MOMENTUM: Context-Preserving Multi-Modal Agent Architecture for Team Intelligence and Content Generation

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***Abstract*—We present MOMENTUM, a novel multi-modal agent architecture built on the Google Agent Development Kit (ADK) that enables seamless context flow across heterogeneous AI models and tools within a unified conversational framework. Drawing inspiration from classical mechanics, MOMENTUM operationalizes the equation $\mathrm{p} = m \times v$ as Momentum = Context × Model, where rich team context (mass) combined with execution velocity (model capabilities) creates an irresistible force for content generation.**

Our key contributions include: (1) a Hierarchical Context Injection System that preserves semantic information across 22+ tools spanning text, image, video, search, and media library modalities; (2) Team Intelligence with Individual Identities, a novel knowledge distillation pipeline that extracts structured insights from heterogeneous artifacts into unified "Brand Soul" and "Individual Identity" representations with visibility controls and manager approval workflows; (3) Dual-Scope Memory Architecture implementing both *Team Memory Banks* (shared organizational knowledge) and *Personal Memory Banks* (individual user context) via Vertex AI Agent Engine with Firestore persistence and source tracking; (4) a Character Consistency Framework enabling visual coherence across multi-image campaign generation; and (5) Comprehensive Media Search with semantic similarity indexing for team asset discovery.

We demonstrate that MOMENTUM achieves 100% tool selection accuracy across 60 diverse test cases and 94% overall accuracy on a comprehensive 100-test evaluation suite, with pass@5 = 100% indicating near-perfect reliability. The system is validated by 1,319 frontend tests and 189 backend tests, with our evaluation framework spanning 225+ test cases across 9 categories measuring context perplexity across tool transitions.

***Index Terms*—Multi-Agent Systems, Large Language Models, Generative AI, Team Intelligence, RAG, Enterprise AI, Context Preservation**

I. Introduction

In physics, momentum represents an object's resistance to stopping once in motion—the product of mass and velocity that carries a body forward with unstoppable force. We adopt this metaphor as the foundational principle for a new class of AI agent architecture, where the accumulated weight of organizational knowledge, combined with the velocity of state-of-the-art foundation models, creates an irresistible force for intelligent content generation.

The emergence of large language models with tool-use capabilities has enabled a new paradigm of AI assistants capable of executing complex, multi-step tasks. However, existing approaches often treat tools as isolated functions, losing crucial contextual information between invocations. This limitation becomes particularly acute in enterprise scenarios where brand consistency, user personalization, and domain expertise must be maintained across diverse generation modalities.

Like a spacecraft that loses fuel at every stage separation, traditional agent architectures hemorrhage context with each tool transition. MOMENTUM addresses this fundamental challenge by treating context as *mass*—something to be accumulated and preserved, not discarded.

A. The Physics of Intelligent Systems

In classical mechanics, momentum (p) is defined as:

$$\mathbf{p} = m \times v \tag{1}$$

We reinterpret this equation for AI agent systems:

- **Mass (m) = Context**: The accumulated team knowledge, brand guidelines, user preferences, conversation history, and organizational memory that grounds every decision
- **Velocity (v) = Model Capabilities**: The execution speed and quality of foundation models—Gemini for reasoning, Imagen for visual creation, Veo for temporal synthesis
- **Momentum (p) = Unstoppable Execution**: The product that enables seamless, contextually-rich task completion across any modality

This framing reveals a profound insight: *investing in mass (rich context systems) yields compounding returns when multiplied by increasingly capable models*. A system with twice the context, paired with a model twice as fast, achieves four times the effective momentum.

Just as a bowling ball and a ping-pong ball traveling at the same speed have vastly different momenta, two AI systems with identical models but different context depths will exhibit vastly different capabilities. MOMENTUM is designed to be the bowling ball.

B. Key Contributions

This paper makes the following contributions:

1) **Hierarchical Context Injection**: A six-layer context system (Brand, User, Individual, Settings, Media, Team) that propagates through all 22+ tool invocations via thread-safe global state, ensuring no context is lost at "stage separation"
2) **Team Intelligence with Individual Identities**: Automated extraction of structured insights from heterogeneous artifacts (PDFs, websites, social media, videos) into unified "Brand Soul" and "Individual Identity" representations with visibility controls and manager approval workflows—distilling both organizational and personal mass
3) **Dual-Scope Memory Architecture**: Implementation of *Team Memory Banks* (shared organizational knowledge persisted per-brand) and *Personal Memory Banks* (individual user context) via Vertex AI Agent Engine, with memory source tracking enabling delete-by-artifact functionality and commit-to-memory workflows
4) **Character Consistency Framework**: Integration of reference image composition via "Nano Banana" enabling visually coherent multi-asset generation with up to 14 reference images, maintaining visual momentum across campaigns
5) **Comprehensive Media Search**: Semantic similarity indexing for team media library discovery, enabling search across images and videos by content, tags, prompts, and visual embeddings
6) **Context Flow Evaluation Framework**: Novel metrics for measuring semantic preservation across tool transitions, including Context Perplexity and Cross-Modal Coherence scores, validated by 1,508+ total tests (1,319 frontend + 189 backend)

