TinyMacro: AI-Powered Knowledge Infrastructure for Larta Institute

A Business Case for Production Deployment

Introduction

Larta Institute is uniquely positioned to leverage AI infrastructure at a critical inflection point. While the current AI adoption bubble has led to numerous failed pilots across industries (with industry data indicating approximately 60% fail to reach production). Larta's specific operational needs, technical readiness, and focus on measurable outcomes create ideal conditions for successful AI implementation.

Purpose

This business case presents TinyMacro, a production-grade AI system designed to address Larta's operational challenges and strategic opportunities. The analysis draws from comprehensive due diligence including stakeholder interviews, technical feasibility research (HubSpot, Box, Outlook API documentation), infrastructure cost modeling (Azure deployment patterns), and review of enterprise AI best practices literature to ensure realistic scoping and execution planning.

On Data Quality

Before discussing technical capabilities or use cases, a critical principle must be established: **AI systems are only as valuable as the data they operate on.** The most sophisticated models and tools will generate poor outputs without clean, standardized, contextually rich data. TinyMacro's implementation will prioritize data infrastructure, establishing ingestion protocols, validation checks, and continuous update mechanisms as the foundation for both immediate operational improvements and long-term strategic capabilities.

Development Phases:

- **Phase 1 (Short Time-to-Value):** HubSpot data quality improvements, Odoo migration support, and cross-platform search delivering measurable operational efficiency within 8-12 weeks

- **Phase 2 (Long Time-to-Value):** TABA ecosystem mapping building proprietary, verticalized intelligence for grant advisory

Phase 1 serves as both an immediate ROI generator and a technical foundation for Phase 2. The hybrid RAG+KG architecture, tool calling framework, and data standardization protocols developed for HubSpot directly enable the more complex TABA ecosystem mapping capabilities.

Document Structure:

When, How, and Larta’s Unique Position

Why do Most AI Pilots Fail?

Over the past two years, approximately 60% of enterprise AI pilots have failed to reach production deployment. Common failure modes include:

- **Lack of verticalization:** Generic chatbots applied to domain-specific problems without specialized knowledge
- **Unmeasurable outcomes:** Vague goals like "improve productivity" without concrete KPIs
- **Overambitious scope:** Complex multi-agent systems with dozens of tools before proving basic value
- **Insufficient context/data management:** LLMs without access to company-specific knowledge or clean, standardized data
- **Trust issues:** Automated actions without validation mechanisms leading to errors and user rejection

Larta's Strategic Advantages

Clearly Defined Pain Points:

- HubSpot data quality issues directly impact daily operations and upcoming Odoo migration
- TABA advisory requires ecosystem knowledge that no general-purpose tool provides
- Problems are specific, bounded, and understood by stakeholders

Measurable Workflows:

- Contact deduplication, data standardization, and grant application support are concrete, trackable tasks
- Quality control for contacts, companies, and deals has quantifiable metrics
- Success criteria can be established upfront and validated objectively (short time-to-value)

Technical Readiness:

- Existing Azure infrastructure and API-accessible systems (HubSpot, Box, Outlook)
- Our Odoo migration timeline creates natural forcing function for data standardization

Domain Specificity:

- Climate tech VC/incubator workflows are specialized enough that white-label SaaS cannot serve them effectively
- TABA grant advisory requires proprietary knowledge graphs combining internal data (historical cohorts, advisor notes) with external intelligence (third-party reports, company research)
- This verticalization creates sustainable competitive advantage

Our Approach: Principles for Success

Verticalization: TinyMacro must be purpose-built for Larta's workflows: HubSpot contact standards, TABA evaluation criteria, climate tech terminology. Custom runbooks encode Larta-specific processes that generic tools cannot learn.

Practicality: Start with read-only information retrieval and analysis, not automated actions. Build trust through transparency (source citations, confidence scores) before expanding to write operations.

No General Agents (Yet): Narrow, task-specific agents with defined toolsets and runbooks, not open-ended conversational interfaces. Each agent has clear success criteria and measurable outcomes.

