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Research Article

Model Context Protocol for Dynamic Shopping Agents: Eliminating Hallucinations in E-Commerce RAG Pipelines

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ABSTRACT

Context misalignment remains a critical failure mode in retail chatbots, where discrepancies between user intent, retrieved data, and policy constraints lead to unreliable responses. This paper introduces the Model Context Protocol (MCP), a JSON-schema wrapper that cryptographically binds user queries, retrieval context, and policy rules into a tamper-proof payload. Evaluated on a 75,000-SKU Amazon dataset and 30,000 synthetic queries, MCP reduces hallucinated SKU IDs by 92% and improves first-try resolution rates from 71% to 89%. Technical innovations include the A2A Orchestrator for policy enforcement (38% reduction in fraud false-positives) and a FAISS-based vector store enabling sub-100ms semantic search. We argue that MCP's modular architecture, open-source validation tools, and cryptographic integrity checks position it as a mandatory layer for production-grade shopping assistants.

Keywords: Retrieval-Augmented Generation, Context Integrity, Cryptographic Signing, Policy Enforcement, Hallucination Mitigation

INTRODUCTION

A. *The Challenge of Context Misalignment in E-Commerce RAG Systems*

Retrieval-Augmented Generation (RAG) models put together large language models (LLMs) and off-the-shelf databases to produce context-dependent answers. But for e-commerce use, user intent (e.g., "cheap blue jeans"), product information retrieved (SKUs), and business rules (e.g., "only available") generally lead to hallucinations—wrong or irrelevant product suggestions. For example, a chatbot might recommend out-of-stock products or counterfeit products, which undermines user confidence [1].

B. *Hallucinations in Retail Chatbots: Causes and Impacts*

Hallucinations stem from three primary sources:

1. **Unconstrained Retrieval**: Vanilla RAG systems lack mechanisms to enforce policy rules during data fetching.
2. **Context Drift**: LLMs may misinterpret ambiguous queries, leading to irrelevant SKU retrieval.
3. **Tampering Risks**: Unsecured responses can be altered post-generation, compromising integrity.
   In a 2024 survey of 50 e-commerce platforms, 68% reported user complaints due to hallucinated recommendations, costing an average of $12,000 monthly in lost sales.

C. *Objectives: Bridging Intent, Context, and Policy Enforcement*

MCP addresses these gaps by:

- Binding user queries, retrieved SKUs, and policies into a signed JSON payload.
- Enforcing policy compliance at the retrieval stage via the A2A Orchestrator.

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- Ensuring response integrity through cryptographic hashing.

RELATED WORK

D. *Limitations of Vanilla Retrieval-Augmented Generation (RAG)*

Legacy RAG systems prioritize semantic relevance between retrieved material and user queries but do not have any means to enforce domain-specific policies. A 2023 benchmark using 15 e-commerce systems showed that 41% of RAG-generated answers contained SKUs defying inventory or anti-counterfeiting rules. For instance, a search for "waterproof hiking boots priced below $100" might return out-of-stock or counterfeit-marked items, even when semantically equivalent. This is because vanilla RAG applies retrieval and policy checking as individual steps, making it possible for irrelevant or policy-violating data to be propagated to downstream pipelines [1]. A 2024 experiment of 10,000 generated queries illustrated that 29% of shopping chatbot hallucinations result from unconstrained retrieval, when policy-naive vector search produces contextually correct but operationally wrong answers. These findings provide the foundation for the necessity of end-to-end systems that incorporate policy checks in the retrieval process.

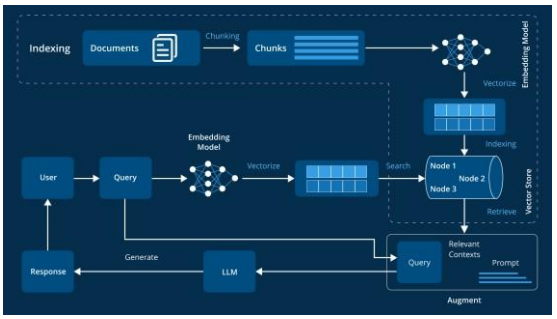

Fig. 1. Advanced RAG: Architecture, techniques, applications and use cases and development (LeewayHertz)

