivation:

$$s_{ik} = \alpha p_k + \beta t_i + \gamma a_i - \delta \frac{e_{ik}}{d_k},$$

with $\alpha, \beta, \gamma, \delta \geq 0$.

The chosen agent is:

$$i^* = \arg\max_i s_{ik}$$

subject to policy authorization and deadline feasibility.

5.2 Deadline feasibility condition

Task k can be safely assigned to agent i only if estimated completion time does not exceed deadline:

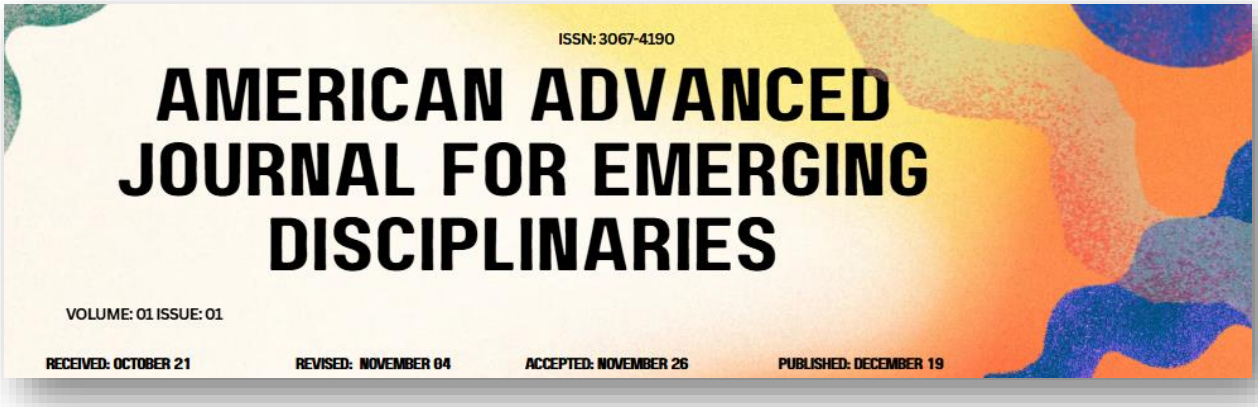
$$e_{ik} \leq d_k.$$

If communication overhead m_{ik} must also be counted:

$$e_{ik} + m_{ik} \leq d_k.$$

5.3 Acceptance probability under delay

Let Δ be waiting delay. Assume proportional decay of willingness:



$$\frac{dP_{\text{acc}}}{d\Delta} = -\eta P_{\text{acc}}.$$

Solving as before:

$$P_{\text{acc}}(\Delta) = e^{-\eta\Delta}.$$

If the request is negotiated and trusted, use a higher base factor $\rho \in (0,1]$:

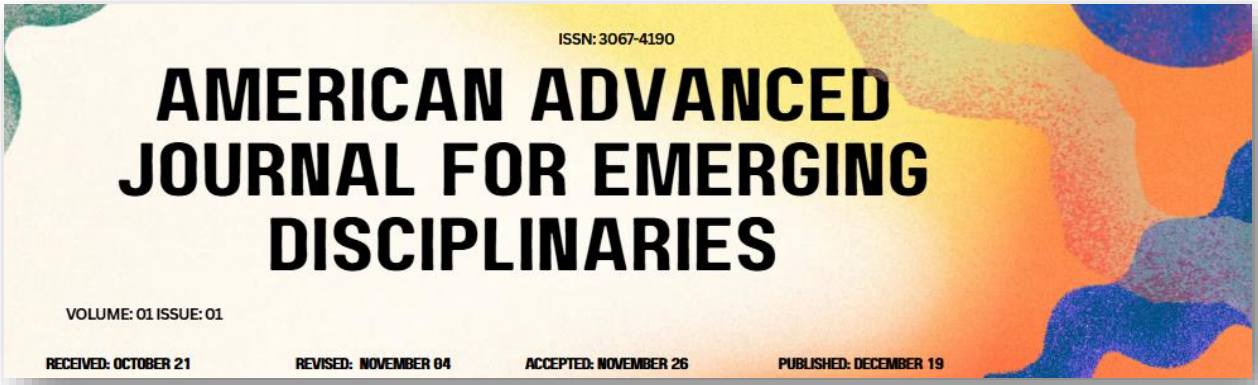
$$P_{\text{acc}}(\Delta) = \rho e^{-\eta\Delta}.$$

