

# Comparative Analysis of Sponsored and Organic Content on Fitness TikTok

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BUS 439 Analytics Project

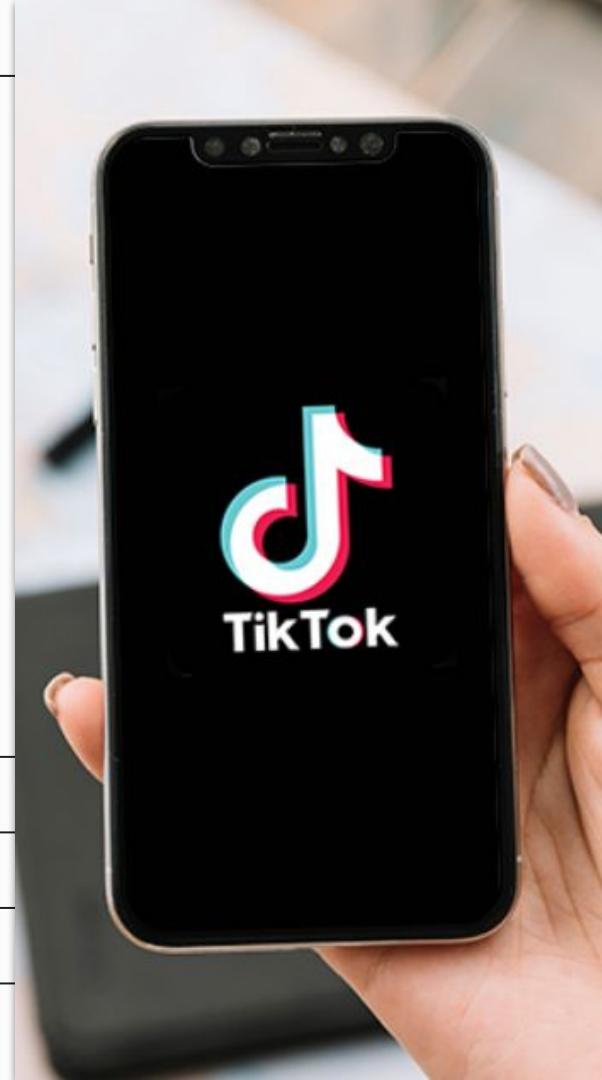
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FALL 2025

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Vibhuti Gandhi

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# Contents

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01

Introduction

---

02

Research Motivation

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03

Methodology

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04

Analysis

---

05

Recommendations

---

06

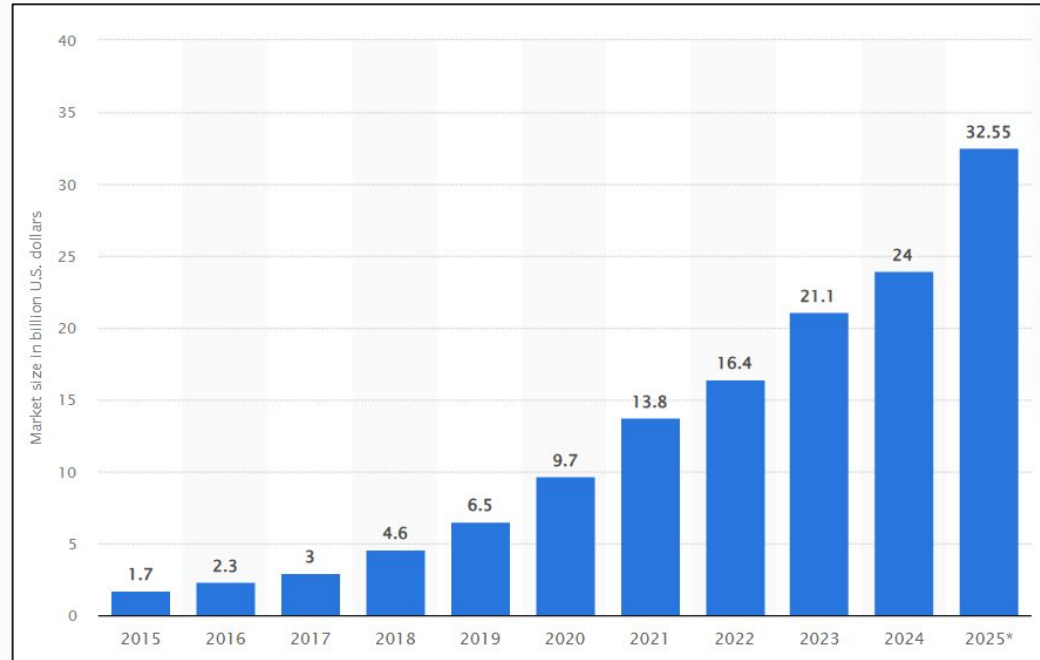
Limitations & Future Work

# Influencer Marketing

With over **80%** of marketers viewing influencer marketing as highly effective, TikTok has rapidly emerged as a leading platform — now preferred by **52%** of brands.

(Influencer Marketing Hub, 2025; ScienceDirect, 2025)

Influencer marketing market size worldwide from 2015 to 2025



# Research Motivation

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Influencers who engage authentically with their audience and share genuine experiences lead to higher consumer engagement, which ultimately drives brand loyalty.

(Baghel, 2024)

## Key Questions:

- What share of fitness content on Tiktok is sponsored?
- How do creators weave sponsorships into videos?
- Can we measure the authenticity of a video?
- What effect does authenticity of a sponsored video have on its engagement?