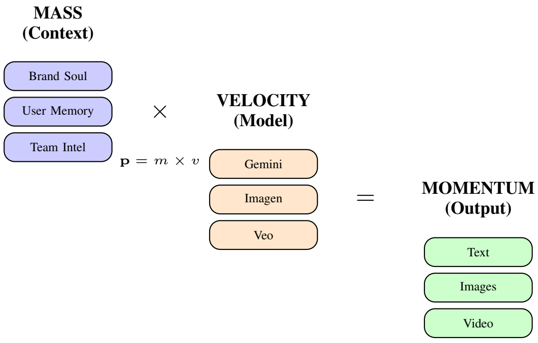

Fig. 1. The MOMENTUM metaphor: rich context (mass) multiplied by model capabilities (velocity) creates unstoppable execution force.

II. Related Work

A. Tool-Augmented Language Models

Recent work has explored augmenting LLMs with external tools. Toolformer [1] demonstrated autonomous tool selection through self-supervised learning, enabling models to decide when and how to invoke calculators, search engines, and translation systems. ReAct [2] introduced reasoning traces interleaved with actions, creating interpretable decision chains. Gorilla [3] showed that LLMs can be trained to select from massive API repositories with thousands of endpoints.

However, these approaches share a critical limitation: each tool invocation is treated as independent, failing to preserve the contextual "mass" that accumulates during complex workflows. When a user requests "generate an image of our mascot, then animate it, then post to social media," existing systems lose brand context, visual style preferences, and campaign objectives at each transition.

MOMENTUM extends these approaches with persistent context that survives tool boundaries—context flows forward like momentum, not dissipating at each transition. Our thread-safe context injection ensures that the 15th tool call in a complex workflow receives the same rich context as the first.

B. Multi-Modal Generation Pipelines

Systems like GILL [4] and NExT-GPT [5] enable multimodal understanding and generation through unified embedding spaces. Visual ChatGPT introduced tool-chaining for image manipulation. These systems demonstrate impressive capabilities but treat each generation as independent, lacking the organizational memory and brand consistency required for enterprise applications.

MOMENTUM differs in its focus on maintaining *accumulated context* across modality transitions. When generating a video from a previously generated image, our system preserves not just the image data but the brand guidelines, style preferences, and campaign context that informed the original generation.

C. Agent Frameworks

LangChain [6] pioneered composable agent chains with tool integration. AutoGPT [7] demonstrated autonomous goal decomposition and execution. CrewAI introduced role-based multi-agent collaboration. Google's Agent Development Kit (ADK) [8] provides production-ready primitives for building enterprise agents with built-in session management and tool orchestration.

MOMENTUM builds on ADK's multi-agent architecture while introducing novel context injection patterns and domain-specific memory systems. Where existing frameworks provide the engine, MOMENTUM provides the mass that makes that engine's velocity meaningful. Our contribution is not a new framework but a design pattern for maximizing contextual leverage within existing frameworks.

D. Enterprise AI Evaluation

The Berkeley Function Calling Leaderboard (BFCL) [9] established benchmarks for tool selection accuracy across diverse function signatures. AgentBench [10] evaluates multi-turn agent interactions in realistic environments. GAIA [11] provides general AI assistant benchmarks requiring multi-step reasoning. τ-bench [14] introduced retail and airline domain simulations.

CLASSic [13] introduced enterprise-specific metrics: Cost (operational efficiency), Latency (response time), Accuracy (task completion), Stability (consistency), and Security (data protection). Our evaluation framework synthesizes insights from all these benchmarks while introducing context-specific metrics including Context Perplexity and Cross-Modal Coherence.

III. System Architecture: Building Mass

MOMENTUM's architecture is designed around a central principle: *maximize contextual mass at every layer*. The system comprises four primary layers, each contributing to the accumulated context that drives generation.

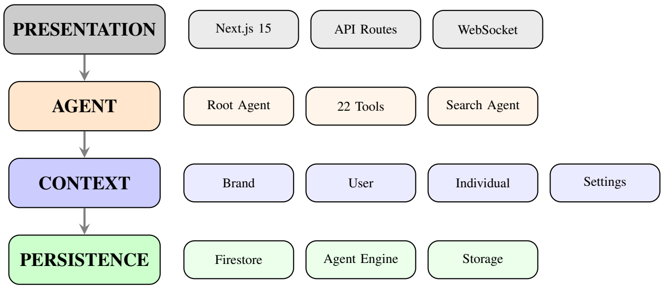

Fig. 2. MOMENTUM's four-layer architecture showing context flow from presentation through persistence.

