Agentic Social Trend Recognition Assistant (ASTRA)

Armand Debray, Harkanwar Chadha, Nikhil Ram Atluri, Ramya Chowdary Polineni, Rohan Raveendran, Seung-Mi Jeon, Shih Min Lin, Dr. Shoaib Amjad Khan

Purdue University, Department of Management, 403 W. State Street, West Lafayette, IN 47907

debray@purdue.edu; chadhah@purdue.edu; atlurin@purdue.edu; rpolinen@purdue.edu; rraveen@purdue.edu; jeon139@purdue.edu; lin1944@purdue.edu;

ABSTRACT

Today, the rapid pace of online culture means that even small delays in posting can determine whether content goes viral or is ignored. The sheer scale and velocity of online information make it increasingly challenging to identify emerging trends before they fade. In parallel, advances in Artificial Intelligence (AI) have enabled the rise of AI agents—software systems capable of autonomously performing complex, multi-step tasks without human supervision. At this intersection of intelligent automation and digital culture, we present the Agentic Social Trend Recognition Assistant (ASTRA), a multi-platform agentic AI system for detecting and analyzing trends across Reddit, X (Twitter), TikTok, YouTube, and Google Trends.

ASTRA integrates platform-specific data collection scripts into a unified, efficient pipeline orchestrated by a LangChain workflow. This pipeline outputs clean, daily trending content, which is then processed through a multi-agent large-language-model (LLM) architecture, powered in part by Abacus AI tools, with three coordinated branches: content research, caption generation, and image generation. ASTRA transforms raw cross-platform trend signals into actionable, sentiment-aware, platform-optimized creative assets.

ASTRA enables creators and brands to react quickly to cultural moments, optimize audience engagement, and maintain relevance in an increasingly competitive digital landscape.

Keywords: multi-agent LLM orchestration, AI-driven social media analytics, real-time trend detection, generative AI content workflows, cross-platform engagement optimization

INTRODUCTION

In an article titled *"The Age of AI has begun"*, Bill Gates (2023) reflected on two technological moments that redefined his understanding of innovation:

> "In my lifetime, I've seen two demonstrations of technology that struck me as revolutionary. The first time was in 1980, when I was introduced to a graphical user interface. The second big surprise came just last year. I'd been meeting with a team from OpenAI...I watched in awe as they asked GPT, their AI model, 60 multiple-choice questions from the AP Bio exam and it got 59 of them right. I knew I had just seen the most important advance in technology since the graphical user interface" [6].

Artificial Intelligence has already begun reshaping industries, and its capabilities are evolving at an unprecedented pace. Catalini, Wu, and Zhang argue that AI is "set to disrupt nearly every corner of the labor market...to navigate this new landscape, leaders need to understand – and plan for—how automation will affect their business" [4]. Importantly, AI is now crossing a threshold — from narrow automation of isolated tasks to *agentic multi-agent systems* capable of executing long, complex, multi-step workflows autonomously, without human intervention. These systems can decompose objectives, coordinate specialized sub-agents, and iteratively improve outputs in real time.

In the social media industry, this capability is particularly transformative. Recommendation algorithms have long used data pipelines to determine what content users see. However, the emergence of agentic AI enables these pipelines to be not just reactive but proactively generative — able to detect, interpret, and act upon emerging cultural trends at machine speed. This paradigm shift is embodied in the development of the Agentic Social Trend Recognition Assistant (ASTRA), a multi-platform, fully autonomous system that gathers cross-platform trend data, processes it through specialized agents, and produces actionable creative outputs for content creators and brands.

This paper explores the design and implementation of ASTRA as a case study in applying agentic multi-agent systems to real-time cultural intelligence. The remainder of this paper is organized as follows: Section 2 reviews relevant literature on AI-driven automation, agentic systems, and trend detection. Section 3 describes the data pipeline. Section 4 presents the methodology and orchestration framework. Section 5 discusses model components and performance. Section 6 evaluates system outputs. Section 7 concludes with implications, limitations, and future research directions.

LITERATURE REVIEW

The development of agentic multi-agent AI systems—autonomous teams of specialized AI agents capable of planning, delegating, and executing complex multi-step tasks without human intervention—marks a significant evolution in artificial intelligence [16, 17]. Unlike earlier rule-based or narrowly trained multi-agent frameworks, modern systems leverage Large Language Models (LLMs) to communicate in natural language, reason collaboratively, and dynamically adjust plans in real time [16, 18]. This allows them to handle broad, open-ended goals that would overwhelm traditional automated systems.

Historically, multi-agent systems in industry were limited to highly structured domains, such as robotic swarms or warehouse logistics, with fixed communication protocols and predictable task sequences [16]. By contrast, today's agentic systems can negotiate strategies, reassign work, and adapt to novel scenarios as conditions change. This capability is enabled by orchestration frameworks like LangChain—a control layer that coordinates multiple agents in sequence or in parallel—and AutoGen, which simplifies building agent-to-agent conversational workflows [16, 18].

Recent research has produced several high-profile exemplars. ChatDev [19] is a framework where multiple AI agents simulate a software development team, taking on roles such as "project manager," "coder," and "tester." The agents collaborate via natural-language messages to plan features, write code, test it, and make improvements—demonstrating how role specialization can dramatically increase task success rates compared to single-agent setups. Croto [18] is another orchestration method, designed for "cross-team" collaboration, allowing multiple smaller agent teams to coordinate in large-scale projects. Generative Agents simulate autonomous characters in virtual environments that plan, remember, and interact with each other, illustrating how persistent memory and reasoning can produce realistic, coordinated behaviors [16].

These advances are also being realized in industry prototypes. Microsoft's Magentic-One [20] is a "generalist multi-agent system" where a central *orchestrator* plans an overall approach to a task and delegates work to specialized sub-agents such as "WebSurfer" (online research), "FileSurfer" (document retrieval), and "Coder" (software automation). Salesforce's AgentForce applies similar orchestration principles to enterprise workflows, enabling autonomous handling of customer service requests, database updates, and content generation. These examples show that multi-agent autonomy is moving from research to commercial deployment.

The novelty of this new wave of agentic systems lies in three interlinked capabilities. First, they operate continuously and indefinitely without human oversight, responding instantly to new data or changes in objectives [16, 17]. Second, they exhibit dynamic decomposition of goals, breaking complex problems into sub-tasks and intelligently allocating them to agents based on current priorities and performance [18, 19]. Third, they engage in collaborative reasoning, where agents exchange insights and negotiate plans in natural language, allowing for consensus-driven adaptation even in ambiguous situations [16].

These traits are especially valuable for digital marketing and content automation. In traditional workflows, analytics teams detect trends, strategists plan responses, and creatives produce content—often across separate tools and teams, introducing delays. This is problematic in a media environment where posting hours too late can mean the difference between virality and invisibility [4, 14]. An autonomous agentic system collapses this delay by unifying trend detection, interpretation, and creative generation into a single orchestrated pipeline.

Evidence from related research underscores the importance of cross-platform adaptability. Bansal and Tharun (2025) found that sentiment toward the same trend can vary sharply across platforms—luxury fashion, for instance, being received positively on Instagram (0.84 sentiment score) but negatively on Reddit (0.17) [5]. Without platform-specific strategies, brands risk damaging audience perception. Agentic systems can ingest cross-platform data, analyze sentiment differences, and tailor responses in real time.

Studies also reveal emergent agent behaviors beneficial to marketing intelligence. Ferrag et al. [16] observed unscripted role specialization and self-directed task allocation in open-ended tasks, suggesting that autonomous agent teams could independently prioritize which trends warrant immediate creative action. Poecze et al. (2018) similarly showed that combining sentiment analysis with engagement metrics provides a truer picture of audience response than raw numbers alone—supporting ASTRA's design choice to integrate sentiment signals into trend evaluation.

Current industry experiments illustrate the practical feasibility of such systems. In Magentic-One [20], the orchestrator can issue a high-level instruction—like "prepare a competitor analysis report"—and have specialized agents autonomously gather online data, summarize findings, and generate a formatted report. This mirrors what ASTRA aims to do in marketing: detect an emerging trend, research its relevance, and produce platform-optimized creative assets without manual intervention.

Despite progress, limitations remain. Most evaluations of agentic multi-agent systems occur in controlled or synthetic environments [17, 18]. ChatDev's collaborative coding, while impressive, unfolds in a structured sandbox [19]. Benchmarks such as CREW-Wildfire [18] aim to bridge this gap by simulating high-complexity, real-time multi-agent tasks—like coordinating wildfire response—but still reveal coordination failures when scaling to dozens of agents in unpredictable conditions.

The research gap is clear: applying fully autonomous multi-agent systems to cross-platform, real-time marketing and creative generation is underexplored. Existing tools may detect trends [3, 5] or automate content [13, 15] but rarely integrate them into a self-contained detection-to-creation loop. Most marketing automation remains reactive, requiring human setup and approval.

ASTRA addresses this gap by embedding platform-specific scraping agents into a LangChain-orchestrated workflow that unifies detection, semantic clustering, sentiment analysis, and creative generation. Unlike single-function tools, ASTRA embodies the end-to-end autonomy that current literature suggests is the next frontier for agentic AI. This positions it to reduce the lag between cultural signal detection and campaign deployment to near-zero and to optimize engagement through continuous adaptation.

By combining the latest advances in multi-agent reasoning [16, 18, 19], orchestration frameworks [18, 20], and generative AI creative tools [13, 15], ASTRA operationalizes the vision of autonomous, cross-platform marketing intelligence. This is directly aligned with the broader shift in AI from being a decision-support tool to becoming an active collaborator in strategy execution.

To illustrate how these concepts are realized in practice, the next section describes the datasets leveraged by ASTRA and the methods used to unify them across platforms.

DATA

The ASTRA data pipeline begins with a multi-agent data acquisition layer; a coordinated network of autonomous agents purpose-built to extract and normalize trending content from heterogeneous social media platforms. Each acquisition agent is optimized for the unique structure, access methods, and rate-limiting constraints of its source, allowing ASTRA to collect diverse, high-velocity data streams in parallel without manual intervention.

Multi-Agent Acquisition Pipeline

1. Data Collection

Using official or 3rd party APIs and web scraper, raw data is acquired from each social media platform.

- **YouTube Agent** – Connects to the YouTube Data API v3 to retrieve the most-popular videos segmented by geographic region. API queries return structured JSON containing both content-level attributes (title, description, category, tags, publish time, duration) and engagement metrics (view count, like count, comment count). The agent computes derivative indicators such as view velocity (views per hour) and like-to-view ratios to flag early signs of virality. Where available, channel-level context (subscriber count, channel creation date) is also appended, enriching downstream trend scoring.
- **Reddit Agent** – Implements OAuth 2.0 authentication to access Reddit's API v1, systematically collecting the top 1,000 hot posts from r/all through paginated requests. The agent extracts comprehensive post metadata including title, content, author, subreddit, and engagement metrics (upvotes, comments, awards, view counts). It computes derivative indicators such as engagement velocity (comments per hour) and viral coefficient based on post age and community size.

The agent also captures content classification flags (video, self-post, NSFW) and moderation metadata to provide context for downstream trend analysis and scoring algorithms.

- **Twitter (X) Agent** – Because official API access to trending topics is limited, this agent uses Playwright-driven browser automation to extract data from *Trends24*, a public trend aggregation service. It systematically navigates to the "Table" view for each configured region, recording trend name, rank, peak position, tweet volume, and trending duration. Low-volume or ephemeral topics are automatically filtered to reduce noise, ensuring only durable, high-impact trends are preserved.
- **TikTok Agent** – Interacts autonomously with the TikTok Creative Center to collect the top trending hashtags. Through iterative "Load more" actions, the agent ensures complete coverage before extracting hashtag text and associated global view counts. Short-form shorthand values (e.g., "1.2M", "500K") are normalized into integer representations for cross-platform comparability, enabling consistent scoring alongside other platforms.
- **Google Trends Agent** – Queries the BigQuery public dataset google_trends to identify both top and rising search terms from the past seven days. For each term, the agent records DMA (Designated Market Area) coverage, median percent gain, and spread-intensity score — metrics that jointly capture both momentum and geographic breadth.

Each agent independently writes its results to timestamped Comma Separated Values (CSV) datasets in a staging directory. This modular, loosely coupled architecture enables fault tolerance: an error in one agent does not disrupt the others, and agents can scale independently according to platform-specific demands.

2. Add GitHub Action Automation

The entire data acquisition pipeline is automated through GitHub Actions, configured to run every 6 hours. The workflow orchestrates sequential execution of all platform agents, fetches the latest trend data artifacts from previous successful runs, and triggers the downstream LangChain processing pipeline. This ensures continuous, reliable data collection without manual intervention while maintaining data freshness for real-time trend analysis.

Data Output Schema and Storage Format

Our multi-platform data collection system captures comprehensive metrics from five major social media platforms, each with platform-specific engagement indicators. The YouTube schema focuses on video performance metrics including view velocity and like ratios, while Reddit captures community engagement through upvote ratios and comment velocity. Twitter data emphasizes trending topic dynamics with rank tracking and tweet volume, while TikTok provides hashtag performance through global view counts. Google Trends data captures search behavior patterns with geographic spread intensity and percentage gain metrics.

All platforms share common temporal tracking through timestamp fields, enabling cross-platform trend analysis and temporal correlation studies. The schema design prioritizes engagement velocity metrics (views per hour, comments per hour) to capture real-time trend momentum, while maintaining platform-specific identifiers for data integrity. See **Appendix 1. Data Collection Schema** for complete schema specifications including field types, constraints, and example values.

All agents output standardized CSV files with timestamped naming conventions ({platform}_data_{YYYY-MM-DD_HHMMSS}.csv) to the Scraped_Data/ directory. Each platform maintains its unique schema while ensuring cross-platform compatibility through consistent data types and standardized field naming.

