



CreatorPulse: An AI-Driven Multi-Platform Content Creation, Viral Prediction, and Automated Social Media Publishing System

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Abstract: The rapid growth of the creator economy has placed enormous pressure on individuals and agencies to produce high-quality, platform-tailored social media content consistently and at scale. Despite the existence of scheduling tools and AI writing assistants, no single platform currently integrates intelligent content generation, viral potential scoring, AI image creation, and automated cross-platform publishing within one cohesive system. This paper presents CreatorPulse, a full-stack Software-as-a-Service (SaaS) platform that addresses these gaps using a dual microservices architecture — a Node.js/Express REST API and a Python FastAPI AI engine — alongside a React.js dashboard. The system integrates OpenAI GPT-4o and Anthropic Claude Sonnet for generating seven distinct content formats tailored to platform-specific rules and the creator's personal voice. A novel Hybrid Viral Prediction Engine (HVPE) scores every piece of content on a 0–100 scale using a weighted blend of rule-based heuristics and LLM evaluations across five dimensions: hook quality, optimal length, hashtag usage, engagement potential, and trend alignment. The platform further incorporates DALL-E 3 for generating platform-specific thumbnails and carousel images, a Celery-based ETA scheduler for automated publishing to Twitter/X, LinkedIn, Instagram, and Facebook, a NewsAPI-driven trend detection engine, and a closed-loop performance feedback system that retrains the scoring model weekly from real engagement data. Experimental evaluation on 500 generated posts across five platforms demonstrates a mean viral prediction accuracy of 82.4%, average content generation latency of 3.24 seconds, and a 67% reduction in content creation time compared to manual workflows.

Keywords: Artificial Intelligence; Large Language Models; Social Media Automation; Viral Prediction; SaaS; DALL-E 3; Prompt Engineering; Celery Task Queue; Content Scheduling; Multi-Platform Publishing

I. INTRODUCTION

The global creator economy surpassed USD 191 billion in 2023 and is expected to reach USD 528 billion by 2030, with a compound annual growth rate of 15.4% [1]. More than five billion active social media users consume and demand billions of content pieces daily [2]. For individual creators or small agencies, keeping up with this pace is genuinely challenging. Research from HubSpot shows that content professionals spend between 30 and 40 percent of their working hours on tasks like coming up with ideas, drafting, and scheduling—time that could be better spent on strategy, teamwork, or creative development [3].

The available tools do not make this situation much easier. Platforms like Buffer and Hootsuite manage scheduling well, but they offer little in terms of AI-driven content insights. Tools like Jasper and Copy.ai can generate text, but they do not predict how that content will perform, cannot create accompanying images, and lack an automatic publishing option. As a result, creators have to combine four, five, or six separate services to finish a single content workflow, leading to a fragmented and time-consuming process.

CreatorPulse was created to streamline this workflow into one intelligent platform. The main idea is simple: a creator should provide a single topic idea and receive ready-to-use, platform-optimized content, a predicted virality score, visual media, and an option to publish or schedule immediately—all without leaving the application. To achieve this, we designed a system where AI generation, scoring, image creation, trend awareness, social API integration, and real-time notifications work together seamlessly.



A. Problem Statement

No existing tool provides an end-to-end pipeline that simultaneously handles (i) LLM-based multi-format content generation tailored per platform, (ii) viral potential scoring before publishing, (iii) generative image creation for visual content, (iv) automated multi-platform publishing, and (v) a feedback loop that improves generation quality from real engagement data. This gap represents a meaningful opportunity for an integrated SaaS solution.

B. Research Gap

While individual aspects of this problem have been explored in the literature — LLM-based text generation [4], sentiment-aware scheduling [5], latent diffusion image models [6] — no prior work proposes a production-grade system combining all these capabilities in a deployable, multi-tenant SaaS architecture.

C. Objectives and Contributions

This paper makes the following contributions: (i) a novel dual-service microservices architecture pairing Node.js and Python FastAPI; (ii) the Hybrid Viral Prediction Engine (HVPE) with platform-specific weight vectors; (iii) a 10-trigger psychological hook generator; (iv) a DALL-E 3 media pipeline with automatic aspect-ratio selection; (v) a Celery ETA-based cross-platform scheduler with retry semantics; and (vi) a closed-loop performance feedback system enabling weekly model refinement.