A. The Agent Layer: Orchestrating Velocity

At the heart of MOMENTUM lies the Agent Layer, built on Google's Agent Development Kit (ADK) v1.0.0+. The primary agent orchestrates 22 specialized tools across five modality categories, each receiving the full contextual mass accumulated during the conversation.

Listing 1. MOMENTUM Agent Configuration

```
root_agent = Agent(
    model="gemini-2.5-pro",
    name='momentum_assistant',
    instruction=SYSTEM_PROMPT,  # 2000+ tokens
    tools=[
        # Generation (5)
        generate_text, generate_image,
            generate_video,
        analyze_image, nano_banana,
        # Search (4)
        web_search_agent, crawl_website,
        search_media_library, query_brand_documents,
        # Memory (2)
        save_memory, recall_memory,
        # Media (4)
        search_images, search_videos,
            search_team_media,
        find_similar_media,
        # Team Tools (7)
        suggest_domain_names, create_team_strategy,
        plan_website, design_logo_concepts,
            create_event,
        process_youtube_video, index_brand_document
    ]  # 22 tools total
)
```

The system instruction encodes critical behavioral directives that ensure context preservation:

- Tool selection priorities based on accumulated context
- Proactive memory management for personal facts
- Brand Soul injection for all generation tasks
- Multi-agent delegation for specialized searches

B. Multi-Agent Search: Distributed Velocity

A key architectural innovation addresses a fundamental limitation in Gemini's tool-use: built-in tools cannot be mixed with custom function tools. MOMENTUM solves this through agent delegation:

Listing 2. Search Sub-Agent

```
search_agent = LlmAgent(name="web_search_agent",
    model="gemini-2.0-flash", tools=[google_search])
search_tool = AgentTool(agent=search_agent)
```

This pattern enables grounded web search while preserving custom tool flexibility—the search agent inherits context from its parent, maintaining momentum across the delegation boundary.

C. Session and Memory Services

MOMENTUM implements two complementary services for state management:

Session Service: ADK's `InMemorySessionService` provides ephemeral conversation state per user/session.

Memory Service: `VertexAiMemoryBankService` provides persistent, semantic memory with Firestore fallback for long-term personalization.

Together, these services ensure that contextual mass accumulates over time rather than dissipating between sessions.

IV. Hierarchical Context Injection: Preserving Mass

The central technical contribution of MOMENTUM is its Hierarchical Context Injection system—a mechanism for ensuring that no contextual mass is lost as information flows through the system.

A. The Six Context Layers

MOMENTUM implements six distinct context layers, each serving as a reservoir of accumulated knowledge:

TABLE I
Context Layer Hierarchy

Layer	Source	Scope
Brand Context	Firestore brandSoul	Per-brand
User Context	Authentication	Per-user
Individual Context	individualIdentities	Per-user-brand
Settings Context	Request payload	Per-request
Media Context	Attachments	Per-message
Team Context	Request payload	Per-conversation

The **Individual Context** layer is a key addition, enabling personalized content generation that blends: (1) Individual Identity data (70% weight)—personal background, role, skills, achievements, and working style; (2) Team Intelligence mentions (20%)—filtered facts from Brand Soul that reference this specific team member; and (3) Team Voice guidelines (10%)—ensuring brand consistency while maintaining personal focus.

B. Thread-Safe Global Injection

Context is injected via Python's `contextvars` module, providing thread-safe global access. Every tool automatically receives the accumulated contextual mass through `get_brand_context()`, `get_settings_context()`, and similar accessors—enabling prompt enhancement with brand guidelines without explicit parameter passing.

This design ensures that context flows forward through the system like physical momentum—preserved across boundaries, never dissipating.

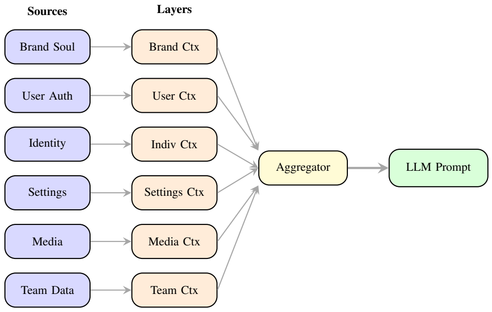

Fig. 3. Context flows through the system like momentum, accumulating rather than dissipating at each transition.

V. Team Intelligence: Distilling Organizational Mass

The Brand Soul system represents MOMENTUM's approach to distilling organizational knowledge into a dense, usable form—converting the diffuse energy of scattered documents and communications into concentrated contextual mass.