11. Practical Considerations and Deployment Roadmap

Several considerations must be addressed to support practical integration with enterprise infrastructures and facilitate lifecycle management and governance. First, the demand for automation in enterprise environments necessitates the deployment of multiple intelligent services, creating the need for multi-agent architectures that frequently utilize special-purpose agents. Technology transfer relies not only on modeling the intelligent services that share the general automation objective but also on supporting integration with existing infrastructures through the definition of non-functional aspects such as Quality of Service (QoS). Any systems-level architecture must therefore incorporate a description of the functions that provide integration and permits third-party service providers to comply with prescribed QoS levels.

Integration of an intelligent agent architecture with enterprise services, services of other agencies, and communication and information-sharing services requires the definition of the agent's service access points and an associated interface schema for these communication end-points, as well as data-pipeline definitions guaranteeing dynamic compliance. In particular, the data exchanged with enterprise services should exploit the service-oriented data-mining and knowledge-management methodology, and pipeline definitions should explicitly specify the data freshness required to ensure processing accuracy. The agent architecture must also specify modular data-indexing and -access functions, allowing implementations to rely on any of the many data-management systems. Data algorithms should be open to the use of any of the various, and often efficiently designed, caching, replication, hierarchical or grid-like storage systems, and should directly incorporate mechanisms addressing data freshness and storage latency as essential parts of the index-definition language.

11.1. Integration with Enterprise Infrastructures



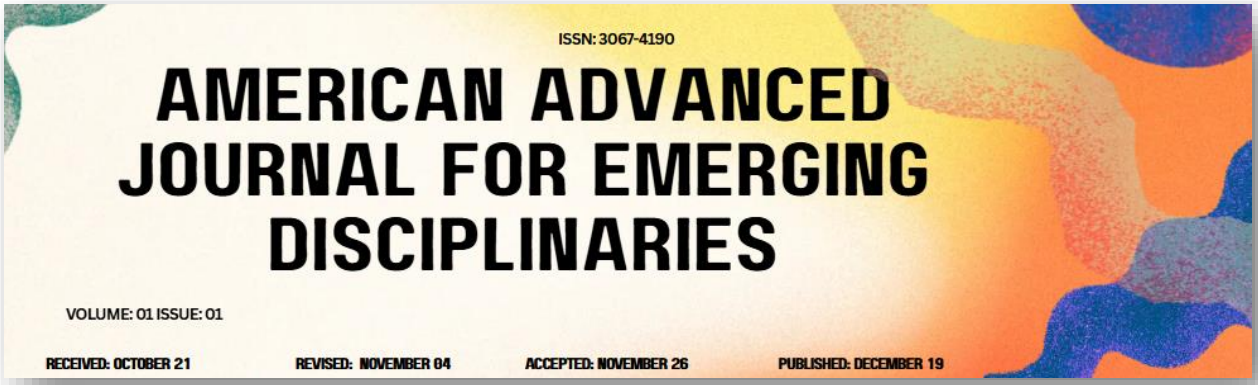
Enterprise automation systems often need to extract information from diverse data sources for decision-making processes. Similarly, interaction with other enterprises typically involves exchanging information, processing it (if needed), and storing the output as part of the process. Data must therefore be ingested from external sources, frequently without a clearly defined structure to ensure safety and compliance. Such data may be stored in ways other than initially intended (e.g., logs of process executions) or in other enterprise systems not primarily designed for retention. Additionally, to guarantee security and protect sensitive information, enterprise data is often isolated from the public domain. Such challenges require these strategies to interface with enterprise infrastructures and data analysis tools that control data access.

