From Person to Brand: Tailoring Content Strategy to Influencer Audience Size

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Abstract

The rise of influencers underscores the growing importance of personal branding in the digital landscape. This study explores how influencers with different follower size can strategically select posting topics and craft messages to enhance their audience engagement. Using BERTopic modeling to analyze topic selection, generative AI for feature annotation to assess message appeal across 16,600 YouTube posts from 63 influencers, and two controlled experiments, we suggest that influencers face the challenge of balancing human-like relatability with brand-like credibility to maximize their appeal. Small influencers, often perceived as more human than brand-like, can boost perceived credibility by consistently aligning content with their domain expertise and employing cognitive appeals. Conversely, large influencers, typically seen as brand-like entities, benefit from humanizing their image by sharing relatable personal stories and adopting affective language. These findings provide actionable insights for influencers, agencies, and brands to optimize content strategies across the influencer growth stage.

Keywords: BERTopic modeling, generative AI analytics, unstructured data analysis, natural language processing, person-brand, influencer marketing

INTRODUCTION

The rapid evolution of social media has transformed influencers into influential human brands, leveraging personal appeal to wield significant influence over audiences and unlock diverse monetization opportunities. By 2024, the influencer marketing industry reached an estimated valuation of $24 billion, reflecting an extraordinary 40.5% annual growth rate since its $1.4 billion valuation in 2016 (Oberlo 2024). This remarkable growth has elevated content creation to an aspirational career path, particularly among younger generations (CNBC 2024; Vox 2022). Surveys show that 57% of Americans aged 13 to 38 would become influencers if given the chance, and the most sought after job for kids in the UK and US was being a vlogger or YouTuber (Morning Consult 2023; BBC 2019). Yet, the journey to influencer status is rife with challenges. While 15.1% of surveyed creators earn over $100,000 annually, nearly half fail to monetize their content (NeoReach 2024), highlighting the allure and realities of the influencer economy and the critical need for strategic approaches to personal brand building.

We focus on YouTube as the context for studying personal brand building for several reasons. YouTube, one of the largest social media platforms, hosts over 63.8 million active creators uploading 500 hours of content every minute (AffMaven 2024). It reached over 2.6 billion monthly active users in 2022, accounting for nearly 45% of all internet users worldwide (Global Media Insight 2024). Its ecosystem includes both large, established influencers and smaller creators, allowing comparisons across influencer types and insight into how audience size and content strategies influence engagement dynamics. Unlike the transient nature of content on other platforms, YouTube's long-form, narrative-driven format allows influencers to craft a distinct voice, visual style, and identity, which are key components of personal branding. Furthermore, YouTube provides monetization opportunities independent of external brand sponsorships, such as ad revenue through the YouTube Partner Program, Super Chats, channel memberships, and merchandise integration. As a result, engagement metrics like views, likes, and subscriber numbers directly translate into personal brand profitability and equity, making YouTube an ideal platform for examining influencer content strategies.

Despite the economic and cultural significance of influencer marketing, existing research has predominantly focused on brand strategies for collaborating with influencers and optimizing the effectiveness of sponsored posts (Gu, Zhang, and Kannan 2024; Hughes, Swaminathan, and Brooks 2019; Leung et al. 2022; Wies, Bleier, and Edeling 2023). In contrast, limited attention has been given to how influencers themselves strategically craft content to grow their personal brands. This gap is critical because influencers operate as dual entities, both human and brand, navigating inherent tensions between relatability and credibility (Fournier and Eckhardt 2019). Our research addresses this gap by exploring how influencers balance being human and brand as they evolve. Smaller influencers benefit from relatability and human appeal but often struggle to establish credibility and social proof. Larger influencers, on the other hand, gain authority and credibility but risk losing relatability, appearing impersonal or overly commercial. We propose that influencers can strategically adjust elements of their content to emphasize either a brand-like or human-like persona, depending on their growth stage and audience dynamics.

We employ a multi-method approach to investigate two critical dimensions of content creation that influence personal branding: topic selection (expertise-aligned vs. personal life-related content) and message appeal (cognitive vs. affective). First, we operationalized video topic alignment with domain expertise and personal life using BERTopic to categorize video topics. Our findings reveal that maintaining a narrow focus on core topics aligned with expertise enhances perceptions of credibility, whereas sharing personal life stories fosters relatability. Second, we leveraged generative AI to extract textual and visual features, uncovering distinct roles for message appeal. Cognitive appeals, such as informative, logical, and rational content, bolster perceptions of credibility and professionalism. Conversely, affective appeals, emphasizing emotional, entertaining, and interactive elements, strengthen personal connection and emotional resonance with the audience. Finally, through controlled experiments, we established causal relationships and explored the underlying mechanisms that shape perceptions of human versus brand qualities.

This research advances understanding of the challenges influencers face in developing and sustaining personal brands by offering a strategic framework for balancing brand credibility and human relatability at different growth stages. For smaller influencers, credibility can be established by consistently aligning content with expertise and using cognitive appeals to emphasize logic and information. For larger influencers, reconnecting with audiences requires strategies that reintroduce human elements, such as sharing relatable personal stories and employing affective appeals to foster emotional resonance. By examining these strategies, our research provides actionable insights to help influencers adapt their content to align with evolving audience relationships and objectives, supporting success in an increasingly competitive market.

THEORETICAL BACKGROUND

Self-Branding as Social Influencers

Existing research on influencer marketing has predominantly concentrated on strategies that enable brands to select the most suitable influencers as brand ambassadors for sponsored campaigns. This body of work highlights several key elements influencing campaign effectiveness, including objectives, promotional messaging, product features, and brand-influencer fit. For example, research has explored the objectives of sponsored campaigns, such as whether they aim to raise brand awareness or drive product trials (Hughes, Swaminathan, and Brook 2019). The use of sensory and emotionally charged language to describe sponsored products has been found to play a significant role in audience engagement (Rizzo et al. 2023; Rizzo et al. 2024), as well as the influence of facial and emotional expressions during livestream retail (Bharadwaj et al. 2022). In terms of brand and sponsorship, key factors include the prominence of sponsorship disclosure (Leung et al. 2022) and the timing of brand appearances in posts, which can significantly influence consumer attention and engagement (Chen, Yan, and Smith 2022). Additionally, the role of brand familiarity has been explored as a driver of consumer trust and recognition (Wies, Bleier, and Edeling 2022). An emerging area of focus is the potential reputational cost of sponsored content. The concept of "reputation burning" posits that posting a sponsored video, as opposed to organic content, can erode an influencer’s authenticity and credibility (Cheng and Zhang 2024).

In this research, we conceptualize influencers not merely as intermediaries in brand promotions but as dynamic entities who simultaneously cultivate personal identities and operate as marketable brands through non-sponsored content. Self-branding, or personal branding, involves crafting an image, reputation, and identity for commercial gain or cultural recognition

(Swaminathan et al. 2020). While limited literature has examined influencer as a human brand, literature on consumers' attachments to celebrities and the strategies celebrities use to construct their identities offers valuable insights for understanding influencer self-branding (Moulard, Garrity, and Rice 2015; Centeno and Wang 2017). A well-developed personal brand enhances audience engagement, fosters trust, improves conversion rates for endorsed products, and increases attractiveness to potential sponsors. Beyond immediate benefits, a strong personal brand provides resilience against shifting trends and platform changes. Influencers with solid self-brands can diversify their revenue streams by launching their own products, courses, or exclusive content, creating sustainable income sources independent of external sponsorships.