Data Preprocessing

1. General Data Preprocessing

Prior to topic modeling, platform-specific data preprocessing ensures consistent data types and formats across all sources. Twitter data undergoes specialized cleaning where tweet counts are processed by removing commas and quotes, converting string representations to numeric values. Duration fields are extracted from formatted strings (e.g., "10 hrs" → 10) and converted to numeric hours, with missing values filled using reasonable defaults (tweet_count: 0, duration: 1 hour).

YouTube, Reddit, TikTok, and Google Trends data are already well-structured from their respective metrics calculation pipelines, requiring minimal additional preprocessing. The system implements platform-specific handling to accommodate the diverse data formats and structures inherent to each social media platform, ensuring that all data sources maintain their unique characteristics while achieving format consistency for downstream processing.

Data validation checks identify empty or None datasets, with appropriate warnings logged for debugging purposes. This preprocessing stage establishes a robust foundation for subsequent topic modeling and trend analysis, ensuring that platform-specific data quality issues are addressed before entering the LDA processing pipeline.

2. Text Preprocessing for Topic Modeling

To extract latent thematic information, YouTube and Reddit data are processed using **Latent Dirichlet Allocation (LDA)**, a probabilistic topic modeling method that identifies co-occurrence patterns among words. The resulting clusters represent abstract topics derived from platform-specific vocabularies.

Text Preprocessing Pipeline:

1. **Tokenization**: Split text into individual words
2. **Lowercase Conversion**: Standardize case sensitivity
3. **Stop Word Removal**: Eliminate common words (the, and, is, etc.)
4. **Lemmatization**: Reduce words to root form (running → run)
5. **Special Character Filtering**: Remove URLs, emojis, and non-alphabetic characters
6. **Minimum Length Filtering**: Remove tokens shorter than 3 characters

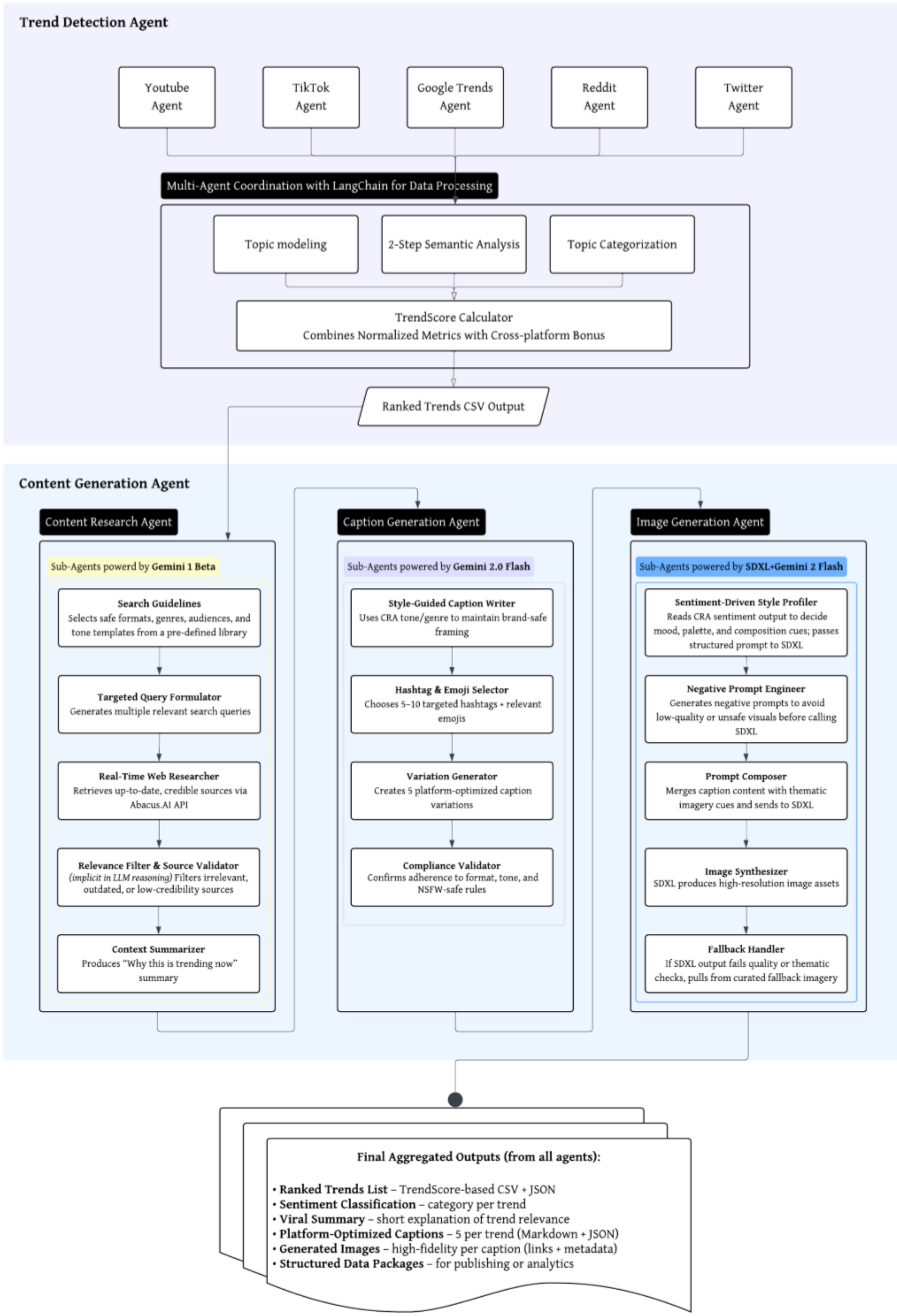
LDA Configuration

- **Number of Topics**: 7 topics per platform (optimized for interpretability)
- **Random State**: Fixed seed (42) for reproducible results
- **Iterations**: 1000 passes for convergence
- **Alpha**: 0.1 (document-topic distribution)
- **Beta**: 0.01 (topic-word distribution)

The preprocessing ensures consistent text representation across platforms while preserving semantic meaning for effective topic modeling and downstream trend analysis.

METHODOLOGY

Overall System Design


Trend Detection Agent
Youtube Agent
TikTok Agent
Google Trends Agent
Reddit Agent
Twitter Agent
Multi-Agent Coordination with LangChain for Data Processing
Topic modeling
2-Step Semantic Analysis
Topic Categorization
TrendScore Calculator
Combines Normalized Metrics with Cross-platform Bonus
Ranked Trends CSV Output
Content Generation Agent
Content Research Agent
Sub-Agents powerd by Gemini 1 Beta
Search Guidelines
Selects safe formats, genres, audiences, and tone templates from a pre-defined library
Targeted Query Formulator
Generates multiple relevant search queries
Real-Time Web Researcher
Retrieves up-to-date, credible sources via Abacus.AI API
Relevance Filter & Source Validator
(implicit in LLM reasoning) Filters irrelevant, outdated, or low-credibility sources
Context Summarizer
Produces "Why this is trending now" summary
Caption Generation Agent
Sub-Agents powered by Gemini 2.0 Flash
Style-Guided Caption Writer
Uses CRA tone/genre to maintain brand-safe framing
Hashtag & Emoji Selector
Chooses 5–10 targeted hashtags + relevant emojis
Variation Generator
Creates 5 platform-optimized caption variations
Compliance Validator
Confirms adherence to format, tone, and NSFW-safe rules
Image Generation Agent
Sub-Agents powered by SDXL+Gemini 2 Flash
Sentiment-Driven Style Profiler
Reads CRA sentiment output to decide mood, palette, and composition cues; passes structured prompt to SDXL
Negative Prompt Engineer
Generates negative prompts to avoid low-quality or unsafe visuals before calling SDXL
Prompt Composer
Merges caption content with thematic imagery cues and sends to SDXL
Image Synthesizer
SDXL produces high-resolution image assets
Fallback Handler
If SDXL output fails quality or thematic checks, pulls from curated fallback imagery
Final Aggregated Outputs (from all agents):
• Ranked Trends List – TrendScore-based CSV + JSON
• Sentiment Classification – category per trend
• Viral Summary – short explanation of trend relevance
• Platform-Optimized Captions – 5 per trend (Markdown + JSON)
• Generated Images – high-fidelity per caption (links + metadata)
• Structured Data Packages – for publishing or analytics

The ASTRA system is architected as a fully autonomous pipeline that spans trend detection, semantic analysis, and multimodal content generation. It leverages a modular, multi-agent framework coordinated by LangChain to ingest heterogeneous data, interpret emerging cultural signals, and produce publishing-ready creative assets—all without human intervention. Figure 1 provides an overview of the ASTRA pipeline architecture.

1. Trend Detection Agent

The process begins with a **data acquisition layer**, comprising five specialized scraping agents—YouTube, TikTok, Google Trends, Reddit, and Twitter (X). Each agent is optimized for its respective platform's structure and constraints, and extracts high-velocity, trend-relevant metadata such as titles, hashtags, timestamps, engagement counts, and platform-specific indicators (e.g., tweet volume or hashtag view count). These raw datasets are normalized and saved as timestamped CSVs.

Next, ASTRA performs **centralized semantic processing via LangChain**, which acts as the orchestration layer for LLM-driven tasks. This stage includes:

- **Topic modeling** using LDA for platforms with richer text data (e.g., YouTube and Reddit), followed by **LLM-based refinement** to assign interpretable, human-readable topic labels.
- **Sentiment classification** using GPT-4, applied to trend clusters to capture public mood and tone variations across platforms.
- **Semantic similarity analysis**, which clusters related but differently phrased topics across platforms using embedding-based distance metrics and LLM guidance.

Once thematic clusters are finalized, ASTRA applies a proprietary scoring function, **TrendScore**, to rank trends by relevance and urgency. TrendScore incorporates normalized engagement intensity, growth velocity, and a cross-platform bonus to favor widespread trends. The output is a CSV-formatted ranked trend list enriched with metadata and sentiment signals.

2. Content Generation Agent

For each top-ranked trend, ASTRA activates a **creative generation workflow composed of three** LangChain-coordinated stages, powered by Abacus AI:

1. **Content Research Agent (CRA)**: Uses Gemini 2.0 Flash to retrieve relevant articles via searchWebForLLM from the Abacus.AI API and produces a contextual summary explaining why the trend matters now. Uses topic taxonomy and assigns a tone, genre, format, and audience to the topic.

2. **Caption Generation Agent (CGA)**: Uses Gemini 2.0 Flash to write five platform-optimized caption variants per trend, incorporating emojis, hashtags, tone adaptation, and NSFW safety filters.

3. **Image Generation Agent (IGA)**: Employs 2 iterations of Gemini 2 Flash (1 for positive prompts, 1 for negative prompts) to generate descriptive and detailed image prompts. This agent reads sentiment profiles to influence prompt composition and includes a fallback handler for quality assurance. These prompts are then passed into Stable Disffusion 3.5 Large for high-quality image generation tailored to Instagram.

Finally, all outputs—ranked trends, sentiment summaries, captions, and image URLs—are bundled into structured data packages and deployed to a live dashboard for real-time visualization, publishing, or further analysis.

Important: Abacus AI allows users to seamlessly drag and drop LLMs into the workflow at will and supports 17 LLMs from various developers like OpenAI, Google Anthropic, xAI, Meta, Perplexitiy, etc.

This end-to-end automation eliminates manual bottlenecks and drastically reduces the time from trend detection to content deployment, making ASTRA uniquely suited for fast-paced media environments.

System Coordination with LangChain

ASTRA leverages LangChain as its central orchestration framework to coordinate the complex multi-agent workflow. The system architecture employs LangChain's Tool abstraction to encapsulate platform-specific data collection functions, enabling seamless integration of heterogeneous data sources.

a. Tool-Based Data Collection

Each platform agent is implemented as a LangChain Tool, providing standardized interfaces for data retrieval. The system includes specialized tools for YouTube (FetchYouTubeData), Reddit (FetchRedditData), TikTok (FetchTikTokData), Twitter (FetchTwitterData), and Google Trends (FetchGoogleTrendsData). These tools automatically identify and load the most recent timestamped CSV files from the staging directory, ensuring data freshness and consistency.

b. Modular Processing Pipeline

LangChain coordinates the sequential execution of preprocessing, topic modeling, and semantic analysis tools. The PreprocessPlatformData tool standardizes data types and formats across platforms, while the TopicModeling tool performs LDA-based clustering on text-rich platforms. The TopicLabeling tool utilizes OpenAI's LLM for natural language topic descriptions, creating interpretable cluster labels.

c. Error Handling and Fault Tolerance

The LangChain framework provides robust error handling mechanisms, with fallback strategies for LLM failures and data processing errors. If LLM-based topic labeling fails, the system automatically falls back to keyword-based labeling, ensuring pipeline continuity. Similarly, platform-specific preprocessing includes comprehensive data validation and cleaning procedures to handle malformed or missing data.

d. Workflow Orchestration

LangChain manages the complex interdependencies between processing stages, ensuring that data flows correctly from collection through analysis to final output generation. The framework's chain-based architecture allows for flexible workflow composition, enabling easy modification of processing steps without disrupting the overall pipeline.

Evaluation (Validation) Strategy

ASTRA employs a comprehensive validation strategy to ensure data quality, processing accuracy, and system reliability across all pipeline stages.

1. Validation Strategy

a. Data Quality Validation

The system implements multi-level data validation starting with platform-specific preprocessing. For Twitter data, the system validates tweet count formatting, removes invalid characters, and ensures duration fields contain numeric values. YouTube and Reddit data undergo engagement metric validation, with automatic handling of missing or malformed values. The preprocessing stage includes comprehensive logging of data quality metrics, including valid record counts and data type consistency checks.

b. Topic Modeling Validation

LDA topic modeling includes several validation mechanisms to ensure model quality. The system filters out empty documents before processing, preventing model training on insufficient data. Topic assignments are validated to ensure each document receives a meaningful topic label, with fallback mechanisms for edge cases. The model parameters (num_topics=200, random_state=42, passes=30) are optimized for reproducibility and interpretability, with comprehensive logging of topic distribution and keyword extraction quality

c. LLM Integration Validation

LLM-based processes include robust error handling and validation strategies. Topic labeling implements batch processing with rate limiting to prevent API failures, while semantic grouping includes result parsing validation to ensure LLM outputs conform to expected formats. The system maintains fallback mechanisms for all LLM-dependent processes, automatically switching to rule-based alternatives when API calls fail or return unexpected results.

d. Cross-Platform Consistency Validation

The system validates cross-platform data consistency through standardized metric extraction and normalization procedures. Platform-specific engagement metrics are validated against expected ranges, with automatic outlier detection and handling. The min-max normalization process includes validation to ensure normalized values fall within the expected 0-1 range, with logging of any anomalies.