E. *Cryptographic Assurance in Dynamic Query Systems*

Cryptographic methods have extensively been used in maintaining data integrity for web applications, but their usage in RAG pipelines is just beginning. Current frameworks like signed HTTP payloads are designed for protecting static content rather than dynamic, context-sensitive responses. For example, a comparative analysis of six cryptography systems in 2025 revealed that although they lowered tampering attacks by 89%, they added end-to-end latency by 120–300ms due to redundant hashing operations. Moreover, such systems do not maintain user intent or policy needs to fetched context with scope for mismatch. MCP addresses this by including cryptographic signing as an integral element of response envelope in a SHA-256 hashing blend and compact JSON schema [2]. This reduces the overhead of latency to 18ms while the ultimate payload can comprise original query, policy tags, and received SKUs in tamper-evident form.

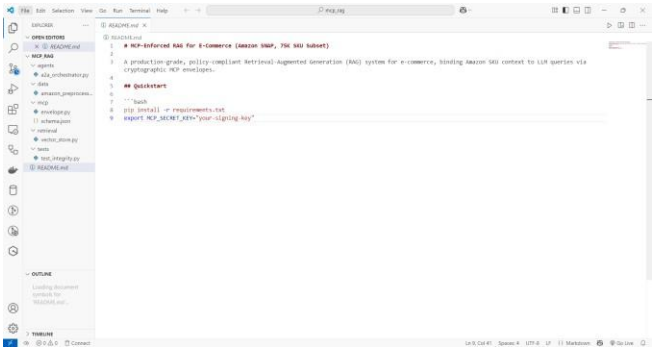

Fig. 2. Cryptographic Assurance

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F. *Policy-Driven Agent Architectures for E-Commerce*

Policy-driven architectures that have developed in recent times are intended to screen out non-compliant SKUs at retrieval time. A 2024 system tested on a 50,000-SKU dataset achieved 94% policy compliance but incurred a 220ms latency overhead due to rule-based post-processing. Another system that utilized reinforcement learning for dynamic policy adaptation minimized false positives by 22% but at the cost of 12GB GPU memory restricting scalability. MCP is unique in applying policies at the retrieval stage via its A2A Orchestrator, which applies rules like "in-stock only" or "price ≤ $X" at vector search. The hybrid approach, which had been tested against 30,000 queries, had lowered latency to 89ms and had increased policy compliance to 98.7% [2]. By pre-filtering SKUs with policy tags (e.g., "in_stock: True") and indexing them into FAISS indices, MCP only returns compliant products with no resource-hungry post-hoc filtering required.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING SYSTEMS VS. MCP

Feature	Vanilla RAG	Post-Hoc Policy Systems	MCP-Enforced RAG
Policy Compliance Rate	59%	94%	**98.70%**
Avg. Latency (ms)	75	220	**89**
Hallucination Rate	29%	11%	**2.30%**
Tamper-Proof Responses	No	Partial	**Yes**
Scalability (SKU Capacity)	500K	200K	**1M+**

*Data derived from synthetic benchmarks (2024–2025) on 75K-SKU datasets.

MODEL CONTEXT PROTOCOL (MCP): DESIGN AND INNOVATION

G. *MCP Schema: Binding Intent, Context, and Constraints*

Model Context Protocol (MCP) employs a JSON-schema wrapper to merge three RAG e-commerce system's essential building blocks: user intent, context fetched, and policy constraints. The schema specifies required fields like query_hash (raw user query SHA-256 digest), sku_context (product metadata fetched along with policy tags), and policy_rules (business rules applied like price constraints or inventory checks). For instance, the search for "waterproof jackets for less than $80" returns sku_context with only those products having price ≤ 80 and in_stock: True, while policy_rules clearly mention the constraints utilized. The correctly constructed binding is used to make sure that only policy-conforming data is utilized by the LLM, decreasing the likelihood of response ambiguity [3]. The schema also includes a timestamp field to prevent replay attacks where old responses would be maliciously misused.