Building a personal brand differs fundamentally from corporate branding because it hinges on striking a balance between the inherently human elements of identity and the strategic imperatives of brand management. This duality introduces unique challenges and opportunities, as influencers must navigate the tension between being perceived as relatable and maintaining emotional connection while also projecting competence and credibility (Fournier and Eckhardt 2019; Thomson 2006).

On the one hand, audiences value influencers who exhibit "brand-like" qualities, such as consistency, credibility, and competence (Erdem and Swait 2004). Research underscores that perceived credibility can be elevated through strategic content choices, including expertise-aligned content and cognitive message appeals. First, credentials differentiate influencers from casual content creators by signaling source expertise (Hughes, Swaminathan, and Brooks 2019; Lou and Yuan 2019). Consistent topic selection further reinforces this expertise by showcasing focused knowledge and sustained commitment to a specific domain. By narrowing their content to specific themes, influencers signal their authority, fostering credibility and recognition as reliable, knowledgeable resources (Jiang et al. 2024). Second, cognitive message appeals—such as informative, rational and logically structured language—amplify perceptions of credibility. These appeals act as heuristics, simplifying audiences' evaluations of the influencer's expertise while simultaneously enhancing their sense of authority. This combination of knowledge conveyance and authoritative tone makes the influencer's messaging more credible (Packard, Li, and Berger 2023).

On the other hand, audiences are often drawn to influencers for their human qualities, such as relatability, authenticity, and emotional warmth (Nistor, Selove, and Villas-Boas 2024; Thomson 2006). These qualities can be enhanced through social embeddedness and the use of affective message appeals. Sharing personal experiences may introduce inconsistencies in the influencer's brand narrative, but it also fosters a sense of authenticity that inanimate brands cannot replicate (Fournier and Eckhardt 2019). Additionally, referencing private moments, particularly those involving close social relationships, enhances perceived similarity, warmth, and curiosity, making the influencer’s content feel more genuine (Chung, Ding, and Kalra 2023). These personal narratives deepen the humanized dimension of the influencer’s brand, strengthening audience connections and emotional engagement. Second, affective message appeals, such as emotionally evocative or interactive language, help reduce psychological distance between influencers and their audiences (Van Boven et al. 2010). Emotional language enhances perceptions of warmth, while interactive communication styles make followers feel personally valued rather than treated as mere metrics (Aaker, Stayman, and Hagerty 1986; Berger and Milkman 2012; Tellis et al. 2019). Together, these approaches deepen the emotional connection between influencers and their audiences, fostering relatability.

This tension between professional credibility and human authenticity presents a unique challenge for influencers, requiring them to strike a balance between brand-like qualities and relatable, personal elements. In the following section, we examine how an influencer's follower count influences audience perceptions of their position on this spectrum.

Small versus Large Influencers

Prior research demonstrates that consumers frequently rely on follower count as a heuristic to evaluate influencer credibility (Wies, Bleier, & Edeling 2022; Nistor, Selove, & Villas-Boas 2024; Rizzo et al. 2024). Building on this work, we theorize a trade-off in influencer perceptions: influencers with smaller followings are perceived as more relatable, human-like entities, whereas influencers with larger followings are viewed as professionalized brand entities. While audience growth enhances perceptions of expertise and legitimacy (De Veirman, Cauberghe, and Hudders 2017), it simultaneously erodes perceived authenticity and interpersonal connection.

Small influencers with fewer followers are often perceived more as human entities than as brands. Typically starting as regular social media users, their content appears authentic and less commercialized, reducing the psychological distance between them and their followers (Park et al. 2021). This closer connection is driven by the perceived similarity between the influencer and their audience, as well as the assumption of intrinsic, non-commercial motivations behind their content creation (Wies, Bleier, and Edeling 2022). These influencers resonate strongly with their audiences, fostering trust and relevance. However, despite this resonance, small influencers may struggle with perceptions of lacking competence. Credibility is often associated with social proof, such as endorsements from reputable brands or a substantial follower count (Lou and Yuan 2019). The absence of these validations can undermine the perceived value of their personal brand, prompting audiences to question whether their content merits attention over that of more prominent creators (Tian, Dew, and Iyengar 2024).

Large influencers, operate at near-celebrity scale, leading audiences to perceive them as brand-like entities. Their extensive reach and visibility often signal greater competence but are accompanied by diminished audience engagement and resonance (Wies, Bleier, and Edeling 2022). This perception of credibility, coupled with a sense of emotional detachment, creates social and status distance between these influencers and their followers (Gu, Zhang, and Kannan 2024), heightening scrutiny of their intentions and messaging. Research shows that as large influencers become increasingly associated with sponsorships and commercial intent, audiences are more likely to activate persuasion knowledge, reducing trust (Rizzo et al. 2024). Similarly, Karagür et al. (2022) found that content from larger influencers is more frequently perceived as advertising, resulting in emotional resonance and relational reciprocity relative to posts by smaller influencers. This shift towards a more transactional and consumeristic relationship undermines attachment and increases the likelihood of audience disengagement.

In the following section, we examine how strategic adjustments in topic selection and message appeal can enable influencers to effectively address the distinct challenges associated with their follower size.

Optimal Content Strategies

Video topic selection poses a critical strategic trade-off for influencers, who must navigate between reinforcement-seeking, focusing on specialized content to maintain consistency, and variation-seeking, which involves diversifying content to beyond their area of expertise (Jiang et al., 2024). Research underscores the importance of source expertise in persuasion, highlighting its influence on shaping consumers' attitudes and behaviors toward brands (Alba and Hutchinson 1987; Homer and Kahle 1990). Expertise also serves as a foundational driver of opinion leadership, further underscoring its role in establishing authority (Grewal, Mehta, and Kardes 2000). For smaller influencers, who lack the inherent social proof of a large following, consistently producing content aligned with their domain expertise is paramount. This approach fosters trust and credibility by reinforcing their identity as reliable, knowledgeable sources. Much like traditional brands known for their specific offerings and dependability, these influencers can build a strong brand identity by repeatedly delivering value within their niche (Park, Milberg, and Lawson 1991). Furthermore, creating a robust "library" of expertise-aligned content not only enhances visibility but also increases their appeal to audiences seeking authoritative voices in specific domains. However, as influencers grow their audience and establish competence, rigid adherence to expertise-focused and formulaic content may diminish engagement. Over time, such predictability can lead to audience fatigue and make it difficult to sustain connection with followers (Fournier and Eckhardt 2019). Formally, we predict that:

H1: *Consistently producing content aligned with their domain expertise is more effective for smaller influencers than for larger influencers.*

Personal experiences are often perceived as authentic because they appear less curated and more reflective of genuine human qualities, such as empathy, emotional intelligence, and approachability—traits that are critical in forming initial connections with audiences (Thomson 2006). By sharing such experiences, influencers can transcend the transactional nature of online interactions, fostering deeper emotional bonds with their followers. These bonds are further strengthened when influencers reference close social relationships, as this enhances perceived similarity, warmth, and curiosity, contributing to the authenticity of their content (Chung, Ding, and Kalra 2023). For larger influencers, sharing relatable experiences serves a strategic purpose: it counterbalances their aspirational status by revealing personal dimensions of their lives. This approach allows them to present a multifaceted identity that blends professional competence with relatable human attributes, thereby fostering a stronger sense of connection with their audience. In contrast, for smaller influencers, relatability is often an inherent expectation due to their smaller following, which naturally promotes a sense of closeness and approachability. As a result, additional efforts to emphasize relatability may have a diminished impact.