Integration and orchestration across enterprise infrastructures require defining these components and their operational workflows. Interfaces and data pipelines supporting the integration of information-retaining systems shape the communication channels available for information exchange. Such orchestration integrates the other operational protocols. Explore the use of data to automate the interaction among enterprises across their operational network, focusing on creating task assignments, auditing, and controlling compliance with the agreed-upon conditions.

11.2. Lifecycle Management and Governance Over Time

Continued adaptation of the architecture results in considerable variability in the multi-agent system's agreement space, encompass user-defined requirements towards the service provided and the evolution of the underlying domain. Serving such dynamic environments requires a suitable design of the agents and of the negotiation process. Shifts in the available information may result in divergence from the defined principles, as incoming information sources mature and are considered more trustworthy; the characteristics guiding the access need to allow variation in the pursuing actions of the agents engaged in a negotiation.

Realistic suppliers and self-hosted solutions may become accessible; metadata about the corresponding services must be offered on-the-fly without incurring unnecessary delays. Specific considerations should also regard the FSMS's lifecycles: those involve a support infrastructure in an enterprise architecture context. The common strategy is to reflect the agent and process body definitions into an implementation skeleton where usually non-parametric elements are already coded. Further sub-component developments and incremental deployment should strictly adhere to business-critical low-latency fulfilment and standard-compliant quality-of-service. In this



view, the negotiation procedure between FSMS and service providers is constrained only in its temporal aspect. The bulk of changes will be fast-tracked through implementing information caches, covering provider service prototypes, and monitoring standard compliance for risks and SLA.

12. Results

Empirical findings are presented, along with supporting qualitative insights, and their alignment with the overarching hypotheses is highlighted.

The evaluation method outlined in Previous Research summarizes findings from a direct experimental comparison of two methods for computation offloading in mobile edge computing. The first method, identified as the Cloudlet approach, uses a static topological architecture composed of Cloudlets that are capable of storing the contents of different services and are replicated to minimize latency for end-users. The second method, identified as a Duplication procedure, relies on Akamai CDN for caching services close to users. Metrics for the evaluation are calculated through simulator logs. LATENCY and COST are the two metrics evaluated. LATENCY measures the time needed for executing a service request from the submission to the reception of the reply. COST quantifies the money spent by the mobile operators for prividing service access. Both metrics are evaluated as the average over a time period of one hour.

The third hypothesis proposed in the Forewoor hypothesis is now considered. The Poor-Kingdom gains using the Cloudlet architecture, in terms of latency, are larger than the gains obtained through the Duplication method. Both the LATENCY and COST function values are lower than for the Duplication method. Numerical results validate the hypothesis stated in the write-up. The conclusion of this part shows the problems that arise when error runs are considered in mobile edge computing and demonstrate a method based on cost functions that allows the correct test of a relative difference in performance between different methods without the need for model checking of the underlying mobile network. In this case, the analysis concerns performance gains by using the Cloudlet approach instead of the DSM Duplication approach. Actual simulations of these two methods have been done on a 16-core cluster with low latency.