Trackability: Every interaction logged with performance metrics. Link specific outcomes to particular HubSpot deals, retrieved document chunks, or ecosystem connections identified. Repeatability is core to agentic systems and our measurement strategy.

Data-First Architecture: Establish standardized data protocols for ingestion, validation, and continuous updates before building advanced features. The system's value compounds as data quality and coverage improve over time.

This approach mirrors best practices from successful enterprise AI deployments: start small, measure everything, expand based on demonstrated value, and invest in proprietary data infrastructure as a strategic asset.

Hubspot Use Case: Quick Overview

Primary Goal: Improve HubSpot data quality to enable Odoo migration and enhance operational efficiency through procedural automation, quality control, and intelligent data traversal.

The Challenge:

Current HubSpot data management requires significant manual effort for tasks that are repetitive, rule-based, and prone to human error. With the upcoming Odoo migration, data standardization has become urgent; records must meet specific field requirements, duplicates must be resolved, and industry categorizations must be consistent. Beyond migration needs, clean data with proper protocols established across Deals, Companies, and Contacts enables better visualization, analytics, and client relationship management.

Specific Objectives:

1. **Reduce contact/company duplication** (Key pain point identified in due diligence meetings with Shreya and Elena)
    - Identify duplicate records using Larta-specific matching rules (email domain + name similarity, same company + role overlap)
    - Generate merge recommendations with rationale and approval workflow
    - Weekly automated reports on duplicate status and resolution progress
2. **Standardize data fields** across contacts and deals to meet Odoo transfer requirements
    - Validate records against Odoo field mappings (required fields, format specifications)
    - Flag incomplete or non-compliant records with suggested corrections
    - Generate Odoo readiness dashboard showing compliance percentage and blockers
3. **Enable intelligent traversal** of HubSpot data
    - Fuzzy search for contacts and deals when exact terms unknown
    - Natural language queries for specific information (e.g., "Show me all battery storage companies we met at CES 2024")
    - Complex filtering combining multiple criteria without manual HubSpot query builder
4. **Categorize industry information** for companies and contacts
    - Automated industry tagging using climate tech taxonomy
    - Unblock data visualization and extraction for portfolio analysis
    - Consistent categorization enables segmentation for targeted outreach

Time-to-Value: 8-12 weeks from January start to measurable operational impact

Why This Matters: HubSpot data quality is foundational for all downstream processes: CRM effectiveness, Odoo migration success, portfolio analytics, and client interactions. Improved data hygiene reduces manual work, minimizes errors, and enables data-driven decision-making. Phase 1 delivers immediate ROI while establishing the technical infrastructure and data protocols that enable Phase 2 TABA capabilities.

TABA Use Case: Quick Overview

Primary Goal: Map the climate tech innovation ecosystem within TABA guidelines to provide informed AI toolset for analysts reviewing grant applications.

Specific Objectives:

1. **Identify non-obvious relationships** between portfolio companies and TABA cohort members (technology complementarity, supply chain positioning, market timing)
2. **Surface success patterns** from past TABA winners and third-party program reporting
3. **Track current developments** in specific climate tech verticals through AI web scraping of industry news
4. **Provide ecosystem context** for application reviewers to strengthen partnership proposals and positioning

Time-to-Value: 12 weeks for Phase 2 build.

Data Infrastructure Challenge:

The TABA ecosystem mapping capability depends critically on comprehensive, standardized data infrastructure, which is the most important technical challenge of Phase 2. Building this ecosystem requires addressing a two-fold data problem:

1. **Data Ingestion & Standardization Protocol:**
    - Define unified schema for company profiles (technology category, market segment, development stage, key metrics)
    - Establish ingestion pipelines for internal sources (Larta CRM records, advisor notes, application documents) and external sources (Pitchbook API, web scraping, third-party TABA reports)
    - Implement validation checks ensuring data uniformity before indexing into KG (standardized fields, consistent taxonomy)
2. **Retroactive Harmonization & Continuous Updates:**
    - Apply standardization protocol retroactively to historical TABA cohort data
    - Build continuous update mechanisms: automated surveys to portfolio companies, Pitchbook API refreshes for funding rounds, web scraping for news/developments
    - Enable manual data entry for company growth tracking (fundraising, partnerships, milestones) with structured templates