# Methodology

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## Sampling

- **25 fitness creators**
- **Stratified** by followers
- High (>1 million): **8 creators**
- Medium (100k to 1 million): **9 creators**
- Low(<100k): **8 creators**
- 100 videos per creator

## Collection

- **yt-dlp scraper**
- Dataset of 2,500 videos
- **Video Metadata** (Views, Likes, Comments, Bookmarks, etc.)
- **Video transcripts**

## Detection

- Multi-signal sponsored content **heuristic classifier**
- **8 detection methods** (Explicit, Implicit, Promo Codes, Brand mentions, CTA Phrases, Transcript Analysis, Engagement Anomaly, Product Recommendation)
- Weighted scoring

## Analysis

- Create metrics for **Engagement & Authenticity**
- Exploratory analysis
- Natural Language Processing (NLP) using **Empath** and **VADER**.

## Insights

- **Matched Pairs Experiment**
- Summary
- Recommendations

# Sponsored Content Detection

**25**

Fitness Creators

**2500**

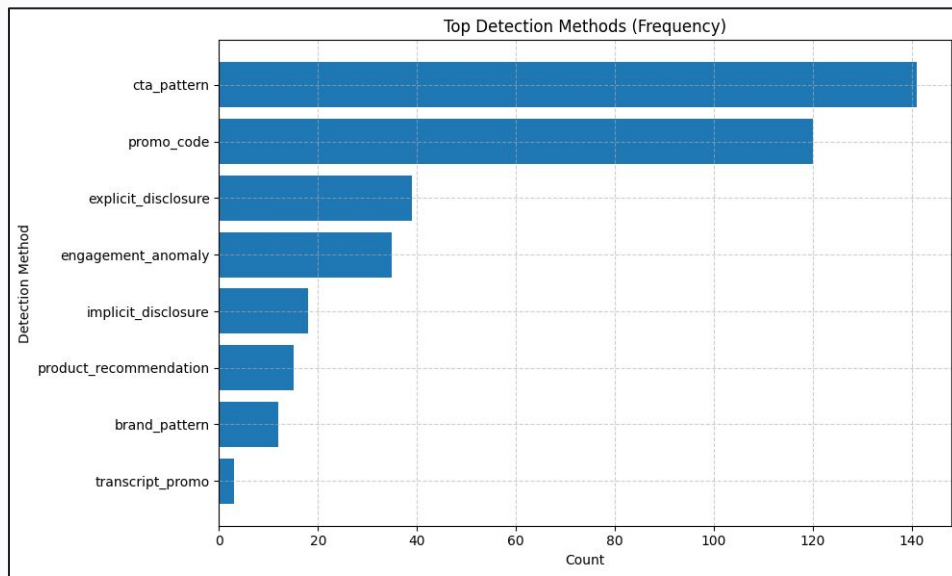
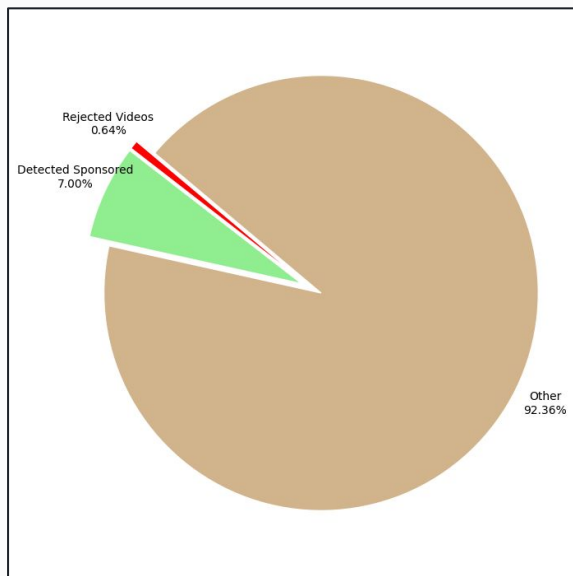
Total videos