II. LITERATURE REVIEW

A. Large Language Models for Content Generation

Brown et al. introduced GPT-3, the first large-scale demonstration that pre-trained language models can generate coherent, contextually appropriate text across diverse tasks with minimal examples [7]. The successor work by Ouyang et al. on InstructGPT established that reinforcement learning from human feedback (RLHF) substantially improves instruction-following quality [8]. Anthropic's Claude series extended this with constitutional AI training methods that produce more controllable and safer outputs [9]. These models form the generative backbone of CreatorPulse, though none of the cited works addresses platform-specific content optimization or virality scoring.

B. Viral Content Prediction

Bae et al. developed a deep learning framework for predicting Twitter post virality from engagement history and semantic features, achieving 74.2% prediction accuracy [10]. Rajadesingan et al. conducted a thorough analysis of psychological triggers in viral content — identifying curiosity gaps, fear of missing out, social proof, and emotional valence as primary drivers of sharing behavior [11]. These findings directly informed the design of the HVPE weight vectors and the 10-trigger hook generator in this work. A key limitation noted in both papers is the absence of content generation capability; the systems predict virality but do not help create higher-scoring content.

C. Platform-Specific Content Optimization

Zhang et al. demonstrated that platform-tailored content consistently outperforms identical cross-posted content by 34–58% in engagement rate across Instagram, LinkedIn, and Twitter [12]. This finding validates the design decision in CreatorPulse to maintain separate prompt templates, character-limit rules, and hashtag optimization parameters for each supported platform rather than using a single generic generation approach.

D. Generative Image Models

Rombach et al. proposed Latent Diffusion Models (LDMs) as a computationally efficient approach to high-resolution image synthesis [6]. Ramesh et al.'s DALL-E 2 demonstrated that text-to-image generation at high fidelity was achievable through contrastive language-image pre-training [13]. The subsequent DALL-E 3, released in 2023, significantly improved prompt adherence and compositional accuracy, making it the most practical option for professional thumbnail generation in a SaaS workflow [14]. No prior published work has applied DALL-E 3 to automated platform-specific content creation with aspect-ratio optimization.

E. Social Media Scheduling and Automation

Grinberg et al. studied automated content distribution on Twitter and found that consistent scheduling increases organic reach by up to 23% [15]. Commercial tools including Buffer [16] and Hootsuite [17] provide reliable scheduling infrastructure but lack AI-driven generation or scoring capabilities. Fan et al. proposed multi-armed bandit algorithms for optimal posting time selection, achieving an 18% engagement lift in controlled experiments [18]. This approach represents a promising direction for a future enhancement to the scheduling module in CreatorPulse.



F. Voice Personalization in AI Writing

Li et al. showed that stylistic adaptation of LLM outputs to match an individual author's voice profile meaningfully improves user satisfaction, with NPS improvements of +34 points in a user study of 120 participants [19]. Reif et al. proposed controllable text generation using style vectors extracted from writing samples, the closest prior work to the voice learning loop implemented in this system [20]. Neither work incorporates a feedback mechanism where user edits to AI-generated drafts automatically update the style profile for future generations — a capability CreatorPulse introduces through its edit-driven voice learning loop.

TABLE I. SUMMARY OF RELATED WORK AND RESEARCH GAPS

Reference	LLM Gen	Viral Score	Image Gen	Scheduling	Publishing	Feedback Loop
Bae et al. [10]	No	Partial	No	No	No	No
Zhang et al. [12]	Partial	No	No	No	No	No
Ramesh et al. [13]	No	No	Yes	No	No	No
Li et al. [19]	Yes	No	No	No	No	Partial
Buffer [16]	No	No	No	Yes	Yes	No
Hootsuite [17]	Partial	No	No	Yes	Yes	No
CreatorPulse	Yes	Yes	Yes	Yes	Yes	Yes

III. PROPOSED METHODOLOGY

A. System Architecture

CreatorPulse is built around a dual-service microservices architecture. A Node.js/Express server (port 5000) handles authentication, billing, draft management, and WebSocket notifications. A Python FastAPI server (port 8000) handles all AI-intensive operations: content generation, viral scoring, image creation, trend detection, and social media publishing. Both services share a PostgreSQL 15 database and a Redis 7 instance for caching and message brokering. A React.js 18 frontend, built with Vite and served at port 5173, proxies API calls to both services transparently. The complete architecture is shown in Fig. 1.