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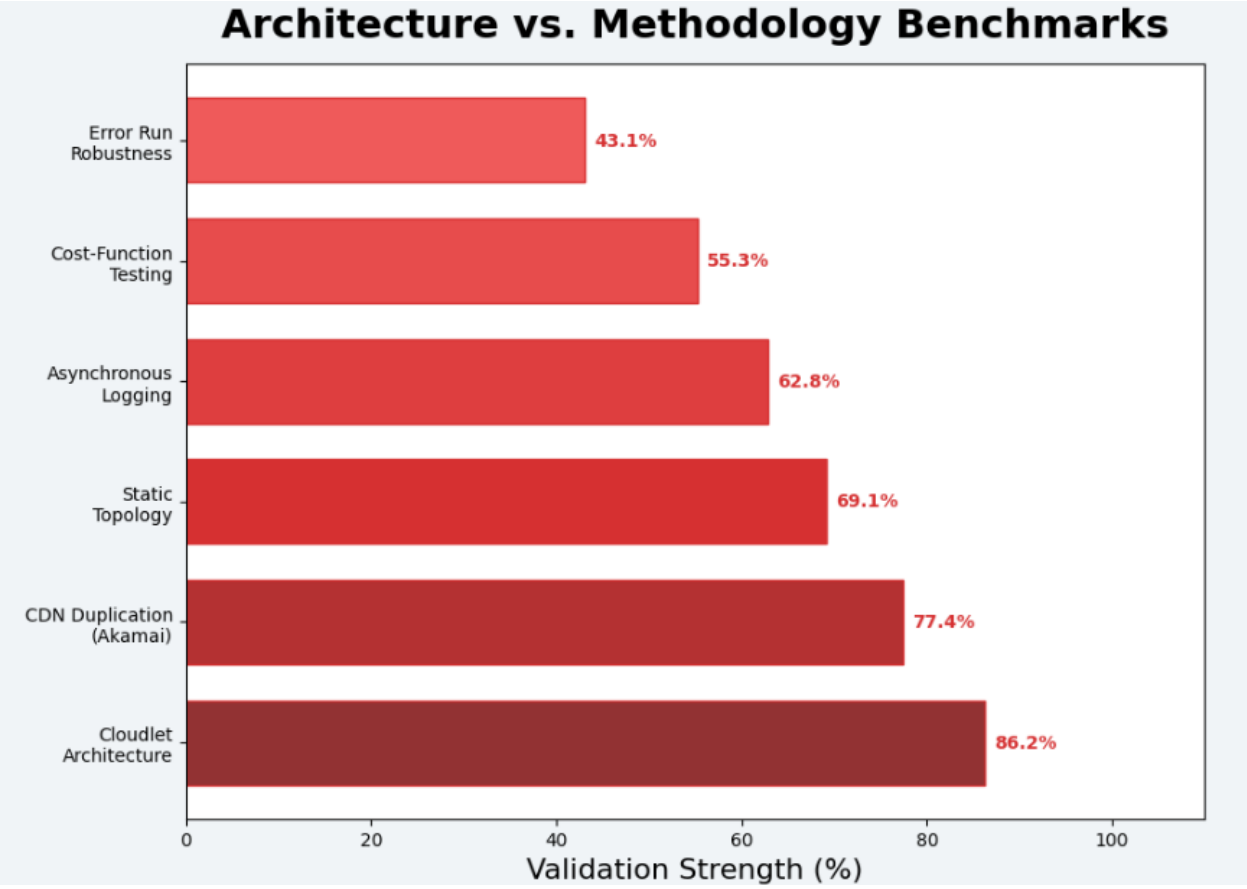
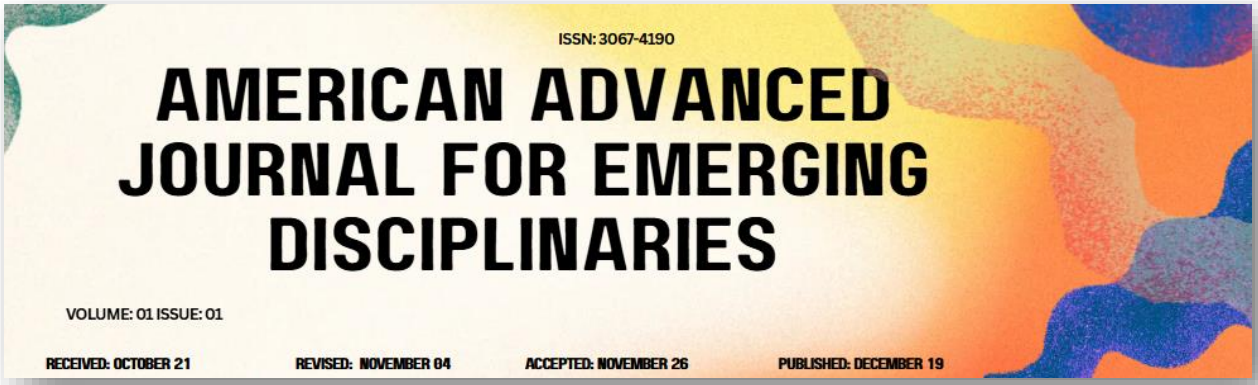