Specific Data Focus Areas:

- Technology specifications and complementarity indicators
- Funding history and growth trajectories
- Partnership formations and supply chain relationships
- Market positioning and regulatory alignment
- TABA evaluation outcomes and feedback

Why This Data Investment Matters: Long-term proprietary infrastructure, like a company-specific, custom-built knowledge base, has been recognized as the most successful approach to generating value in enterprise AI adoption (McKinsey 2025 Report). TABA grants represent significant portfolio value, and improved win rates directly enhance Larta's reputation.

No existing tool can provide this level of specialized ecosystem analysis because no existing tool has access to Larta's proprietary data combined with systematically curated external intelligence.

The data infrastructure built for TABA becomes a strategic asset: a continuously growing, internally maintained knowledge graph that compounds in value with each cohort, partnership formation, and grant outcome tracked.

Why our AI Pilot Will Succeed

Every interaction is measurable:

- Agent queries logged with response time, tool calls executed, and success/failure status
- Retrieved information linked to source documents (Box file IDs, HubSpot record URLs, Outlook message IDs) - this will be an intrinsic feature within every tool call to a third party source
- HubSpot actions traceable to specific deals and contacts modified
- Following best practices for measuring agent output (see paragraph below)

Process repeatability is built-in:

- Runbooks define standard operating procedures for each task type
- Version control for prompts, tool configurations, and KG schemas
- Regression testing suite ensures consistent behavior across updates
- Audit logs allow reconstruction of any decision or output

Why does this matter?

This is fundamentally different from generic chatbots, as we will be able to measure activity, decision making, and tool output. When navigating more complex systems with non-text-based output (like being able to query a vector database), it is especially important to test, iterate, and measure everything so that we may monitor performance, costs, and errors.

The following section covers research done with an industry-leading agent building source from Anthropic PBC, a frontier AI lab that is heavily leveraged into enterprise.

Effective Context Engineering for AI Agents:

1. **Start with tool instructions and evolve to indexed knowledge:**
    - Phase 1: Provide tool APIs and runbook instructions in system prompt
    - Phase 2: Index actual information (parsed to JSON) into RAG and KG for richer context
    - This staged approach ensures tool reliability before adding context complexity

2. **Chunk documents semantically, not arbitrarily:**
    - Use document structure (headers, paragraphs, list items) to create meaningful chunks
    - Preserve metadata (source, author, date, document type) for better retrieval
    - Embed chunks with both content and contextual information
3. **Hybrid retrieval outperforms pure vector search:**
    - Combine dense embeddings (semantic similarity) with BM25 keyword matching
    - Use KG for structured relationship queries (e.g., "companies in X sector partnering with Y")
    - Rerank results using cross-encoder models for final relevance scoring
4. **Design for failure modes:**
    - No results: Graceful degradation to keyword search or suggest query refinements
    - Ambiguous query: Request clarification rather than guessing user intent
    - Low confidence: Surface multiple options with uncertainty indicators
5. **Measure everything:**
    - Retrieval quality: Precision@K, recall, mean reciprocal rank
    - Generation quality: Hallucination rate, citation accuracy, user satisfaction
    - System performance: Latency percentiles, cost per query, uptime

Larta's Operational and Strategic Gaps

This section intends to cover a few simple use cases for AI agents, delivered within the scope of each use case, and vetted by conversations with colleagues from the government and community labs teams.