**175**

Sponsored videos

**16**

Rejected videos

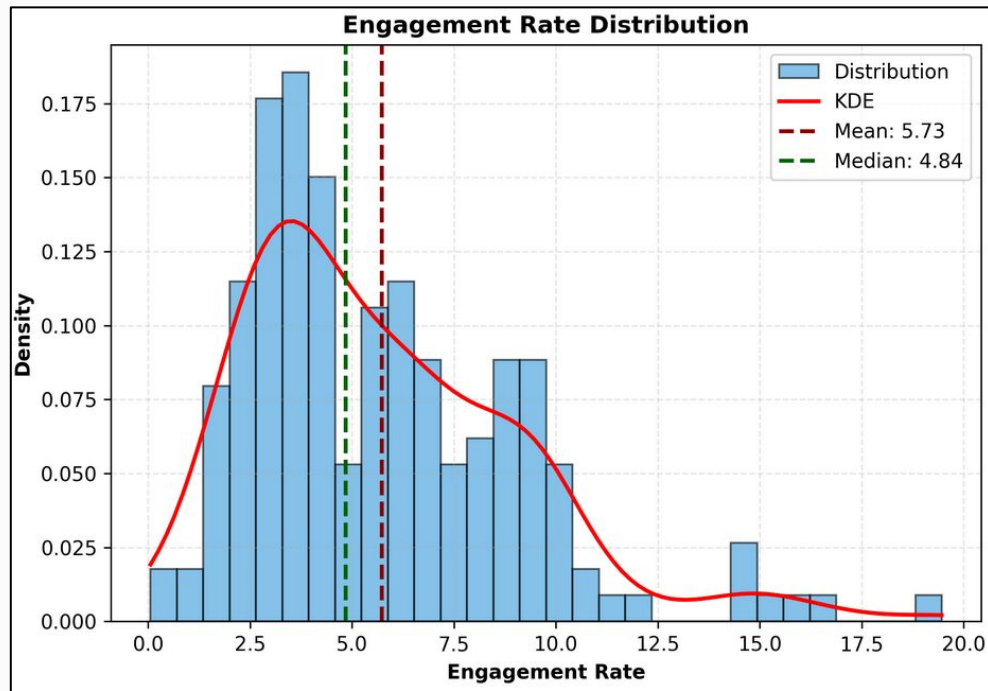


# Engagement as a Measure of Success

Accurately Measures How Well the Content Resonates

Normalizes Performance Across Different Creators and View Counts

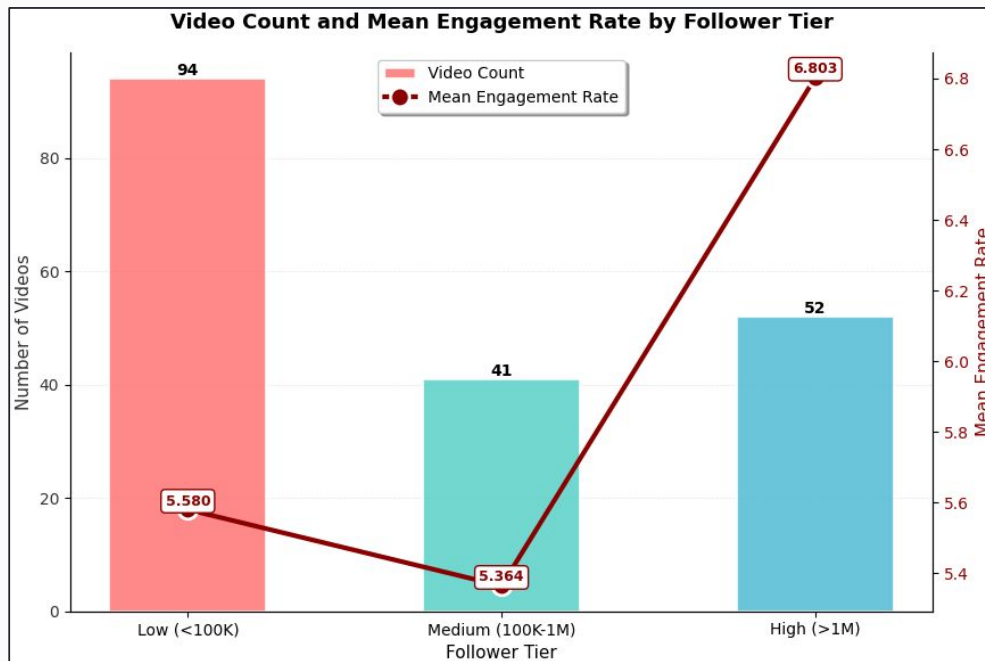
Provides the Best Available Proxy Since Sales/Click Data Is Missing



$$\text{Engagement Rate} = (\text{Likes} + \text{Comments} + \text{Reposts}) / \text{Views}$$

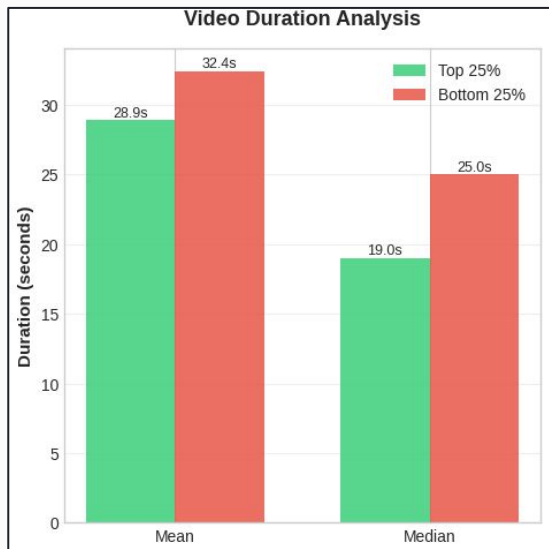
# Engagement of Sponsored Videos

High-follower creators achieve the **highest mean engagement rate (6.80%)** on sponsored content, followed by low-follower creators (**5.58%**), while medium-tier creators (**5.36%**) show the lowest engagement despite having the fewest videos in the dataset.

