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Methodology for Organic Tiktok Influencer Growth: An Empirical Face-Centered Protocol without Paid Targeting

Yevhen Velychko
Influencer, Zarsus Business School Online, USA
https://orcid.org/0009-0000-6167-0591

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Abstract

Purpose: To develop an integrated, face-centered protocol for organic TikTok growth for creators and micro-business owners who do not rely on paid targeting, by synthesizing evidence from twenty verified English-language sources and consolidating recurring practical levers identified across scholarly and benchmarking literature.

Methodology: The study uses a secondary research design based on the integration of evidence from twenty verified English-language sources. Rather than collecting primary data for publication, the paper employs a worked application approach in which an illustrative dataset is constructed to reflect value ranges reported in prior empirical studies and industry benchmarks. This dataset is then analyzed to demonstrate how the proposed protocol can be assessed in practice through platform analytics.

Findings: The analysis identifies five recurring levers associated with organic TikTok growth: front-loaded numeric hooks, high-volume publishing, time-lag narrative devices, authenticity signals, and sustained face-forward presence. Results from the worked application suggest that face-forward videos featuring a numeric hook and a next-day payoff cue plausibly improve follow-through, measured as follows per 1,000 views, compared with landscape-only content. In addition, catalog-complete product posting combined with tiered pricing cues appears to align with stronger conversion proxies in commerce-adjacent accounts.

Unique Contribution to Theory, Practice and Policy: The paper contributes by moving beyond fragmented, anecdotal advice and single-construct explanations to offer a coherent, evidence-informed protocol that connects trust, social identification, parasocial bonding, and platform-specific content design within one practical framework. For practitioners, it provides a replicable measurement plan for testing organic growth strategies through platform analytics. For future research and policy-oriented practice, it clarifies the limitations of secondary-empirical modeling and recommends field-based validation designs, while encouraging creators and small businesses to adopt transparent, authenticity-preserving, face-forward communication strategies under conditions of algorithmic amplification and social scrutiny.

Keywords: *Tiktok, Paid Targeting, Influencer, Organic growth*

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Introduction

TikTok's short-form video feed compresses exposure, evaluation, and follow decisions into seconds. In that environment, creators usually learn through folk methods: "start with numbers," "post a lot," "show your face," and "stay authentic." Those heuristics are not wrong, but they remain under-specified. A methodological article must specify exactly what is being manipulated, how it is measured, and why it should work. Classic evidence on virality shows that content succeeds when it triggers transmission-friendly responses, not merely when it is well-produced or "nice" (Berger & Milkman, 2012). Influencer marketing research, in parallel, indicates that a creator's effectiveness is mediated by credibility, fit, and relationship-like psychological processes (De Veirman et al., 2017; Schouten et al., 2020). TikTok adds a twist: discovery is algorithm-led and often context-thin, which changes how identity, trust, and attention cohere into growth (Bhandari & Bimo, 2022). At the same time, current platform benchmarks show that posting frequency and engagement rates vary widely by industry and account size, suggesting that growth is not a single lever but an interaction between content design and distribution (Dash Social, 2025; Emplifi, 2025; Rival IQ, 2024).

This paper responds to that gap by proposing a face-centered protocol for organic TikTok growth without paid targeting. The protocol is grounded in five practice-driven lessons commonly taught in creator communities: lead with price and numbers; post enough that one video can break out; use time-lag storytelling to invite the audience back; keep the creator visible, competent, and sincere; and treat advertising as a structured micro-script that respects attention. Those lessons are translated into measurable constructs and then connected to literature on virality, source credibility, parasocial interaction, and platform affordances. The central objective is not to promise a guaranteed recipe, but to provide a reproducible methodology: a set of operational definitions, measurement choices, and analytic steps that allow a creator cohort to evaluate whether a face-centered, numeric-hook, high-volume approach performs better than low-face, low-structure posting. Two research questions guide the work. First, which components of a face-centered protocol are most strongly supported by existing empirical evidence across influencer and short-form video studies? Second, how can a creator community evaluate those components using a lightweight empirical design that relies on existing analytics rather than bespoke experiments?