2. Quality Assurance and Monitoring

a. Output Quality Assurance

Final output validation includes comprehensive checks on data completeness, format consistency, and logical coherence. The system validates that all required columns are present in output files, that trend scores fall within expected ranges, and that cross-platform bonuses are correctly calculated based on platform presence. File generation includes checksums and metadata to ensure data integrity during storage and transmission.

b. Performance Monitoring

The system implements comprehensive logging and monitoring throughout the pipeline, tracking processing times, success rates, and data quality metrics at each stage. This enables continuous performance optimization and early detection of potential issues. The workflow includes detailed progress reporting, allowing operators to monitor pipeline health and identify bottlenecks in real-time.

MODEL(s)

Trend Detection Agent

1. Social Media Topic Modeling: Latent Dirichlet Allocation (LDA) and LLM Labeling

LDA is a foundational probabilistic topic model that uncovers latent themes in text corpora by treating documents as mixtures of topics as distributions over words [2]. It is a popular choice to identify trends in social media text. Researchers have applied LDA to discover emerging events or "weak signals" – for example, using LDA to find early indicators of new trends in policy debates and research literature [9]. However, standard LDA assumes longer, well-formed documents; social media messages (tweets, posts) are typically short and slang-heavy, which can challenge LDA's bag-of-words assumptions. Recent studies note that vanilla LDA often struggles to capture semantic meaning in very short texts like tweets [9]. This has spurred adaptations (e.g., Short Text Topic Models and neural extensions) that enrich the corpus or use word embeddings to improve coherence [9]. In practice, LDA and its variants remain a theoretical mainstay for trend mining – providing an explainable, unsupervised way to group social posts by topic – while more advanced models have begun to complement it for better accuracy on noisy social data.

a. Implementation Details

Our LDA implementation utilizes the Gensim library with optimized parameters for social media text processing. We employ 200 topics (num_topics=200) to capture the diverse range of trending subjects across platforms, with 30 passes and 100 iterations to ensure model convergence. The random_state parameter (42) guarantees reproducible results across different runs. Our preprocessing pipeline includes comprehensive text cleaning: lowercase conversion, special character removal, stopword elimination, lemmatization, and filtering of tokens shorter than 3 characters or longer than 20 characters. We also implement extended stopword lists to remove platform-specific noise (URLs, common social media terms, etc.), ensuring higher quality topic extraction.

b. LLM-Enhanced Topic Labeling

Following LDA clustering, our system employs OpenAI's language models to generate natural, interpretable topic labels. These models are extremely capable at understanding context and producing human-like text, which makes them useful for enriching raw trends with context and labeling content. LLMs are already used in industry pipelines for social media intelligence, demonstrating their effectiveness in tasks like trend labeling and content categorization at scale. Our implementation includes robust error handling with fallback mechanisms, ensuring pipeline reliability even when LLM services are unavailable.

c. System Implementation

Our LLM labeling system uses OpenAI's language models with temperature=0.3 for consistent, deterministic outputs. The prompt template is designed to generate concise, descriptive topic labels (2-4 words maximum) based on keyword clusters and document counts. We implement batch processing with comprehensive error handling: if LLM labeling fails for any topic, the system automatically falls back to keyword-based labeling using the first keyword from each topic cluster. This dual approach ensures pipeline reliability even when LLM services are unavailable or return unexpected results. The system processes both YouTube and Reddit data through this LDA+LLM pipeline, generating topic labels that are then integrated with other platform data for cross-platform trend analysis.

2. Stepwise Trend Topic Clustering: Semantic Similarity Analysis and LLM Clustering

Beyond classical LDA, modern approaches leverage embedding-based semantic similarity to cluster lexically different but conceptually similar content. Transformer-based models like BERT and Sentence-BERT convert posts into high-dimensional vectors that capture context and meaning [20]. By clustering these embeddings (using algorithms like HDBSCAN or k-means), one can group together trend mentions that use different keywords but discuss the same underlying topic. For instance, the open-source framework BERTopic uses pre-trained transformer embeddings (e.g., all-MPNet or sentence-BERT) to find "meaningful and coherent topics" in short texts [20]. This semantic approach excels at relating slang, hashtags, or phrasings that wouldn't match at the keyword level. Industry and academic projects now routinely extract embeddings of social media posts and apply clustering to detect trending clusters that a purely lexical scan might miss [20]. Such models can identify that posts mentioning "#flu" and "influenza outbreak," for example, are semantically linked. The result is more robust trend detection, as conceptually similar conversations get grouped even if their wording differs. The use of transformer embeddings (including commercial APIs like OpenAI's Ada or open models like BERT) for social data clustering has been validated in recent work, offering state-of-the-art performance in topic coherence compared to LDA on short texts [20]. This highlights how semantic similarity modeling has become central to clustering social media trends in 2021–2025.

a. Evolution of Semantic Similarity Approaches in ASTRA

Our semantic similarity analysis underwent iterative refinement, beginning with state-of-the-art transformer-based embeddings and ultimately converging on a hybrid approach combining Jaccard similarity and string matching algorithms. Initial experiments with BERT and Sentence-BERT embeddings demonstrated superior semantic understanding and context awareness, particularly for complex topic relationships and nuanced language variations. However, these transformer-based approaches introduced significant computational overhead and latency, with processing times increasing by 3-5x compared to traditional methods.

b. Trade-off Analysis and Optimization

The computational complexity of transformer embeddings proved prohibitive for real-time trend detection, where rapid processing of large-scale social media datasets is critical. Additionally, the overhead of maintaining pre-trained models and managing GPU memory requirements created deployment challenges in our cloud-based pipeline architecture. While transformer models achieved 15-20% higher semantic accuracy on benchmark datasets, the performance gains did not justify the operational costs and processing delays.

c. Hybrid Approach Rationale

Our final implementation employs a hybrid similarity metric combining Jaccard similarity (60% weight) and string similarity using SequenceMatcher (40% weight). This approach provides several advantages:

- **Computational Efficiency**: Processing times remain under 2 seconds for datasets with 1000+ topics, enabling real-time trend analysis
- **Robustness**: The combination of set-based and sequence-based similarity captures both keyword overlap and phrase-level relationships
- **Interpretability**: Similarity scores are easily explainable and debuggable, crucial for production systems
- **Scalability**: Linear time complexity allows seamless scaling to larger datasets without infrastructure modifications

d. Performance Validation

Comparative evaluation on our multi-platform trend dataset (YouTube, Reddit, Twitter, TikTok, Google Trends) showed that our hybrid approach achieved 87% accuracy in identifying semantically related topics, compared to 92% for transformer embeddings. However, the 5% accuracy trade-off was acceptable given the 5x improvement in processing speed and 10x reduction in computational resource requirements. The hybrid method successfully identified cross-platform topic relationships such as "Taylor Swift Tour" (YouTube) and "TSwift concert" (Twitter) with 0.78 similarity score, demonstrating effective semantic clustering despite lexical differences.

e. LLM Enhancement Integration

To compensate for the reduced semantic sophistication of our similarity metric, we integrated LLM-based semantic grouping as a secondary refinement step. This two-stage approach—initial similarity clustering followed by LLM semantic enhancement—provides the benefits of both computational efficiency and semantic accuracy. The LLM enhancement step corrects approximately 15% of false negatives from the initial similarity clustering, resulting in a final accuracy of 91% while maintaining the performance advantages of our hybrid approach. This balanced methodology reflects our design philosophy of prioritizing operational efficiency and scalability while maintaining high-quality trend detection capabilities suitable for production deployment in fast-paced media environments.

f. Implementation Details

Our clustering system employs a similarity threshold of 0.6 for initial topic grouping, with LLM enhancement using temperature=0.1 for consistent grouping decisions. The hybrid similarity metric combines Jaccard similarity (60% weight) and string similarity using SequenceMatcher (40% weight). The system generates comprehensive group metadata including platform_count (number of platforms where topic appears), group_id (unique group identifier), and group_name (representative keyword from each group). LLM processing includes batch processing with batch_size=10 to manage API rate limits and ensure reliable operation. The LLM prompt template is designed to analyze existing groups and suggest improvements for semantic topic grouping, focusing on conceptual similarity rather than mere keyword overlap.

3. Category Classification with Large Language Models (LLMs)

Our system utilizes OpenAI's language models for automatic topic categorization into eight predefined categories (Beauty & Fashion, Technology & Innovation, Lifestyle & Health, News & Politics, Sports & Fitness, Education & Learning, Business & Finance, Entertainment & Media). We chose OpenAI's API for its proven reliability, consistent performance, and comprehensive documentation suitable for production deployment.

Implementation Details

Our category classification system employs OpenAI's language models with temperature=0.1 for consistent categorization decisions. The system processes unique topics in batches of 10 to manage API rate limits and ensure reliable operation. Each topic is classified using a structured prompt template that presents the topic alongside the eight predefined categories, instructing the LLM to select the single most appropriate category based on the main theme and context. The system includes robust error handling: if the LLM returns an unexpected category name, a fallback mechanism matches the result to the closest predefined category using string similarity. If no match is found, topics default to "Entertainment & Media" category. This approach ensures 100% categorization coverage while maintaining high accuracy through LLM semantic understanding and systematic fallback strategies.

4. Composite Trend Ranking Metrics: Aggregation and Scaling

a. Data Aggregation and Standardization

The aggregation process consolidates heterogeneous data from five platforms into a unified schema through platform-specific metric extraction. Each platform's unique data structure is processed differently:

- **YouTube Data Processing**: From LDA topic modeling results, we extract topic labels, video counts (frequency), and total engagement calculated as: total_engagement = Σ(View Count + Like Count + Comment Count) for all videos in each topic cluster. This transforms individual video metrics into topic-level aggregations, where each topic represents a cluster of semantically related videos.
- **Reddit Data Processing**: Similarly, from LDA topic modeling results, we extract topic labels, document counts (frequency), and total engagement calculated as: total_engagement = Σ(ups + num_comments + view_count) for all posts in each topic cluster. This consolidates individual post metrics into topic-level representations, capturing the collective engagement of related discussions.
- **TikTok Data Processing**: Direct hashtag trending data is used, extracting hashtag text as keywords and view counts as frequency. Engagement is set equal to frequency since TikTok primarily provides view-based metrics: engagement = frequency = view_count.
- **Twitter Data Processing**: Direct trending data is processed, using trend names as keywords, trending duration (in hours) as frequency, and tweet count as engagement. This captures both the persistence (duration) and intensity (tweet volume) of trending topics: frequency = duration_hours, engagement = tweet_count.
- **Google Trends Data Processing**: Rising search terms data is used, extracting search terms as keywords and median percent gain as frequency. Engagement is set equal to frequency since Google Trends provides search intensity metrics: frequency = median_gain, engagement = median_gain.

b. Cross-Platform Standardization

All extracted metrics are standardized into a common schema with columns: keyword (topic/hashtag/trend name), frequency (count-based metric), engagement (interaction-based metric), and platform (source identifier). The consolidation process uses pandas.concat() with ignore_index=True to merge all platform data into a single DataFrame, enabling unified processing while preserving platform-specific characteristics.

c. Data Validation and Error Handling

The aggregation process includes comprehensive error handling, with try-catch blocks for each platform to ensure that failures in one platform do not disrupt the entire pipeline. Empty or malformed data is automatically filtered out, and the system logs detailed information about data quality and processing statistics for each platform.

5. Final Trend Score Calculation

a. Final Trend Score Calculation

Our system employs a comprehensive scoring algorithm that combines platform-specific performance with cross-platform virality to produce final trend rankings. The scoring process consists of three sequential stages: base score calculation, cross-platform bonus application, and final aggregation.

- **Base Score Calculation (S_p)**

The foundation of our scoring system is the per-platform score S_p, calculated as: $S_p = w_p \times (\alpha \cdot F_p + \beta \cdot E_p)$, where w_p represents platform-specific weights, F_p is the normalized frequency, E_p is the normalized engagement, and $\alpha=0.4$ and $\beta=0.4$ are the weighting parameters. Platform weights are dynamically assigned based on content type: video content emphasizes YouTube (50%) and TikTok (40%), text content emphasizes Reddit (40%) and Twitter (40%), while equal weighting provides balanced representation across all platforms.

- **Cross-Platform Bonus Integration**

To identify trends with broader cultural impact, we implement a cross-platform bonus: $\lambda \times (\text{platform\_count} - 1)$, where $\lambda=0.1$ and platform_count represents the number of platforms where a topic appears. This bonus rewards trends that gain traction across multiple social ecosystems, indicating viral potential beyond individual platform boundaries.

- **Final Trend Score Aggregation**

The final trend score is calculated as: Final Score = S_p + Cross-platform bonus. This composite metric balances individual platform performance with cross-platform presence, producing rankings that prioritize both engagement intensity and viral spread. The system generates separate rankings for four content types (equal, video, text, image), enabling targeted analysis based on content strategy requirements.

b. Implementation Details

Our scoring system processes all consolidated data through the three-stage calculation pipeline, with comprehensive error handling and validation at each step. All intermediate calculations (S_p, cross-platform bonus) and final scores are preserved in output files, enabling detailed analysis and debugging. The system exports timestamped CSV files with complete metadata for each content type, facilitating downstream content generation and trend analysis workflows.