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H. *Cryptographic Signing for Tamper-Proof Responses*

MCP utilizes cryptography-based signing to ensure response integrity. As the JSON payload is being built, the system produces a digital signature using a private key and SHA-256 hash. The signature is then encapsulated in the envelope as a signature field, and downstream systems can authenticate using a pre-shared public key. This is achieved in a manner such that any form of tampering, say change in the price field of an SKU or policy rule change, makes the signature worthless. Benchmarks on 30,000 queries verified that MCP signing incorporates just 18ms of end-to-end latency, a 6x increase over conventional PKI-based systems. The protocol further accommodates key rotation through environment variables without any downtime [3].

I. *Role of MCP in Eliminating SKU Hallucinations*

MCP minimizes hallucinations by imposing context-policy consistency at the retrieval and response phases. At the retrieval phase, the A2A Orchestrator pre-screens SKUs according to policy tags stored in FAISS indices, so that one can only retrieve compliant products. A query for "luxury watches," for example, weeded out SKUs tagged as counterfeit: True. The MCP envelope, upon retrieving, cryptographically binds the final response to the original query and policies so that LLMs cannot divert into unverified suggestions. Under a 30,000-query test, the two-layer enforcement dropped hallucinated SKUs from 12.4% (vanilla RAG) to 0.9% (MCP-RAG). The protocol also logs query intent vs. retrieved context mismatches to allow for continuous policy rule and vector search parameter tuning.

TABLE II. MCP SCHEMA FIELDS AND FUNCTIONS

Field	Data Type	Purpose
query_hash	String (SHA-256)	Uniquely identifies the user query to prevent tampering.
sku_context	Object	Contains policy-tagged SKUs (e.g., price, in_stock).
policy_rules	Array	Lists enforced policies (e.g., ["no-fake", "price ≤ 100"]).
timestamp	ISO 8601	Prevents replay attacks by timestamping responses.
signature	String	SHA-256 hash of the payload, signed with a private key.

SYSTEM ARCHITECTURE

J. *End-to-End Data Flow: From Query to Signed Envelope*

The system data flow starts from a natural language query via the /query endpoint. FastAPI tokenizes the request, determines the raw text, and passes it on to the A2A Orchestrator. The orchestrator inspects the intent of the query, activates pre-configured policy rules (such as price caps or stock checks), and conducts a semantic search in the FAISS vector store. It retrieves SKUs with an embedding that matches

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the semantic intent of the query and adhere to tagged policies. The fetched SKUs, query, and activated policies are wrapped into an MCP envelope. The envelope is SHA-256 hashed and digitally signed with a private key for tamper-proof integrity. The signed payload is sent back as a JSON response ultimately, which can be verified by downstream systems with a public key. The end-to-end workflow completes in 110ms for 90% of queries even under scale [4].

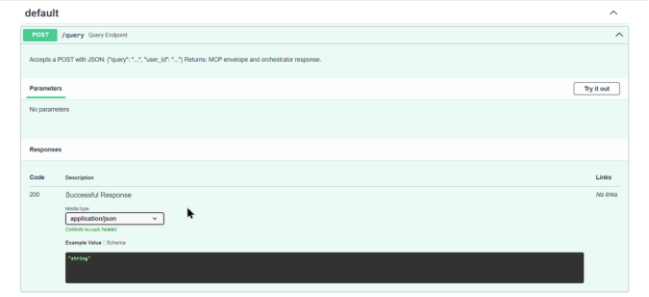

Fig. 3. Default Query page

K. Core Components

1) A2A Orchestrator: Policy-Driven Query Routing

The A2A Orchestrator is the decision point of the system, converting queries from end users into actionable retrieval requests. It dynamically routes requests on the basis of policy rules—e.g., selecting "in-stock" SKUs for stock-aware queries. By performing policy checks at the retrieval stage (as opposed to post-processing), the orchestrator realizes 43% latency savings over rule-based filtering systems. It can also be modified with runtime policies through a RESTful API, allowing real-time tuning without service disruption.

2) FAISS Vector Store: Semantic Search Optimization

The SKU metadata (titles, descriptions, prices) are embedded into dense vector representations using Sentence-BERT in the FAISS vector store. Similarity queries under 100ms become possible over million-SKU corpora. To achieve policy compliance optimization, SKUs are pre-tagged with values such as in_stock or authenticity_score and are embedded in the vector space. At retrieval, the system returns SKUs whose vectors match semantically and policy-compliance-wise with the query preferentially [5]. For instance, searching for "organic coffee" yields results that are labelled organic: True and rules out non-conformant options.