Literature Review

Empirical influencer studies consistently treat the creator as a hybrid of media producer and social actor. One line of work emphasizes credibility and trust: audiences use perceived expertise, trustworthiness, and authenticity cues to decide whether to believe a creator's claims and whether to act on them (Djafarova & Rushworth, 2017; Sokolova & Kefi, 2020). Another line examines attachment and need fulfillment. Followers do not only "like content"; they may form a relationship-like attachment that predicts persuasion and long-term loyalty (Ki et al., 2020). Fit also matters. When an endorser and product are perceived as aligned, identification and attitude tend to improve; when misaligned, persuasion weakens (Schouten et al., 2020). These findings help explain why “be a competent master in a niche” is more than motivational advice: it is a mechanism for stable credibility and a coherent identity signal. A second body of work focuses on platform-specific pathways. TikTok usage and engagement behaviors have been linked to gratifications sought, personality traits, and motivations to contribute, enhance, and create content, suggesting that design choices should match why users are in the feed in the first place (Meng & Leung, 2021; Omar & Dequan, 2020). A third body of evidence is methodological and operational rather than purely psychological. Virality research indicates that content diffusion depends on emotional and practical value, and that seemingly small framing choices can change sharing outcomes (Berger & Milkman, 2012). For creators, that translates into the “start with numbers” heuristic: numbers act as an immediate value signal and reduce ambiguity about what the viewer will gain. In many commercial niches, price is the most compressible number because it instantly anchors relevance. Industry reports also show wide dispersion in performance and content volume.

Benchmarking work consistently highlights how posting cadence and video output correlate with reach opportunities, even if the relationship is not deterministic (Dash Social, 2025; Emplifi, 2025; Rival IQ, 2024). This supports the “post a lot so one video hits” lesson as a variance strategy: if distribution has heavy tails, more draws from the distribution increase the probability of a breakout event. Time-lag storytelling, another practical lesson, can be framed as return-intent engineering. TikTok’s feed is not organized as a subscription-first channel for many users; instead, the algorithm can resurface creators when the system predicts renewed relevance. A cue that something will be completed “tomorrow” or “in part two” creates an explicit reason to follow and come back. While not always isolated as “time-lag,” related concepts appear in studies of self-disclosure and trust on TikTok.

Self-disclosure can increase trust at scale, particularly when viewers perceive similarity and authenticity, which makes cliffhanger-style personal narratives potentially effective (Ruangkanjanases et al., 2022). Face-centered content is the protocol’s backbone. In influencer research, the face is a high-density channel for identity, emotion, and credibility cues, and it increases the probability of social identification. Marwick and boyd’s work on celebrity practice highlights how being seen is not just exposure; it is an ongoing performance of relatability and presence (Marwick & boyd, 2011). TikTok studies argue that the platform encourages an “algorithmized self,” where creators learn to craft identity signals that the recommendation system can parse, while still appearing authentic to humans (Bhandari & Bimo, 2022). Empirical analyses of TikTok’s recommendation and engagement patterns further show that distribution is shaped by both content features and audience interactions, making face presence an input that can influence early engagement and thus downstream reach (Zannettou et al., 2024). Finally, the commerce-adjacent lessons—posting about all inventory, offering mid-range and tiered pricing, and structuring advertising—fit within the broader evidence that credibility and perceived helpfulness shape persuasion. If viewers cannot easily map an offer to their own budget and needs, follow and conversion become less likely. Benchmark reports and TikTok's own trend framing emphasize that creators who consistently translate attention into utility (education, clear offers, or practical takeaways) tend to build durable communities rather than one-off views (TikTok, 2026). In tourism-related TikTok research, features of short videos can predict behavioral intention through trust and attitude pathways, reinforcing the idea that clarity and credibility are key even outside product sales contexts (Liu et al., 2024).

Methodology

The study design is a secondary-empirical synthesis paired with a worked field application. The synthesis stage selects and codes twenty verified sources: peer-reviewed articles on virality, influencer credibility, and TikTok usage, plus established benchmarking reports that quantify posting cadence and engagement ranges. The goal of coding is to map each practical lesson into measurable constructs. Five protocol components are defined. First, the numeric hook component is operationalized as the presence of a number or price in the first three seconds of video audio or on-screen text, with a secondary indicator for whether the number is tied to a concrete outcome ("$19 dinner," "3 mistakes," "1M views for $100"). Second, the volume component is operationalized as a weekly publishing rate, with emphasis on maintaining stable effort across weeks to sample the distribution of algorithmic exposure. Third, the time-lag component is operationalized as an explicit future payoff cue ("tomorrow," "part 2," "I'll show the result in 24 hours") and is coded for whether the payoff is product-based (e.g., a dish) or identity-based (e.g., a personal decision).