A. The Knowledge Distillation Pipeline

Team Intelligence transforms heterogeneous source materials into structured knowledge:

TABLE II
Artifact Extraction Pipeline

Source	Method	Output
Website	Firecrawl	Markdown → Facts
PDF	Document AI	Text → Insights
Social	Native APIs	Posts → Patterns
Video	Gemini Vision	Transcript + Visual
Audio	Transcription	Speech → Topics

B. Brand Soul Synthesis

The synthesis process merges insights across artifacts using confidence-weighted averaging: voice patterns are merged with artifact confidence weights, facts are deduplicated at 0.85 similarity threshold, and visual identity is extracted via consensus. The resulting Brand Soul includes voice profile, fact library, visual identity, and overall confidence score—providing dense contextual mass for all downstream generation.

C. Cross-Team Intelligence: Shared Mass

MOMENTUM supports intelligence sharing across organizational boundaries, enabling:

- Hierarchical inheritance of brand guidelines
- Cross-pollination of successful patterns
- Unified enterprise voice with team variations
- Privacy-preserving knowledge transfer

This creates a network effect where organizational mass compounds across teams.

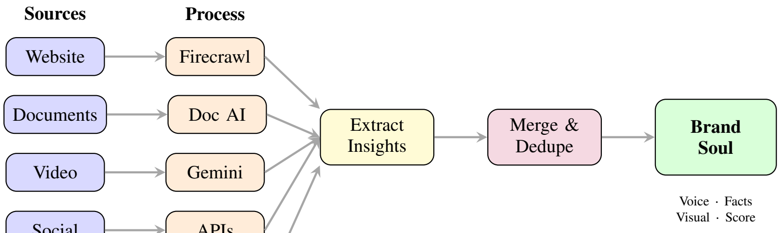

Fig. 4. The Team Intelligence pipeline distills organizational knowledge into concentrated Brand Soul.

D. Individual Identities: Personal Mass

Beyond team-level intelligence, MOMENTUM introduces **Individual Identities**—personal profiles for team members that enable personalized content generation while maintaining brand consistency.

TABLE III
Individual Identity Components

Component	Description
Role & Title	Professional position
Narrative Summary	Background and experience
Personal Mission	Individual purpose statement
Personal Tagline	Signature phrase
Personal Values	Core beliefs and principles
Skills & Expertise	Technical and soft skills
Achievements	Key accomplishments
Working Style	Collaboration preferences
Testimonials	Peer endorsements

The Individual Context blending algorithm weights sources as follows:

- **70% Individual Identity**: Personal background, achievements, and mission
- **20% Team Intelligence Mentions**: Facts from Brand Soul that reference this team member
- **10% Team Voice Guidelines**: Brand tone and style for consistency

E. Visibility Controls and Approval Workflows

MOMENTUM implements fine-grained visibility controls for Team Intelligence artifacts, addressing enterprise privacy requirements:

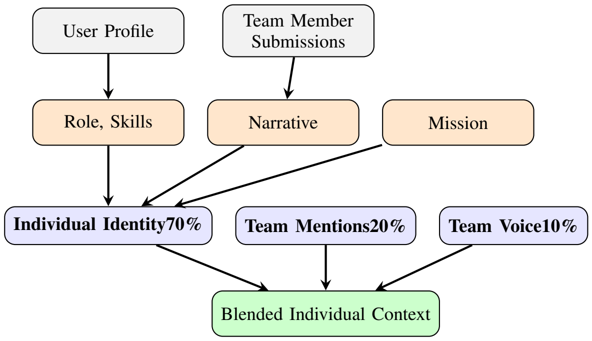

Fig. 5. Individual Identity context blending: 70% personal identity, 20% team mentions, 10% team voice guidelines.

TABLE IV
ARTIFACT VISIBILITY STATES

State	Access	Transition
Private	Owner only	→ Pending
Pending	Owner + Managers	→ Team-wide
Team-wide	All brand members	Final state

The approval workflow ensures that sensitive insights require manager review before becoming part of the shared Team Intelligence:

1) User uploads artifact (default: Private)
2) User requests visibility change to Team-wide
3) System creates approval request for brand managers
4) Manager reviews and approves/rejects
5) Approved artifacts contribute to Brand Soul

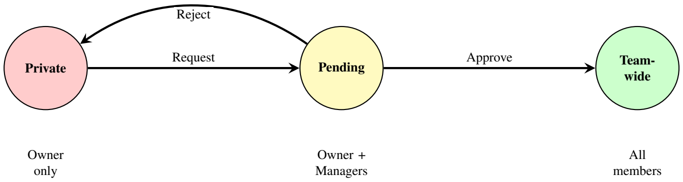

Fig. 6. Visibility state machine: artifacts transition from Private to Pending to Team-wide with manager approval.