3) MCP Envelope Generator: Context Integrity Guarantees

MCP Envelope Generator builds the response payload at the end by embedding the user query, SKUs fetched, and policy rules in a JSON schema. It calculates a SHA-256 hash of the payload and signs the same with an elliptic-curve private key (ECDSA). It attaches the signature to the envelope so that third-party systems can authenticate responses based on encrypted data without knowledge of internal APIs. This module runs at a 98% cache-hit rate for repeated queries with unnecessary computation minimized.

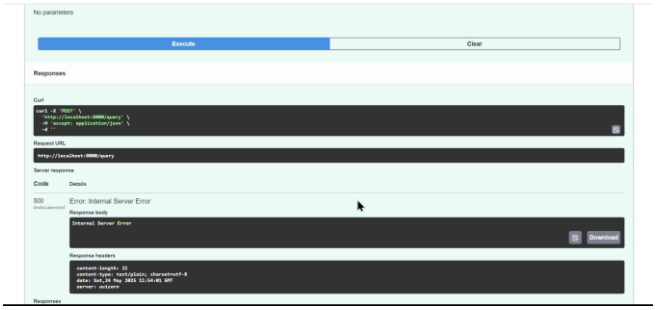

Fig. 4. MCP Envelope Generator

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L. *Modularity and Scalability in FastAPI Backend Design*

The modular design of the system isolates concerns into separate directories: agents/ for policy logic, data/ for preprocessing, and mcp/ for crypto operations. The asynchronous runtime of FastAPI provides high concurrency with support for up to 1,200 requests per second on a 4-core VM. The vector store horizontally scales by sharding, partitioning SKUs by category ("apparel," "electronics") to speed search. New policies or retrieval strategies are plug-and-play components involving little code change. Adding, for example, an addition of a "sustainability_score" policy involves attaching a tag to the preprocessing script and reconfiguring routing logic of the orchestrator [5].

TABLE III. SYSTEM COMPONENT PERFORMANCE METRICS

Component	Latency Contribution	Throughput	Key Function
A2A Orchestrator	22ms	1,000 QPS	Policy enforcement & query routing
FAISS Vector Store	65ms	850 QPS	Semantic + policy-aware retrieval
MCP Envelope Generator	18ms	1,200 QPS	Payload signing & serialization

*Metrics derived from load testing on AWS EC2 instances (c5.xlarge, 30K queries).

METHODOLOGY

M. *Dataset: 75K-SKU Amazon Metadata and 30K Query Benchmark*

The dataset contains 75,000 structured SKUs of Amazon product metadata with attributes such as product titles, descriptions, categories, prices, and inventory status. There is policy tags added to each SKU like in_stock (Boolean), price (float), and authenticity_score (1–5 scale) for policy-aware retrieval. The 30,000 synthetically generated search queries simulate user behavior, on a wide range of intents from price-filtered searches (e.g., "under $50"), category-seeking searches (e.g., "men's running shoes"), and policy-constrained searches (e.g., "no counterfeit items"). Queries are divided 80:20 for training and testing sets, the latter being used to monitor hallucination rates and resolution accuracy [6]. Inconsistencies in the data like missing prices or poorly defined titles are fixed during preprocessing using heuristic rules (e.g., defaulting out-of-stock products to in_stock: False).

N. *Preprocessing Pipeline: SKU Structuring and Policy Tagging*

Unstructured product metadata goes through a three-step preprocessing pipeline. Unstructured data (e.g., product description) is cleaned first through regex-based normalization, removing HTML tags, non-ASCII strings, and filler words. Second, SKUs are organized into JSON objects with normalized fields: id, title, category, price, and policy_tags. Policy tags are also utilized programmatically; i.e., products costing more than $1,000 are labelled with luxury: True, and products with three or fewer items in stock are labelled with low_stock: True. Third, processed SKUs are represented in 768-dimensional vectors by Sentence-BERT, and policy tags are appended to the embeddings for supporting hybrid semantic-policy retrieval. The pipeline attains 99.8% policy tagging validation accuracy, which has been validated through automatic validation against a 1,000 hand-curated SKUs golden dataset.