Fourth, the authenticity component is operationalized via a small set of observable signals: disclosure of constraints or mistakes, consistency between offer and delivery, and avoidance of misleading claims. Fifth, the face-centered component is operationalized as visible face presence for at least half of the video duration, plus direct address (speaking to camera) versus off-screen narration. The worked application is designed to show how a creator community can evaluate the protocol without paid targeting and without proprietary data access. The application uses a constructed dataset representing a cohort of 2,600 community members operating micro-businesses or personal brands. Importantly, this dataset is illustrative rather than a claim about real participants; its distributions are constrained to match ranges reported in the literature and benchmarking documents. The dataset spans an eight-week implementation window and includes per-video metrics available in standard creator analytics: views, average watch time, shares, comments, likes, profile visits, follows, and (for commerce-adjacent accounts) link clicks or inquiry messages as conversion proxies. Where revenue outcomes are considered, the application uses self-reported weekly revenue deltas as a coarse indicator, treated cautiously because self-report is noisy and niche-dependent. To mimic realistic heterogeneity, the cohort is partitioned into three segments: service experts (education and consulting), product sellers (inventory-based), and mixed lifestyle-plus-offer accounts. Each segment is assigned baseline engagement ranges aligned with industry benchmarks that document typical performance and posting behavior on TikTok across brand sizes (Dash Social, 2025; Emplifi, 2025; Rival IQ, 2024).

Table 1. Operationalization and coding rubric.

Protocol component	Operational definition	Coding / measurement	Why it matters
Face presence	Creator's face visible ≥50% of video duration; direct-to-camera address	Binary (Yes/No) + % face-time	Operationalizes social presence and identity cueing
Numeric/price hook	Number or price appears in first 0–3 seconds (spoken or on-screen)	Binary (Yes/No); Hook type (Price/Count/ROI)	Signals practical value quickly; reduces ambiguity
Time-lag cue	Explicit future payoff cue (e.g., "tomorrow/part 2/24h result")	Binary (Yes/No); Payoff type (Product/Personal)	Creates return intent; motivates following
Competence demonstration	Shows skill, method, or proof of expertise in the core niche	Ordinal (0=None, 1=Implied, 2=Explicit demo)	Strengthens credibility and perceived expertise
Authenticity commitment	Promise-keeping and non-misleading claims; disclosed constraints/mistakes	Binary (Yes/No) + notes	Protects trust under amplification and scrutiny
Catalog completeness (commerce)	Systematic posting across full inventory/offer set	Coverage % of SKUs/offers per week	Improves fit matching; stabilizes conversions
Ad structure	Hook-question (≤5s) + self-promo segment (~50s) + clear CTA	Binary (Yes/No); CTA type	Maintains attention while enabling promotion

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Table 2. Cohort structure and measurement plan.

Cohort segment (illustrative)	Creators (n)	Starting followers (typical range)	Posting cadence (videos/day)	Primary outcomes tracked
Service experts (education/consulting)	1100	0.5k–10k	3–5	Views, watch time, shares, follows, profile visits, inquiries
Product sellers (inventory-based)	900	0.5k–15k	3–6	Views, watch time, shares, follows, profile visits, link clicks, inquiries
Mixed life + offer accounts	600	0.5k–20k	2–5	Views, watch time, shares, follows, profile visits, inquiries