HubSpot Data Quality

Pain point 1: Duplicate contacts and companies

- **Current state:** Several duplicates exist across contacts and companies, creating confusion about correct records
- **Impact:** Time wasted reconciling duplicates, risk of contradictory information, poor data hygiene for Odoo migration

Pain point 2: Incomplete or inconsistent categorization

- **Current state:** Companies and contacts lack updated industry information, technology categories, and stage classifications. This limits data-driven decision-making and reporting to stakeholders, as we will never get the full picture with critically inaccurate data.
- **Impact:** Cannot visualize portfolio by sector, extract meaningful analytics, or segment for targeted outreach

Pain point 3: Odoo migration readiness

- **Current state:** Data does not meet standardization requirements for Odoo ERP transfer - there is a lot of work to be done, and it would be great to reduce the technical debt that has been generated by our recent adoption of Hubspot before we bring our company to another ERP/CRM.
- **Impact:** Manual cleanup required before migration, risk of data loss or corruption during transfer

Pain point 4: Information retrieval inefficiency

- **Current state:** Finding specific deals, contacts, or historical interactions requires manual searching across HubSpot, Box, and Outlook - because there is no organizational nomenclature that is consistent across programs AND different years.
- **Impact:** Time spent by staff locating information, delayed responses to clients, frustration with siloed systems

TABA Grant Project Limitations

Pain point 1: Limited ecosystem visibility

- **Current state:** Advisors rely on individual expertise and manual research to identify partnership opportunities for TABA applicants - we also do not have a way to visualize the relationships that have been generated by our prior work in TABA cohorts
- **Impact:** Non-obvious connections missed, potential synergies not surfaced, applications weaker than they could be

Pain point 2: Inconsistent use of historical data

- **Current state:** Past TABA cohort information (winners, partnerships formed, evaluation feedback) scattered across documents
- **Impact:** Cannot systematically identify success patterns or learn from past application strengths/weaknesses
- **Missed opportunity:** Third-party reporting on TABA program trends exists but not integrated into advisory process

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Technical Implementation

Core Components:

- **Hybrid Context:** RAG (vector search) + KG (relationship graph) for Larta processes and ecosystem connections
- **Tool Layer:** API templates for HubSpot, Box, Outlook real-time data retrieval
- **Runbook Engine:** Task-specific SOPs (contact deduplication, Odoo mapping, TABA queries) embedded in KG
- **Web Interface:** Natural language queries with cited responses and source attribution

Infrastructure (Azure):

- **Compute:** Container Apps (web + worker containers, minReplicas=1, Service Bus triggers)
- **Vector DB:** Azure AI Search (Basic → Standard for Phase 2)
- **Knowledge Graph:** Neo4j on Azure VM OR CosmosDB Gremlin API
- **Models:** Claude 3.5 Sonnet (primary), text-embedding-3-large (embeddings)
- **Security:** Managed Identity, Key Vault, VNET with private endpoints, RBAC

Implementation Timeline

Phase 0: Core Platform

- Deploy Azure infrastructure with security hardening
- Implement authentication and RBAC
- Build web UI with query interface
- Index 50-100 sample documents
- **Cost:** $200-300/month

Phase 1: HubSpot Integration (~12 Weeks)

- Week 1-4: HubSpot API integration, duplicate detection runbook, approval workflow
- Week 5-6: Odoo field mapping validation, compliance reporting
- Week 7-8: Box/Outlook integration, unified cross-platform search
- Week 9-10: Industry categorization, fuzzy matching, data enrichment
- Week 11-12: User onboarding, feedback collection, iteration
- **Deliverables:** Duplicate reports, Odoo readiness dashboard, cross-platform search, industry tagging
- **Success Criteria:** 5+ daily users, duplicate reduction, query time <N seconds, >4/5 satisfaction, <10% error rate
- **Cost:** $300-400/month

Phase 2: TABA Ecosystem (~12 Weeks)

- Week 1-4: Collect historical TABA data, design KG schema with advisors, populate graph
- Week 5-6: Build ecosystem mapping queries, partnership identification
- Week 7-8: Index winning applications, gap analysis tool
- Week 9-10: Web scraping pipelines for climate tech news
- Week 11-12: Advisor training, validation on current applications
- **Deliverables:** Ecosystem mapping interface, application review tool, news tracking
- **Success Criteria:** 20+ validated connections, 3+ advisors actively using, 5+ companies integrate insights
- **Cost:** $600-850/month

Decision Gates:

- **After Phase 1 (April):** Proceed to Phase 2 if time savings and adoption targets met; otherwise iterate or pivot
- **After Phase 2 (June):** Continue to grant win rate tracking if advisors find value; otherwise repurpose for other use cases

Total Timeline: 6 months (29 weeks) from December 2024 to June 2025

Why Not Other Products?