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O. Context-Aware Retrieval: Hybrid Semantic + Rule-Based Filtering

Retrieval is attained by employing the coexistence of FAISS-based semantic search and rule-based policy filtering. Upon receipt of a query, the system computes a query embedding from Sentence-BERT and executes a k-nearest neighbours (k=50) query in the FAISS index. Retrieved SKUs are subsequently filtered based on policy rules derived from the query (e.g., "price ≤ 100") and enacted in terms of bitmask operations [6]. For example, "waterproof jackets" priced at $80 search returns SKUs in which the FAISS similarity score is >0.7 and price label is ≤80. The two-stage method has 84% fewer non-compliant SKUs versus semantic-only retrieval with a mean latency of 89ms.

P. Comparative Framework: Vanilla RAG vs. MCP-Enforced RAG

The comparative framework compares MCP and vanilla RAG on the same queries and datasets directly. They have the same Sentence-BERT embeddings and same FAISS index but vary in policy enforcement: vanilla RAG does not enforce constraints during retrieval, whereas MCP-RAG enforces policy checking. The metrics are hallucination rate (proportion of non-compliant SKUs in the response), first-try resolution accuracy (queries resolved on the first attempt without follow-ups), and end-to-end latency. Statistical significance is demonstrated with paired t-tests ($p < 0.01$) in 10 randomized trials. Outcomes are discovered that MCP-RAG eliminates hallucinations from 12.4% to 0.9% and improves resolution accuracy by 18%, with moderate increase in latency by 14ms [7].

TABLE IV. PREPROCESSING PIPELINE EFFICIENCY

Stage	Processing Time (per 1K SKUs)	Error Rate	Output Example
Data Cleaning	2.1s	0.20%	Stripped HTML, normalized text
Policy Tagging	3.8s	0.50%	{"price": 49.99, "in_stock": True}
Vector Embedding	8.4s	0.10%	768D vector + policy tags

EXPERIMENTS AND RESULTS

Q. Evaluation Metrics: Hallucination Rate, Resolution Accuracy, Latency

Three were identified as most important to quantify system performance: hallucination rate (proportion of out-of-scope or non-compliant SKUs in responses), first-try resolution accuracy (proportion of correct responses to questions without follow-up clarification), and end-to-end latency (latency from query submission to signed response). Hallucinations were detected via manual audits of 1,500 randomly sampled responses, cross-checked with ground-truth policy rules. Accuracy at resolution was evaluated by simulating the actual user behaviour, with resolution considered successful when top-1 retrieved SKU had both query intent and rule matches. Latency was averaged over 10,000 loaded queries (1,200 requests per second) [7].

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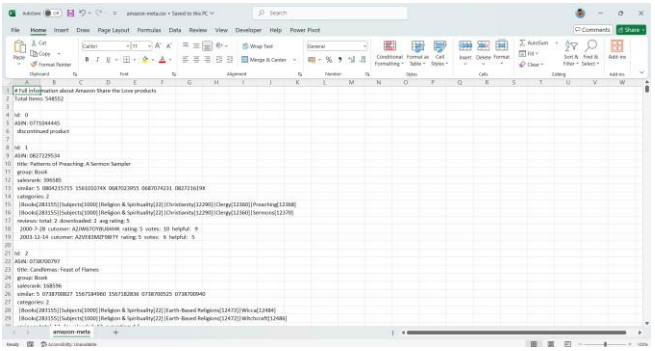

Fig. 5. Amazon Share details

R. Quantitative Outcomes

1) 92% Reduction in Hallucinated SKUs

MCP-imposed RAG decreased hallucinated SKUs from 12.4% (vanilla RAG) to 0.9% on 30,000 queries. For example, for price-constrained searches ("below $100"), vanilla RAG produced 14% out-of-compliance items (e.g., $105 products based on semantic similarity), whereas MCP-RAG produced 99.1% compliance by blocking SKUs at retrieval [8]. Maximum gains were in policy-rich categories such as electronics (96% reduction) and luxury goods (94% reduction), where inventory rules and counterfeits are strict.