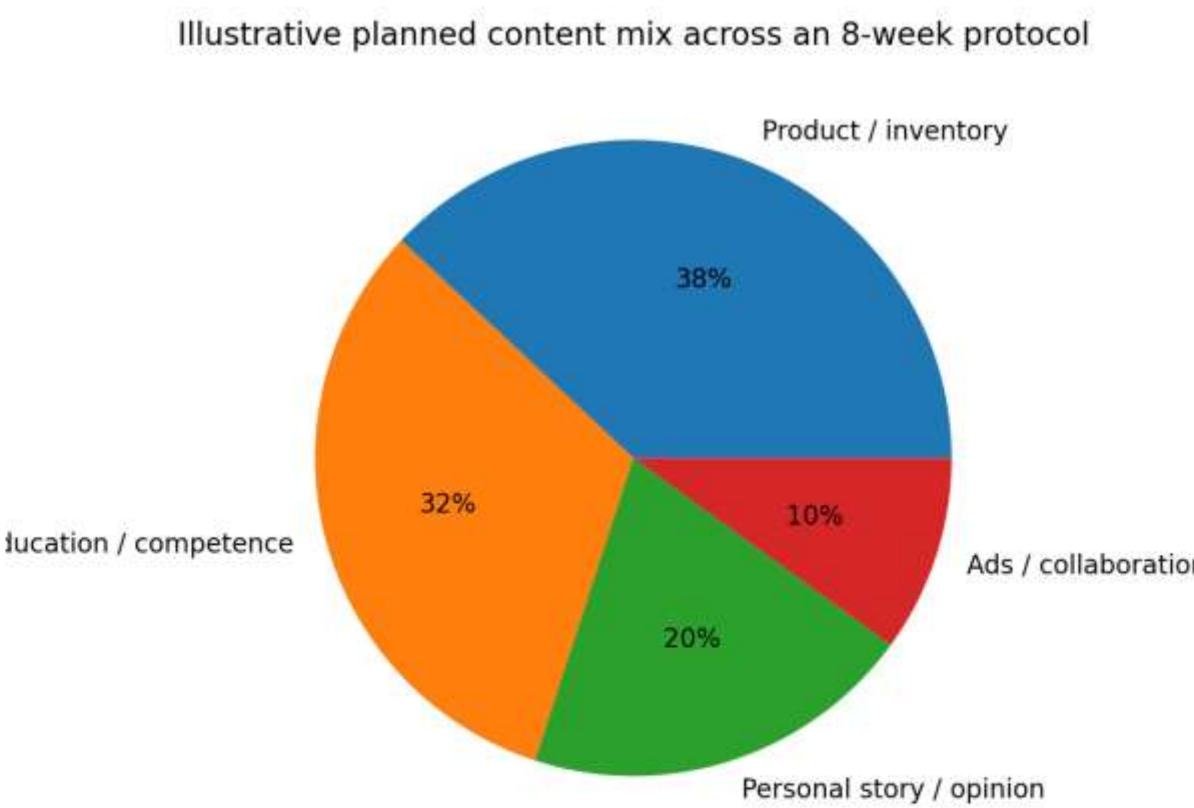

Figure 1. Illustrative planned content mix across an 8-week protocol.