H2: *Sharing personal life-related content is more effective for larger influencers than for smaller influencers.*

Secondly, linguistic strategies, specifically cognitive versus affective appeals, are important in shaping how influencers are perceived along the continuum from brand-like entities to human-like figures. Prior research has explored cognitive appeals, such as logical arguments, reason-based content, and informative language, alongside affective appeals, including humor, emotional engagement, and interactive content, in the context of marketing persuasion and consumer decision-making (e.g., Faraji-Rad and Pham 2017; Hong and Chang 2015; Shiv and Fedorikhin 1999; Tu, Kwon, and Gao 2022). Cognitive appeals are effective in conveying brand-related traits like competence and expertise, while affective appeals foster interpersonal connections and social resonance, qualities typically associated with human relationships (Packard, Li, and Berger 2023). Smaller influencers often lack the social proof (e.g., follower count, brand partnerships) that larger influencers inherently possess. To compensate, cognitive appeals emulate traditional branding approaches and help establish their expertise and authority.

H3: *Cognitive appeals are more effective for smaller influencers as compared to larger influencers.*

In contrast, large influencers, whose established reputations already signal competence, benefit more from affective strategies. Emotional and interactive content help humanize their image, counteracting perceptions of excessive commercialism or detachment. By fostering "parasocial" relationships with their audience, large influencers enhance relatability, emotional connection, and authenticity, ensuring sustained loyalty and engagement as their platforms grow (Labrecque 2014).

H4: *Affective appeals are more effective for larger influencers as compared to smaller influencers.*

OVERVIEW OF EMPIRICAL RESEARCH

This research integrates large-scale YouTube data analysis with randomized controlled experiments to examine influencers' content strategies through the lenses of topic selection and language appeal. Study 1 analyzes a dataset of 16,600 YouTube videos from 63 influencers, employing BERTopic modeling to assess expertise alignment and personal life-related content, alongside GPT-based feature annotation to quantify cognitive and affective appeals. The findings test the hypothesis that smaller influencers benefit from expertise-aligned, cognitively engaging content, while larger influencers see greater success by sharing personal life stories and employing affective appeals. Studies 2 and 3 use experimental methods to establish causality and explore the underlying mechanisms. Study 2 focuses on topic selection, showing that consistent expertise alignment significantly enhances credibility and engagement for smaller influencers but exhibits diminishing returns for larger influencers. Conversely, sharing personal stories helps larger influencers appear more relatable and human, increasing audience engagement and subscription likelihood. Study 3 examines the role of message appeal, highlighting how cognitive and affective approaches shape audience perceptions along a continuum from a relatable human persona to a competent brand image. Cognitive appeals are more effective for smaller influencers, enhancing perceptions of credibility and expertise, whereas affective appeals are more effective for larger influencers, fostering relatability and emotional connection.

STUDY 1: EMPIRICAL MODELING WITH YOUTUBE FIELD DATA

Data

Our data collection followed a two-stage process to ensure comprehensive sampling and representation across a diverse range of influencer categories. In the first stage, we leveraged a curated list of influencers provided by the third-party agency HypeAuditor. The selection criteria focused on channels managed by individual creators rather than groups or corporations, with content primarily in English. To ensure diversity in content while maintaining comparability across influencer follower-size tiers, we implemented a stratified sampling approach across seven distinct content categories: fitness and health, DIY and life hacks, food and drink, fashion, beauty, tech and design, and travel. Within each category, we randomly selected three mega influencers (1M+ followers), three mid-tier influencers (375K–1M followers), and three micro influencers (100K–375K followers), following industry classifications (e.g., Metricool 2025). This approach resulted in a dataset comprising 63 YouTube channels.

For each channel, we collected both channel-level and video-level data on Jan 2022. Channel-level data included descriptive attributes such as the channel description, join date, location, claimed category, gender, and race. At the video level, we extracted detailed metrics, including video titles, descriptions, post dates, lengths, thumbnails, and engagement metrics such as views and likes.

Unlike prior research focusing on sponsored posts (e.g., Rizzo et al. 2024), our study examines self-branding on YouTube, where content creators can monetize directly through platform-based advertising without relying on external brand collaborations. As YouTube's guidelines and consumer protection laws, such as such as FTC regulations in the U.S., require creators to use clear and explicit disclosures for sponsored content, we systematically searched for these terms—such as "ad," "ads," "advertisement," "advertising," "sp," "sponsored," and "collaboration"—in the video descriptions across our dataset. This search identified 3 sponsored videos, confirming that our dataset mainly comprises organic content.

We illustrate our data structure in Figure 1 and provide a model-free summary by influencer size in Table 1. Content choice and message appeal do not differ significantly across micro, mid-tier and mega influencers. The likes-to-views ratio remains stable at approximately 3.5%, while the viewer-to-follower decreases as influencer size increases. Summary statistics for control variables are in Table 2, with additional breakdowns by gender, race, and category in Appendix A.

Youtuber size	Num of videos	% of video expertise-aligned	% of videos personal-life related	Avg cog appeal	Avg aff appeal	Likes/views ratio	View/follower ratio
Low-profile	3178	58%	3.1%	7.03	5.59	3.82%	44%
Medium-profile	4551	50%	3.9%	6.93	5.77	3.41%	32%
High-profile	8871	54%	2.0%	6.80	5.59	3.19%	19%

Table 1: Model-Free Summary by Influencer Size

Independent variable

Our primary independent variables are (1) the alignment between a video's content and the YouTuber's declared area of expertise, (2) whether the video is related to youtuber's personal life, (3) the cognitive appeal used in video title, and (4) affective appeal used in video title. We also examining their interactions with the Youtuber's follower size. In the following sections, we detail the operationalization and measurement of each variable.

Expertise Alignment. To categorize YouTube videos into distinct topics, we employed the BERTopic model (Grootendorst 2022), which utilizes transformer-based BERT embeddings to generate contextually rich and semantically meaningful topic representations. BERTopic offers significant advantages over traditional topic modeling methods, such as Latent Dirichlet Allocation (LDA), which depend on word co-occurrence patterns and often struggle with short or sparse texts. BERTopic excels in handling concise and diverse text data, making it a better choice for categorizing YouTube titles. Our implementation began with standard text preprocessing of all video titles, followed by the creation of text embeddings using Sentence Transformers. To manage the complexity of the high-dimensional embedding space, we applied the Uniform Manifold Approximation and Projection (UMAP) method for dimensionality reduction. UMAP effectively preserved the essential structure of the data while simplifying it for subsequent analysis. Given the hierarchical and interrelated nature of YouTube video topics, we employed a hierarchical version of DBSCAN (Density-Based Spatial Clustering of Applications with Noise) for clustering. This approach allowed us to identify coherent topic clusters while accounting for noise and nested relationships within the dataset. After fine-tuning the BERTopic model, we identified 33 distinct topics. Each video in our dataset was assigned to a single topic that best aligned with its content. See Figure 2 for basic hierarchical clustering results and Appendix B for descriptions and keywords of each identified category.