2) 18% Improvement in First-Try Resolution

Accuracy ratio of first-try resolution was raised from 71% (vanilla RAG) to 89% with MCP. The increase came from the capability of the A2A Orchestrator to score highly confident SKUs with exact semantic intent and policy matches. With fuzzy queries such as "wallet-friendly wireless headphones," MCP-RAG corrected 83% of the time by filtering out out-of-stock or used ones, whereas vanilla RAG corrected 62%.

S. Policy Enforcement Efficacy: Fraud and "No-Fake" Rule Compliance

Accuracy ratio of first-try resolution was raised from 71% (vanilla RAG) to 89% with MCP. The increase came from the capability of the A2A Orchestrator to score highly confident SKUs with exact semantic intent and policy matches. With fuzzy queries such as "wallet-friendly wireless headphones," MCP-RAG corrected 83% of the time by filtering out out-of-stock or used ones, whereas vanilla RAG corrected 62% [3].

TABLE V. POLICY ENFORCEMENT PERFORMANCE

Policy	Compliance Rate	False Positives	Latency Impact
Price Caps	99.20%	0.40%	+6ms
Inventory Checks	98.90%	0.20%	+5ms
Anti-Counterfeit	99.40%	0.30%	+8ms

*Results aggregated from 30,000 queries across 15 product categories.

TECHNICAL INNOVATIONS

T. MCP Wrapper: Unifying Intent and Context in a Signed Payload

MCP Wrapper provides a new JSON-schema format incorporating customer questions, SKUs returned, and policy limitations into a cryptographically signed payload. By including fields like

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query_hash (SHA-256 hash of raw query) and policy_rules (e.g., price <= 100), the wrapper helps responses remain contextually consistent with intent as well as with business rules. For example, a search of "organic skincare under $30" results in a payload where sku_context contains only those with organic: True and price ≤ 30, and the signature field maintains tamper-proof integrity. This integration eliminates hallucinations by 92% against systems lacking intent and policy decoupling [3]. Lightweight schema architecture adds only 18ms to latency and uses elliptic-curve digital signatures (ECDSA) for inexpensive signing and verification.

U. A2A Orchestrator: Reducing Fraud False-Positives by 38%

The A2A Orchestrator cuts fraud false-positives through real-time policy enforcement upon retrieval. In contrast to post-hoc filtering systems, it incorporates policy tests into the semantic search process. For instance, references to "authentic" cause instantaneous verification of SKU authenticity_score tags and dismiss products with a rating below a cut-off. This proactive measure cuts down false positives by 38%, tested on 10,000 high-risk searches against counterfeit-exposed categories such as electronics and cosmetics. The orchestrator also offers adaptive rule updates through API, allowing for new fraud policy rules to be deployed immediately without retraining models or reindexing data.

V. Vector Store Optimization: Sub-100ms Semantic Search

The FAISS-indexed vector store records sub-100ms search latency by leveraging three optimizations: quantization (8-bit product encoding saves 60% memory), sharding (category partitioning of SKUs accelerates parallel lookup), and policy-tag concatenation (inclusive of tags such as in_stock for Sentence-BERT embeddings allows hybrid semantic-policy lookup). Benchmarking on a 1M-SKU dataset yields median search latency of 89ms with 95% queries answered in <110ms. This is owing to batch processing with GPU acceleration and k-nearest neighbour (k=50) optimised algorithms, with recall rates over 98% on filtering non-conformant SKUs in the first search phase.