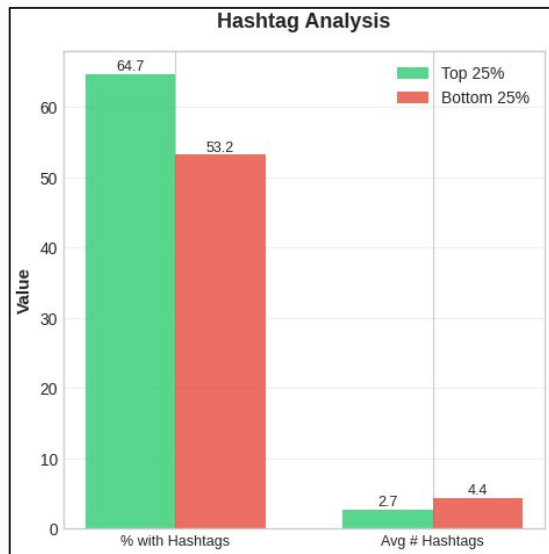




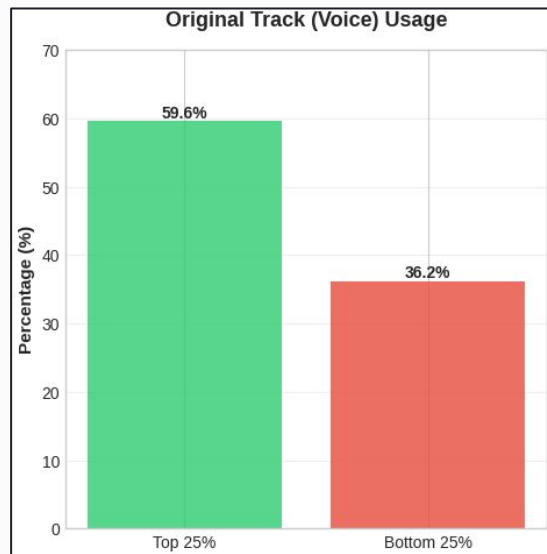
# Pattern Analysis of Sponsored Videos



Shorter videos tend to perform better!  
Ideal length: **19-30 seconds**




Use no more than **3 Hashtags!**

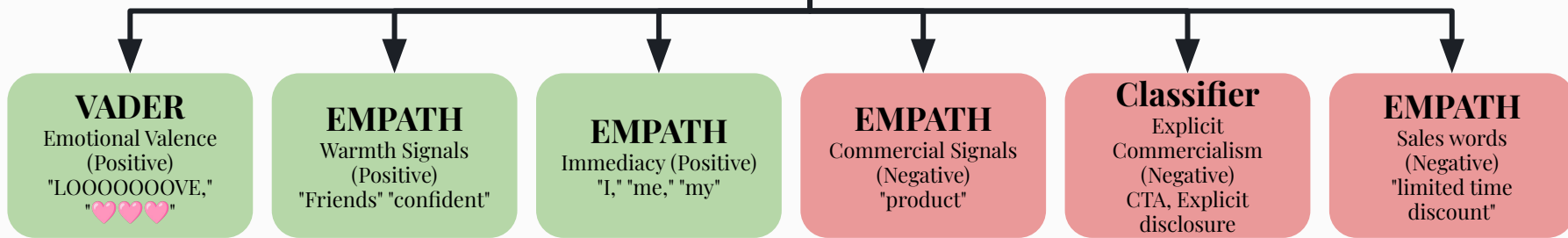


Use your **own voice** instead of music!

# Capturing Authenticity

## Video Description:

"I absolutely LOOOOOOOVE this product !!! It makes me feel so confident.  
All my friends use it! Check the link in bio for a limited time discount. #self-love  
#ad #company"



## VADER "The Tone"

We chose this over standard sentiment tools because VADER is tuned for social media. It understands that CAPS LOCK indicates intensity and that emojis carry weight. This gives us our 'Emotional Valence' score.

## EMPATH "The Topic"

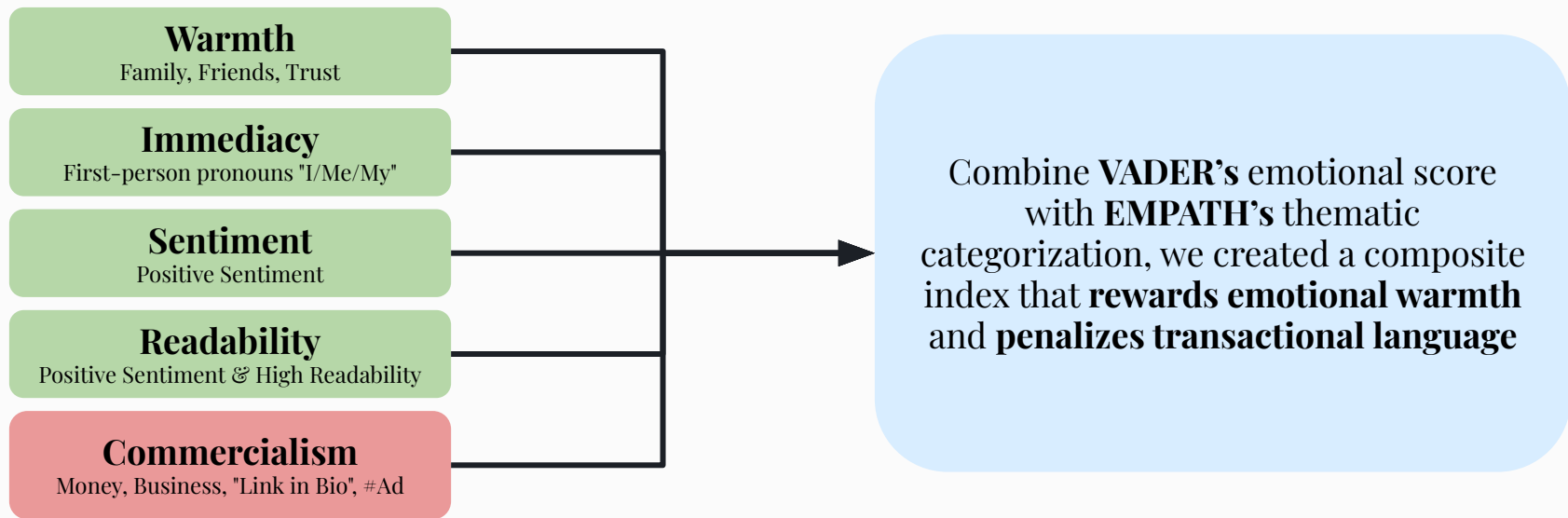
Unlike VADER, which measures tone, Empath measures topics. We programmed it to scan for two opposing clusters: Warmth Categories: Words related to family, trust, and friends. Commercial Categories: Words related to money, business, and transactions. This allows us to detect when a creator shifts from storytelling to selling.

# Quantifying Authenticity

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$$\text{Authenticity Score} = \frac{\sum(\text{Warmth}, \text{1st Person}, \text{Readability}) - \sum(\text{Commercial Intent})}{5}$$

All variables are z-scored to create a balanced 0-100 index.



# Experiment Design

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## Data Ingestion

**Input:** Raw export of TikTok video metadata.

**Filtering:** Removed missing descriptions & standardized dates from TikTok Descriptions.

**Engagement Metric:** Calculated (Likes + Comments + Reposts) / Views.

Final N: 2,463 videos across 25 Creators.

## Feature Engineering

**Tools:** Empath (Lexical Categories) & VADER (Sentiment).

**Output:** Normalized "Authenticity Score" (0-100).

## The Control Strategy

**Challenge:** Videos perform differently depending on trends/seasonality.

**Logic:** Matched-Pair Design. For every 1 Sponsored video, we selected 3 Organic videos from the same creator posted at the closest possible date.