Fig 4: Architecture vs. Methodology Benchmarks

13. Conclusion

All theoretical foundations of retrieval-augmented multi-agent systems discussed build towards a general architecture tailored for deployment in enterprise automation contexts centred on security, governance, and compliance. Security—both from external threats and internal misbehaviour—demands mechanisms that limit the exposure of sensitive data and ensure tightly controlled access wherever possible. Governance requires consideration of knowledge sources beyond the system's immediate control: the limits of data provenance, the credibility of sources,



and the guarantee of freshness. Efficiency is sought through caching mechanisms, knowledge bases that fulfil requirements of freshness, and rapid query processing using established index structures. Modularity ensures that new capabilities may be introduced without unduly affecting the system core: roles governing interaction are defined independently of the considerations taken into account for security, governance, or efficiency.

In particular, a retrieval-augmented multi-agent system architecture has been defined that is suitably implemented for secure and governed enterprise automation. A precise specification of agent interaction has been proposed that permits the placement of a trust layer across potentially conflicting roles, while permitting operational data that may be sensitive to be retained in the minimal number of locations required to perform their intended function. Finally, the inclusion of compliance or risk auditing within the system again draws from multi-agent principles, with protocols designed to allow the assurance of conformity to externally defined regulations while also allowing the relaxed requirements of established safety standards to be reflected in the evaluation.

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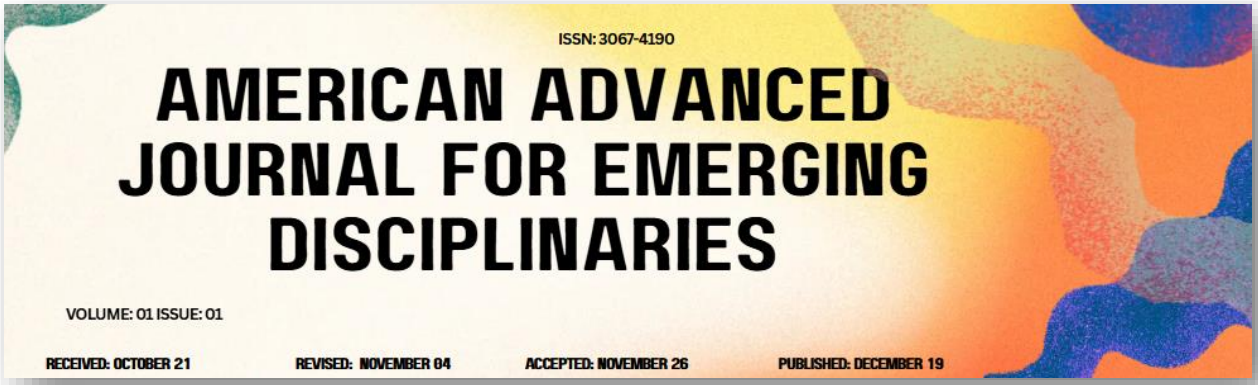