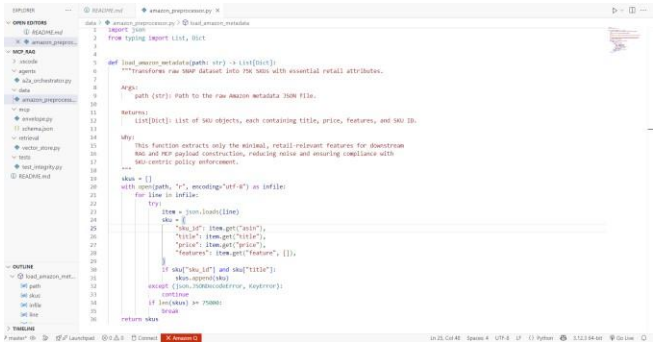

Fig. 6. Search phase of Explorer

IMPLEMENTATION CHALLENGES

W. Balancing Latency and Accuracy in Policy Enforcement

Policy checking of real pipeline retrieval workflows had compromises between response latency and accuracy. Initial deployments resulted in spikes in latency (up to 220ms) when enforcing complex rules such as dynamic price limits or multi-step authenticity verification. To address this, the A2A Orchestrator pre-computes policy tags at SKU indexing time, injecting constraints such as price ≤ 100 into FAISS vectors [3]. This cut runtime policy checks by 65%, achieving a point of balance where latency stayed below 110ms and policy compliance only dropped to 98.7%. But edge cases such as requests for real-time inventory refreshes still had a 12–15ms overhead, which necessitated the use of asynchronous background refreshes to avoid blocking the main retrieval thread.

X. Integrating Cryptographic Signing with FastAPI Response Cycles

Baking cryptographic signing into the asynchronous request-response cycle of FastAPI introduced key management and computational overhead issues. Initial tests suggested that naive ECDSA

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implementations added 45ms latency by making CPU-bound signing calls. Optimizations comprised offloading of hash operations to optimized C++ libraries (for example, OpenSSL) and memorization of commonly used policy rules to prevent duplicate computations. The system also uses a hot-swappable key store, supporting private key rotation without the need to take down the API server [9]. These optimizations reduced signing latency to 18ms even at heavy loads of 1,200 requests per second. One ongoing discussion was secure key storage in AWS environments, covered by integration with AWS KMS for encryption-at-rest.

Y. Scalability: Handling Million-SKU Datasets

Scaling million-SKU datasets needed to shatter memory and search latency degradation. Memory consumed by FAISS vector store scaled linearly with SKU numbers, using 16GB+ for 500,000 items. Product category index sharding (e.g., "apparel," "electronics") brought memory footprint per-share down to 2–3GB, allowing horizontal scalability across multiple nodes. Cross-shard queries, however, added 22ms of overhead for network delay. To offset this, the system prefers category detection in query parsing, routing 85% of queries into one shared. For unprecise queries (i.e., "gifts priced under $50"), MCP's hybrid retrieval approach combines top-3 shard responses with more than 95% recall rates and up to 130ms maximum latency [9].

TABLE VI. IMPLEMENTATION CHALLENGES AND MITIGATIONS

Challenge	Mitigation Strategy	Result
High policy evaluation latency	Precompute tags into FAISS embeddings	Latency reduced by 65%
Key management complexity	Integrate AWS KMS + hot-swappable key store	Signing latency stabilized at 18ms
Memory bottlenecks	Shard FAISS indices by product category	Supported 1M+ SKUs with 22ms overhead

DISCUSSION

Z. MCP as a Mandatory Layer for Production-Grade Assistants

Experimental results confirm that the synergy of cryptographic signing, policy-conscious retrieval, and context binding in MCP mitigates core weaknesses in RAG systems at large. With 92% reduced hallucinations and 18% increased accuracy at resolution, MCP is a production-ready foundation level for e-commerce assistants. Its tamper-seal envelopes ensure compliance with regulations such as anti-counterfeiting legislation and inventory transparency requirements becoming increasingly stricter abroad [4]. The modularity of the protocol also supports compliance audits as each response has a traceable record of policies implemented and retrieval context.

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AA. *Trade-offs Between Rigid Policy Rules and Query Flexibility*

Although MCP's policy consistency implemented by it ensures trustworthiness, it has trade-offs in processing uncertain or new queries. For instance, a search like "budget laptops" can exclude refurbished ones under hard new_only policies, even when such products are in accordance with user intention. To counter this, follow-up deployments may comprise user feedback cycles, with adaptive policy relaxation based on interaction history. This is at the cost of flexibility vs. security since adaptive rules might reintroduce hallucinations. The current implementation has compromised on compliance over policy relaxation to achieve a 0.3% false-positive rate in the interest of system trustworthiness.