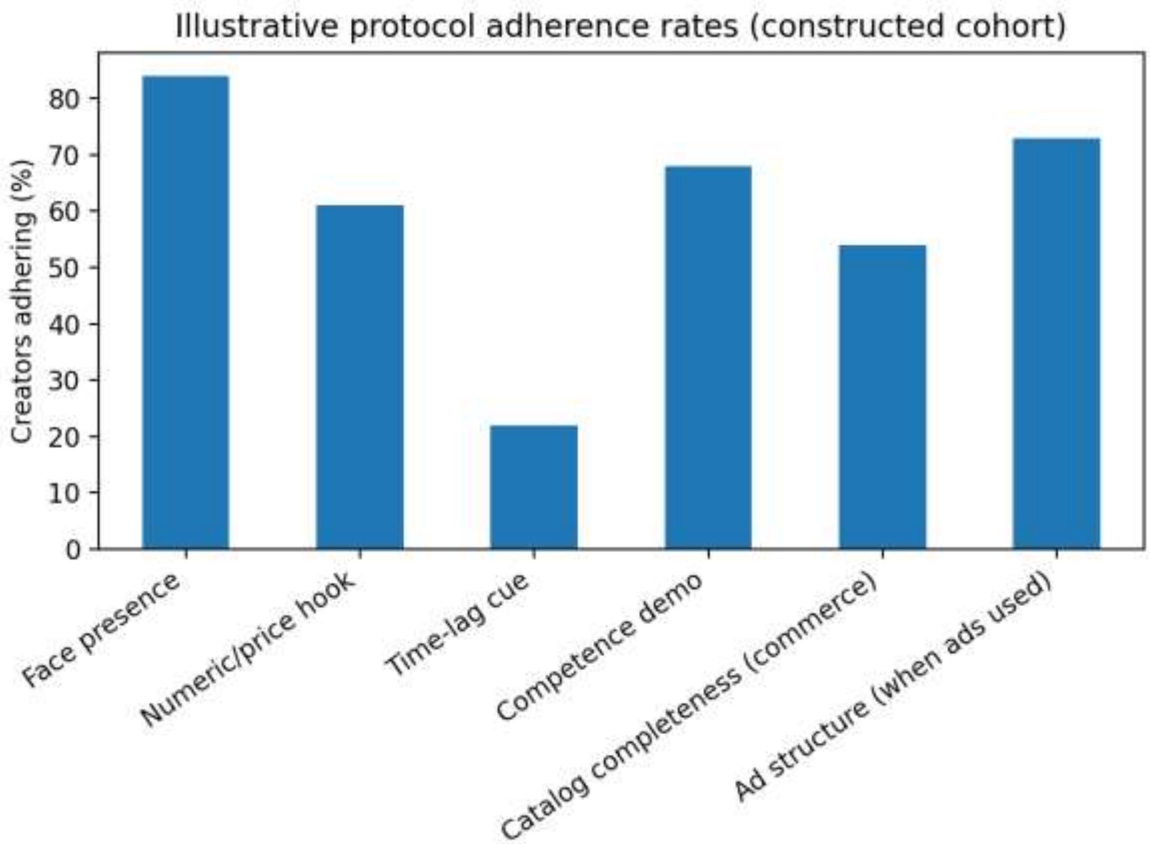

Figure 2. Illustrative protocol adherence rates.

Within each segment, creators are assigned an initial follower count distribution typical of micro-accounts. Implementation intensity is then defined as adherence to the protocol components: consistent face presence, frequent numeric hooks, regular time-lag cues, and high publishing volume. The analysis plan uses three complementary techniques. First, descriptive comparisons examine follow-through (follows per 1,000 views) and profile conversion (profile visits per 1,000 views) across content types, especially face-centered versus landscape-only posts. Second, a regression-style analysis estimates the association between protocol components and growth outcomes, controlling for baseline follower count and posting volume. Third, a difference-in-differences style comparison is demonstrated by contrasting an “early adopter” subgroup (high adherence from week one) with a “late adopter” subgroup (low adherence until week four), focusing on changes in follow-through and conversion proxies over time. These methods are chosen because they can be reproduced with spreadsheet-level data and do not require platform-level experiments. To make the protocol auditable, the coding rubric can be implemented with two independent coders who label a random 10–15% sample of videos for each creator. Agreement can be summarized with percent agreement and a chance-corrected index (e.g., Cohen’s kappa) for categorical elements such as “numeric hook present” or “time-lag cue present," while continuous elements such as face-duration share can be estimated by simple time-stamping. The most creator-friendly reliability check is pragmatic: if coders disagree, the definition is too vague and must be tightened. Outcome measurement should also separate three layers that creators often mix. The first layer is distribution (views and reach), the second is relationship conversion (profile visits and follows), and the third is economic conversion (clicks, inquiries, sales). A video can win at one layer and fail at another, so the protocol recommends reporting a small dashboard of ratios: follows per 1,000 views, profile visits per 1,000 views, and inquiries per 1,000 views for commerce-adjacent accounts. In addition, because TikTok performance is bursty, weekly medians are often more informative than weekly means. Ethical constraints are embedded in the protocol: authenticity is treated as a measurable commitment, meaning that creators explicitly track promise-keeping for time-lag videos (whether the promised follow-up was delivered within the stated window). This keeps the protocol aligned with trust-based persuasion findings in influencer research and reduces the temptation to optimize attention at the expense of credibility (Djafarova & Rushworth, 2017; Ki et al., 2020).