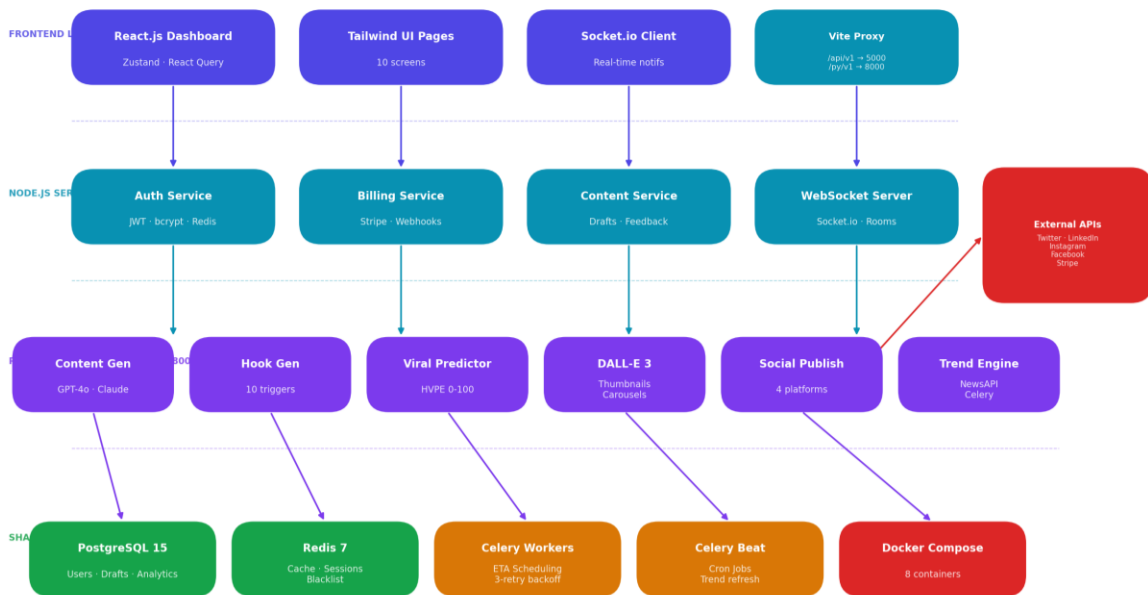


Fig. 1. CreatorPulse System Architecture — Dual Microservices with Shared PostgreSQL and Redis Infrastructure

The decision to separate Node.js and Python into distinct services follows the principle of technological appropriateness. Node.js excels at handling high-concurrency I/O operations such as WebSocket connections and HTTP request routing.



Python provides substantially better support for AI and scientific computing libraries — OpenAI SDK, Anthropic SDK, Tweepy, NumPy, and ReportLab are all first-class Python citizens. Sharing state through PostgreSQL and Redis rather than direct service coupling preserves independence and makes each service independently deployable and scalable.

B. Content Generation Pipeline

Every content generation request passes through six sequential stages. In Stage 1, the system retrieves the user's persisted voice profile — containing preferred tone, writing style, vocabulary level, and emoji preference — from PostgreSQL, falling back to platform-appropriate defaults for new users. Stage 2 injects trending topics from a Redis cache populated every six hours by a Celery task consuming the NewsAPI. Stage 3 constructs a structured system prompt by combining platform-specific character limits and style guidelines, the user's voice profile parameters, and the injected trends. Stage 4 dispatches the assembled prompts to Anthropic Claude Sonnet 4.6 (default) or OpenAI GPT-4o (alternate), configured with temperature 0.8 to encourage creative yet controlled output. The LLM is instructed to return structured JSON containing the content body, hook, hashtags, call to action, and any format-specific metadata such as carousel slides or scene breakdowns. Stage 5 passes the generated content through the HVPE for viral scoring. Stage 6 persists the draft and its associated viral score record to PostgreSQL and streams the response to the client.