**Result:** 700 paired observations.

## Statistical Inference

**Method:** Mixed Linear Models (MLM).

**Why?** To control for clustering (Video i is nested within Creator j).

**Variables:** Fixed Effects: Sponsorship status, Follower count.  
Random Effects: Creator ID.

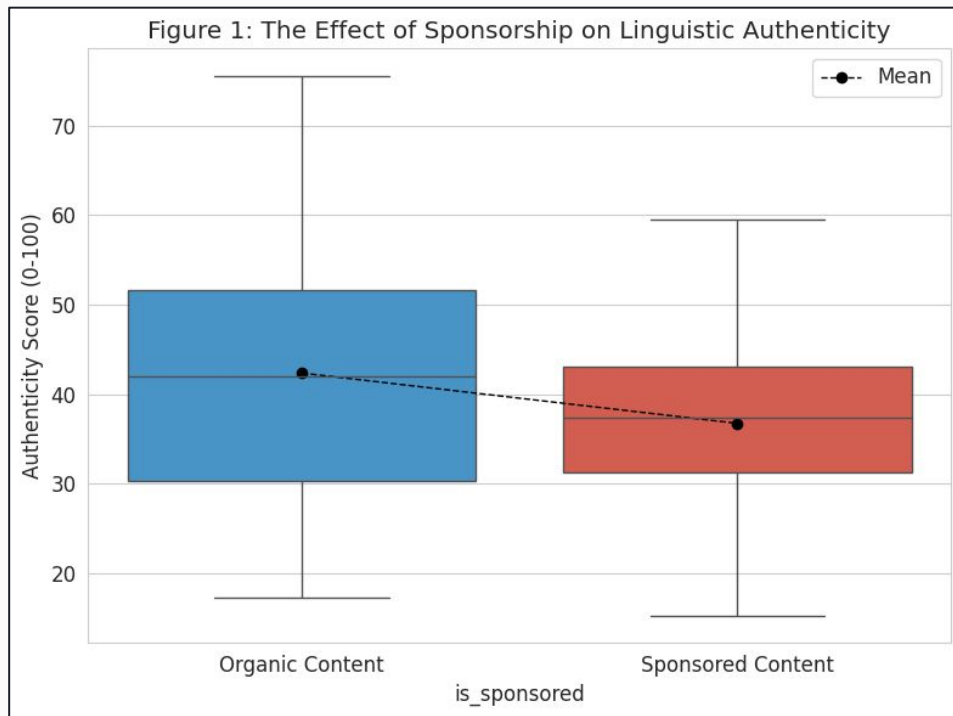
## Goal

To detect if creators change their linguistic style when posting sponsored content and if audiences punish them for it.

# The "Sell-Out" Effect

There is a **statistically significant drop in authenticity** when a video is sponsored ( $t = -5.005$ ,  $p < 0.001$ ).

Organic Mean: 42.35 | Sponsored Mean: 36.72.

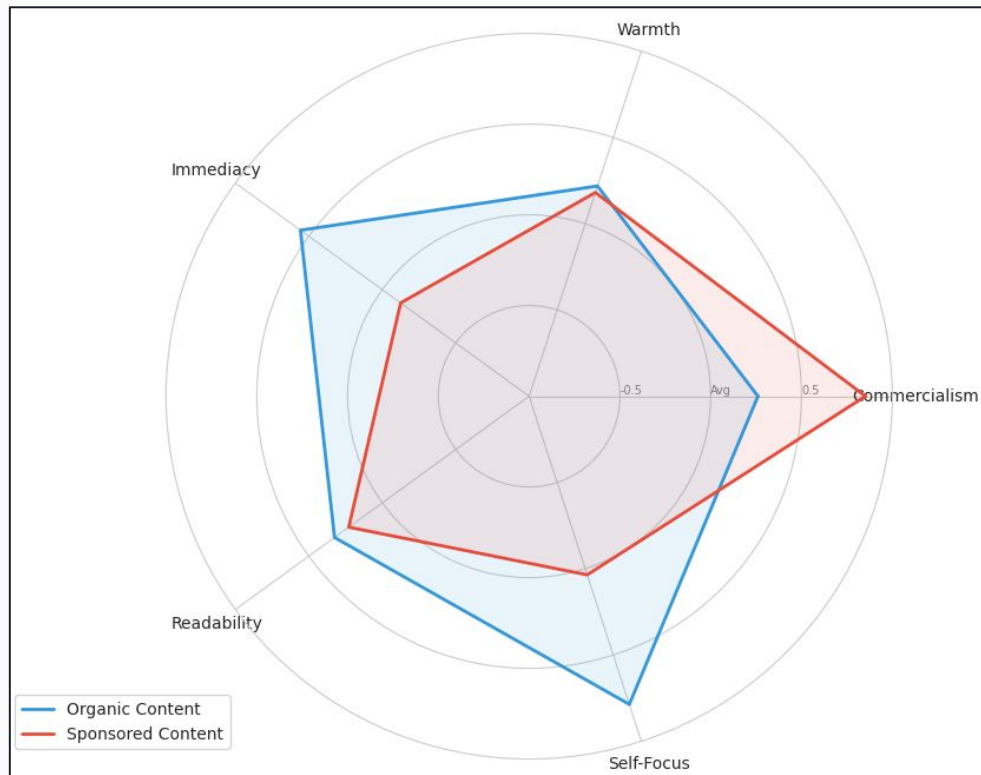


# The Change in Authenticity

Self-focus and immediacy takes a big hit in sponsored content vs. organic content, **dropping by ~60% in sponsored posts.**

Warmth and Readability stays relatively the same.

Naturally, Commercialism sees a big increase!