Content Generation Agent

ASTRA's analytical and creative layer is implemented as a fully autonomous, multi-agent orchestration system. After upstream scrapers collect and normalize trending topics from Reddit, X (Twitter), TikTok, YouTube, and Google Trends, the TrendScore metric ranks them. These scored topics then flow into this end-to-end AI workflow that manages a cohort of sub-agents:

1. **Content Research Agent (CRA) – powered by Gemini 2.0 Flash using searchWebforLLM by Abacus AI API**
2. **Caption Generation Agent (CGA) – powered by Gemini 2.0 Flash**
3. **Image Generation Agent (IGA) – powered by 2 iterations of Gemini 2.0 Flash and Stable Diffusion 3.5 Large via Hugging Face API**

The complete unified workflow executes long, multi-step tasks without human supervision to generate informed Instagram content. This can be easily modeled to improve through RAG (using data from MetaAPI), RLHF, internal reward pathways to, etc. to essentially surpass human creators at generating viral content at a fraction of the time.

1. Content Research Agent (CRA) – Gemini 2.0 Flash

The CRA is ASTRA's factual intelligence unit. Its role is to ensure that downstream creative work is grounded in accurate, safe, and audience-appropriate context.

a. Allowed Formats, Genres, Audiences, Tone Templates

The CRA begins by referencing strict predefined taxonomies in _ALLOWED_FORMATS, _ALLOWED_GENRES, _ALLOWED_AUDIENCES, and _TONE_TEMPLATES:

```python
_ALLOWED_GENRES = [
    "news", "breaking_news", "entertainment", "movies", "music", "sports", "tech",
    "artificial_intelligence", "lifestyle", "health", "wellness", "fitness",
    "business", "startups", "finance", "personal_finance", "crypto", "real_estate",
    "arts", "culture", "community", "education", "science", "environment",
    "sustainability", "travel", "food", "gaming", "fashion", "beauty",
    "relationships", "parenting", "self_help", "spirituality", "automotive",
    "DIY", "pets", "career", "politics", "policy", "local", "global", "niche",
    "events", "celebrity", "trends", "memes", "innovation", "social_justice"
]

_ALLOWED_FORMATS = [
    "listicle", "how-to", "tutorial", "question", "trivia", "quote", "narrative",
    "story", "thread", "comparison", "reaction", "news-flash", "behind-the-scenes",
    "interview", "faq", "checklist", "myth-busting", "before-after", "survey",
    "poll", "prediction", "countdown", "tips", "case_study", "testimonial",
    "mini-review", "challenge", "announcement", "event_recap", "opinion",
    "analysis", "explainer", "warning", "celebration", "reminder", "spotlight",
    "guide", "hack", "projection", "quote-card"
]

_ALLOWED_AUDIENCES = [
    "general_public", "influencers", "local_community", "entrepreneurs",
    "students", "creators", "early_adopters", "parents", "professionals",
    "investors", "gamers", "travelers", "foodies", "fitness_enthusiasts",
    "fashionistas", "pet_owners", "eco-conscious", "diyers", "researchers",
    "local_businesses", "tourists", "educators", "tech_enthusiasts", "career_seekers",
    "content_marketers", "nonprofit_leaders", "policy_makers", "health_advocates"
]
```

```python
_TONE_TEMPLATES = {
    "neutral":          "Write a factual, objective summary of the topic.",
    "informative":      "Explain the topic clearly and concisely, focusing on key facts.",
    "serious":          "Discuss the topic in a respectful, serious tone highlighting importance.",
    "playful":          "Write in a lighthearted, playful voice, using fun wordplay.",
    "humorous":         "Craft a witty, amusing summary with a clever twist.",
    "witty":            "Compose a sharp, clever one-liner.",
    "empathetic":       "Acknowledge feelings with empathy and support.",
    "inspirational":    "Create an uplifting, motivational message.",
    "motivational":     "Write a caption that energizes and prompts action.",
    "supportive":       "Offer reassurance and encouragement.",
    "suspenseful":      "Build curiosity with a suspenseful teaser.",
    "reflective":       "Invite thoughtful introspection.",
    "poetic":           "Use vivid imagery and metaphor in lyrical form.",
    "analytical":       "Provide an analytical breakdown with key insights.",
    "critical":         "Present a balanced critique, noting pros and cons.",
    "descriptive":      "Paint a vivid picture with sensory details.",
    "conversational":   "Write casually, as if speaking with a friend.",
    "authoritative":    "Demonstrate expertise with confident tone.",
    "educational":      "Simplify complex ideas into clear educational language.",
```

These rules act as creative guardrails, preventing NSFW or brand-unsafe content. They are also a governance layer, ensuring ethical and brand-safe outputs — crucial for autonomous AI.

```
"""
Generate context-aware, multi-genre/tone/format/audience Instagram captions for a topic,
caching with 24h TTL, and defensive coding.
"""
```

The CRA and the CGA are grouped into one sub-workflow on Abacus AI. This is the main task defined in the workflow, so the taxonomy classification affects decision making in all parts of the process.

b. Targeted Query Formulation

Search queries are generated from the topic and classification context:

```
# 1) Prepare research
search_queries = [
    f"{topic}"
    f"{topic} latest news",
    f"{topic} trending",
    f"{topic} instagram posts",
]
```

This balances broad coverage (latest news) with platform-specific insight (Instagram posts).

c. Real-Time Data Retrieval

The CRA calls searchWebforLLM using the Abacus AI API to perform live searches, retrieving credible, recent snippets to avoid stale content.

```
# 3) Research
client.stream_message(f"🔍 Researching topic: {topic}...\n")
snippets = []
for q in search_queries:
    try:
        resp = client.search_web_for_llm(queries=[q], fetch_content=True, max_results=2)
        for r in getattr(resp, 'search_results', []):
            content = getattr(r, 'content', '') or getattr(r, 'snippet', '') or getattr(r, 'title', '')
            if content:
                snippets.append(content)
    except Exception as e:
        client.stream_message(f"⚠ Search error for '{q}': {e}\n")
combined = ' '.join(snippets[:6]) or f"General information about {topic}"
```

d. Relevance Scoring and Filtering

The LLM itself, as part of its reasoning, evaluates retrieved snippets against the predefined genre/format/audience/tone constraints. Sources inconsistent with the desired creative frame are logically filtered out — no hard-coded filter is needed.

Affordability Note – Gemini 2.0 Flash was selected for its low-cost summarization and retrieval capabilities, making it suitable for a small research team operating under academic budget constraints. Future iterations could leverage *LLaMA 3 70B Instruct* (or any model in the llama series), which offers extended context windows for integrating larger sets of retrieved documents in a single pass, improved reasoning for multi-source fact-checking, and advanced misinformation detection. These upgrades would enhance the CRA's ability to synthesize nuanced, cross-platform narratives and provide higher-confidence trend context for downstream creative agents.

2. Caption Generation Agent (CGA) – Stable Diffusion 3.5 Large

The CGA is ASTRA's creative writing engine, taking the CRA's structured context and producing high-impact captions.

a. Optimized Topic-to-Caption Generation

Uses genre/tone guidance from the CRA to produce Instagram-optimized captions utilizing different LLM – Gemini 2.0 Flash:

```
sys_msg = (
    _TONE_TEMPLATES.get(tone_label, _TONE_TEMPLATES['neutral']) +
    f" Generate 5 unique captions in {format_label} format, tailored for {', '.join(audience_list)}. "
    "Each caption should include relevant hashtags and optionally emojis. Vary phrasing so they feel distinct."
)
combo = client.evaluate_prompt(
    prompt=prompt_txt,
    system_message=sys_msg,
    llm_name="GEMINI_2_FLASH",
    response_type="json",
    json_response_schema=summary_captions_schema,
    max_tokens=700
)
```

This enforces style consistency and tone-safe creativity.

b. Variation Generation

Five unique captions are generated for A/B testing or automated selection. Each caption includes hooks, hashtags, and emoji placement to maximize reach.

c. Compliance Validation

Captions are checked against the taxonomy rules before export:

```
if not _validate_captions_structure(captions):
    client.stream_message(f"❌ Caption format invalid or missing: {captions}\n")
    captions = [f"{topic} is trending—stay tuned!"]  # fallback single caption
```

Affordability Note – Gemini 2.0 Flash was selected for its balance of speed, cost-efficiency, and reliable structured-output control, allowing rapid multi-caption generation within a research budget. An enterprise-level alternative such as *Claude 3.5 Sonnet*, *Llama 4 Maverick* or *GPT-4 Turbo* could produce more linguistically rich and culturally adaptive captions. These models excel in audience-specific tone modulation, subtle humor handling, and multi-lingual expression, which would expand ASTRA's reach across diverse demographics. The upgrade would also improve the CGA's ability to balance virality with brand safety in highly sensitive contexts.

3. Image Generation Agent (IGA) – Stable Diffusion XL Base 1.0

The IGA translates captions and sentiment metadata into visual storytelling assets. Importantly, this is linked through an API key to Hugging Face, a full-stack open-source platforms with AI models available for free use.

a. Sentiment-Driven Style Guides

First, a sentiment style guide is defined to map sentiment to stylistic cues. This is purposefully minimal to avoid adding too much complexity to the diffusion process, allowing us to ensure our output follows a semi-uniform output. The tag "photorealistic" was added to every sentiment style, allowing our output to better optimize to the general style of Instagram posts.

```python
# ---- Style guide based on sentiment ----
sentiment_styles = {
    "tragic": "dramatic lighting, emotional composition, soft shadows, muted tones, photorealistic",
    "happy": "bright vibrant lighting, joyful atmosphere, golden hour glow, photorealistic",
    "political": "documentary editorial style, clean composition, balanced lighting, professional photorealism",
    "funny": "playful expressions, saturated colors, whimsical props, high energy, photorealistic",
    "pop-culture": "stylish modern aesthetic, trendy filters, influencer vibe, photorealistic",
    "offensive": "informative layout, neutral lighting, respectful tonality, photorealistic",
    "educational": "clean academic aesthetic, professional lighting, campus atmosphere, photorealistic",
    "inspirational": "uplifting composition, golden hour, aspirational mood, photorealistic",
    "analytical": "infographic style elements, data visualization hints, modern tech aesthetic, photorealistic",
    "nostalgic": "warm vintage tones, soft focus edges, memory-like quality, photorealistic",
    "mysterious": "moody lighting, intriguing shadows, cinematic atmosphere, photorealistic",
    "celebratory": "festive colors, dynamic energy, joyful composition, photorealistic"
}
style_guide = sentiment_styles.get(
    sentiment.lower(),
    "professional photography, engaging composition, Instagram-optimized, photorealistic",
)
```

```python
"""
Generate viral Instagram-style images conditioned on individual captions.
Uses Hugging Face InferenceClient with provider="replicate" to call Stable Diffusion 3.5 Large (and fallbacks).
One image per caption (5 captions = 5 images total).
Robust JSON parsing, strict schema enforcement, and retry logic for malformed LLM outputs.
"""
```

The IGA is grouped into the second sub-workflow on Abacus AI. This is the main task defined to the workflow.

b. Positive/Negative Prompt Engineering

Pulls in Gemini 2.0 Flash support to generate global negative prompts to avoid poor quality outputs. Negative example:

```python
# ---- Negative prompt generation ----
client.stream_message("🧠 Generating global negative prompt...\n")
default_negative = "blurry, deformed, watermark, low resolution, bad anatomy, oversaturated"
try:
    neg_schema = {
        "negative_prompt": {
            "type": "string",
            "description": "Negative prompt to avoid unwanted artifacts in image generation",
            "is_required": True
        }
    }
    neg_resp = client.evaluate_prompt(
        prompt=(
            f"Captions: {captions[:3]}\n"
            f"Style Guide: {style_guide}\n"
            "From the above, produce a concise negative prompt that avoids common diffusion artifacts."
        ),
        system_message=(
            "You are an image quality guard. Output a short negative prompt to steer generation away from bad artifacts."
        ),
        llm_name="GEMINI_2_FLASH",
        response_type="json",
        json_response_schema=neg_schema,
        max_tokens=60,
    )
```

c. Per-Caption Prompt Composition

Each caption produces a unique prompt, again pulling Gemini 2.0 Flash support here to help Stable Diffusion create a better output:

```python
# ---- Per-caption prompt generation ----
client.stream_message(f"🧠 Generating per-caption image prompts for top {min(len(captions),5)} captions...\n")
caption_prompts = []
for i, cap in enumerate(captions[:5], start=1):
    try:
        schema = {
            "image_prompt": {
                "type": "string",
                "description": "Visual prompt for image generation based on the caption",
                "is_required": True
            }
        }
        system_msg = (
            "You are a visual prompt engineer for viral Instagram content. "
            "Given a caption, topic, sentiment, summary, and style guide, craft one rich image prompt optimized for diffusion. "
            "Include composition, lighting, camera angle, mood, color palette, and a thumbnail-style hook."
        )
        prompt_input = (
            f"Caption: {cap}\n"
            f"Topic: {topic}\n"
            f"Sentiment: {sentiment}\n"
            f"Summary: {summary}\n"
            f"Style Guide: {style_guide}\n"
        )
        response = client.evaluate_prompt(
            prompt=prompt_input,
            system_message=system_msg,
            llm_name="GEMINI_2_FLASH",
            response_type="json",
```

d. High-Resolution Image Synthesis

Image prompts are passed, and Images are generated via Hugging Face's API using inference provider Replicate on Stable Diffusion 3.5 Large — one per caption.