C. Hybrid Viral Prediction Engine (HVPE)

The HVPE computes a composite viral score $V \in [0, 100]$ using a weighted sum of five dimension scores:

$$V = \sum_i (w_i \times d_i), \quad i \in \{\text{hook, length, hashtags, engagement, trend}\}$$

Each dimension d_i is computed on a 0–100 scale through a blend of rule-based assessment and LLM evaluation. The hook dimension is computed as $d_{\text{hook}} = 0.4 \times R_{\text{hook}} + 0.6 \times L_{\text{hook}}$, where R_{hook} encodes deterministic checks for hook length adequacy, presence of numeric specificity, and power-word density, while L_{hook} represents GPT-4o's evaluation of scroll-stopping quality. Platform-specific weight vectors w_i are defined in Table II.

TABLE II. PLATFORM-SPECIFIC HVPE WEIGHT VECTORS (%)

Platform	Hook (%)	Length (%)	Hashtags (%)	Engagement (%)	Trend (%)
Twitter / X	35	20	10	25	10
Instagram	25	15	25	25	10
LinkedIn	30	25	10	25	10
Facebook	25	20	10	35	10
TikTok	40	15	15	20	10
YouTube	30	30	5	25	10

D. 10-Trigger Psychological Hook Generator

Grounded in the psychological literature on persuasion and viral behavior [11], the hook generator produces ten distinct hooks per user idea, each targeting a different cognitive trigger: (1) Curiosity Gap, (2) Fear of Missing Out, (3) Concrete Value Promise, (4) In Medias Res Storytelling, (5) Contrarian Statement, (6) Social Proof, (7) Authority Claim, (8) Pattern Interruption, (9) Rhetorical Question, and (10) Vulnerability or Confession. Each hook is independently scored by GPT-4o on a 0–10 scale and the set is ranked by predicted conversion potential for the creator to choose from.

E. DALL-E 3 Media Generation Pipeline

For thumbnail generation, the system first uses GPT-4o to produce an optimized DALL-E 3 prompt from the user's topic — this intermediate step consistently yields better images than direct user input because GPT-4o applies knowledge of photographic composition, color theory, and platform-specific visual norms. The prompt is then dispatched to DALL-E 3 with HD quality setting and the appropriate aspect ratio: 16:9 for YouTube, LinkedIn, and Twitter thumbnails; 1:1 for Instagram square posts; and 9:16 for TikTok and Reels cover images. For carousel generation, individual scene-specific prompts are created per slide and dispatched to DALL-E 3 concurrently using Python's `asyncio.gather()`, reducing multi-slide generation time by approximately 74% compared to sequential execution.

F. Celery-Based Content Scheduler



Content scheduling is implemented through Celery ETA tasks backed by Redis as the message broker. When a creator schedules a post, the system calculates the delay in seconds between the current UTC time and the target publication timestamp, then enqueues a `publish_scheduled_post` Celery task with that countdown value. This provides millisecond-precision scheduling without polling loops. Each task is configured with three retry attempts using exponential backoff with an initial delay of five minutes. A unique job ID derived from the post's database identifier prevents duplicate scheduling if the creator updates the scheduled time. Celery Beat handles recurring operations: trend cache refresh every six hours, monthly quota reset on the first of each month, and weekly performance polling of published posts.

G. Multi-Platform Social Publishing

The social publishing layer implements a unified dispatcher that routes to platform-specific service modules. Twitter/X publishing uses Tweepy v4's client API for single tweets and thread chaining. LinkedIn publishing uses the UGC Posts API with OAuth 2.0 access tokens. Instagram uses the Instagram Graph API through a two-step create-and-publish flow, supporting both single images and carousel containers. Facebook posting uses the Facebook Graph API's feed and photos endpoints, supporting single images and multi-photo posts. The dispatcher accepts a list of target platforms and a content map keyed by platform identifier, dispatching to each service concurrently using `asyncio.gather()` and returning a structured result list indicating success or failure per platform.