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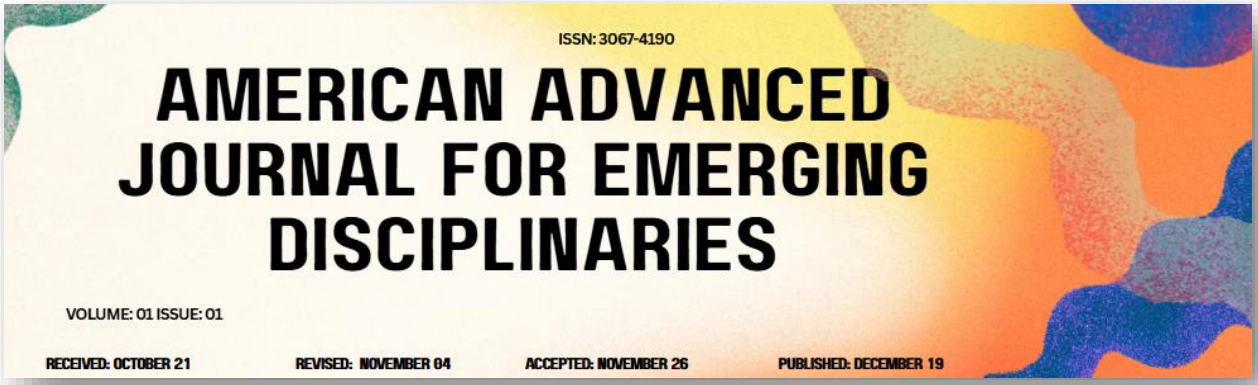

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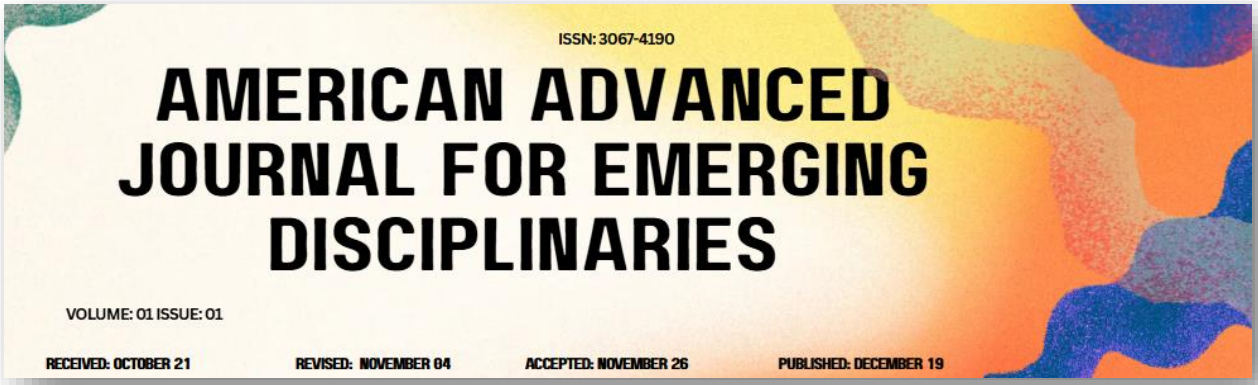

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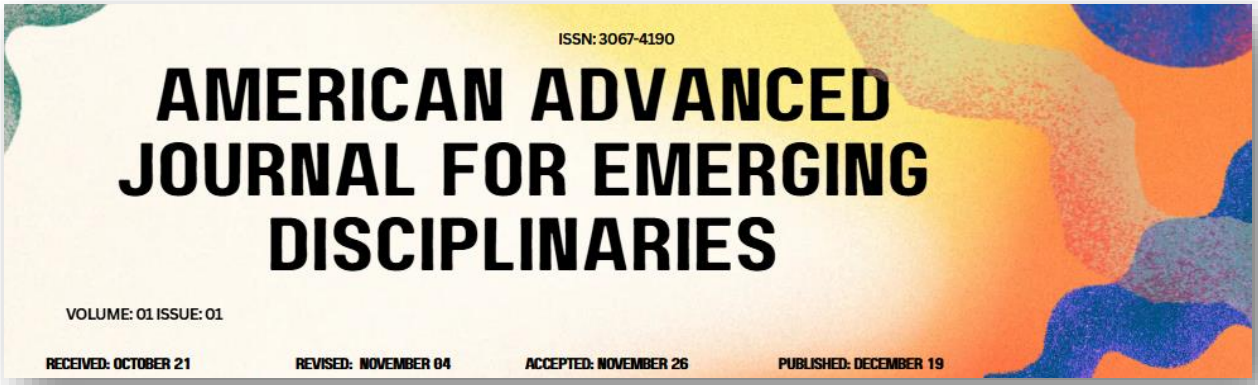