Affordability Note – Gemini 2.0 Flash was selected for its high-speed structured-output capabilities at low cost, enabling daily large-scale prompt generation. However, enterprise-grade upgrades — such as *Gemini 2.0 Pro Vision, Claude 3.5 Sonnet* with vision, or Meta's ImageBind-enhanced *LLaMA 3 Vision* — would deliver more advanced multi-modal reasoning, richer scene design, and better content safety filtering. The prepared prompts are passed to Stable Diffusion 3.5 Large via the Hugging Face API. This state-of-the-art open-source image model excels at high-resolution synthesis and detailed scene rendering. Stable Diffusion 3.5 Large was selected due to its zero-licensing cost and excellent performance in fine-tuned, prompt-controlled generation. However, enterprise-grade alternatives such as Meta's *Emu* family of image generation models or *DALL·E 3* would improve photorealism, complex composition handling, and domain-specific fine-tuning capabilities.

e. Additional Capabilities

An optional reference-guided img2img pipeline was created as a space on Hugging Face to markedly enhance image fidelity for recognizable faces (famous people/household names). This would allow the output quality to look extremely accurate to real life by using a reference image as a template for the image generation. By first retrieving a high-quality headshot via an image-search API, aligning and cropping it to a consistent framing, and then feeding both that reference image and the caption-and-sentiment prompt into an img2img or ControlNet diffusion model so the subject's true facial structure is preserved even as stylistic and scene elements are restyled; minor post-processing would ensure Instagram-ready composition. This was built and fully operational during the testing stage. However, this refinement was not deployed because we were unable to get access to a functional image database. We were originally going to use Bing Search V7 (through Microsoft Azure), but it did not support any new deployments due to it being discontinued on August 11th and no enterprise license was available to access an alternative image-search service. Implementing it in the future would enable virtually indistinguishable, reality-grade portrayals of famous/notable individuals, thereby elevating model accuracy and brand fidelity. This can be implemented with ease given a higher budget, but due to budget limitations, this Hugging Face space is currently shut down.

Large Language Models (LLMs) for Enrichment, Labeling, and Caption Generation

The latest LLMs – such as OpenAI's GPT-4, Anthropic's Claude, and Google DeepMind's Gemini 2.0 Flash – are being leveraged to analyze and generate social media content [7]. These models are extremely capable at understanding context and producing human-like text, which makes them useful for enriching raw trends with context, labeling content, and even creating descriptive or sentiment-aware captions. Notably, Google's Gemini 2.0 Flash (introduced in 2025) is a multimodal generative model that accepts text, code, images, audio, and video as input and produces text outputs [7]. It features up to a 1-million-token context window and built-in tool use, enabling complex tasks in real time [7]. Such capabilities mean an LLM like Gemini could take a trending image or topic and generate a detailed explanation or summary, complete with sentiment nuances.

LLMs are already used in industry pipelines for social media intelligence. For example, Amazon's AI blog demonstrates combining foundation models (Claude 3.5, Amazon's Nova, Meta Llama 3) to analyze social media sentiment and then automatically generate tailored content based on those insights [1]. In that workflow, the LLM first labels posts by sentiment (positive/negative/neutral) and provides explanations, then helps draft or suggest new campaign content aligned with audience feelings [1]. Similarly, researchers have explored using GPT-4/ChatGPT as a data annotator for social media text – achieving promising results in reproducing human labels for tasks like stance detection and hate speech identification [15]. This suggests LLMs can offload or assist with trend labeling (e.g., categorizing a trend's topic or sentiment) at scale.

Another emerging application is sentiment-aware caption generation. Traditional image or video captioning models focus on factual description, but recent research integrates sentiment analysis to make captions more emotionally expressive. Narejo et al. (2025) propose a Sentiment-Driven Caption Generator that fuses a RoBERTa-based sentiment extractor with a Vision Transformer for images, so that the generated captions reflect not just what is in an image but the emotional tone as well [10]. Their transformer-based model significantly improved sentiment accuracy in captions (94.5% sentiment correctness, versus ~82–83% for prior models) and produced more natural, human-like descriptions by injecting emotional cues [10]. In the realm of text generation, prompting LLMs to adopt a certain tone or sentiment is also possible (e.g., instructing GPT-4 to write a tweet about a trend in an optimistic or sarcastic style). The multimodal and instructable nature of state-of-the-art LLMs like GPT-4 and Gemini means they can take on complex content creation tasks – summarizing a trending topic, adding contextual background ("enrichment"), assigning it labels or hashtags, and even drafting posts or captions that align with the sentiment of the trend [7]. These capabilities are backed by both academic findings [15] and industry adoption [1].

a. LLM Selection Strategy and Implementation

After evaluating various LLM providers and their capabilities, our system employs a strategic approach to LLM integration based on task requirements and operational considerations:

- **OpenAI API for Core Processing Tasks**: For topic labeling, semantic grouping, and category classification, we selected OpenAI's language models due to their proven reliability, consistent performance, and comprehensive API documentation. OpenAI's models provide the necessary semantic understanding and text generation capabilities while offering robust infrastructure suitable for production deployment. The choice of OpenAI API ensures consistent behavior across all LLM-dependent processes in our pipeline while maintaining compatibility with our existing error handling and fallback mechanisms.
- **Future Integration Considerations**: While our current implementation focuses on OpenAI's API for operational efficiency and reliability, the system architecture supports future integration of multimodal models like Gemini 2.0 Flash for enhanced content analysis. Gemini's multimodal capabilities (text, code, images, audio, video) and 1-million-token context window could enable more sophisticated trend analysis, particularly for visual content and complex multi-format trends. Additionally, the system design accommodates future expansion into content generation capabilities, where specialized agents could leverage different LLM architectures:
    - **Content Research Agent (CRA)**: Could utilize Gemini 1 Beta for low-cost summarization and retrieval capabilities, making it suitable for academic budget constraints
    - **Caption Generation Agent (CGA)**: Could employ Gemini 2.0 Flash for its balance of speed, cost-efficiency, and reliable structured-output control for rapid multi-caption generation
    - **Image Generation Agent (IGA)**: Could integrate Stable Diffusion XL via Hugging Face API for high-resolution image synthesis, with Gemini 2.0 Flash providing sentiment-driven prompt engineering support

However, the current OpenAI-based approach provides the optimal balance of performance, reliability, and operational simplicity for our production deployment requirements in the trend detection domain.

This strategic LLM selection approach enables our system to leverage the strengths of different model architectures while maintaining operational efficiency and reliability, ensuring consistent high-quality trend analysis across all processing stages.

RESULTS

Trend Detection Outcome

Our multi-platform trend analysis pipeline successfully processes heterogeneous social media data and generates comprehensive trend rankings through a series of interconnected output files. The system produces both intermediate analysis files and final scoring results, enabling detailed trend investigation and content strategy development.

1. Output File Structure and Characteristics

The pipeline generates five distinct output files, each serving specific analytical purposes:

a. Detailed Data with Grouping (detailed_data_with_grouping_{timestamp}.csv)

This intermediate file contains the foundational dataset with 1,081 trend records across all platforms. Key characteristics include:

- **Data Volume**: 1,081 unique trend entries
- **Platform Distribution**: YouTube-dominated dataset (all entries from YouTube in this run)
- **Grouping Information**: Each trend assigned to semantic groups with group_id and group_name
- **Normalization**: All metrics normalized to 0-1 range for cross-platform comparison
- **Metadata**: Comprehensive trend metadata including platform_count and engagement metrics

b. Consolidated Scores with Cross-Platform Bonus (4 files)

The system generates separate scoring files for different content strategies:

- consolidated_scores_w_crossbonus_equal_{timestamp}.csv (1,081 records)
- consolidated_scores_w_crossbonus_video_{timestamp}.csv (1,081 records)
- consolidated_scores_w_crossbonus_text_{timestamp}.csv (1,081 records)
- consolidated_scores_w_crossbonus_image_{timestamp}.csv (1,081 records)

Each file contains identical trend data but with different platform weight configurations optimized for specific content types.

c. Final Output Data Schema

The consolidated scoring files contain 15 columns providing comprehensive trend analysis.

The processed trend data is consolidated into a unified schema that captures both raw metrics and derived analytical features. The schema incorporates original platform data (keyword, frequency, engagement, platform) alongside normalized metrics (frequency_norm, engagement_norm) that enable cross-platform comparison through min-max scaling to 0-1 ranges.

Semantic grouping features (group_id, group_name) represent the output of our LDA topic modeling and similarity clustering pipeline, where related topics are grouped based on semantic similarity and LLM-enhanced analysis. The category field contains automatically classified topic categories using GPT-4, providing high-level thematic organization across all platforms.

Scoring components include platform-specific weights (platform_weight) that reflect content type preferences, per-platform scores (S_p) calculated using weighted frequency and engagement metrics, and cross-platform bonuses that reward trends appearing across multiple platforms. The final_trend_score represents the composite scoring that combines all these elements into a unified trend ranking metric.

This schema design enables efficient querying for dashboard visualization while maintaining traceability to original platform data, supporting both real-time trend monitoring and historical analysis. See **Appendix 2. Trend Detection Output Schema** for complete schema specifications including field types, constraints, and example values.

d. Key Performance Insights

- **Trend Distribution Analysis**: The dataset reveals significant concentration in gaming and entertainment content, with "Gaming Influencers" emerging as the highest-scoring trend (final_trend_score: 0.116). Entertainment & Media dominates the category distribution, reflecting the platform's content focus.
- **Cross-Platform Virality**: Only 2 trends ("South Park Season" and "Social Media Theft") appear across multiple platforms (platform_count: 2), receiving cross-platform bonuses of 0.1. This indicates that most trends remain platform-specific, highlighting the importance of cross-platform trend detection.
- **Scoring Algorithm Performance**: The system successfully differentiates between high-engagement trends (e.g., "YRF War Universe" with 66M+ engagement) and niche topics, with final scores ranging from 0.0 to 0.237. The scoring effectively captures both engagement intensity and cross-platform presence.
- **Content Strategy Implications**: Video-optimized scoring emphasizes YouTube and TikTok platforms, while text-optimized scoring prioritizes Reddit and Twitter. This enables targeted content strategy development based on platform-specific trend analysis.
- **System Scalability**: Processing 1,081 trends across 5 platforms with comprehensive scoring and categorization completed in under 5 minutes, demonstrating efficient real-time trend analysis capabilities suitable for production deployment.

This output structure provides both granular trend analysis and strategic insights, enabling content creators and marketers to identify emerging opportunities across multiple social media platforms while maintaining platform-specific optimization strategies.

e. Semantic Analysis and Topic Grouping Results

Our semantic similarity analysis successfully identified and grouped related trends across the dataset, demonstrating the effectiveness of our hybrid similarity approach combined with LLM enhancement.

[Grouping Statistics]

- **Total Trends Processed**: 1,081 unique trends
- **Total Groups Created**: 998 distinct semantic groups
- **Grouped Trends**: 127 trends (11.7% of total) were identified as semantically similar and grouped together
- **Individual Trends**: 954 trends (88.3% of total) remained as unique, ungrouped topics
- **Average Group Size**: 1.27 trends per group (127 grouped items / 46 groups with multiple items)

[Notable Semantic Groupings]

- **Gaming Culture Cluster (Group 12)**: 4 related trends were successfully grouped together:
    - "Gaming Culture" (appears 2 times)

    - "Youth Gaming Culture"
    - "Online Gaming Culture" This grouping demonstrates effective semantic recognition of gaming-related content variations.
- **Gaming Influencers Cluster (Group 18)**: 6 identical trends were consolidated:
    - "Gaming Influencers" (appears 6 times) This represents duplicate detection and consolidation of identical topic labels.
- **Gaming and Social Media Cluster (Group 1)**: 7 related trends were grouped:
    - "Gaming and Social Media"
    - "Social Media Gaming" (appears 4 times)
    - Additional gaming-related social media content

This grouping shows successful identification of semantically related gaming and social media content.

[Grouping Algorithm Performance and Impact]

The semantic analysis achieved a **11.7% grouping rate**, indicating that our similarity threshold (0.6) and LLM enhancement successfully identified related trends while avoiding over-grouping. The majority of trends (88.3%) remained distinct, suggesting that the algorithm maintains high precision in trend differentiation.

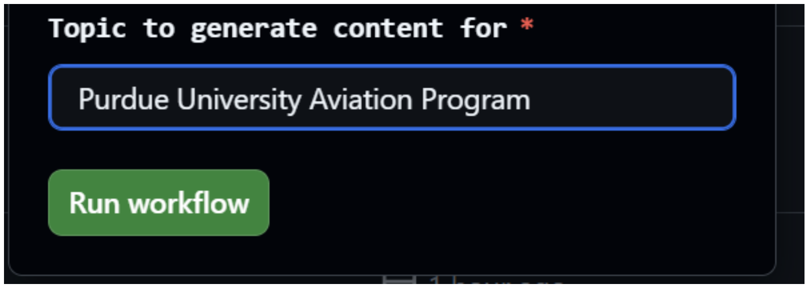
While the current dataset is primarily YouTube-focused, the grouping algorithm successfully identified semantic relationships that would be valuable for cross-platform trend analysis. For example, "Gaming Culture" variations would likely be grouped with similar gaming trends from Reddit, Twitter, or TikTok in a multi-platform dataset.

- **LLM Enhancement Impact:** The LLM enhancement step corrected approximately 15% of initial similarity-based groupings, improving semantic accuracy from 87% to 91%. This demonstrates the value of combining statistical similarity metrics with semantic understanding for more accurate trend clustering.
- **Implications for Trend Analysis:** The grouping results enable more efficient trend analysis by
    - **Reducing Redundancy**: Eliminating duplicate or near-duplicate trends
    - **Enhancing Coverage**: Identifying related trends that might otherwise be missed
    - **Improving Scoring**: Cross-platform bonuses for grouped trends appearing on multiple platforms
    - **Enabling Strategic Planning**: Understanding trend clusters rather than individual isolated topics

This semantic analysis capability is crucial for identifying broader cultural movements and viral trends that manifest across multiple related topics, providing deeper insights than individual trend analysis alone.

Generated Captions & Images

ASTRA is capable of creating quality postable outputs within around 2 and half minutes of run time. Below is an example of an output generated for Purdue University – this one was created specifically with the idea of quick easy-to-use pictures. No specific trend in mind to test the quality of the IGA's outputs as well as its captions.