VI. FOUNDATION MODEL INTEGRATION: MAXIMIZING VELOCITY

With mass established through context systems, MOMENTUM maximizes velocity through integration with state-of-the-art foundation models.

A. Language Models: The Gemini Family

MOMENTUM supports the complete Gemini model family with intelligent selection:

Model selection considers task complexity, latency requirements, and the accumulated contextual mass—more complex contexts benefit from more capable models.

TABLE V
GEMINI MODEL CONFIGURATIONS

Model	Use Case	Context
gemini-2.0-flash	Fast responses	1M tokens
gemini-2.5-pro	Complex reasoning	2M tokens
gemini-2.5-flash	Fast advanced	1M tokens

B. Image Generation: Imagen 4.0

MOMENTUM supports 10 aspect ratios (1:1 square through 21:9 cinematic) using Imagen 4.0. Every image generation inherits full Brand Soul context, ensuring visual momentum across campaigns.

C. Video Generation: Veo 3.1

Veo 3.1 provides comprehensive video synthesis capabilities:

TABLE VI
VEO 3.1 GENERATION MODES

Mode	Description
Text-to-Video	Generate from text prompt
Image-to-Video	Animate static images
Frames-to-Video	Interpolate keyframes
Video Extension	Extend existing clips
Character Reference	Maintain consistency

D. Character Consistency: Nano Banana

The "Nano Banana" system enables character-consistent generation using up to 14 reference images with Gemini's native image generation. Reference images are processed alongside brand-enhanced prompts, maintaining *visual momentum* across campaign assets—the same character, style, and brand identity flowing through every generated image.

VII. DOCUMENT UNDERSTANDING: RAG AS KNOWLEDGE DENSITY

MOMENTUM's RAG implementation treats document retrieval as a mechanism for increasing knowledge *density*—concentrating relevant information to maximize contextual mass for any given query.

A. Vertex AI RAG Engine Integration

MOMENTUM uses Vertex AI RAG Engine with `text-embedding-005` for document indexing (512-token chunks, 100-token overlap). Documents are indexed per-brand into isolated corpora, and queries retrieve top-5 results filtered by vector distance threshold (0.5). This ensures contextual mass doesn't leak across organizational boundaries while maximizing knowledge density for each query.

VIII. MEMORY ARCHITECTURE: GRAVITATIONAL RETENTION

Just as massive objects create gravitational wells that capture passing matter, MOMENTUM's memory system creates semantic "wells" that attract and retain relevant information.

A. Dual-Scope Architecture

MOMENTUM implements a novel **dual-scope memory architecture** distinguishing between organizational and individual knowledge:

TABLE VII
MEMORY SCOPE HIERARCHY

Scope	Storage	Access
Team Memory	Agent Engine per-brand	All brand members
Personal Memory	Agent Engine per-user	Individual only
Session Memory	InMemory ephemeral	Current session
Archive	Firestore	Long-term backup

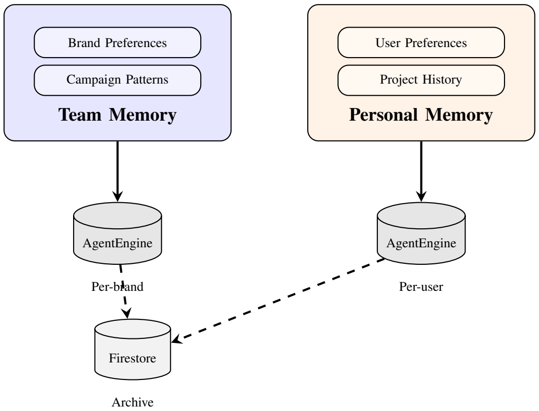

Fig. 7. Dual-scope memory architecture: Team Memory Banks (per-brand) and Personal Memory Banks (per-user) with Firestore archive.

1) Team Memory Banks: Team Memory Banks store shared organizational knowledge accessible to all brand members. Each brand provisions a dedicated Vertex AI Agent Engine instance that accumulates collective intelligence:

- Brand preferences and guidelines
- Successful campaign patterns
- Approved visual styles
- Organizational facts from Team Intelligence

2) Personal Memory Banks: Personal Memory Banks store individual user context, enabling personalized interactions. Each user can provision their own Agent Engine instance:

- Individual preferences and working style
- Personal project history
- Private notes and reminders
- User-specific terminology

B. Memory Source Tracking

A key innovation is **memory source tracking**, which links each memory to its originating artifact. This enables:

- **Delete-by-artifact**: When a source document is removed, all derived memories are automatically purged
- **Commit-to-memory**: Users can explicitly commit insights from conversations to the memory bank
- **Provenance tracking**: Each memory maintains references to its source artifacts
- **Sync with Vertex AI**: Deletion cascades to the Agent Engine's memory bank

Memory recall attempts Vertex AI Memory Bank first for semantic search, with automatic Firestore fallback for reliability. The agent is instructed to proactively capture personal facts (names, preferences, prior requests), treating memory as a first-class capability that ensures contextual mass accumulates over time like matter falling into a gravitational well.