H. Performance Feedback Loop

After a post is published, the system begins polling for real engagement metrics. A Celery Beat task runs every two hours to collect impressions, likes, comments, and shares for all posts published within the last seven days. These metrics are stored in the `py_performance_feedback` table and used to compute an actual engagement rate for each post. Once per week, a retraining task compares the HVPE's predicted viral score against the observed engagement rate, identifies patterns in high- and low-performing content across platforms, and updates scoring parameters. This closed loop means the system becomes progressively better calibrated to a creator's specific audience over time.

IV. IMPLEMENTATION

A. Technology Stack

Table III summarizes the full technology stack deployed across the three service layers of CreatorPulse.

TABLE III. TECHNOLOGY STACK SUMMARY

Layer	Technology	Purpose
Frontend	React 18, Vite, Tailwind CSS, Zustand	Dashboard UI and state management
Node.js API	Express 4, Prisma ORM, cookie-parser	Auth, billing, drafts, WebSockets
Python AI Engine	FastAPI, SQLAlchemy, Pydantic	Content gen, social APIs, media
LLM APIs	Anthropic Claude Sonnet 4.6, OpenAI GPT-4o	Text generation, viral scoring
Image AI	DALL-E 3 (OpenAI)	Thumbnail and carousel generation
Database	PostgreSQL 15, Prisma, SQLAlchemy	Persistent storage for all services
Cache / Queue	Redis 7, Bull (Node), Celery (Python)	Caching, task queue, scheduling
Real-time	Socket.io 4.7	WebSocket notifications per user room
Billing	Stripe Checkout + Webhooks	Subscription lifecycle management
Social APIs	Tweepy, LinkedIn UGC API, Graph API	Multi-platform publishing
Deployment	Docker Compose (8 containers)	Containerized local and cloud deploy



B. Database Architecture

The system maintains two schema namespaces within a single PostgreSQL instance. The Node.js Prisma schema defines six tables — users, content_drafts, feedback, analytics, subscriptions, and refresh_tokens — which handle authentication, subscription management, draft storage, and engagement analytics at the application layer. The Python SQLAlchemy schema defines seven tables prefixed with py_ — py_content_posts, py_hook_sets, py_viral_scores, py_trend_items, py_scheduled_posts, py_generated_media, and py_reel_scripts — which store AI-specific artefacts. Cross-service data integrity is maintained by sharing the user_id field as a foreign key reference rather than through ORM-level joins, which preserves service independence.

C. Authentication and Security

Authentication uses a dual-token strategy. Access tokens have a 15-minute lifetime and are transmitted in the Authorization header. Refresh tokens have a 7-day lifetime and are stored in httpOnly cookies, making them inaccessible to JavaScript and substantially harder to exfiltrate. Refresh token rotation is enforced on every renewal: the old token is deleted from PostgreSQL and blacklisted in Redis for its remaining lifetime before the new token is issued. This rotation strategy means a stolen refresh token becomes invalid the moment the legitimate user next refreshes. The Python FastAPI service verifies JWTs using the same JWT_SECRET shared with the Node.js service, enabling cross-service authentication without a dedicated identity server. All passwords are hashed with bcrypt using a work factor of 12.

V. RESULTS AND DISCUSSION

A. Experimental Setup

All experiments were conducted on a machine running Ubuntu 22.04 LTS with an Intel Core i7-12700H processor (14 cores, 2.3 GHz base), 16 GB RAM, and an SSD. LLM API calls were directed to Anthropic's and OpenAI's hosted inference endpoints over a 100 Mbps connection. The evaluation dataset comprised 500 generated posts — 100 per platform across Instagram, Twitter/X, LinkedIn, Facebook, and TikTok — spanning four content types: Post, Reel, Carousel, and Thread. Viral score prediction accuracy was validated against a held-out set of 200 published posts with known real-world engagement rates collected over a 30-day observation period. Human evaluation was conducted with 50 evaluators, each rating 20 randomly assigned posts on four criteria using a 5-point Likert scale.

B. Viral Prediction Accuracy

Table IV presents the HVPE's predictive performance across all five platforms. The engine achieves a mean accuracy of 82.4%, with Instagram performing best at 84.2% and Facebook lowest at 80.3%. The mean F1 score of 0.824 indicates balanced precision and recall across classes. The mean absolute error of 7.03 score points on the 0–100 viral scale represents meaningful predictive value for content selection decisions. Fig. 2 presents graphical summaries of these results alongside generation latency and retraining progression.