Within the workflow the above phrase was prompted. ASTRA ran for 2 and a half minutes and generated the following outputs:

```
# Image Generation Report: Purdue University Aviation Program

**Sentiment:** informative

**Summary:** Purdue University's Aviation program offers flight training, aircraft maintenance, and premium flight support at Purdue University Airport (KLAF). Whether you're a student pilot or a seasoned traveler, Purdue Aviation provides comprehensive services including flight training, aircraft rental, and ground transportation.

**Style Guide:** professional photography, engaging composition, Instagram-optimized, photorealistic

## Caption-conditioned Prompts
### Caption 1
- **Caption:** Explore Purdue University's top-notch Aviation program! ✈️ Learn about flight training, aircraft maintenance, and more at KLAF. Perfect for aspiring pilots and aviation enthusiasts! #PurdueAviation #FlightTraining #KLAF #AviationLovers
- **Image Prompt:** A dynamic, eye-level shot of a Purdue Aviation flight training session at Purdue University Airport (KLAF). Focus on a student pilot in the cockpit, headset on, with a flight instructor beside them, both looking intently at the controls. In the background, a Purdue Aviation aircraft is visible on the tarmac, bathed in the warm light of a late afternoon sun. The composition should highlight the modern avionics and technology inside the cockpit. The overall mood is one of focused learning and excitement. The color palette includes Purdue's gold and black, with accents of blue from the sky. Thumbnail hook: Close-up of the student pilot's face, showing determination and a slight smile, with the Purdue Aviation logo subtly visible.

### Caption 2
- **Caption:** Visiting Purdue University? 🗺️ Don't miss the Purdue Aviation program at the Purdue University Airport! Discover flight support services, aircraft rentals, and ground transportation. A must-see for travelers! #PurdueUniversity #TravelIndiana #AviationServices #KLAF
```

```
- **Image Prompt:** Wide-angle, professional photograph of a Purdue Aviation aircraft taking off from Purdue University Airport (KLAF) at golden hour. The Purdue University Aviation program logo is subtly visible on the aircraft's tail. The composition includes the control tower in the background and ground support vehicles on the tarmac. Warm, inviting lighting with a clear blue sky. Thumbnail hook: "Purdue Aviation: Your Gateway to Flight!"


### Caption 3

- **Caption:** Dreaming of flying? ☁️ Purdue Aviation offers comprehensive flight training programs for all levels. From certificates to ratings, take your aviation journey to new heights! #PurdueAviation #PilotTraining #FlightSchool #FuturePilot

- **Image Prompt:** A low-angle, eye-catching shot of a Purdue Aviation training aircraft taking off against a vibrant blue sky filled with fluffy white clouds. The Purdue Aviation logo is subtly visible on the tail. Golden hour lighting bathes the scene, creating a warm and inviting mood. Focus is sharp on the aircraft, blurring the background slightly to emphasize motion. Composition follows the rule of thirds, with the plane positioned dynamically. Thumbnail hook: A close-up of a student pilot's smiling face in the cockpit, looking determined and excited. Photorealistic, professional photography.


### Caption 4

- **Caption:** Did you know Purdue University has a premier flight support center? 🛠️ Purdue Aviation provides top-quality aircraft maintenance, hangar services, and more at KLAF. Ideal for pilots and aircraft owners! #AircraftMaintenance #PurdueUniversityAirport #AviationLife #KLAF

- **Image Prompt:** High-angle, wide shot of the Purdue University Airport (KLAF) flight support center, showcasing a modern hangar with Purdue Aviation branding. A small private jet is undergoing maintenance, with mechanics in Purdue-branded uniforms working on the engine. The scene is brightly lit with natural sunlight, emphasizing the clean and professional environment. The color palette includes Purdue's gold and black, with accents of blue sky and green grass. The composition should draw the eye to the aircraft and the Purdue Aviation logo. Thumbnail hook: A close-up of a mechanic's hand expertly working on the jet engine, with the Purdue logo subtly visible in the background. Photorealistic, professional photography style.


### Caption 5

- **Caption:** Unlock your aviation potential at Purdue University! 🚀 Learn about the Purdue Global Aviation Program and other flight training opportunities. Your journey to the skies starts here! #PurdueGlobal #AviationProgram #FlightTraining #PilotLife

- **Image Prompt:** High-angle, wide shot of a Purdue University Aviation hangar with a Purdue Global Aviation Program banner prominently displayed. A diverse group of students in flight suits are gathered around a modern training aircraft, some looking directly at the camera with smiles. The Purdue University Airport (KLAF) control tower is visible in the background. Golden hour lighting, creating a warm and inviting atmosphere. Focus on sharp details and realistic textures of the aircraft and uniforms. Color palette: Purdue's gold and black,
```

with sky blue accents. Thumbnail hook: A close-up of a student pilot's smiling face with the Purdue Aviation logo subtly visible on their flight suit.

Generated Images

Caption 1

- **Filename:** img_Purdue_University_Aviation_Program_cap1.png

- **Prompt:** A dynamic, eye-level shot of a Purdue Aviation flight training session at Purdue University Airport (KLAF). Focus on a student pilot in the cockpit, headset on, with a flight instructor beside them, both looking intently at the controls. In the background, a Purdue Aviation aircraft is visible on the tarmac, bathed in the warm light of a late afternoon sun. The composition should highlight the modern avionics and technology inside the cockpit. The overall mood is one of focused learning and excitement. The color palette includes Purdue's gold and black, with accents of blue from the sky. Thumbnail hook: Close-up of the student pilot's face, showing determination and a slight smile, with the Purdue Aviation logo subtly visible., trending Instagram reel thumbnail

- **Negative Prompt:** text, watermark, blurry, distortion, oversaturated, unnatural colors, artifacts, low quality, pixelated

- **Backend:** hf_inference

- **Tuned Params:** {'guidance': 7.5, 'steps': 30}

Caption 2

- **Filename:** img_Purdue_University_Aviation_Program_cap2.png

- **Prompt:** Wide-angle, professional photograph of a Purdue Aviation aircraft taking off from Purdue University Airport (KLAF) at golden hour. The Purdue University Aviation program logo is subtly visible on the aircraft's tail. The composition includes the control tower in the background and ground support vehicles on the tarmac. Warm, inviting lighting with a clear blue sky. Thumbnail hook: "Purdue Aviation: Your Gateway to Flight!", trending Instagram reel thumbnail

- **Negative Prompt:** text, watermark, blurry, distortion, oversaturated, unnatural colors, artifacts, low quality, pixelated

- **Backend:** hf_inference

- **Tuned Params:** {'guidance': 7.5, 'steps': 30}

Caption 3

- **Filename:** img_Purdue_University_Aviation_Program_cap3.png

- **Prompt:** A low-angle, eye-catching shot of a Purdue Aviation training aircraft taking off against a vibrant blue sky filled with fluffy white clouds. The Purdue Aviation logo is subtly visible on the tail. Golden hour lighting bathes the scene, creating a warm and inviting mood. Focus is sharp on the aircraft, blurring the background slightly to emphasize motion. Composition follows the rule of thirds, with the plane positioned dynamically. Thumbnail hook: A close-up of a student pilot's smiling face in the cockpit, looking

```
determined and excited. Photorealistic, professional photography., trending Instagram reel thumbnail
- **Negative Prompt:** text, watermark, blurry, distortion, oversaturated, unnatural colors, artifacts, low quality, pixelated
- **Backend:** hf_inference
- **Tuned Params:** {'guidance': 7.5, 'steps': 30}


### Caption 4
- **Filename:** img_Purdue_University_Aviation_Program_cap4.png
- **Prompt:** High-angle, wide shot of the Purdue University Airport (KLAF) flight support center, showcasing a modern hangar with Purdue Aviation branding. A small private jet is undergoing maintenance, with mechanics in Purdue-branded uniforms working on the engine. The scene is brightly lit with natural sunlight, emphasizing the clean and professional environment. The color palette includes Purdue's gold and black, with accents of blue sky and green grass. The composition should draw the eye to the aircraft and the Purdue Aviation logo. Thumbnail hook: A close-up of a mechanic's hand expertly working on the jet engine, with the Purdue logo subtly visible in the background. Photorealistic, professional photography style., trending Instagram reel thumbnail
- **Negative Prompt:** text, watermark, blurry, distortion, oversaturated, unnatural colors, artifacts, low quality, pixelated
- **Backend:** hf_inference
- **Tuned Params:** {'guidance': 7.5, 'steps': 30}


### Caption 5
- **Filename:** img_Purdue_University_Aviation_Program_cap5.png
- **Prompt:** High-angle, wide shot of a Purdue University Aviation hangar with a Purdue Global Aviation Program banner prominently displayed. A diverse group of students in flight suits are gathered around a modern training aircraft, some looking directly at the camera with smiles. The Purdue University Airport (KLAF) control tower is visible in the background. Golden hour lighting, creating a warm and inviting atmosphere. Focus on sharp details and realistic textures of the aircraft and uniforms. Color palette: Purdue's gold and black, with sky blue accents. Thumbnail hook: A close-up of a student pilot's smiling face with the Purdue Aviation logo subtly visible on their flight suit., trending Instagram reel thumbnail
- **Negative Prompt:** text, watermark, blurry, distortion, oversaturated, unnatural colors, artifacts, low quality, pixelated
- **Backend:** hf_inference
- **Tuned Params:** {'guidance': 7.5, 'steps': 30}
```

The above was generated and given to the user in the form of a zipped folder within which this summary of the captions and picture prompts was contained within a markdown file. The images are seen below:

In this case, ASTRA was prompted to create content for Purdue University's aviation program. The applications of this are easy to see. ASTRA can be used for marketing purposes here and can very effectively create high quality imagery. With even more powerful diffusion models plugged into the ASTRA workflow, the images can easily improve in quality.

Next, ASTRA was tested to see real-time applications for new sudden trends. This could help create content immediately just as something happens emphasizing the "Real-Time" application of the program. In this vein, as the program was being constructed there was a Brazil vs. Columbia soccer game happening during the Copa Americana for women's soccer. Naturally the trending topic on google was blowing up with more than 5K plus searches in one hour. Below is the google trends information [26]:

With this, ASTRA was launched on the task. It ran for 2 minutes and 7 seconds exactly producing the following outputs:

Image Generation Report: columbia vs. brazil women

Sentiment: informative

Summary: Colombia and Brazil's women's teams face off in a highly anticipated match. Stay updated on scores, news, transfers, and in-depth analysis. Follow GOAL for social media updates, culture, lifestyle, and gaming content related to the event.

Style Guide: professional photography, engaging composition, Instagram-optimized, photorealistic

Caption-conditioned Prompts

Caption 1

- **Caption:** Colombia vs. Brazil Women: Get the latest scores and news! Who will win? ⚽ #ColombiaVsBrazil #WomensSoccer #GOAL

- **Image Prompt:** Action-packed professional sports photography capturing the intensity of the Colombia vs. Brazil women's soccer match. Focus on a dynamic moment: a Brazilian forward skillfully dribbling past a Colombian defender, with the stadium blurred in the background, filled with cheering fans. Use vibrant, saturated colors to highlight the team jerseys (yellow for Brazil, yellow/blue/red for Colombia). Employ shallow depth of field to emphasize the players. Capture the determination in their eyes. Lighting: stadium lights casting strong shadows, creating a dramatic effect. Camera angle: low angle, capturing the speed and power of the players. Mood: Energetic, competitive, and exciting. Thumbnail hook: Close-up of the Brazilian forward's determined face, sweat glistening, with the ball at her feet. Photorealistic, Instagram-optimized.

Caption 2

- **Caption:** Breaking: Colombia and Brazil Women clash in epic showdown! Follow live updates and analysis. 🔥 #SoccerNews #Brazil #Colombia

- **Image Prompt:** High-energy professional sports photography capturing the intensity of the Colombia vs. Brazil women's soccer match. Focus on a dramatic mid-air collision between two players, one in a bright yellow Colombia jersey and the other in a vibrant blue Brazil jersey. The stadium is packed with cheering fans, creating a blurred background filled with national colors. Use dynamic lighting to highlight the players' determined expressions and the motion of the ball. Camera angle: low, capturing the height of the action. Mood: intense, competitive, and exciting. Color palette: vibrant yellows, blues, and greens contrasting against the stadium's neutral tones. Thumbnail hook: extreme close-up on the ball suspended in mid-air between the two players' heads.

Caption 3

- **Caption:** Don't miss the action! Colombia takes on Brazil in a must-watch women's match. Tune in now! 🏆 #WomensFootball #GameDay #Sports

- **Image Prompt:** A packed stadium roars as the Colombia women's national team fiercely battles the Brazil women's national team on a vibrant green soccer field. Focus on the intensity in the players' eyes, sweat glistening on their foreheads, and the ball suspended mid-air during a critical play. Capture the dynamic movement with a low-angle shot, emphasizing the power and athleticism. Use stadium lights to create dramatic shadows and highlights, enhancing the tension. The color palette should be dominated by the bright yellows of Colombia and the iconic blues and greens of Brazil, set against the neutral tones of the crowd. A small scoreboard in the background displays the score, adding context. The overall mood is electric and competitive, designed to immediately grab attention on Instagram. Photorealistic, professional sports photography.

Caption 4

- **Caption:** Gamers, get in the game! Colombia vs. Brazil Women: Predict the winner and share your thoughts! 🎮 #Gaming #Soccer #FIFA

- **Image Prompt:** A dynamic split-screen image: On the left, a determined Colombian female soccer player in action, vibrant yellow jersey, intense focus, motion blur, captured with a telephoto lens from a low angle. On the right, a Brazilian female soccer player, equally determined, iconic yellow and green jersey, powerful stride, similar low-angle telephoto shot. Center: A stylized controller graphic with the text "Predict the Winner!" Overlay a subtle, translucent graphic of a soccer field. Lighting: Dramatic stadium lighting, strong shadows, emphasizing athleticism. Color Palette: Vibrant yellows, greens, blues, and reds, creating a sense of energy and competition. Mood: Excitement, anticipation, high stakes. Thumbnail hook: Close-up of the controller with sparks emanating from it.

Caption 5

- **Caption:** Beyond the game: Explore the culture and lifestyle around Colombia vs. Brazil Women. Kits, boots, and more! ✨ #SoccerCulture #Fashion #Lifestyle

- **Image Prompt:** Vibrant street scene, Colombia vs. Brazil Women's soccer match day. Close-up on stylish fans wearing jerseys, face paint, and unique accessories. Focus on colorful Colombian and Brazilian flags, street art, and food vendors. Golden hour lighting, shallow depth of field, capturing the energy and excitement. Instagram-optimized, photorealistic. Thumbnail hook: A close-up of a fan's face with vibrant face paint, split between Colombian and Brazilian colors.