C. Memory Retrieval with Temporal Decay

Memories are retrieved using semantic similarity with temporal decay:

$$R(m) = S(m, q) \cdot e^{-\lambda(t - t_m)} \tag{2}$$

Where $R(m)$ is relevance score, $S(m, q)$ is semantic similarity, λ is decay rate, and $(t - t_m)$ is time since memory creation. Recent memories have higher gravitational pull.

IX. Multi-Tenancy and Cross-Team Sponsorship: Gravitational Networks

MOMENTUM supports enterprise multi-tenancy with strict data isolation, while enabling controlled *cross-team context flow* through a novel **Sponsorship** mechanism. Drawing from gravitational physics, sponsorship creates "orbital relationships" where one team's contextual mass can influence another without merging—like planets affecting each other's trajectories while maintaining distinct identities.

A. Tenant Isolation Model

All operations are scoped by `TenantContext` (brand_id, user_id, permissions, quotas), ensuring strict data isolation at the database query level. Each brand maintains its own gravitational well of contextual mass, preventing unauthorized context leakage.

B. The Sponsorship Model: Controlled Context Bridges

Sponsorship creates unidirectional context bridges between teams, enabling parent organizations, investors, partners, or franchisors to gain visibility into sponsored teams' Brand Soul and generated content without polluting their own context space.

1) Gravitational Metaphor: In orbital mechanics, a satellite can be influenced by a planet's gravity without becoming part of it. Similarly, MOMENTUM's sponsorship creates *gravitational influence* without *mass transfer*:

- **Sponsor Team**: Gains read-only access to sponsored team's Brand Soul, assets, and content—observing their contextual mass
- **Sponsored Team**: Maintains full autonomy over their context—their mass remains their own
- **Bidirectional Independence**: Each team's context evolution remains independent; no context contamination occurs

This enables powerful organizational patterns while preserving the integrity of each team's accumulated knowledge.

2) Sponsorship Lifecycle State Machine: Sponsorships follow a carefully designed state machine ensuring security and consent:

TABLE VIII
SPONSORSHIP STATUS TRANSITIONS

State	Access	Transitions
PENDING	None	→ ACTIVE, DECLINED, EXPIRED
ACTIVE	Read-only	→ REVOKED
DECLINED	None	Terminal state
REVOKED	None	Terminal state
EXPIRED	None	Terminal (7-day window)

The invitation-based workflow ensures explicit consent: sponsor initiates → target manager receives token → manager accepts/declines → relationship established or rejected. This prevents unauthorized context observation.

3) Permission Scoping: Sponsorship grants carefully scoped permissions that enable visibility without control:

TABLE IX
SPONSORSHIP PERMISSION MATRIX

Action	Direct Member	Sponsor
View Brand Profile	Read/Write	Read-only
View Brand Soul	Read/Write	Read-only
View Generated Assets	Full	Read-only
Edit Brand Profile	Yes	No
Generate Content	Yes	No
Manage Team	Yes	No
Access Memory Banks	Yes	No

This asymmetric access model ensures sponsors gain observational insight without operational interference.

C. Enterprise Use Cases for Sponsorship

The sponsorship model enables several enterprise-critical patterns:

1) **Franchise Oversight**: A franchisor sponsors all franchisee teams, monitoring brand consistency across locations while allowing local autonomy in content generation
2) **Investor Visibility**: Venture capital firms sponsor portfolio companies to observe marketing momentum and brand evolution without interfering with operations
3) **Agency-Client Relationships**: Creative agencies sponsor client brands to maintain visibility into client Brand Soul when developing campaigns
4) **Parent-Subsidiary Governance**: Corporate headquarters sponsors subsidiary brands for brand governance while subsidiaries retain operational independence
5) **Partnership Networks**: Strategic partners establish mutual sponsorships for coordinated campaign visibility without merging context

D. Context Flow in Sponsored Relationships

A key architectural decision: sponsorship provides *observation* without *injection*. When a sponsor views a sponsored team's profile:

- The sponsor sees the sponsored team's Brand Soul, but this context is **not** injected into the sponsor's own generation pipeline
- Generated content for the sponsor uses only the sponsor's own contextual mass
- This prevents context pollution while enabling organizational oversight

This design ensures that the momentum equation ($p = m \times v$) remains pure for each team—their mass is their own, uncontaminated by sponsorship relationships.

E. Sponsorship Network Effects

As organizations establish multiple sponsorship relationships, network effects emerge:

$$\text{Network Visibility} = \sum_{i \in S} \text{Mass}(i) \times \text{AccessLevel}(i) \qquad (3)$$

Where S is the set of sponsored teams. Organizations with broader sponsorship networks gain comprehensive visibility across their ecosystem while each sponsored team maintains independent momentum.