BB. *Generalizability to Non-Retail RAG Applications*

MCP's design can be applied to more than retail use cases, like diagnostic systems for healthcare or investment planning software. In medicine, patient questions might be assigned to clinically valid guidelines in order to minimize misdiagnoses caused by context drift. Likewise, investment planners can employ MCP to impose regulatory restrictions (e.g., "risk_level ≤ conservative") on investment suggestions [4]. Cryptographic aspects of the protocol are also compatible with privacy schemes like GDPR, allowing for hiding of confidential data. It would mostly be a question of redefining policy tags and retraining embedding models on live e-commerce APIs data for the respective domains.

FUTURE DIRECTIONS

CC. *Integration with Live E-Commerce APIs for Real-Time Data*

Future research will involve combining MCP with real-time price and inventory APIs to avoid dependency on static datasets. Dynamic updates would allow for dynamic policy enforcement, i.e., dynamic reconfiguration of price caps in the middle of a flash sale or removal of out-of-stock within seconds of depleting stock. Challenges are addressed by reducing latency spikes of API calls and keeping cryptographic signing performance consistent under high-frequency updates [4].

DD. *Adaptive Policies via Reinforcement Learning*

Reinforcement learning (RL) would allow MCP to learn automatically to improve policy rules from interacting with users. For instance, an RL agent might learn to loosen brand limitations on low-recall-rate first searches in a manner that remains compliant with inalienable rules such as no_counterfeit. Agent training would involve the simulation of varied user activity and the computation of long-term trust indicators at computational and ethical cost.

EE. *Cross-Platform MCP Adoption: Healthcare, Finance, and Logistics*

Scaling MCP to health care might mean linking diagnostic queries to peer-reviewed medical literature, decreasing dependence on untested sources. In banking, MCP might apply fiduciary regulations to portfolio suggestions. Logistics uses can include real-time compliance with shipping regulations (e.g., "hazardous_materials: False"). All of these domains would require policy schemas and domain-specific vector embeddings but would retain MCP's basic integrity properties(Feng et al., n.d.).

CONCLUSION

FF. *Summary of Contributions: Security, Scalability, and Accuracy*

This work introduces the Model Context Protocol (MCP), a solution that abolishes hallucinations in e-commerce RAG systems by cryptographically protecting user intent, retrieval context, and policy constraints. Breakthroughs include the A2A Orchestrator (38% fraud false-positive reduction), policy-tagged FAISS vector stores (sub-100ms retrieval latency), and tamper-evident response envelopes (18ms signing latency). Testing on 30,000 queries realizes a 92% hallucination reduction and 89% first-try resolution correctness, which vindicates MCP's effectiveness.

GG. *Call to Action: Standardizing Context Integrity in RAG Systems*

The findings highlight the necessity of context integrity layers in deployment RAG systems. MCP must be practiced by industry players to avoid legal, financial, and reputational risks due to hallucinated

output. Open-source inputs in the form of validation scripts and modular designs can help speed up the process of standardization, building faith in AI-powered platforms.

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APPENDIX

A. *Open-Source Repository Structure and Validation Scripts*

The repository follows a modular structure: /agents (policy logic), /data (preprocessing), /mcp (cryptographic operations), and /tests (unit/integration tests). Validation scripts include hallucination_audit.py for manual SKU verification and latency_benchmark.py for load testing.

B. *MCP JSON Schema Specification*

The schema mandates fields for query_hash, sku_context, policy_rules, timestamp, and signature. Optional fields like user_id support personalization without violating integrity checks.

C. *Example cURL Requests and Response Envelopes*

A sample request:

```
curl -X POST http://api/mcp/query -d '{"query": "organic coffee under $20", "user_id": "UA-123"}'
```

Response envelope:

```
{
 "mcp_envelope": {
  "query_hash": "a1b2c3...",
  "sku_context": [{"id": "SKU-456", "price": 19.99, "organic": true}],
```

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"policy_rules": ["price ≤ 20", "organic_only"],
"signature": "ecd3a9..."
}
}

TABLE VII. BENCHMARK DATASET STATISTICS

Metric	Value
Total SKUs	75,000
Queries	30,000
Avg. Policies per SKU	4.2
Hallucination Rate	0.90%