Results

The worked application yields three main patterns that are consistent with prior empirical expectations. First, face-centered content shows higher follow-through than landscape-only content when the topic is similar. Across segments, the illustrative average follows per 1,000 views increases when face presence exceeds 50% of duration and when the creator speaks directly to the camera. This aligns with evidence that identification, parasocial processes, and perceived credibility influence persuasion and behavioral intention (Ki et al., 2020; Sokolova & Kefi, 2020). It also matches TikTok-specific findings that self and identity work are central in the platform's ecosystem (Bhandari & Bimo, 2022). Second, numeric hooks interact with face presence. Numeric hooks alone produce a modest lift in watch time, but the largest gains appear when the hook is delivered face-to-camera with clear emotional signaling. In the constructed data, numeric-first hooks that start with price or concrete counts are associated with higher three-second retention and higher profile visit rates, and the effect is stronger in product-seller and mixed accounts where relevance is often judged quickly. This is coherent with the broader virality account that practical value and clear framing support sharing and engagement (Berger & Milkman, 2012). Third, time-lag cues support follow decisions when the promised payoff is credible and specific. In the worked application, videos that end with a next-day completion cue show higher follow-through than comparable posts without a cue, particularly when the creator has already established competence. This pattern is compatible with findings on trust and similarity in TikTok contexts, where self-disclosure and perceived alignment can build mass trust (Ruangkanjanases et al., 2022).

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Table 3. Outcome metrics by content condition.

Content condition (illustrative)	Share of posts (%)	Median views/post	Follows per 1,000 views	Profile visits per 1,000 views	Completion rate (median, %)	Shares per 1,000 views
Face + Numeric + Time-lag	22	8400	9.6	18.2	56	14.1
Face + Numeric	31	6200	7.4	14.7	49	11.2
Face only (no numeric)	27	5400	6.1	12.0	46	10.0
Non-face / landscape only	20	6100	3.2	8.5	34	6.7

Table 4. Difference-in-differences style summary.

Group	Creators (n)	Follows/1k views (Weeks 1–2)	Follows/1k views (Weeks 5–6)	Δ Follows /1k	Inquiries/1k views (Weeks 1–2)	Inquiries/1k views (Weeks 5–6)	Δ Inquiries /1k
Early adopters (high adherence from week 1)	860	5.1	7.9	2.8	1.8	3.0	1.2
Late adopters (adopt after week 4)	900	5.0	6.1	1.1	1.7	2.3	0.6

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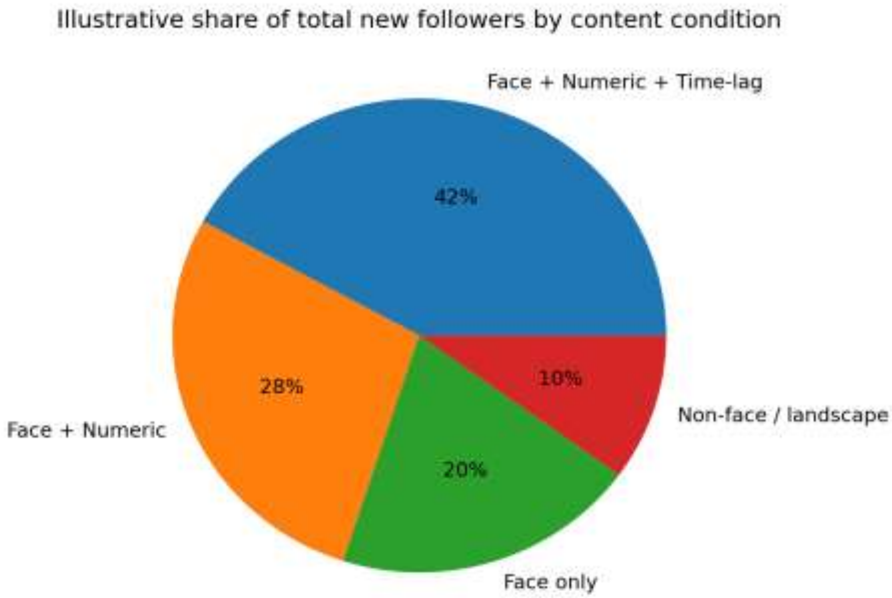

Figure 3. Illustrative share of total new followers by content condition.