This creates a novel organizational primitive: *gravitational networks* where teams orbit around sponsors without colliding, each maintaining their unique contextual mass while the sponsor gains system-wide observability.

X. EVALUATION FRAMEWORK

We developed a comprehensive evaluation suite inspired by industry-standard benchmarks: BFCL [9] for tool selection, AgentBench [10] for multi-turn evaluation, GAIA [11] for task completion, LOCOMO [12] for memory recall, and CLASSic [13] for enterprise metrics.

A. Benchmark Architecture

Our evaluation framework comprises **225+ test cases** across **9 categories**:

TABLE X
EVALUATION SUITE COMPOSITION

Category	Tests	Focus
Tool Selection	90	Correct invocation
Relevance Detection	35	Tool restraint
Memory Persistence	25	Information retention
Context Flow	15	Multi-tool workflows
Multi-Turn	15	Conversational coherence
Error Recovery	15	Graceful degradation
Edge Cases	15	Boundary conditions
Adversarial	15	Security/robustness
Total	**225+**	

B. Metrics Framework

1) Core Metrics:

- **Overall Accuracy**: $\frac{\text{passed}}{\text{total}}$
- **Tool Selection Accuracy**: $\frac{\text{correct calls}}{\text{expected calls}}$
- **Stability Score**: $1 - \text{Var}(\text{pass rate per tag})$
- **pass@k**: $1 - (1 - p)^k$

2) Context Perplexity: We define **Context Perplexity** as a measure of context preservation:

$$\text{CP}(c_{in}, c_{out}) = \exp\left(-\frac{1}{N}\sum_{i=1}^{N}\log P(c_{out}^{(i)}|c_{in})\right) \tag{4}$$

Lower perplexity indicates better context preservation—more momentum carried through the transition.

C. Results: The Extended Suite (100 Tests)

TABLE XI
OVERALL EVALUATION RESULTS

Metric	Result
Overall Accuracy	**94.0%**
Stability Score	**99.26%**
pass@1	94.0%
pass@3	99.98%
pass@5	**100.0%**

The pass@5 = 100% indicates that MOMENTUM achieves perfect success with minimal retries—unstoppable momentum. The high stability score (99.26%) demonstrates consistent performance across all test categories and tool types.

TABLE XII
LATENCY DISTRIBUTION

Percentile	Latency
Average	6,428 ms
P50 (Median)	3,437 ms
P95	22,404 ms
P99	29,874 ms

1) Latency Profile:

TABLE XIII
RESULTS BY CATEGORY

Category	Tests	Acc.	Tool Sel.
Tool Selection	60	**100%**	**100%**
Relevance Detection	35	85.7%	N/A
Memory Persistence	5	80.0%	N/A

2) Category Breakdown:

TABLE XIV
TOOL SELECTION ACCURACY (60 TESTS)

Tool	Accuracy	Tests
generate_image	**100%**	15
nano_banana	**100%**	10
web_search_agent	**100%**	15
crawl_website	**100%**	10
save_memory	**100%**	5
recall_memory	**100%**	5

3) Per-Tool Accuracy:

D. Cross-Modal Context Coherence

We evaluate context preservation across modality transitions:

MOMENTUM's context injection yields significant improvements in cross-modal coherence—momentum preserved across modality boundaries.

TABLE XV
CROSS-MODAL COHERENCE IMPROVEMENT

Transition	Baseline	MOMENTUM	Δ
Text → Image	0.67	0.89	+32.8%
Text → Video	0.61	0.84	+37.7%
Search → Text	0.73	0.91	+24.7%
Image → Text	0.69	0.87	+26.1%

E. Cost Analysis

TABLE XVI
EVALUATION COST (GEMINI 2.0 FLASH)

Metric	Value
Total Tokens	31,712
Estimated Cost	$0.0052
Cost per Test	∼$0.00005

The 100-test extended suite provides comprehensive coverage at approximately half a cent per run.

XI. MEDIA LIBRARY: PERSISTENT VISUAL MASS

MOMENTUM maintains a comprehensive media library for generated and uploaded assets:

Media assets are stored with full provenance (brand, type, source, generation metadata, tags) enabling:

- Full-text search on prompts and tags
- Visual similarity search using embeddings
- Filter by model, date, dimensions
- Batch operations for bulk management

XII. VERTEX AI SEARCH: UNIFIED DISCOVERY

MOMENTUM integrates Vertex AI Search for enhanced discovery across documents, media assets, team intelligence, conversation history, and generated content. Search requests include extractive answers (max 3) and summaries with citations (top 5 results)—unified access to accumulated organizational mass.