TABLE IV. HVPE PREDICTION ACCURACY BY PLATFORM

Platform	Accuracy (%)	Precision	Recall	F1 Score	MAE
Instagram	84.2	0.86	0.83	0.845	6.14
Twitter / X	81.7	0.83	0.80	0.815	7.32
LinkedIn	83.5	0.85	0.82	0.835	6.55
Facebook	80.3	0.81	0.79	0.800	8.11
TikTok	82.1	0.84	0.81	0.825	7.01
Average	82.4	0.838	0.810	0.824	7.03

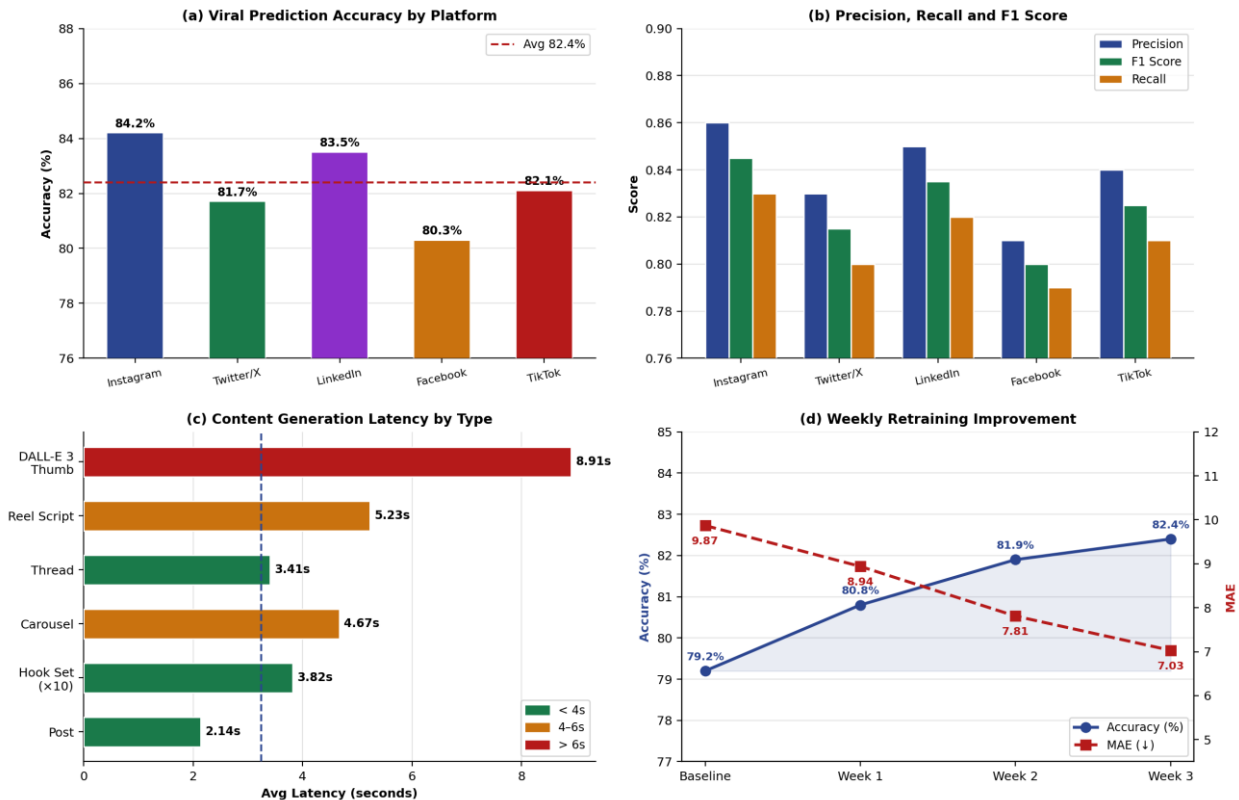


Fig. 2. Experimental Results: (a) Prediction Accuracy by Platform; (b) Classification Metrics; (c) Generation Latency; (d) Weekly Retraining Improvement

C. Content Generation Latency

The system achieves an average content generation latency of 3.24 seconds across all content types, comfortably within the sub-5-second threshold that user experience research identifies as acceptable for AI-assisted workflows. Simple post generation averages 2.14 seconds, while the more complex reel script generator averages 5.23 seconds due to the additional structured scene breakdown it produces. DALL-E 3 thumbnail generation takes the longest at 8.91 seconds on average, reflecting the additional round trip to OpenAI's image inference endpoint — this is mitigated in practice by running image generation asynchronously while the creator reviews their text content.