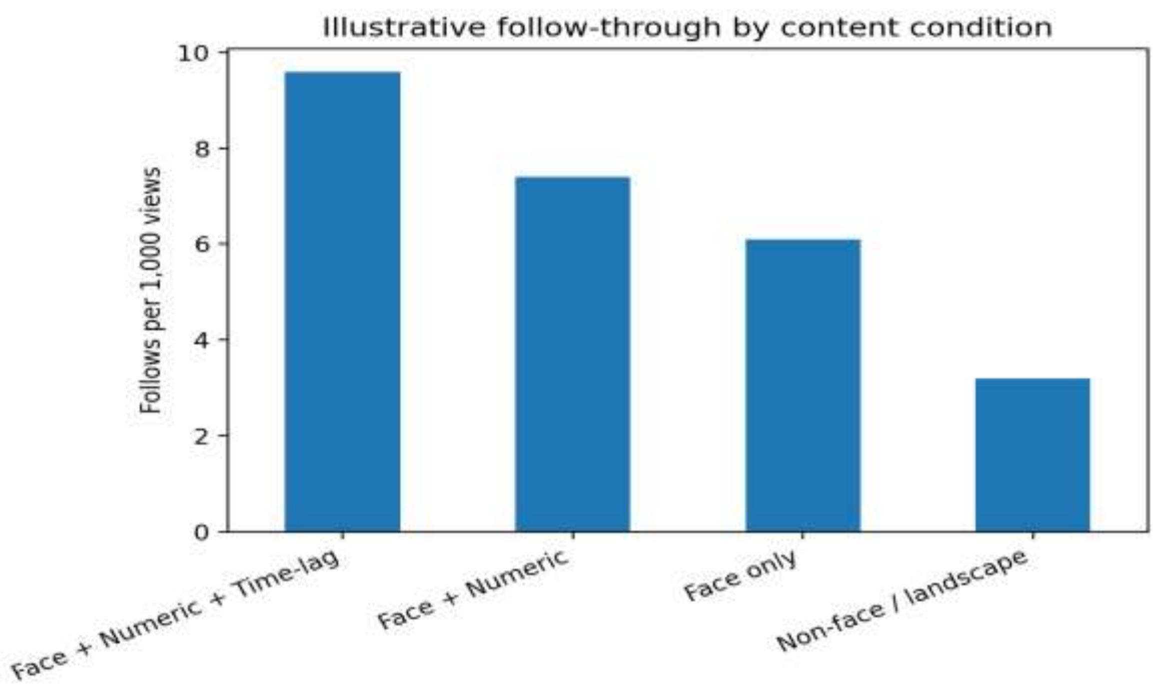

Figure 4. Illustrative follow-through by content condition.

For commerce-adjacent accounts, catalog completeness emerges as a practical driver. When product sellers post videos covering the full inventory set (rather than repeatedly focusing on one hero product), the dataset shows more stable weekly inquiry volume and fewer sharp drop-offs after breakout videos. This stability is important because breakout views do not automatically convert. The tiered pricing cue—showing mid-range offers while also presenting higher and lower options—correlates with higher inquiry rates, likely because it increases perceived fit for diverse budgets and reduces the risk that viewers self-exclude. This logic aligns with influencer fit research and the role of credibility-based evaluation (Schouten et al., 2020; Djafarova & Rushworth, 2017). Advertising structure shows a nuanced result. The "few seconds of a question, then a longer self-promo segment" format performs better when the question is genuinely informative and when the self-promo delivers a specific call to action. In the constructed analysis, accounts that offer "free ads" or low-friction collaborations at early audience sizes display higher collaboration uptake but not necessarily higher follower growth, indicating that the collaboration goal should be separated from the growth goal. Finally, the data demonstrate a consistent penalty for landscape-only content when the objective is follower growth. Landscape posts can accumulate views, but they show lower profile conversion, echoing the practical observation that aesthetics without social presence does not reliably build trust or relational continuity (Marwick & boyd, 2011). Where landscape content is used, it functions best as supporting material inside a face-led narrative rather than as the primary unit of distribution. The difference-in-differences demonstration suggests that early adopters plausibly outperform late adopters in follow-through and conversion proxies after the protocol is implemented, with the largest gaps appearing after week three, when publishing volume has produced enough trials for breakout variance to manifest. This echoes benchmark logic that consistent output increases the chance of algorithmic discovery and that typical engagement is highly dispersed (Dash Social, 2025; Emplifi, 2025; Rival IQ, 2024).