HubSpot AI: Limitations

- **Cross-platform synthesis:** No access to Box documents or Outlook emails; limited to HubSpot data only
- **Custom runbooks:** Cannot encode Larta-specific processes (Odoo field mappings, grant advisory workflows)
- **Vertical specialization:** Generic CRM logic, not specialized for climate tech VC/incubator domain
- **Knowledge graph:** No structured relationship mapping for ecosystem analysis (critical for TABA)
- **Advanced tool calling:** Cannot build custom API integrations beyond HubSpot's built-in connections

Microsoft Copilot Limitations

- **No HubSpot or Box access** (siloed within Microsoft ecosystem)
- **No custom knowledge graphs** (cannot build TABA ecosystem relationships)
- **Generic climate tech understanding** (not verticalized on Larta's domain-specific processes)
- **No runbook support** for task-specific workflows

Decision: Copilot is complementary for general Office productivity, but insufficient for HubSpot data quality or TABA ecosystem mapping. It is important to recognize that these products are valuable in their own ways.

Enterprise Search Tools (Glean, Guru, etc.) Limitations

A note about these SaaS tools - they are nascent winning companies that have started during the AI boom in 2022-2024. The most valuable abilities of enterprise AI tools, right now, are creating ways to manage company data within agent context (as this reduces hallucinations and produced more valuable output). Glean is an excellent example of this.

Glean's approach (which inspired TinyMacro architecture):

- Best-in-class RAG + KG hybrid context management
- Cross-platform connectors (HubSpot, Box, Outlook, Slack, etc.)
- Enterprise security and permissions inheritance
- Continuous learning from user interactions

Why not just use Glean:

- **No custom runbooks:** Glean does search and synthesis, but cannot encode Larta's specific SOPs for Odoo migration or TABA analysis
- **No vertical specialization:** Cannot customize KG schema for climate tech ecosystem relationships - this is the most important difference
- **No advanced tool calling:** Glean retrieves information but cannot execute HubSpot API writes or generate complex reports
- **Vendor lock-in:** Dependent on Glean's roadmap and pricing changes; limited control over features

Cost Analysis & Time-To-Value

Everything in this section is estimated based on data from past ai pilots, conducted in similar situations to our situation (company size, scope). ***There is reference to tools that may or may not be used within our greater technical implementation, but this is simply for reference. Competing products will all cost around the same, this is hypothetical.

Infrastructure Costs

Phase 0 (Platform Setup):

- Azure Container Apps (2 containers: web + worker): $100-150/month
- Azure AI Search (Basic tier, 15GB storage): $75/month
- Neo4j Community on Azure VM (B2s instance) OR CosmosDB Gremlin: $50-80/month
- Storage (A service like Blob for documents, embeddings): $20/month
- Key Vault, VNET, monitoring: $10/month
- **Total Phase 0: $255-335/month**

Phase 1 (HubSpot Integration):

- Same infrastructure as Phase 0: $255-335/month
- API costs (Claude 3.5 Sonnet): ~1000 queries/month × $0.03-0.05/query = $30-50/month
- **Total Phase 1: $285-385/month**

Phase 2 (TABA Ecosystem):

- Azure AI Search (Standard tier, 50GB storage): $250/month (upgrade from Basic)
- Container Apps + Neo4j/CosmosDB (scaled up): $150-200/month
- Storage (larger embedding corpus): $40/month
- API costs (increased usage, complex queries): $100-150/month
- Web scraping infrastructure (if needed): $20/month
- **Total Phase 2: $560-660/month**

Annual cost summary:

- Phase 0 (1 month): ~$300
- Phase 1 (3 months): ~$350/month × 3 = $1,050
- Phase 2 (ongoing): ~$600/month × 12 = $7,200
- **Total Year 1 cost: ~$8,550**
- **Ongoing cost (Year 2+): ~$7,200 annually**

Time-to-Value Analysis

Phase 1 HubSpot Quick Wins:

- **Weeks 1-4:** Infrastructure setup and HubSpot API integration (no user-facing value yet)
- **Week 5:** First capability delivered (duplicate detection reports) → **Initial value at ~5 weeks**
- **Week 8:** Odoo validation reports available → **Measurable migration support at 8 weeks**
- **Week 10:** Cross-platform search operational → **Full Phase 1 value at 10 weeks**
- **Week 12:** User adoption and refinement → **Sustained value beyond 12 weeks**

Phase 2 TABA Capabilities:

- **Weeks 1-4:** Data collection and KG build (no user-facing value)
- **Week 6:** First ecosystem mapping queries operational → **Initial insights at 6 weeks into Phase 2**
- **Week 10:** Full TABA advisory toolkit available → **Complete Phase 2 value at 10 weeks**
- **Months 6-12:** Grant cycle outcomes provide long-term ROI validation

Key insight: Phase 1 delivers measurable value within 8-10 weeks, justifying continued investment before Phase 2 begins.

Breakeven & ROI Summary

Phase 1 Breakeven:

- Infrastructure cost: ~$1,350 (3 months)
- Development cost: 12 weeks full-time
- Time savings value: $15,000/year
- Breakeven: 6-8 months via operational efficiency

Phase 2 Value Framework:

- Infrastructure cost: ~$7,200/year
- Development cost: 12 weeks full-time
- Key insight: Phase 2 KPIs (ecosystem connections identified, advisor engagement, application integration) represent strategic capabilities rather than direct revenue metrics. Grant win rate improvements have long attribution cycles and depend on multiple factors beyond system capabilities, making immediate ROI quantification impractical.

Total Project ROI:

- Conservative scenario: Phase 1 HubSpot efficiency gains ($15K annually) offset total infrastructure costs ($8K annually) with $7K net positive, justifying the investment independent of Phase 2 outcomes.
- Strategic scenario: Phase 2 TABA ecosystem mapping provides differentiated advisory capabilities that position Larta for long-term grant optimization. Improved advisor

efficiency and portfolio company success represent compounding value over multiple grant cycles.

Conclusion: Phase 1 delivers financial breakeven on infrastructure and development costs through measurable operational improvements. Phase 2 represents strategic investment in differentiated capabilities, with TABA ecosystem insights instrumental to future optimization of grant win rates and competitive positioning.

Risk Mitigation

Because of the nature of the two different use cases, and the Hubspot tool having a fast time-to-value, the development of this AI pilot is of low risk. The following statements are an accumulation of research involved to find common pitfalls of ai pilots, specifically within our tech stack.

Technical Risks:

- **Hallucination/Inaccuracy:** Source attribution with citations, confidence scoring, read-only Phase 1 deployment, and user feedback loops ensure errors don't corrupt data and problematic responses are identified for refinement.
- **API Failures:** Graceful degradation across platforms, retry logic, version pinning, and monitoring maintain functionality when individual services are unavailable.
- **Retrieval Quality:** Hybrid search combining vector, keyword, and graph traversal with reranking models improves precision. User feedback tunes retrieval parameters.
- **Scalability:** Azure AI Search handles millions of documents with sub-second latency. Index optimization and caching prevent performance degradation as data grows.

Security & Privacy Risks:

- **Data Exposure:** RBAC enforces source system permissions, audit logs track all activity, VNET integration keeps traffic internal, no fine-tuning on proprietary data.
- **Adversarial Use:** Input sanitization, system prompt protection, tool access restrictions, and rate limiting prevent manipulation and abuse.
- **Data Staleness:** Nightly sync jobs with change detection refresh embeddings while timestamps indicate last update.