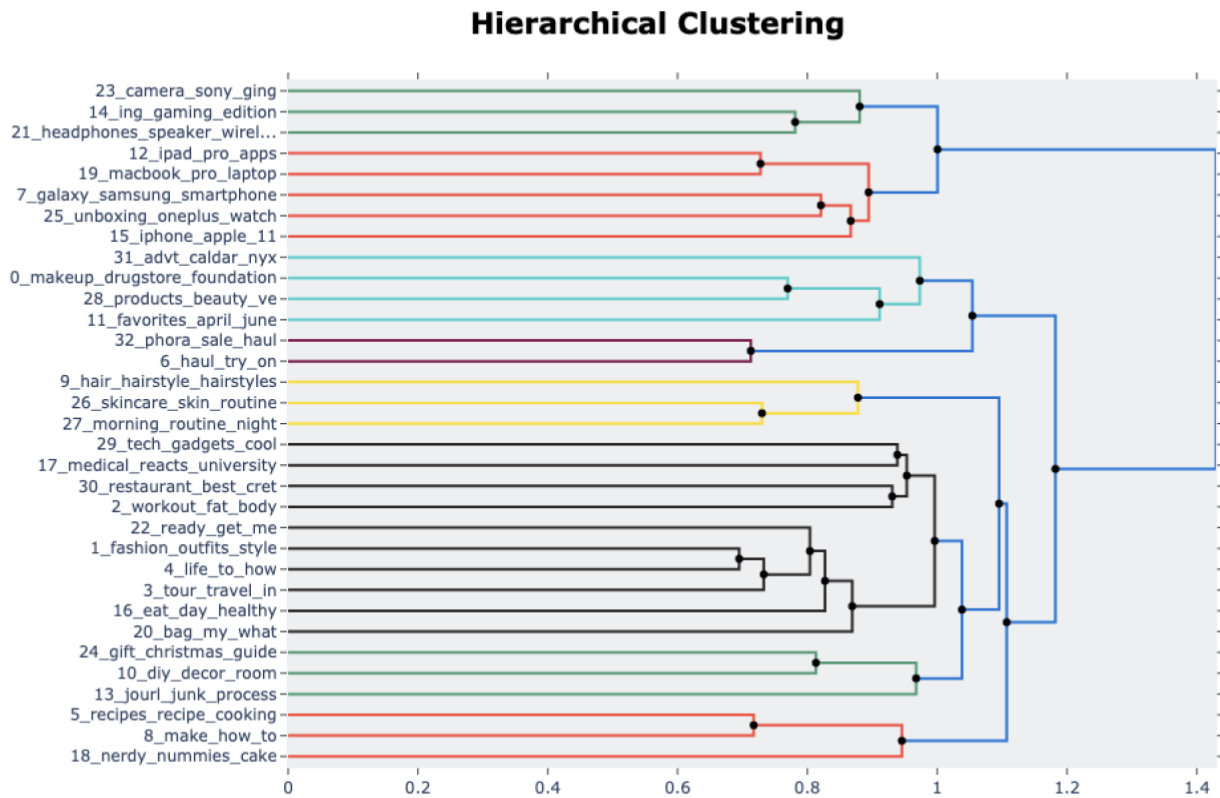

Figure 2: Topic Hierarchical Clustering Results

With the identified topics, we assessed the alignment between video content and influencer expertise. A trained coder, blind to our hypotheses and research design, evaluated each influencer's assigned category label from HypeAuditor and their self-declared expertise in the channel description. Using binary coding (1 = within expertise, 0 = beyond expertise), the coder determined whether each of the 33 topics identified by BERTopic fell within the influencer's domain of expertise. For instance, an influencer categorized under "Fitness and Health" with a self-description as a "Certified Personal Trainer (ACE)" would have videos classified under the topic "2_Workout_Fat_Body" coded as within expertise (1), while videos falling outside this category were coded as beyond expertise (0).

To ensure robustness, we incorporated topic similarity into our analysis by constructing a variable named "distance to expertise". The procedure is illustrated in Figure 3. Specifically, we calculated the cosine distances between the centroids of the 33 identified topic clusters, generating a 33-by-33 distance matrix. An intertopic distance map is presented in Appendix B. Since each YouTube video was assigned to one of the 33 topics, we used the distance matrix to calculate the minimum cosine distance between the video's assigned topic and the centroids of the topic clusters corresponding to the influencer's expertise. For example, if an influencer specialized in fitness (e.g., "2_Workout_Fat_Body" coded as within expertise) and the video posted fell under the same topic, the expertise distance for that video was zero, indicating perfect alignment. If a video was categorized beyond the influencer's core expertise (e.g., "5_Recipes_Recipe_Cooking" for a fitness YouTuber), we calculated the cosine distance between the video's topic and the influencer's expertise topic ("2_Workout_Fat_Body"). For influencers claiming expertise in multiple areas (e.g., fitness and healthy eating: "2_Workout_Fat_Body" and "16_Eat_Day_Healthy"), and posting a video categorized as "5_Recipes_Recipe_Cooking," we calculated the cosine distance from the video's topic to both expertise topics and selected the smaller value as the video's distance to the influencer's expertise. This approach accounts for varying degrees of alignment between content and expertise areas.

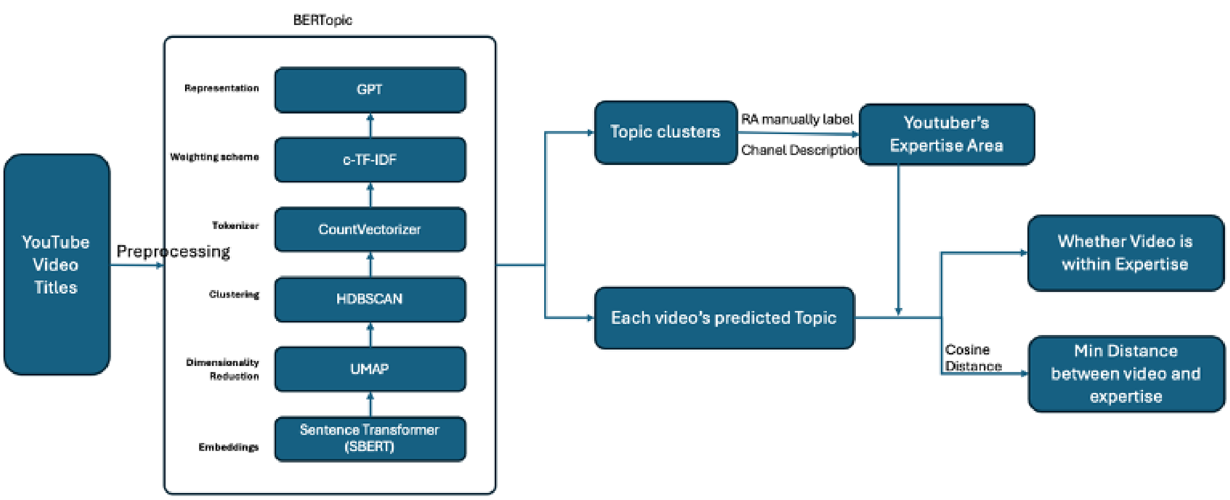

Figure 3: Flowchart for Operationalizing Expertise Alignment using BERTopic

Personal Life-Related Content. To identify whether a video was related to an influencer's personal life, we utilized two complementary approaches: (1) keyword-based identification and (2) leveraging the "4_life_to_how_thing" topic cluster derived from BERTopic modeling.