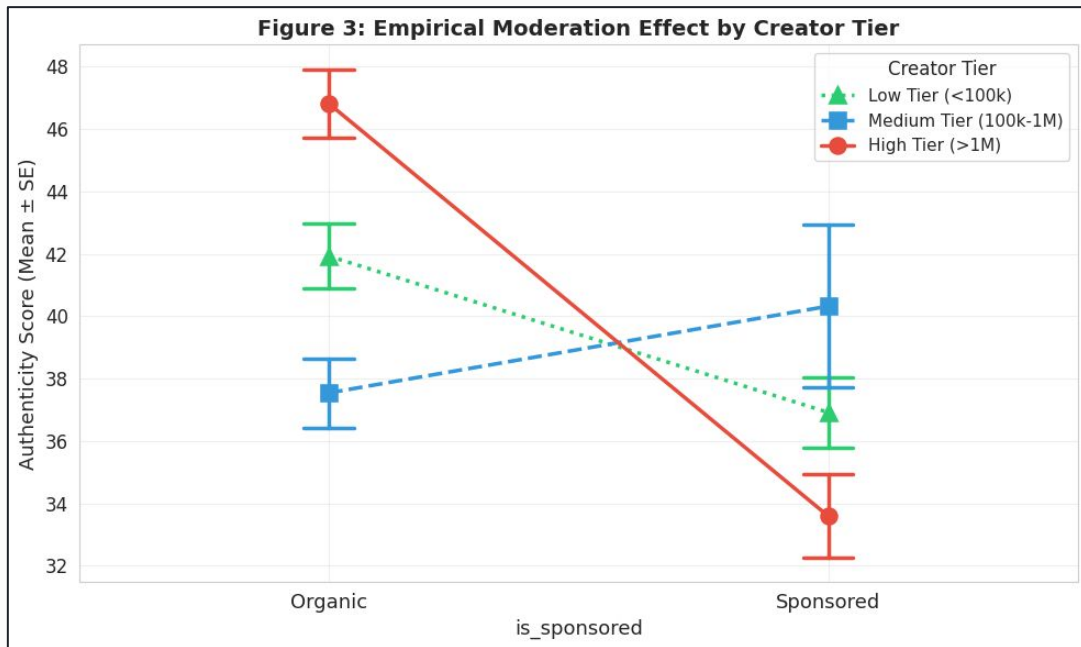
# Moderation Analysis

The **bigger the influencer**, the **faker they sound** in ads.

Creators with 1M+ followers drop 10 points in authenticity vs. just 1.6 points for smaller creators

We employed a mixed-effects linear regression with random intercepts for creators to account for within-creator clustering.

The model converged successfully (REML estimation, Log-Likelihood = -2793.78)



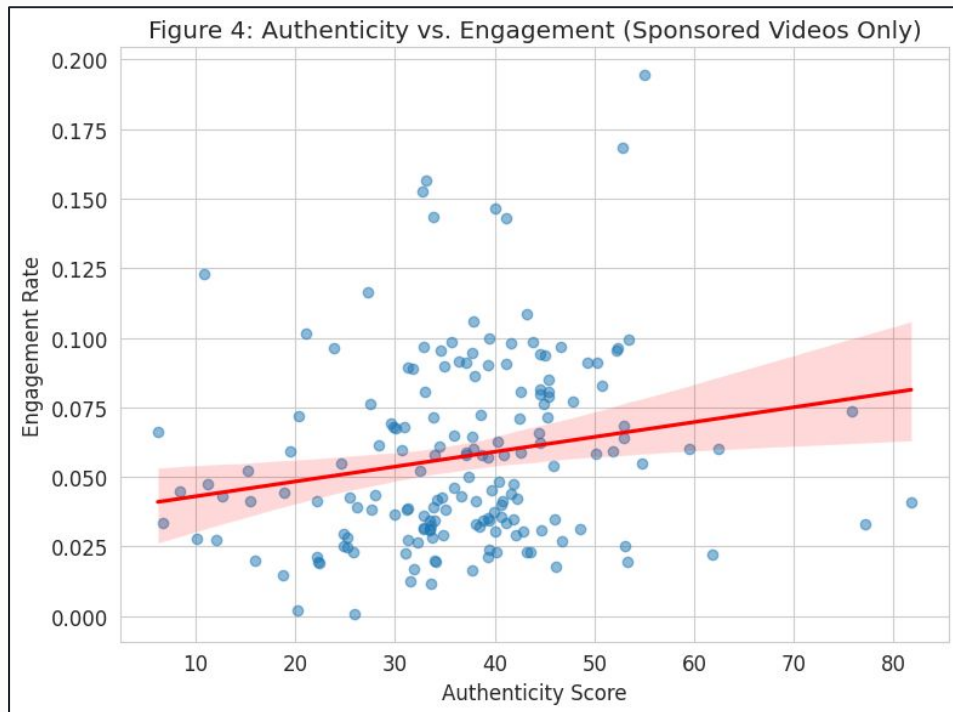
# Does Authenticity Pay?

Even within an ad, sounding like a human (using "I", showing warmth, avoiding sales jargon) **correlates with significantly higher likes, comments and shares.**

Regression controlled for follower count and word count.