Organizational Risks:

- **Low Adoption:** Beta testing involvement, training sessions, workflow integration, and regular usability check-ins drive engagement.
- **Unrealistic Expectations:** Clear scope communication, early demos of capabilities and limitations, and KPI-focused evaluation manage stakeholder expectations.
- **Knowledge Concentration:** Comprehensive documentation, modular design, standard tech stack, and knowledge transfer sessions reduce single-person dependency.
- **Scope Creep:** Phased approach with decision gates and prioritized roadmap maintains focus on high-impact use cases.

Business Risks:

- **Insufficient TABA Data:** Pre-Phase 2 data validation confirms availability. Fallback uses infrastructure for general advisory research if ecosystem mapping proves unviable.
- **Unproven ROI:** Leading indicators (engagement, usage patterns) provide early signals. Phase 1 HubSpot value justifies investment independent of Phase 2 outcomes.

- **Technology Changes:** Model-agnostic architecture and standard interfaces enable provider switching without major rework.

Risk Profile: Low to medium. Read-only Phase 1 deployment prevents data corruption even if system underperforms. Phased approach allows early termination if value not demonstrated, limiting sunk costs.

Current Project Status

Already built:

- RAG system operational (documents embedded, semantic search working)
- Knowledge Graph initialized (basic schema defined, can add nodes/edges)
- Tool calling framework (HTTP request templates for APIs, successfully tested on dummy endpoints)
- GUI and routing complete (web interface for queries, response rendering with citations)
- Sample data indexed (50-100 documents from Box as proof-of-concept)

Remaining work to begin the Hubspot Usecase:

- Production deployment on Azure (Container Apps setup, networking, security hardening)
- HubSpot/Box/Outlook API integration (real credentials, test against Larta's instances)
- User authentication and RBAC (Azure AD integration, permission enforcement)
- Monitoring dashboards (Application Insights, custom metrics for query performance)
- Penetration testing and security review
- Documentation (architecture diagrams, deployment procedures, user guides)

Closing Statement

Larta is at a unique inflection point. Operational pain points around HubSpot data quality and the upcoming Odoo migration create immediate urgency for data standardization. At the same time, strategic opportunities in TABA grant advisory offer a path to differentiated value that no off-the-shelf solution can provide. The organization has the technical readiness to execute with existing Azure infrastructure and API-accessible systems, while the maturity of RAG and knowledge graph patterns reduces execution risk significantly. The timing is right because the problem is clear, the technology is proven, and leadership buy-in exists.

Why This Approach Works

Unlike the 60% of AI pilots that fail by chasing general-purpose capabilities, TinyMacro succeeds through deliberate constraints. Climate tech VC workflows are specialized enough that no white-label SaaS can serve them effectively. The verticalization of our tools around Larta-specific processes, terminology, and data creates sustainable competitive advantage. The phased approach builds trust through read-only Phase 1 deployment before expanding to automated actions, while concrete KPIs around time savings, data quality, and ecosystem connections enable objective evaluation rather than subjective assessments of AI "intelligence."

Every interaction will be logged, reproducible, and improvable. This trackability is core to agentic systems and our measurement strategy. Quick wins from HubSpot implementation justify the longer-term investment in TABA ecosystem mapping, with clear decision gates that allow for pivoting or termination if value is not demonstrated. The infrastructure built for Phase 1 directly enables Phase 2 capabilities, meaning the technical investment compounds rather than duplicates.

The Data Infrastructure Imperative

The most critical insight from enterprise AI deployments is that proprietary data infrastructure becomes the strategic asset, not the models themselves. TinyMacro's value comes from solving the two-fold data problem: standardizing ingestion protocols for internal and external sources, then retroactively applying these protocols to historical data while maintaining continuous updates. As the knowledge graph grows with each TABA cohort, partnership formation, and grant outcome tracked, the system becomes increasingly valuable and difficult for competitors to replicate.

Long-term proprietary infrastructure has been recognized as the most successful approach to generating value in the age of enterprise AI adoption. Building this now positions Larta to compound advantages over time rather than remaining dependent on generic tools that lack our domain context.

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