For the keyword-based method, we curated a comprehensive list of terms commonly associated with personal life content in YouTube video titles, including keywords associated with daily life recording (e.g. "life update," "life lately," "day in the life," "what's been going on," "school vlog," and "my morning routine"), revealing personal details ("Q&A," "about me," "raw moments," "opening up," and "behind the scenes") as well as terms linked to major life events (e.g., "graduation," "getting engaged," "wedding," "pregnancy," "relocation," and "career change"). Videos containing one or more of these keywords were coded as personal life-related content (1), while those without these keywords were coded as not related to personal life (0). Using this method, we identified 450 personal life-related videos. This keyword-based approach provided a precise focus on life-related content directly tied to influencers' personal details, making it the primary method for our analysis.

The second method utilized BERTopic modeling to identify topic clusters that captured life-related content. As detailed in Figure 2 and Appendix B, Topic 4, labeled "life_to_how_things," emerged as a relevant cluster. This topic was characterized by keywords such as "life," "day," "my," "habits," and "time." Sample video titles from this cluster included content related to influencer's own personal life details, such as "Studying, Cooking, and Netflix | Day in the Life During Lockdown" and "The Truth About Being a Small YouTuber." Meanwhile, it also included general lifestyle advice, such as "Make Your World More Beautiful with This Simple Idea" and "Declutter Your Digital Space: DAY SEVEN | Simplify Your Life Challenge." This cluster contained 1,313 videos. This method captured broader life-related themes, and we used this method as a robustness check, with findings reported in Appendix D.

Message Appeal. Previous literature has predominantly relied on word-based approaches, such as LIWC and VAD, to extract linguistic patterns and perform psychological analysis from textual data (Banerjee and Urminsky 2024; Chang, Mukherjee, and Chattopadhyay 2023; Rizzo et al. 2024). While LIWC is a well-established tool with validated dictionaries, its reliance on predefined word categories limits its ability to capture nuanced meanings. It treats the presence of a word as indicative of a psychological state, ignoring sentence structure, tone, and context. In this study, we propose an innovative application of large language models (LLMs), specifically GPT, to analyze the textual information in YouTube titles. GPT models, leveraging their advanced architecture and pretraining on an extensive and diverse corpus of text, excel at grasping subtle linguistic features (Gilardi et al., 2023). This makes them uniquely suited for analyzing the semantic properties of YouTube titles, enabling more precise and context-aware psychological insights.

To leverage advancements in natural language processing, we utilized the GPT-3.5-turbo API to evaluate specific message appeal aspects in YouTube video titles. Drawing on prior research on affective and cognitive processing (e.g., Banerjee and Urminsky 2024, Faraji-Rad and Pham 2017; Hong and Chang 2015; Shiv and Fedorikhin 1999; Tu, Kwon, and Gao 2022), we developed precise definitions for cognitive and affective appeals. For robustness check, cognitive appeal was further divided into three sub-traits: informative, rational, and logical. Similarly, affective appeal comprised three sub-traits: emotional, humorous, and interactive. To ensure consistency, we trained ChatGPT by providing detailed definitions of these traits, along with examples and a structured chain of thought for annotation guidance (see table 2). Each YouTube title was presented as a prompt, and ChatGPT was asked to rate the title on all traits using a 1 to 10 scale. To ensure reliability, each title was rated five times, and the average score was used as the final output for analysis. This approach allowed us to systematically quantify the cognitive and affective dimensions of message appeals in video content. See Appendix C-1 for details on the analysis procedure.

To evaluate the accuracy and reliability of various text analysis approaches, we first constructed a ground truth dataset using a rigorous labeling process: A sample of 500 randomly selected YouTube video titles from our dataset was independently coded on eight predefined text features by three expert coders, all trained psychology graduate students (see Appendix C-2 for details). Additionally, to create a non-expert human annotation sample, 317 undergraduate students from a major research university were recruited to rate the same 500 video titles on the same eight features, with each title evaluated by five students. We also employed a traditional text analysis tool, LIWC (Linguistic Inquiry and Word Count), to compute the cognitive and affective appeal of the 500 titles based on its predefined categories: cognition and affect. LIWC outputs were normalized to a 1–10 scale for comparability.

Next, we compared the outputs from GPT annotations, non-expert human annotations, and LIWC outputs against the ground truth dataset. As illustrated in Figure 4, GPT annotations outperformed both non-expert human annotations and LIWC outputs in terms of accuracy when benchmarked against the ground truth. The advantage of GPT-based annotation was particularly evident in its scalability and cost-efficiency, making it a practical solution for analyzing large datasets that would otherwise be prohibitively expensive and logistically unfeasible with human annotators.

To further validate the robustness of GPT-based annotation, we conducted additional tests using LIWC-related measures. For cognitive appeal, we operationalized it using LIWC's dimensions of analytical thinking, clout, cognition, and cognitive processes. For affective appeal, we utilized LIWC's affect and emotion dimensions. Results across these alternative operationalizations remained consistent (see Appendices D-3 and D-4). These results underscore the accuracy, scalability, and robustness of GPT-based annotation as a valuable tool for text analysis in marketing research.

Feature		Description
Cognitive Main & Sub-Dimensions	***Cognitive Appeal***	***Engages the viewer by providing logical reasoning, intellectual faculties, and valuable information.***
	Informative	Delivers valuable knowledge, data, or insights through detail-oriented and fact-based communication.
	Logical	Ensures coherence and a structured flow of arguments, making the message sound and internally consistent.
	Rational	Emphasizes reasoning, practical explanations, and cause-and-effect relationships to support decision-making.
Affective Main & Sub-Dimensions	***Affective Appeal***	***Engages the viewer, creating a connection through feelings or moods.***
	Emotional	Uses language or storytelling to evoke emotions such as empathy, excitement, or nostalgia.
	Interactive	Encourages the viewer to respond, react, or participate through calls to action or engagement prompts.
	Humorous	Incorporates humor or wit to entertain and amuse the viewer.