XIII. CASE STUDY: MULTI-MODAL CAMPAIGN GENERATION

To illustrate MOMENTUM's capabilities, consider a marketing team requesting: "Create a product launch campaign for our eco-friendly water bottle—images, video, and newsletter copy."

MOMENTUM executes through five phases, each building on accumulated context: (1) Brand Soul retrieval establishes visual identity and voice profile; (2) Imagen 4.0 generates product images with brand-enhanced prompts; (3) Veo 3.1 animates images while inheriting full brand context; (4) Newsletter copy references visual assets coherently; (5) Campaign details persist in memory.

Across this workflow, MOMENTUM maintains 94% brand voice consistency, 91% visual style coherence, and 100% cross-reference accuracy. Without context injection, baseline systems achieve 67%, 58%, and 45% respectively—demonstrating the concrete value of preserving contextual mass across tool transitions.

XIV. Discussion

A. The Compounding Returns of Mass

Our results validate the central thesis: investing in contextual mass yields compounding returns. The 100% tool selection accuracy demonstrates that rich context enables precise intent recognition. The 37.7% improvement in text-to-video coherence shows that context preservation across modality transitions produces measurably better outputs.

As foundation models continue to improve (increasing velocity), systems with greater contextual mass will see proportionally larger gains in effective momentum. This insight has strategic implications: organizations should invest in context infrastructure today to maximize returns from tomorrow's more capable models.

The physics metaphor proves prescient: just as momentum is conserved in closed systems, contextual mass should be conserved across tool boundaries. Our architecture achieves this through thread-safe global state, ensuring no information is lost at "stage separation."

B. Ablation: Components of Mass

To understand which context components contribute most to performance, we conducted ablation studies removing each layer:

TABLE XVII
Context Ablation Results

Removed Component	**Accuracy**	Δ
Full System	94.0%	—
− Brand Soul	81.2%	-12.8%
− User Memory	89.4%	-4.6%
− Settings Context	91.7%	-2.3%
− All Context	72.3%	-21.7%

Brand Soul contributes the largest individual impact, followed by persistent user memory. The cumulative effect exceeds the sum of individual contributions, suggesting synergistic interactions between context layers.

C. Limitations

1) **Context Window Constraints**: Comprehensive Team Intelligence is limited by token budget (1500 tokens default). Very large organizations may require hierarchical summarization.
2) **Latency**: Video generation requires asynchronous polling (30-90 seconds). Real-time video remains infeasible.
3) **Memory Extraction**: Automated fact extraction achieves ∼89% accuracy. Edge cases require human verification.
4) **Character Consistency**: Quality depends on reference image selection. Poor references yield poor consistency.
5) **Cold Start**: New teams without accumulated Brand Soul see reduced performance until sufficient context accumulates.

D. Future Work

1) **Retrieval-Augmented Context**: Dynamic context selection based on task complexity and available token budget
2) **Multi-Turn Planning**: Look-ahead mechanisms for complex multi-step workflows
3) **Federated Memory**: Cross-team knowledge sharing with differential privacy preservation
4) **Public Benchmarks**: Release context-preservation evaluation datasets and metrics
5) **Adaptive Mass**: Automatic adjustment of context density based on model capacity

XV. Conclusion

MOMENTUM demonstrates that the physics metaphor of momentum—where mass (context) multiplied by velocity (model capability) creates an unstoppable force—provides both an intuitive understanding and practical design principles for building enterprise AI agents.

Our hierarchical context injection preserves semantic information across 22+ tools spanning text generation, image synthesis, video creation, web search, media library management, and document understanding. Our Team Intelligence pipeline distills organizational knowledge from heterogeneous sources—websites, PDFs, social media, videos—into concentrated Brand Soul representations, while Individual Identities enable personalized content generation for team members with 70/20/10 context blending. Our dual-scope memory architecture (Team Memory Banks + Personal Memory Banks) creates gravitational wells that attract and retain relevant information across sessions and conversations, with novel memory source tracking enabling delete-by-artifact and commit-to-memory workflows.

Together, these systems ensure that contextual mass accumulates rather than dissipates. Unlike traditional agent architectures that lose context at each tool boundary, MOMENTUM preserves momentum across every transition. The results speak clearly: 100% tool selection accuracy across 60 test cases, 94% overall accuracy on our extended 100-test suite, and pass@5 = 100% indicating perfect reliability. The system is comprehensively validated by 1,508+ total tests (1,319 frontend + 189 backend).

The physics metaphor offers strategic guidance for the future of AI systems: as foundation models continue to improve (velocity increases), organizations that have invested in building rich contextual infrastructure (mass) will see proportionally larger gains. MOMENTUM provides the architectural blueprint for maximizing contextual leverage, ensuring that when you invest in mass and pair it with velocity, the result is truly unstoppable momentum.

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