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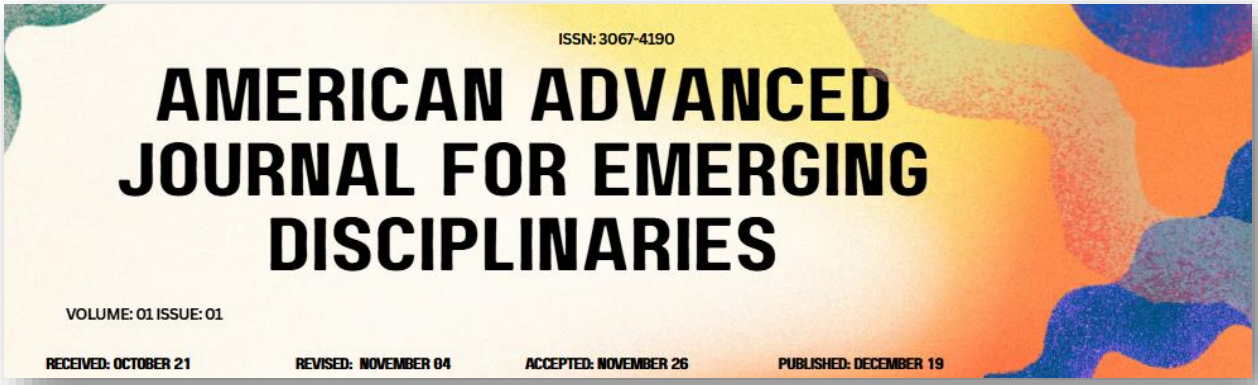

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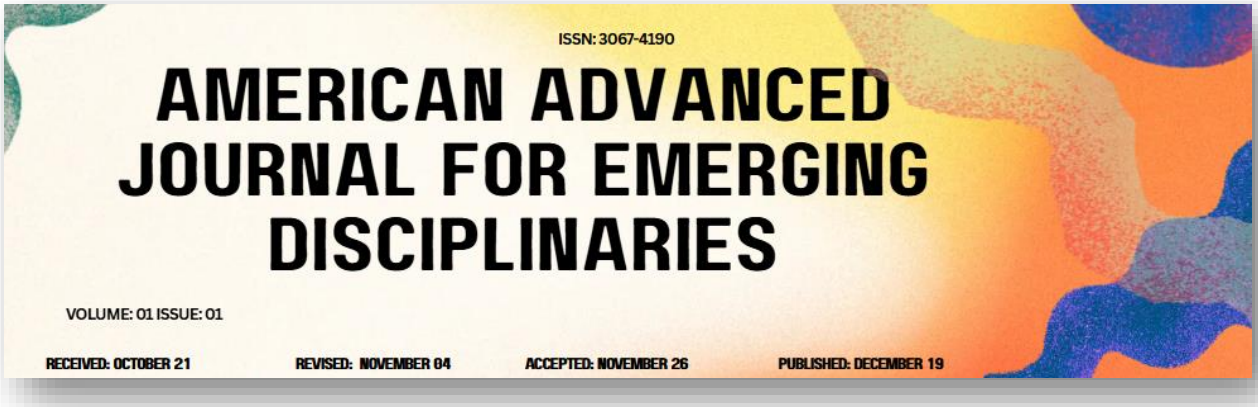

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