Table 2: Features Definitions Provided for ChatGPT Annotation

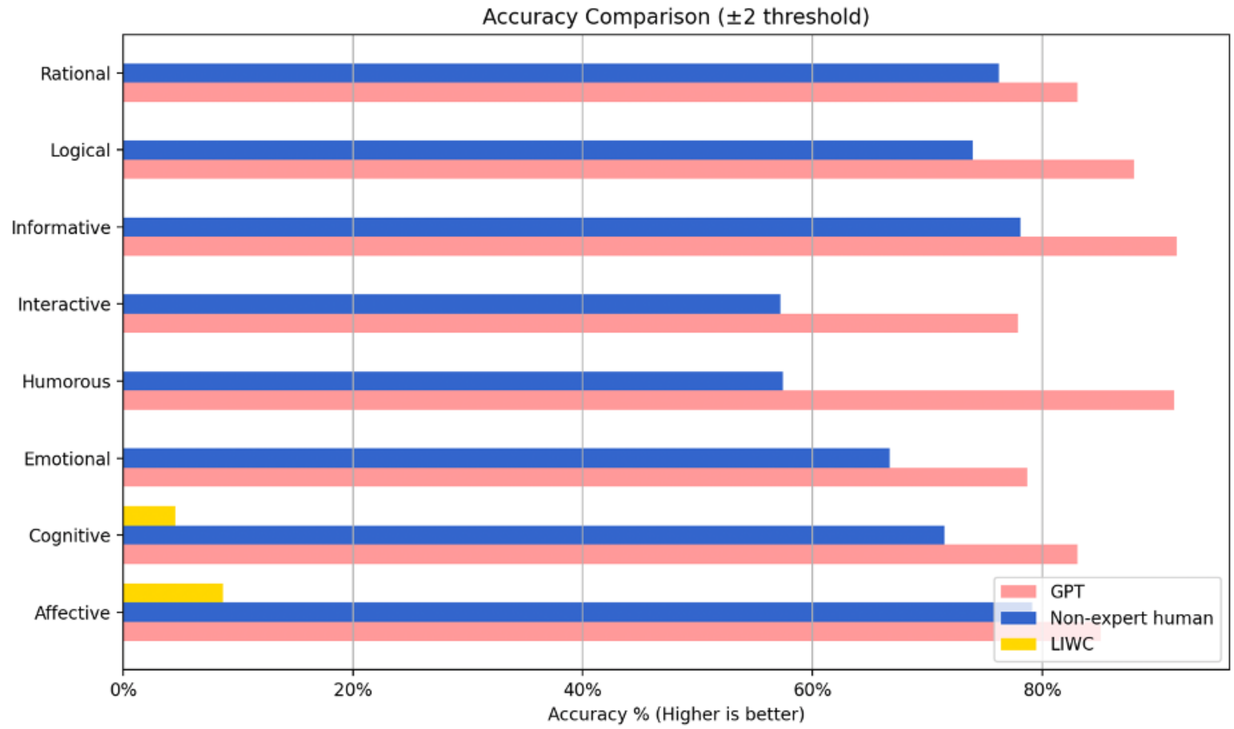

Figure 4: Accuracy Comparison Between GPT Annotation, Non-Expert Human Annotation, and LIWC Output Against Ground Truth Dataset

Key Moderators

Influencer's Follower Size. The existing literature on influencer follower size has employed diverse approaches to measure and categorize this variable. Some studies treat follower size as a continuous measure (e.g., Karagür et al. 2022; Nistor, Selove, and Villas-Boas 2024; Tian et al. 2024; Wies, Bleier, and Edeling 2023), while others use binary or categorical thresholds to create groupings (e.g., Gu, Zhang, and Kannan 2024; Rizzo et al. 2024). For instance, Cheng and Zhang (2024) ranked influencers by subscriber counts, dividing them into three categories: small, medium, and large audiences. In line with prior research, we adopt a continuous measure of follower size for our primary analysis to maintain precision and comparability. To confirm the consistency of our results across different classification methods, we validate our findings by categorizing influencers into three distinct tiers: mega (1M+ followers), mid-tier (375K–1M followers), and micro (100K–375K followers), comprising 21 influencers in each group.

Dependent Variable

We use the number of views and likes for each video as complementary dependent variables. To address the inherent skewness in the distribution of views and likes, we applied a logarithmic transformation. This adjustment ensures that our analysis appropriately accounts for the disproportionate weight of outliers, providing a more robust and interpretable representation of the data. While both views and likes provide valuable insights, they capture different aspects of audience engagement.

The Number of Views. Video views are a fundamental measure of audience attention, a prerequisite for achieving broader outcomes such as engagement and subscription (Smith and Fischer 2020). In an era of liquid modernity, the ability to capture attention has become a key marker of status (Eckhardt and Bardhi 2020). For YouTubers, views are critical to both financial success and personal brand equity, given the platform's monetization model and the central role of audience attention in brand-building. Financially, views directly translate into ad revenue through pre-roll, mid-roll, and banner ads, making them a clear indicator of profitability. Beyond revenue, high view counts signal an influencer's ability to attract an audience, reinforcing their relevance within their niche. Moreover, YouTube's recommendation algorithm favors videos with higher view counts, amplifying content visibility and expanding reach. This self-reinforcing cycle strengthens an influencer's competitive position, solidifying their brand presence and influence in the digital space.

The Number of Likes. The number of likes reflects active audience engagement and approval. Unlike views, which may include passive or incidental interactions (e.g., autoplay or brief skimming), likes represent an intentional action, capturing the viewer's positive sentiment toward the content. As a deliberate expression of approval, likes provide a more precise measure of an influencer's genuine appeal. They are less susceptible to inflation from external factors such as clickbait or paid promotions, offering a cleaner and more reliable indicator of audience engagement and content resonance.

Video-Level Control

Our control variables are categorized as either at the video level or at the YouTuber level. We first discuss the video-level control variables.

Lower-level Image Features. Besides the video title displaying the content of the video, The first impression of each video comes from the cover page. Therefore, we compute lower-level image features of the cover page to control for the effect of color, composition or attractiveness of the cover page that may have on our dependent variable (Zhang et al. 2021). The detailed list of our image features can be found in table 3. The tools for extracting these image features can be found in Web Appendix E.

Cover Page Features	
	Description
Lower-level image features	
Color	
Warm hue	Colors in the image that are red, orange, or yellow in tone.
Brightness	The level of light or luminance in the image.
Satuation	The intensity or purity of colors in the image.
Image Clarity	The sharpness and definition of the image.
Composition	
Rule of third	A compositional principle dividing the image into nine equal segments
Visual balance intensity	The distribution of visual weight or emphasis across the image.
Visual balance color	The distribution and harmony of colors within the image.
Figure-background relationship	
Size difference	The variation in sizes of objects or elements within the image.
Color difference	The range of color variations and contrasts within the image.
Texture difference	The variety of surface qualities or patterns in the image.

Table 3: Extracted Visual Features from Cover Pages

Video Length. Video duration, displayed at the bottom right of a video's cover page, plays a key role in viewer engagement. Our dataset includes videos ranging from 1 minute to 1 hour, with an average length of 12 minutes.

Pronoun Presence. Pronoun usage in video titles can influence viewer engagement (Chung, Ding, & Kalra 2023). We identify pronouns using the Linguistic Inquiry and Word Count (LIWC) tool and include this as a control variable. In our dataset, 27.41% of titles contain pronouns: 20.24% use first-person, 6.88% use second-person, and 1.24% use third-person pronouns.

YouTuber-Level Control

Besides controlling for the video level characteristics, our dependent variables may have very different baselines across different youtubers, in addition to controlling for the youtuber fixed effect, we also break the observable youtuber characteristics into a list of youtuber-level controls to see which characteristics of youtuber may be associated with higher views propensity.

Num of Video Posted. We measure YouTuber effort and devotion in their channels by the total number of videos posted. On average, each YouTuber has uploaded 361 videos.

Posting Frequency. We calculate posting frequency as the average number of days between uploads. The mean posting frequency is one video every 12.9 days.

Category. We utilize predefined content categories provided by the third-party agency HypeAuditor. Our dataset comprises seven distinct categories: fitness & health, DIY & life hacks, food & drink, fashion, beauty, tech & design, and travel.

Gender & Race. We also controlled for the gender (male, female) and race (white, black, asian, mixed, other) of the content creators.