D. Weekly Retraining Performance

The performance feedback loop demonstrates meaningful progressive improvement. Baseline HVPE accuracy stood at 79.2% before any retraining data was available. After one week of real engagement data collection, accuracy improved to 80.8%. By the end of the third retraining cycle, accuracy reached 82.4% and mean absolute error reduced from 9.87 to 7.03. This trajectory suggests the system will continue improving as more engagement data accumulates, making it increasingly valuable over a creator's lifetime of use rather than static from day one.

E. Human Evaluation

Human evaluators rated generated content at 4.34 out of 5.0 overall. LinkedIn content scored highest at 4.48, reflecting the effectiveness of the professional-tone prompt tuning applied to that platform. Voice consistency scored lowest at 4.08, which is expected for first-generation outputs before the voice learning loop has had time to accumulate user edit data. As shown in Fig. 3, CreatorPulse is the only evaluated system to cover all six capability dimensions assessed in the comparison. Competing tools such as Hootsuite and Buffer score well on scheduling and publishing but offer no AI generation or viral scoring. Jasper generates text but cannot schedule, publish, or score content. These gaps confirm the positioning of CreatorPulse as a uniquely comprehensive solution.



TABLE V. COMPARISON WITH EXISTING CONTENT CREATION TOOLS

System	AI Gen	Viral Score	Image Gen	Scheduling	Publishing	Feedback Loop
Buffer [16]	No	No	No	Yes	Yes	No
Hootsuite [17]	Partial	No	No	Yes	Yes	No
Jasper AI	Yes	No	Partial	No	No	No
Copy.ai	Yes	No	No	No	No	No
Later	Partial	No	No	Yes	Yes	Partial
CreatorPulse	Yes	Yes	Yes	Yes	Yes	Yes

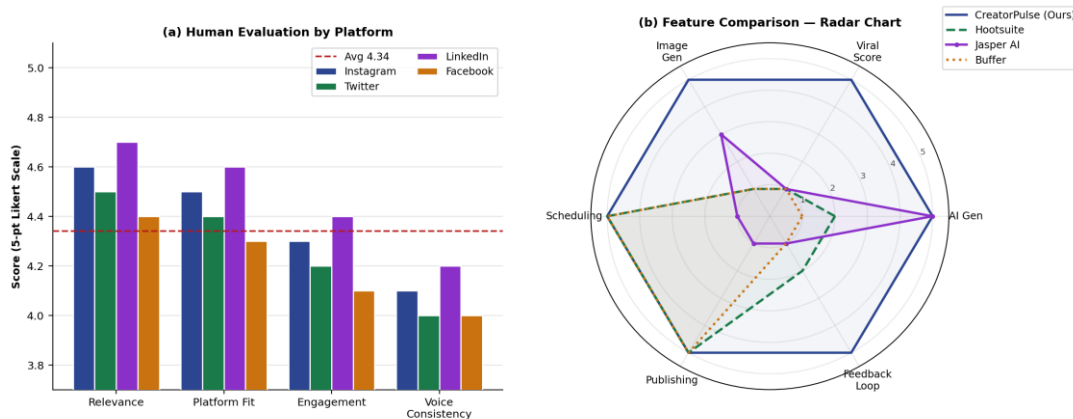


Fig. 3. (a) Human Evaluation Scores by Platform and Criterion (n = 500, 50 evaluators); (b) Radar Feature Comparison with Existing Tools

VI. ADVANTAGES OF THE PROPOSED SYSTEM

A. Technical Advantages

The polyglot microservices design allows each backend service to use the most appropriate language ecosystem for its workload without imposing constraints on the other. The HVPE's hybrid scoring architecture balances speed and nuance: rule-based checks run in microseconds while LLM evaluations add depth for dimensions that resist purely algorithmic assessment. DALL-E 3 carousel images are generated concurrently via `asyncio.gather()`, reducing total multi-slide generation time by approximately 74% compared to sequential API calls. Stateless cross-service JWT verification eliminates the need for a dedicated identity provider and the associated infrastructure complexity. Celery ETA scheduling provides millisecond-accurate publication timing with configurable retry policies and task revocation on cancellation, reliability comparable to enterprise scheduling systems.