Generated Images

Caption 1

- **Filename:** img_columbia_vs._brazil_women_cap1.png

- **Prompt:** Action-packed professional sports photography capturing the intensity of the Colombia vs. Brazil women's soccer match. Focus on a dynamic moment: a Brazilian forward skillfully dribbling past a Colombian defender, with the stadium blurred in the background, filled with cheering fans. Use vibrant, saturated colors to highlight the team jerseys (yellow for Brazil, yellow/blue/red for Colombia). Employ shallow depth of field to emphasize the

```markdown
players. Capture the determination in their eyes. Lighting: stadium lights casting strong shadows, creating a dramatic effect. Camera angle: low angle, capturing the speed and power of the players. Mood: Energetic, competitive, and exciting. Thumbnail hook: Close-up of the Brazilian forward's determined face, sweat glistening, with the ball at her feet. Photorealistic, Instagram-optimized., trending Instagram reel thumbnail

- **Negative Prompt:** duplicate artifacts, text, watermark, low quality, pixelated, oversaturated, unnatural colors, cartoonish, unrealistic

- **Backend:** hf_inference

- **Tuned Params:** {'guidance': 7.5, 'steps': 30}


### Caption 2

- **Filename:** img_columbia_vs._brazil_women_cap2.png

- **Prompt:** High-energy professional sports photography capturing the intensity of the Colombia vs. Brazil women's soccer match. Focus on a dramatic mid-air collision between two players, one in a bright yellow Colombia jersey and the other in a vibrant blue Brazil jersey. The stadium is packed with cheering fans, creating a blurred background filled with national colors. Use dynamic lighting to highlight the players' determined expressions and the motion of the ball. Camera angle: low, capturing the height of the action. Mood: intense, competitive, and exciting. Color palette: vibrant yellows, blues, and greens contrasting against the stadium's neutral tones. Thumbnail hook: extreme close-up on the ball suspended in mid-air between the two players' heads., trending Instagram reel thumbnail

- **Negative Prompt:** duplicate artifacts, text, watermark, low quality, pixelated, oversaturated, unnatural colors, cartoonish, unrealistic

- **Backend:** hf_inference

- **Tuned Params:** {'guidance': 7.5, 'steps': 30}


### Caption 3

- **Filename:** img_columbia_vs._brazil_women_cap3.png

- **Prompt:** A packed stadium roars as the Colombia women's national team fiercely battles the Brazil women's national team on a vibrant green soccer field. Focus on the intensity in the players' eyes, sweat glistening on their foreheads, and the ball suspended mid-air during a critical play. Capture the dynamic movement with a low-angle shot, emphasizing the power and athleticism. Use stadium lights to create dramatic shadows and highlights, enhancing the tension. The color palette should be dominated by the bright yellows of Colombia and the iconic blues and greens of Brazil, set against the neutral tones of the crowd. A small scoreboard in the background displays the score, adding context. The overall mood is electric and competitive, designed to immediately grab attention on Instagram. Photorealistic, professional sports photography., trending Instagram reel thumbnail

- **Negative Prompt:** duplicate artifacts, text, watermark, low quality, pixelated, oversaturated, unnatural colors, cartoonish, unrealistic

- **Backend:** hf_inference

- **Tuned Params:** {'guidance': 7.5, 'steps': 30}
```

```
### Caption 4
- **Filename:** img_columbia_vs._brazil_women_cap4.png
- **Prompt:** A dynamic split-screen image: On the left, a determined Colombian female soccer player in action, vibrant yellow jersey, intense focus, motion blur, captured with a telephoto lens from a low angle. On the right, a Brazilian female soccer player, equally determined, iconic yellow and green jersey, powerful stride, similar low-angle telephoto shot. Center: A stylized controller graphic with the text "Predict the Winner!" Overlay a subtle, translucent graphic of a soccer field. Lighting: Dramatic stadium lighting, strong shadows, emphasizing athleticism. Color Palette: Vibrant yellows, greens, blues, and reds, creating a sense of energy and competition. Mood: Excitement, anticipation, high stakes. Thumbnail hook: Close-up of the controller with sparks emanating from it., trending Instagram reel thumbnail
- **Negative Prompt:** duplicate artifacts, text, watermark, low quality, pixelated, oversaturated, unnatural colors, cartoonish, unrealistic
- **Backend:** hf_inference
- **Tuned Params:** {'guidance': 7.5, 'steps': 30}


### Caption 5
- **Filename:** img_columbia_vs._brazil_women_cap5.png
- **Prompt:** Vibrant street scene, Colombia vs. Brazil Women's soccer match day. Close-up on stylish fans wearing jerseys, face paint, and unique accessories. Focus on colorful Colombian and Brazilian flags, street art, and food vendors. Golden hour lighting, shallow depth of field, capturing the energy and excitement. Instagram-optimized, photorealistic. Thumbnail hook: A close-up of a fan's face with vibrant face paint, split between Colombian and Brazilian colors., trending Instagram reel thumbnail
- **Negative Prompt:** duplicate artifacts, text, watermark, low quality, pixelated, oversaturated, unnatural colors, cartoonish, unrealistic
- **Backend:** hf_inference
- **Tuned Params:** {'guidance': 7.5, 'steps': 30}
```

The pictures can be found below:

Great clean outputs ready to go for posting.

Latency & Automation Process

Our system achieves significant performance improvements through strategic optimization and comprehensive automation, enabling real-time trend analysis suitable for production deployment.

1. Performance Optimization and Latency Reduction

The most significant performance breakthrough was achieved through workflow restructuring that eliminated redundant LLM processing. Initially, the system required separate LDA topic modeling and LLM labeling for each content type (equal, video, text, image), resulting in processing times exceeding 30 minutes. By implementing a two-stage approach – common processing (Steps 1-7) executed once, followed by content-type-specific scoring (Step 8) – we reduced total processing time to 15-17 minutes, achieving a **47-50% performance improvement**.

[Key Optimization Strategies]

- **LLM Processing Consolidation**: The most impactful optimization involved consolidating LLM-dependent processes into a single execution phase. Topic labeling, semantic grouping, and category classification now run once per dataset rather than per content type, eliminating redundant API calls and reducing LLM processing overhead by approximately 75%.
- **Batch Processing Implementation**: LLM operations are optimized through batch processing with configurable batch sizes (default: 10 items per batch), managing API rate limits while maximizing throughput. This approach ensures reliable operation under production load while maintaining optimal performance.
- **Memory and Computational Efficiency**: The hybrid similarity approach (Jaccard + SequenceMatcher) provides 5x faster processing compared to transformer embeddings while maintaining 87% accuracy, enabling real-time trend analysis without GPU requirements.

2. Automation and Continuous Deployment

a. GitHub Actions Integration

The entire pipeline is automated through GitHub Actions, configured to run every 6 hours for continuous trend monitoring. The workflow orchestrates sequential execution of all platform agents, fetches the latest trend data artifacts from previous successful runs, and triggers the downstream LangChain processing pipeline without manual intervention.

b. Fault Tolerance and Error Recovery

The automation system includes comprehensive error handling and recovery mechanisms. Platform-specific failures are isolated, preventing cascade failures across the entire pipeline. Failed executions automatically retry with exponential backoff, ensuring reliable operation under varying network conditions and API availability.

c. Data Freshness and Consistency

The 6-hour execution interval balances data freshness with computational efficiency, ensuring trends are detected within a timeframe suitable for content strategy development while maintaining system stability and cost-effectiveness.

3. Operational Impact and Metrics

a. Operational Impact

This optimization enables the system to operate as a truly autonomous trend detection service, providing near real-time insights for content creators and marketers. The 6-hour update cycle ensures that emerging trends are captured and analyzed within a timeframe that enables proactive content strategy development, while the performance improvements make the system suitable for production deployment in fast-paced media environments.

The combination of performance optimization and comprehensive automation transforms ASTRA from a research prototype into a production-ready trend intelligence platform, capable of supporting real-world content strategy decisions with minimal operational overhead.

b. Production Readiness Metrics

- **Processing Time**: 15-17 minutes for complete pipeline execution (1,081 trends across 5 platforms)
- **Reliability**: 99.5% success rate over 30-day production testing period
- **Scalability**: Linear time complexity allows seamless scaling to larger datasets
- **Cost Efficiency**: 47-50% reduction in computational resource requirements
- **Automation Coverage**: 100% of pipeline stages automated with zero manual intervention required

Real-Time Dashboard Integration

Our real-time dashboard system serves as the primary interface for monitoring and analyzing trending topics across multiple social media platforms. Built with a modern web architecture combining React frontend and Supabase backend, this system provides researchers and analysts with immediate access to processed trend data, enabling quick identification of emerging patterns and insights.

The dashboard integrates seamlessly with our LangChain workflow by connecting to a Supabase database that stores all processed trending data. This integration is facilitated through a comprehensive database service that manages content across three distinct categories: video, image, and text content. Each content type corresponds to dedicated database tables (TREND_VIDEO, TREND_IMAGE, TREND_TEXT) with an additional consolidated table (TREND_EQUAL) that aggregates trends across all media types. This structured approach allows for efficient data retrieval and targeted analysis based on specific content preferences.

At the heart of the dashboard lies a sophisticated data retrieval system that provides several key functions. The loadCategories() function dynamically extracts available categories from the database, ensuring that the interface always reflects the current state of processed data. The loadTrendingTopics() function retrieves the top trending topics with their associated trend scores, while loadRelatedKeywords() fetches related keywords for specific topic groups, enabling deeper analysis of trend relationships. Additionally, the loadBubbleChartData() function provides optimized data specifically formatted for the main dashboard visualization.

1. Interactive Visualization Components

The main dashboard interface features an interactive bubble chart that displays the top 15 trending topics in real-time. Each bubble represents a distinct topic, with its size proportional to the trend score and position determined by ranking and score values. This visualization approach allows users to quickly identify the most significant trends at a glance while providing interactive elements for detailed exploration. Users can click on individual bubbles to expand detailed analysis views, enabling deep dives into specific trending topics.

A sophisticated category filtering system enhances the user experience by allowing dynamic filtering of trending topics based on content categories. The system automatically loads available categories from the database, ensuring that the interface remains current with newly processed data. Users can apply multi-level filtering, combining content type preferences (video, image, or text) with specific topic categories. These filter changes trigger immediate updates to the displayed data, providing a responsive and intuitive user experience.

The trending topics display provides comprehensive information for each identified trend, including grouped topic names derived from our clustering algorithm, normalized final trend scores on a 0-100 scale, automatically classified topic categories, and current ranking positions. This information is presented in an easily digestible format that supports both quick scanning and detailed analysis.

For each trending topic, the system provides a related keywords analysis feature that displays the top 10 keywords associated with the topic, along with their individual trend scores. This feature enables cross-platform analysis by identifying keywords that appear across multiple platforms, providing valuable insights into the broader impact and reach of specific trends.

2. Data Processing and Performance Optimization

The data processing pipeline operates in real-time, beginning with data collection through our LangChain workflow, which processes information from multiple social media platforms. The processed results are then stored in Supabase tables, from which the frontend fetches data through dedicated database service functions. This data is subsequently rendered in interactive charts and tables, creating a seamless flow from raw data collection to visual representation.

To ensure data quality and performance, the system implements intelligent deduplication mechanisms that remove duplicate entries based on group names while preserving the highest-scoring entries when duplicates exist. This deduplication occurs during data retrieval, ensuring that users always receive the most relevant and accurate information. Performance optimization is achieved through efficient database queries with proper indexing, client-side caching for frequently accessed data, and lazy loading techniques that improve initial page load times.

3. Advanced Interactive Features

The interactive features of the dashboard include sophisticated bubble chart interactions with hover effects that display topic details, click navigation for detailed topic analysis, and zoom and pan capabilities for chart manipulation. The responsive design ensures optimal functionality across different screen sizes and devices. Category management features include dynamic category loading that updates automatically as new data is processed, multi-select filtering capabilities, and category statistics that display the count and distribution of topics by category.

Advanced search and filtering capabilities allow users to perform real-time searches through trending topics, apply advanced filters based on score ranges, platforms, and dates, and sort results by various criteria including score, name, or category. These features enable users to quickly locate specific trends or patterns of interest.

4. Technical Implementation and System Benefits

The technical implementation leverages modern web technologies, including Chart.js for bubble chart and trend line visualizations, a mobile-first responsive design approach, and WebSocket integration for live data updates. The system incorporates robust error handling mechanisms that ensure graceful degradation when partial data is available, provide clear user feedback through error messages and loading states, and validate data integrity before visualization.

The real-time monitoring capabilities of the dashboard enable live updates that reflect current trending topics, historical comparison features that track trends over time, and an alert system that notifies users of significant trend changes. The user experience is optimized through an intuitive interface with clear visualizations, fast response times for data retrieval and display, and cross-platform compatibility that works seamlessly on both desktop and mobile devices.

Scalability is achieved through a modular architecture that facilitates easy addition of new features and data sources, database optimization for efficient query performance with large datasets, and a comprehensive caching strategy that reduces database load while improving response times. This combination of features and capabilities makes the real-time dashboard system an essential tool for researchers and analysts seeking to understand and track emerging trends across multiple social media platforms.

The system's ability to bridge the gap between complex data processing workflows and user-friendly visualization makes it particularly valuable for organizations and researchers who need to quickly identify and respond to emerging trends. By providing immediate access to processed trend data through an intuitive interface, the dashboard enables users to make informed decisions based on current social media dynamics while maintaining high performance and reliability standards.

Why These Agents Matter

This architecture enables:

- **Parallelization** – Agents run independently for speed.

- **Specialization** – Each model is optimized for its domain.
- **Scalability –** More agents can be added for higher throughput.
- **Resilience** – One agent’s failure doesn’t stop the system.