	Mean	**std**	**Min**	**Max**
Video_Views	985621.58	3398146.00	126.00	204501500.00
Likes	25126.82	84058.96	6.00	3991787.00
Video Content Control				
Image				
Hue	55.56	25.16	0.00	164.62
Warmhue_percentage	27.22	17.99	0.00	97.57
Saturation	69.17	32.91	0.00	234.96
Brightness	160.38	34.64	7.25	252.44
Brightness contrast	4901.14	1960.63	28.15	14847.35
Intensity balance	0.59	0.08	0.13	2.85
Color balance	0.64	0.09	0.15	2.96
Area diff	289783.53	190371.58	52.00	881850.00
Color diff	128.77	28.60	19.97	250.06
Texture diff	0.01	0.01	0.00	0.29
Clarity	888.13	906.25	6.67	18712.17
Text				
Title length	15.57	5.74	3.00	47.00
Pronoun in Title -I	2.91	6.55	0.00	66.67
Pronoun in Title -We	0.26	2.16	0.00	50.00
Pronoun in Title -You	0.84	3.37	0.00	50.00
Pronoun in Title -Shehe	0.09	1.10	0.00	33.33
Pronoun in Title -They	0.05	0.83	0.00	33.33
YouTuber Level Control				
Number of Videos Posted	659.39	457.52	17.00	1602.00
Posting Frequency	7.31	6.01	2.60	102.20

Table 4: Descriptive Statistics for Video-Level and YouTuber-Level Controlled Variables

Model

We examine the relationship between influencer size and content strategy, modeling this relationship using the following linear equation:

$$\begin{aligned} Ln(Likes_{ij} + 1) \\ &= \beta_0 + \beta_1 TopicChoice_i + \beta_2 LnSub_j + \beta_3 TopicChoice_i * LnSubs_j \\ &+ VideoCharacteristics_i + YoutuberCharacteristics_j + \varepsilon_{ij} \end{aligned}$$

$$\begin{aligned} Ln(Likes_{ij} + 1) \\ &= \beta_0 + \beta_1 MessageAppeal_i + \beta_2 LnSub_j + \beta_3 MessageAppeal_i * LnSubs_j \\ &+ VideoCharacteristics_i + YoutuberCharacteristics_j + \varepsilon_{ij} \end{aligned}$$

Our analysis is conducted at the video-YouTuber level, where subscripts i and j denote individual videos and their respective creators. In our primary model, Ln(Likes +1) represents total video likes, capturing audience engagement. We replicate the analysis by substituting likes with views, where Ln(Views +1) serves as a proxy for total video reach and attention. This dual approach allows us to assess how influencer size and content strategy impact both engagement and visibility. The independent variables (X_i) capture video-level characteristics, including cover image features, video length, and pronoun usage in the title. We also control for time-varying influencer characteristics, such as posting frequency and cumulative video count. Our primary coefficient of interest, β, estimates the effect of influencer size and content strategy on content strategy effectiveness.

Analysis. We employed linear regression models to examine how influencer size shapes content strategy and its impact on video engagement, measured by the natural log of views and likes. Specifically, we analyzed the effects of topic selection (expertise-aligned vs. personal life) and message appeal (cognitive vs. affective). Table 4 presents results for video likes, while Table 5 focuses on likes as the dependent variable. Each model includes the primary predictors—expertise alignment, personal life stories, cognitive appeal, and affective appeal—along with their interaction with influencer size, measured by the natural log of subscriber count.

	Dependent Variable : Ln(Likes + 1)											
Primary Predictors	**Expertise Alignment**			**Personal Life Topic**			**Cognitive Appeal**			**Affective Appeal**		
Follower Size (Continous)	1.005***	0.758***	1.114***	1.005***	0.717***	1.000***	1.017***	1.284***	1.623***	0.997***	0.439***	0.836***
Expertise-Aligned Content	0.009	0.927***	2.504***									
Expertise Aligned Content*Follower Size		-0.063***	-0.175***									
Personal Life Content				-0.198***	-3.659***	-3.881***						
Personal Life Content * Follower Size					0.260***	0.267***						
Cognitive Appeal							0.209***	1.351***	1.460***			
Cognitive Appeal * Follower Size								-0.079***	-0.086***			
Affective Appeal										0.072***	-0.545***	-0.339***
Affective Appeal * Follower Size											0.051***	0.028***
Video Level Control												
Title length	0.002		0.001	0.002		0.002	-0.012***		-0.014***	-0.003		-0.001
Pronoun in Title -I	0.008***		0.008***	0.008***		0.008***	0.011***		0.011***	0.006***		0.006***
Pronoun in Title -We	-0.015***		-0.014***	-0.014***		-0.014***	-0.010**		-0.010**	-0.016***		-0.016***
Pronoun in Title -You	0.028***		0.026***	0.028***		0.027***	0.026***		0.024***	0.027***		0.027***
Pronoun in Title -Shehe	-0.009		-0.009	-0.009		-0.01	-0.002		-0.001	-0.012		-0.013
Pronoun in Title -They	0.041***		0.038***	0.041***		0.041***	0.044***		0.044***	0.040***		0.040***
Hue	0.005***		0.005***	0.005***		0.005***	0.005***		0.005***	0.005***		0.005***
Warmhue_percentage	0.007***		0.007***	0.007***		0.007***	0.007***		0.007***	0.007***		0.007***
Saturation	-0.001		0	-0.001		-0.001	-0.001		-0.001	-0.001		-0.001
Brightness	0.004***		0.004***	0.004***		0.004***	0.004***		0.004***	0.004***		0.004***
Brightness contrast	0		0	0		0	0		0	0		0
Intensity balance	-0.973**		-0.852*	-0.958**		-0.969**	-0.918**		-0.954**	-0.977**		-0.919**
Color balance	0.712*		0.58	0.696		0.703*	0.705*		0.762*	0.711*		0.643
Area diff	0		0	0		0	0		0	0		0
Color diff	0		0	0		0	0		0	0		0
Texture diff	77.891***		73.346***	78.183***		78.316***	73.194***		70.978***	76.320***		75.644***
Clarity	-0.001***		-0.001***	-0.001***		-0.001***	-0.001***		-0.001***	-0.001***		-0.001***
YouTuber Level Control												
Number of Videos Posted	-0.002***		-0.002***	-0.002***		-0.002***	-0.001***		-0.002***	-0.001***		-0.001***
Posting Frequency	0.012***		0.011***	0.012***		0.012***	0.011***		0.010***	0.011***		0.012***
Gender (Baseline: Male)												
Female	0.221***		0.227***	0.222***		0.219***	0.304***		0.304***	0.204***		0.198***
Race (Baseline: Other Race)												
Asian	0.212***		0.214***	0.210***		0.214***	0.260***		0.275***	0.200**		0.207**
Black	0.440***		0.416***	0.435***		0.436***	0.550***		0.558***	0.426***		0.404***
Mixed	0.513***		0.490***	0.514***		0.530***	0.533***		0.613***	0.469***		0.486***
White	0.339***		0.329***	0.336***		0.341***	0.403***		0.441***	0.308***		0.305***
Category (Baseline:Travel)												
Food & Drink	-0.222***		-0.160***	-0.224***		-0.222***	-0.362***		-0.371***	-0.224***		-0.247***
Beauty	0.138***		0.189***	0.137***		0.137***	0.069*		0.021	0.135***		0.121***
DIY & Life Hacks	-0.353***		-0.366***	-0.351***		-0.348***	-0.450***		-0.452***	-0.357***		-0.359***
Health & Fitness	-0.383***		-0.382***	-0.382***		-0.377***	-0.516***		-0.494***	-0.371***		-0.378***
Fashion	0.021		-0.002	0.02		0.023	-0.018		0.008	0.02		0.021
Tech & Design	0.444***		0.454***	0.441***		0.448***	0.343***		0.297***	0.465***		0.465***
R-squared	0.529	0.416	0.535	0.53	0.416	0.531	0.538	0.431	0.543	0.53	0.428	0.531
R-squared Adj.	0.528	0.416	0.534	0.529	0.416	0.53	0.537	0.431	0.542	0.53	0.428	0.53
N	16600	16600	16600	16600	16600	16600	16600	16600	16600	16600	16600	16600