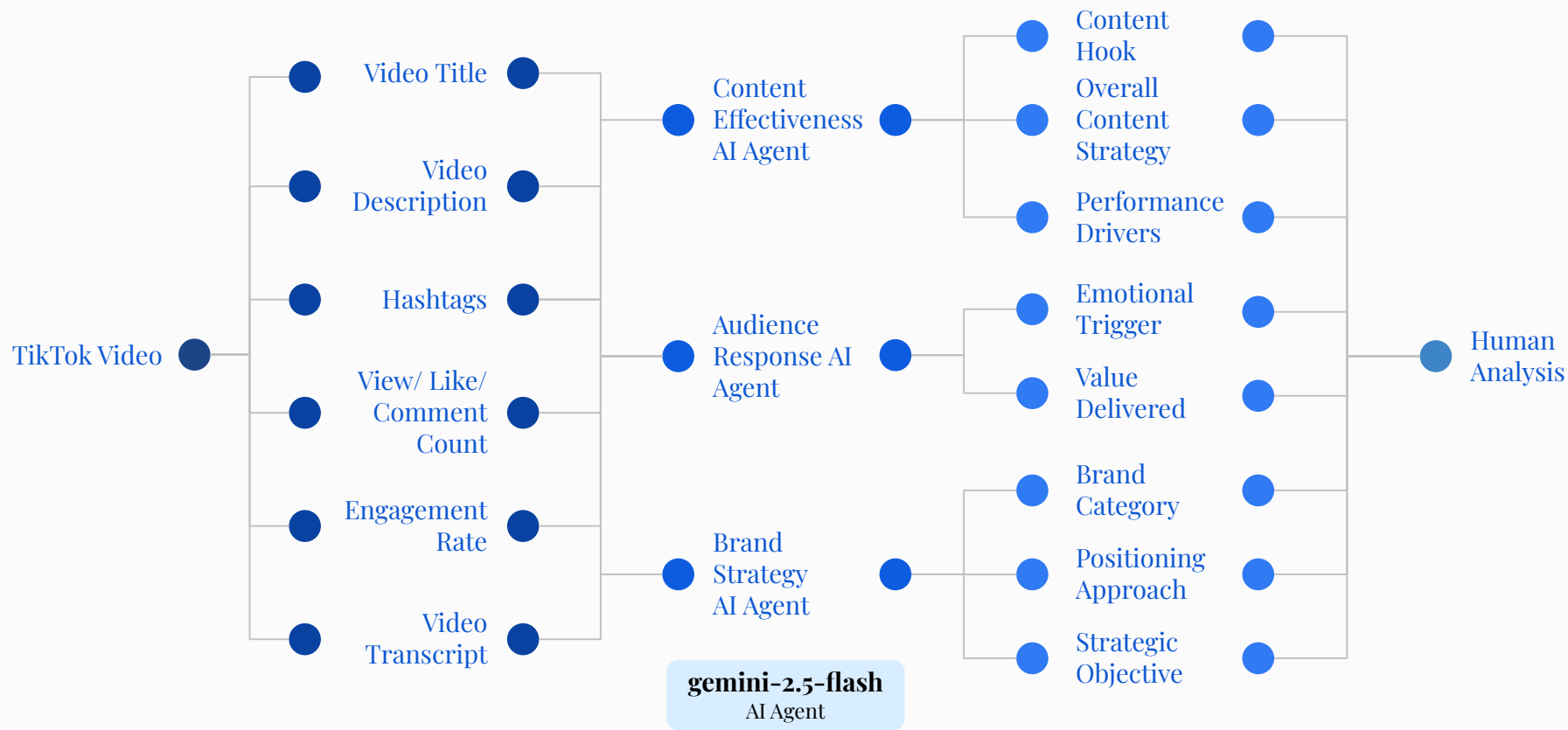
Finding: **Authenticity is a positive predictor of Engagement Rate** (Coef = +0.19,  $p < 0.001$ ).

Result: The interaction is **negative and significant** (Coef = -4.027).