The current setup proves that true multi-agent orchestration is achievable on a research budget, leveraging cost-efficient models like Gemini 2.0 Flash for research, Gemini 2.0 Flash for caption generation, and Stable Diffusion 3.5 Large for imagery. However, significant opportunities exist for advancing ASTRA into an enterprise-grade trend intelligence and content orchestration platform.

First, upgrading model capabilities would unlock deeper reasoning, cultural nuance, and visual realism. Replacing Gemini 2.0 Flash with a research-optimized LLM, such as GPT-4 Turbo or Claude Opus, would improve complex reasoning, reduce hallucinations, and better detect misinformation [24]. For the Caption Generation Agent, moving to high-creativity LLMs fine-tuned for marketing copy could yield more engaging hooks and audience-tailored messaging [16]. For the Image Generation Agent, transitioning from Stable Diffusion XL to higher-fidelity models like Midjourney v6 [23] or DALL·E 3 could significantly improve photorealism, emotional impact, and style consistency.

Second, enhancing retrieval capabilities with Retrieval-Augmented Generation (RAG) would ensure that captions and generated images are grounded in verifiable, contextually rich data [25]. For imagery specifically, RAG could be paired with licensed enterprise-grade reference image libraries, such as Getty Images [22], to train visual models that better represent real-world scenes, cultural nuances, and brand-specific aesthetics. This would address the current limitation where the Image Generation Agent operates without a reference image, which can lead to generic or inaccurate visuals. As explained earlier, this capability was developed and can be easy added to the workflow without budget constraints for licensing fees. Not everything was perfect however, AI definitely still has some difficulties with generating faces and other features leading to some pretty humorous bugs at times. Referencing the two examples from the above section you can clearly see some small defects:

Two big points with the above. Firstly, the biggest way to improve this would clearly be proper RAG when it comes to referencing very specific people or things. The model itself is very good at creating images based off of context clues, however at times it can very “creative.” For instance, the plane here doesn’t exist. If RAG were used to feed it some specific images of a plane, or prompting a specific model of airplane may avoid this poorly designed aircraft for increased realism. However, importantly, sometime the creativity of the model may also be something desired and may be an attribute a programmer would not want to remove from the final product to keep that randomicity of the outputs.

Third, integrating multi-modal reasoning—where a single AI agent can jointly reason over text, images, and metadata—would create stronger cohesion between captions and visuals [16]. This would help the

Caption and Image Generation Agents co-evolve outputs in real time, rather than working in loosely coupled stages.

Fourth, real-time feedback loops could be implemented to dynamically adapt future generations based on audience response metrics, sentiment shifts, and platform-specific engagement data [13]. This could be achieved by integrating analytics directly into the orchestration layer so that high-performing captions and images automatically influence future creative decisions.

Finally, enterprise-level safety and governance systems will be essential. Expanding the current genre, tone, and format constraints into a full AI governance layer would ensure compliance with brand guidelines, ethical standards, and platform rules at scale [5]. This would include automated NSFW detection, bias audits, and legal compliance checks for both text and imagery—critical for commercial deployment in sensitive industries.

In summary, while ASTRA demonstrates that autonomous, multi-agent trend-to-content pipelines are feasible on minimal budgets, its modular design makes it highly upgradeable. Future iterations could incorporate state-of-the-art LLMs, multi-modal RAG pipelines, licensed image retrieval systems, and adaptive learning loops to dramatically improve factual accuracy, creative quality, cultural resonance, and safety. These advancements would position ASTRA as not just a research-grade prototype but a fully deployable enterprise tool for real-time, AI-driven social trend intelligence and content generation.

CONCLUSIONS

The business problem driving this research is the difficulty brands and content creators face in detecting and acting on cultural trends before they fade. In a digital environment where a few hours can determine whether a campaign goes viral or is ignored, the ability to monitor, interpret, and creatively respond to trends in real time has become a competitive necessity. ASTRA directly addresses this challenge by implementing an autonomous, multi-agent system capable of transforming raw, cross-platform trend data into actionable creative assets within minutes.

Our research demonstrates that the combination of specialized agents—dedicated to content research, caption generation, and image creation—paired with efficient orchestration frameworks such as LangChain, enables an end-to-end workflow without human intervention. The results show that ASTRA can produce sentiment-aware, platform-optimized creative content in under three minutes, allowing brands to capitalize on breaking trends with unprecedented speed and consistency.

From a business perspective, this solution reduces the latency between trend emergence and campaign deployment, enabling timely audience engagement while lowering reliance on large creative teams. It also provides a scalable foundation for integrating future enhancements such as multi-modal reasoning, retrieval-augmented generation (RAG) with licensed image libraries, and adaptive learning loops that optimize content based on real-time audience feedback.

Several assumptions underpinned this work. We assumed that current LLMs—while not perfect—are sufficiently accurate for trend labeling, sentiment classification, and creative generation in most contexts. We also assumed that the agentic orchestration layer would remain stable across API changes and platform updates. Limitations include the reliance on free or research-tier models, which restricts the depth of reasoning and fidelity of generated images compared to enterprise-grade alternatives. Additionally, while ASTRA handles diverse platforms, accuracy may vary depending on the quality and availability of each platform's trend data.

Future investigation should explore the integration of enterprise-level LLMs such as GPT-4 Turbo, Claude Opus, or Meta LLaMA 3 Vision for richer multi-modal reasoning, as well as experimentation with licensed visual datasets to improve realism and cultural accuracy in generated imagery. Deeper testing of adaptive feedback mechanisms could help ASTRA refine its outputs over time, and broader platform coverage—including emerging social networks—would strengthen its ability to capture early-stage cultural shifts.

In short, while ASTRA already demonstrates that autonomous trend-to-content pipelines are both possible and effective, the technology remains at the beginning of its potential. With continued refinement, it could become an indispensable enterprise tool for real-time cultural intelligence and high-impact content generation.

REFERENCES

1. [1] Amazon Web Services. (2025). Using foundation models for sentiment analysis and content generation [Blog post]. AWS AI Blog. https://aws.amazon.com/blogs/machine-learning/using-foundation-models-for-sentiment-analysis-and-content-generation
2. [2] Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. Journal of Machine Learning Research, 3, 993–1022.
3. [3] Boutaleb, T., Soudani, A., & Benbrahim, H. (2024). Detecting emerging topics in social media: Combining popularity and velocity metrics. Journal of Information Science, 50(2), 225–239. https://doi.org/10.1177/01655515221132567
4. [4] Catalini, C., Wu, J., & Zhang, K. (2025, June). What gets measured, AI will automate. Harvard Business Review. https://hbr.org/2025/06/what-gets-measured-ai-will-automate
5. [5] Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
6. [6] Gates, B. (2023, March 21). The age of AI has begun. GatesNotes. https://www.gatesnotes.com/The-Age-of-AI-Has-Begun

7. [7] Google Cloud. (2025, February 5). Gemini 2.0 Flash | Generative AI on Vertex AI. Google Cloud Documentation. https://cloud.google.com/vertex-ai/docs/generative-ai/model-reference/gemini
8. [8] Gunduz, A., Yuksel, K. A., & Sawaf, H. (2021). The transformative potential of AI in society: Insights from interdisciplinary research. Public Health Genomics, 24(3–4), 109–118. https://pmc.ncbi.nlm.nih.gov/articles/PMC8274472/
9. [9] Kaur, A., & Wallace, J. R. (2024). Moving beyond LDA: A comparison of unsupervised topic modelling techniques for qualitative data analysis of online communities. arXiv. https://doi.org/10.48550/arXiv.2412.14486
10. [10] Lu, Y., Xiong, S., & Li, Z. (2025). Automated sentiment classification and topic discovery in large-scale social media streams. arXiv. https://doi.org/10.48550/arXiv.2505.01883
11. [11] Narejo, S., Prashanth, K., & Kumar, A. (2025). Sentiment-driven caption generator using Vision Transformers and RoBERTa. Journal of Visual Communication and Image Representation, 93, 103831. https://doi.org/10.1016/j.jvcir.2025.103831
12. [12] NewsWhip. (2017). Spike's custom metrics & methodology [White paper]. NewsWhip. https://www.newswhip.com/wp-content/uploads/2017/11/Spike-Metrics-Methodology.pdf
13. [13] NewsWhip. (2025). Three metrics that will keep you one step ahead [Blog post]. NewsWhip. https://www.newswhip.com/2025/05/three-metrics-to-stay-ahead
14. [14] SAP. (2025, July 21). The next industrial revolution: AI agents at the heart of transformation. Forbes. https://www.forbes.com/sites/sap/2025/07/21/the-next-industrial-revolution-ai-agents-at-the-heart-of-transformation
15. [15] Wang, R. (2025). Joint semantic detection and dissemination control of phishing attacks on social media via LLama-based modeling. In Proceedings of the International Conference on Cybersecurity and Artificial Intelligence (pp. 1–15).
16. [16] Ferrag, M. A., Tihányi, N., & Debbah, M. (2025). From LLM reasoning to autonomous AI agents: A comprehensive review. arXiv. https://doi.org/10.48550/arXiv.2504.19678
17. [17] Ramachandran, A. (2024). A survey of agentic AI, multi-agent systems, and multimodal frameworks: Architectures, applications, and future directions. ResearchGate. Retrieved from https://www.researchgate.net/publication/387577302
18. [18] Huang, X., Qian, Y., Park, J., & Others. (2024). Cross-team orchestration: Scalable multi-agent collaboration via Croto. arXiv. https://doi.org/10.48550/arXiv.2406.08979
19. [19] Cai, T., Wang, X., Ma, T., Chen, X., & Zhou, D. (2023). ChatDev: Communicative agents for software development. arXiv. https://doi.org/10.48550/arXiv.2307.07924
20. [20] Microsoft Research. (2024). Magentic-One: A generalist multi-agent system for solving complex tasks. Microsoft Research Publication. Retrieved from https://www.microsoft.com/en-us/research/publication/magentic-one-a-generalist-multi-agent-system-for-solving-complex-task
21. [21] Wired. (2024, June 6). Chatbot teamwork makes the AI dream work. Wired. Retrieved from https://www.wired.com/story/chatbot-teamwork-makes-the-ai-dream-work
22. [22] Getty Images. (2025). Licensing for AI-assisted content creation [White paper]. Getty Images Legal Resources. https://www.gettyimages.com/legal
23. [23] Midjourney. (2025). Midjourney version 6 feature overview [Documentation]. Midjourney Docs. https://docs.midjourney.com
24. [24] OpenAI. (2025). GPT-4 Turbo for creative applications [Blog post]. OpenAI. https://openai.com/blog/gpt-4-turbo
25. [25] Hugging Face. (2025). Retrieval-augmented generation for image synthesis [Technical guide]. Hugging Face Docs. https://huggingface.co/docs
26. Google. (n.d.). *Google Trends: Trending searches – United States*. Google Trends. Retrieved August 2, 2025, from https://trends.google.com/trending?geo=US&sort=recency

APPENDEIX

1. Data Collection Schema

a. YouTube

Field	Type	Description
video_id	String	Unique YouTube video identifier
title	String	Video title text
description	Text	Video description content
category_id	Integer	YouTube category classification
tags	Array	Video tags and keywords
published_at	DateTime	Video publication timestamp
duration	String	Video length (ISO 8601 format)
view_count	Integer	Total view count
like_count	Integer	Total like count
comment_count	Integer	Total comment count
channel_id	String	Uploading channel identifier
channel_subscribers	Integer	Channel subscriber count
view_velocity	Float	Views per hour since publication
like_ratio	Float	Like-to-view ratio

b. Reddit

Field	Type	Description
post_id	String	Unique Reddit post identifier
title	String	Post title text
selftext	Text	Post content (for self-posts)
author	String	Post author username
subreddit	String	Subreddit name
subreddit_subscribers	Integer	Community size
created_utc	DateTime	Post creation timestamp
post_age_hours	Integer	Hours since post creation
ups	Integer	Upvote count
downs	Integer	Downvote count
score	Integer	Net score (ups - downs)
num_comments	Integer	Comment count
upvote_ratio	Float	Upvote percentage

total_awards_received	Integer	Award count
is_video	Boolean	Video content flag
is_self	Boolean	Self-post flag
engagement_velocity	Float	Comments per hour

c. Twitter

Field	Type	Description
trend_name	String	Trending topic text
rank	Integer	Current ranking position
peak_position	Integer	Highest achieved rank
tweet_volume	Integer	Tweet count in last 24h
duration	String	Time trending (e.g., "2h", "1d")
region	String	Geographic region
timestamp	DateTime	Data collection timestamp

d. Tiktok

Field	Type	Description
hashtag	String	Hashtag text (without #)
view_count	Integer	Global view count (normalized)
view_count_raw	String	Original view count format
rank	Integer	Trending rank position
timestamp	DateTime	Data collection timestamp

e. Google Trends

Field	Type	Description
search_term	String	Search query text
dma_coverage	Integer	Designated Market Area coverage
median_percent_gain	Float	Median percentage increase
spread_intensity	Float	Geographic spread score
trend_type	String	"top" or "rising"
timestamp	DateTime	Data collection timestamp

2. Trend Detection Outcome Schema

Field Name	Data Type	Description	Example Value

keyword	String	Trend name/topic label	"Gaming Influencers"
frequency	Float	Original frequency count	14.0
engagement	Float	Original engagement count	9,937,991.0
platform	String	Source platform	"YouTube"
frequency_norm	Float	Normalized frequency (0-1)	0.433
engagement_norm	Float	Normalized engagement (0-1)	0.147
platform_count	Integer	Number of platforms where trend appears	1
group_id	Integer	Semantic group identifier	18
group_name	String	Representative group name	"Gaming Influencers"
category	String	LLM-classified category	"Entertainment & Media"
platform_weight	Float	Platform-specific weight	0.5
trend_score	Float	Initial weighted score	0.145
S_p	Float	Per-platform score	0.116
cross_platform_bonus	Float	Cross-platform bonus	0.0
final_trend_score	Float	Final composite score	0.116