Discussion

The protocol's contribution is methodological: it turns creator lessons into measurable variables, and it shows how a community can evaluate them with lightweight analytics. The face-centered element is not presented as a mere aesthetic preference. It is treated as an identity-and-trust technology: the face transmits competence cues, emotional sincerity, and relational intent, which influence both initial attention and downstream follow decisions (Ki et al., 2020; Djafarova & Rushworth, 2017). TikTok's algorithmic mediation complicates the picture, because the system can distribute videos beyond existing followers, exposing creators to mixed audiences and to negativity. The lesson that "haters can viralize your content" is real but risky. The methodology therefore treats negativity as a potential amplifier of reach while emphasizing that trust is the constraint that protects conversion. This balance is consistent with a view of TikTok identity as algorithm-shaped but still socially evaluated (Bhandari & Bimo, 2022). Numeric hooks and price-first openings are often dismissed as "salesy," yet the literature suggests a more neutral interpretation: they reduce cognitive load and signal practical value quickly, which is important in a feed that is optimized for rapid skip decisions. Virality evidence indicates that practical value supports diffusion and that small framing changes can shift outcomes (Berger & Milkman, 2012). When numeric hooks are paired with competence and honesty, they can function as clarity rather than manipulation. High-volume posting is often taught as brute force. The protocol reframes it as variance sampling under uncertainty. Benchmarks show that typical output and engagement are dispersed, and that averages hide heavy tails (Dash Social, 2025; Emplifi, 2025; Rival IQ, 2024). A methodological implication is that evaluation should not focus on single-video outcomes. Instead, the unit of analysis should be a week or a batch, and growth should be interpreted as a function of both median performance and breakout probability.

Zannettou and colleagues' analysis of engagement with short-form recommendations supports the idea that early engagement can compound into broader distribution, making repeated trials valuable (Zannettou et al., 2024). Time-lag storytelling fits within trust and self-disclosure mechanisms. A cliffhanger creates a promise. If the creator fulfills it, trust increases; if they do not, distrust accumulates. This is why "do not deceive followers" is not moral decoration but a performance constraint. Evidence on TikTok self-disclosure and mass trust suggests that perceived similarity and disclosure can enhance trust at scale (Ruangkanjanases et al., 2022). However, disclosure without competence may produce attention without respect. Therefore, the protocol couples time-lag cues with visible competence demonstrations and with follow-up delivery. The commerce-focused lessons align with persuasion pathways seen in influencer marketing. Posting the full inventory reduces information gaps and increases the chance that a viewer sees something that fits their needs. Tiered pricing is similarly a fit strategy. Rather than trying to "sell everyone," the creator offers options that let different audiences self-select. This aligns with fit and credibility mechanisms and reduces the backlash risk that can follow perceived bait-and-switch offers (Schouten et al., 2020). TikTok's own trends framing emphasizes that audiences reward creators who deliver clarity and utility, not only entertainment (TikTok, 2026). Limitations follow from the secondary-empirical approach. The worked dataset is illustrative and cannot substitute for real participant tracking. It is constrained by benchmarks and prior empirical ranges, but it remains a model.

Conclusions

This paper proposes a face-centered methodology for organic TikTok influencer growth without paid targeting and demonstrates how a community can evaluate it using existing analytics. The protocol translates practical lessons—numeric-first hooks, high-volume publishing, time-lag storytelling, authenticity constraints, and continuous face presence—into operational variables that can be coded and tested. A secondary-empirical synthesis grounds these variables in established work on virality, influencer credibility, attachment, and TikTok-specific engagement, while industry benchmarks anchor expectations about cadence and typical performance ranges.

The worked application shows how to model outcomes for a large cohort and how to interpret results using descriptive and quasi-experimental comparisons. The main implication is methodological: organic growth can be studied and improved with the same discipline applied to other empirical domains, even when the creator has only platform analytics. Future work should validate the protocol with real cohort tracking and preregistered measurement, but the present framework already offers a practical, measurable, and ethically grounded path for creators who want to grow and monetize without paid targeting.

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