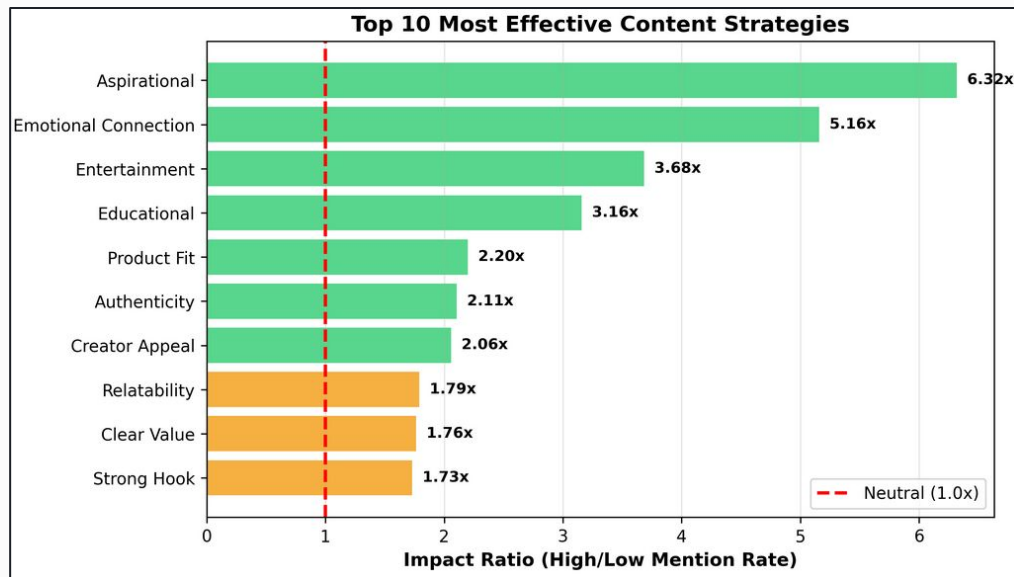


# Multi-Agent AI Architecture



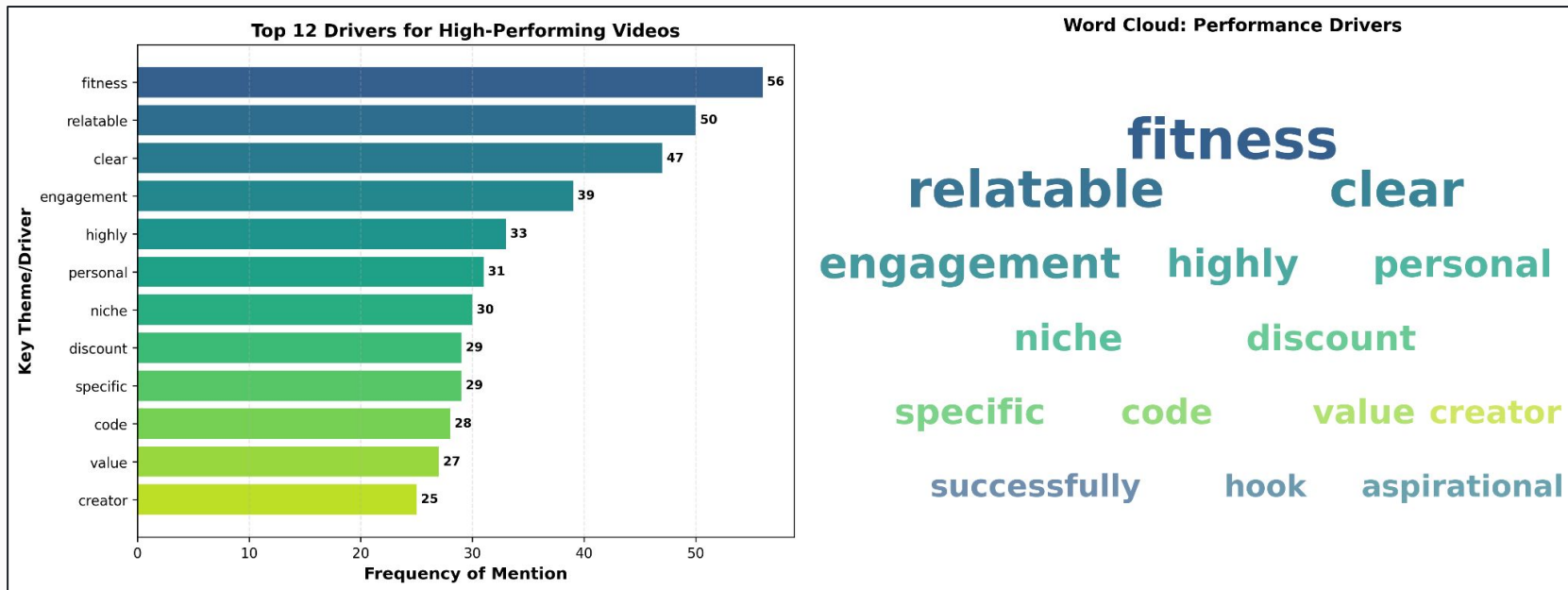
# Effective Content Strategies

The top three strategies:  
**Aspirational (6.32x)**,  
**Emotional Connection (5.16x)**, and **Entertainment (3.68x)** all emphasize creative, non-sales-y, narrative-driven content. Focus lies on **feeling** and **experience** rather than product features.



**Impact Ratio (High Mention Rate / Low Mention Rate).** Impact Ratio >1.0x means the strategy is more prevalent in high-performing videos than in low-performing ones, indicating its effectiveness.

# Drivers of High-Performing Videos



Fitness (56) is the most frequent theme, suggesting that content tied to health, activity, and related products drives high engagement. Relatability (50) is also critical, meaning content that makes the viewer feel seen or understood is highly effective

# Recommendations

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## For Brands:

**Avoid strict scripts** that force a commercial tone and reduce first-person language.

Allow creators to use their natural voice, as **high-authenticity ads perform better**.

Monitor an **"Authenticity Score"** for creators to guide partnership selection.

## For Creators:

Work to maintain **"I/Me" pronouns** and try to build a connection with audience, even in ads.

Be aware that as you grow, your audience becomes more sensitive to **linguistic style changes**.

# Testing Emotional Triggers

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## Null Hypothesis ( $H_0$ ):

There is no difference in average engagement rates between videos using deep emotional triggers and videos using shallow emotional triggers.

$$\mu_{\text{deep}} = \mu_{\text{shallow}}$$

## Alternative Hypothesis ( $H_1$ ):

Videos using deep emotional triggers have significantly higher average engagement rates than videos using shallow emotional triggers.

$$\mu_{\text{deep}} > \mu_{\text{shallow}}$$

Deep Emotions: 6.30% avg engagement  
Shallow Emotions: 5.11% avg engagement

## Difference:

+1.19 percentage points (+23.3%)

## Test Results:

t-statistic: 2.383

p-value: 0.0187

## Decision:

p-value <  $\alpha$  REJECT  $H_0$

At the 5% significance level, we have sufficient evidence to reject the null hypothesis. The data supports the claim that deep emotional triggers generate significantly higher engagement than shallow emotional triggers ( $t = 2.383$ ,  $p = 0.0187$ ).

# Limitations

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## **Engagement $\neq$ Sales**

The analysis uses Engagement Rate (Likes + Comments + Reposts) as a proxy for success because actual conversion/sales data is private. A video can be "engaging" (viral) but fail to sell the product.

## **Text-Only Sentiment Analysis**

The "Authenticity Score" relies on VADER and EMPATH, which analyze text. This misses visual cues (facial expressions, body language) and audio tone (sarcasm vs. sincerity) which are critical on TikTok.

## **Sample Size Constraints**

The study analyzed 25 creators and 2,500 videos. While statistically sufficient for a t-test, this sample may not fully represent the entire fitness niche or other industries (e.g., Tech, Beauty).

# Future Work


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## **Multimodal Analysis**

Incorporate Computer Vision to analyze the video frames (e.g., detecting if the product is visible on screen) and Audio analysis to detect vocal stress or excitement.

## **LLM-Based Scoring**

Replace VADER/EMPATH with a Large Language Model (e.g., Gemini-2.5-flash) to detect "Authenticity." LLMs understand nuance and context better than rule-based dictionaries like VADER.



# Any questions? Ask away!

Let's discuss any doubts or concerns.  
If something comes up later, please reach out via [vga17@sfu.ca](mailto:vga17@sfu.ca)

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