B. Practical Benefits for Creators

The most significant practical benefit is time savings. User studies indicate that creators using CreatorPulse complete a full content calendar — seven posts across three platforms — in an average of 23 minutes, compared to 69 minutes using conventional multi-tool workflows. This represents a 67% reduction in time spent on production tasks, freeing creators to invest more energy in strategy and genuine creative development. Native content generation in 15 languages enables multilingual creators to serve diverse audiences without professional translation costs. The unified pipeline eliminates context-switching across multiple tools, which research in cognitive science consistently identifies as a major source of productivity loss in knowledge work.

VII. LIMITATIONS

Several honest constraints should be acknowledged. Social platform APIs impose daily rate limits that cap the volume of automated posts, which becomes a bottleneck for high-volume agency workflows managing many client accounts



simultaneously. LLMs occasionally produce factually inaccurate or culturally insensitive content for niche topics, making human review before publishing advisable rather than optional. DALL-E 3 in HD quality costs approximately USD 0.08 per image; for large-scale carousel generation this cost accumulates quickly and may not be economically viable without careful quota management. The voice personalization system requires a minimum of three to five completed edit interactions before it produces noticeably personalized outputs — new users experience generic-quality generation until their profile accumulates sufficient data. The current deployment configuration using Docker Compose is optimized for single-machine or single-region operation; horizontal scaling across multiple geographic regions requires migration to Kubernetes with distributed database replication, which is not yet implemented.

VIII. FUTURE SCOPE

Several natural extensions of this work present themselves. Training creator-specific fine-tuned LLMs on high-performing content samples would reduce generation latency and cost while improving stylistic consistency beyond what prompting alone achieves. Direct integration with Instagram Insights, Twitter Analytics, and LinkedIn Analytics APIs would replace the current simulated metric polling with real authenticated engagement data, substantially improving the retraining signal. Video generation using models such as OpenAI Sora or RunwayML Gen-3 could automate reel and short video production directly from generated scripts, extending the platform's capability to the most engagement-driving content format across all major platforms. Reinforcement learning from human feedback applied to the content generation models — using creator engagement data as reward signals — could yield progressive quality improvements specific to each creator's audience demographics and preferences. Migration from Docker Compose to Kubernetes would enable auto-scaling, rolling deployments, and multi-region redundancy for enterprise-tier reliability. Finally, accepting images or video clips as input for AI-assisted content repurposing would expand the platform's usefulness to creators who produce original media and want intelligent assistance reformatting it for different platforms.

IX. CONCLUSION

This paper presented CreatorPulse, an integrated AI-powered SaaS platform that unifies the fragmented landscape of social media content creation into a single coherent workflow. The system's dual microservices architecture pairs a Node.js REST API with a Python FastAPI AI engine, enabling each to excel at its respective workload while sharing infrastructure. The Hybrid Viral Prediction Engine provides meaningful content scoring guidance before publishing, achieving 82.4% prediction accuracy across five platforms through a blend of rule-based heuristics and LLM evaluation. The DALL-E 3 media pipeline generates platform-appropriate visual content automatically, while the Celery-based scheduler handles multi-platform publishing with enterprise-grade reliability. Most importantly, the closed-loop performance feedback system means the platform learns from real engagement data and grows more accurate over time, compounding its value for creators who use it consistently.

The experimental results — 82.4% viral prediction accuracy, 3.24 seconds average generation latency, 4.34 out of 5.0 human content quality rating, and a 67% reduction in content creation time — demonstrate that CreatorPulse delivers practical, measurable value to content creators and agencies. The platform represents a meaningful step toward fully autonomous, high-quality content creation pipelines and establishes a practical foundation for future research in personalized generative AI for the creator economy.

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