Table 5: Study 1 Results, Number of Likes as Dependent Variable

In the expertise-alignment models, our baseline analysis, which controls for video content and influencer-level characteristics, reveals no significant main effect of posting within an influencer's expertise on likes (b = .0009, p = n.s.). However, when we introduce an interaction term between expertise alignment and follower size, we find a significant negative interaction (b = -0.175, $p < .001$). This supports Hypothesis 1, indicating that the effectiveness of expertise-aligned content diminishes as an influencer's follower count increases. A Johnson-Neyman analysis identifies the significance region at Ln(X) = 14.01 to 14.54, suggesting that expertise-aligned content benefits influencers with fewer than 1.23 million followers (68.2% of influencers and 47.5% of videos in our dataset fall below this threshold) but backfires for those with more than 2.06 million followers (23.8% of influencers and 45.7% of videos in our dataset exceed this threshold). These findings suggest that consistently producing content aligned with domain expertise provides social proof and enhances credibility for smaller influencers, while revealing a threshold beyond which excessive expertise-focused content may lead to audience fatigue and reduced engagement for large influencers.

In the personal life stories models, our baseline analysis, controlling for video content and influencer-level characteristics, reveals a negative main effect of sharing personal life-related content on likes (b = -.198, p < .001). This may be because, compared to instructional or expertise-driven content, personal life stories are perceived as offering less actionable value. Consumers often engage with social media content to learn, be entertained, or solve a problem, and personal anecdotes may not fulfill these needs as effectively. However, when we introduce an interaction term between personal life stories and follower size, we find a significant positive interaction (b = .267, p < .001). This supports Hypothesis 2, indicating that the effectiveness of personal life-related content increases as an influencer's follower count grows. A Johnson-Neyman analysis identifies the significance region at Ln(X) = 14.09 to 15.21, showing that personal life-related content negatively impacts influencers with fewer than 1.35 million followers (69.8% of influencers and 48.6% of videos in our dataset fall below this threshold) but enhances engagement for those with more than 4.03 million followers (14.3% of influencers and 32.6% of videos in our dataset exceed this threshold). These findings suggest that lower-profile influencers may see reduced engagement from sharing mundane life updates, as they are perceived as ordinary individuals. In contrast, large influencers, seen as aspirational figures, can enhance their relatability by sharing personal content.

Our analysis of message appeal reveals that both cognitive (b = .209, p < .001) and affective (b = .072, p < .001) appeals enhance a video's likability. However, their interaction with an influencer's follower size follows distinct patterns. Specifically, the interaction between cognitive appeal and follower size is significantly negative (b = -0.086, p < .001), supporting Hypothesis 3. This indicates that the effectiveness of cognitive appeal diminishes as an influencer's follower count increases. A Johnson-Neyman analysis identifies the significance threshold at Ln(X) = 16.65, suggesting that cognitive appeal enhances engagement for influencers with fewer than 15.56 million followers (93.7% of influencers and 85.8% of videos in our dataset fall below this threshold) but becomes ineffective for those exceeding this follower count.

In contrast, the interaction between affective appeal and follower size is significantly positive ($b = 0.028$, $p < .001$), supporting Hypothesis 4. This suggests that affective appeal becomes increasingly effective as an influencer's follower count grows. A Johnson-Neyman analysis identifies the significance threshold at Ln(X) = 12.95, indicating that affective appeal positively impacts influencers with more than 420,836 followers (60.3% of influencers and 79.2% of videos in our dataset exceed this threshold) but remains ineffective for those with fewer followers.

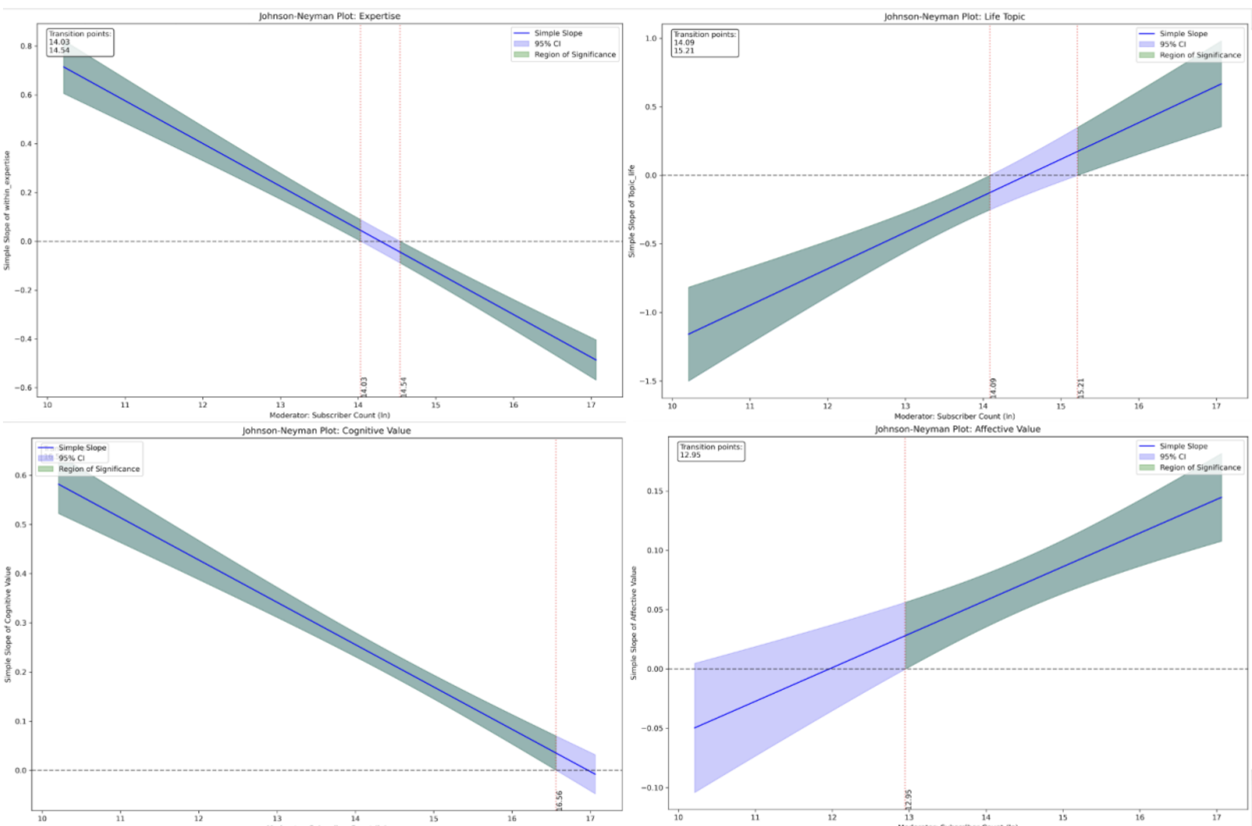

Figure 5: Interaction between Content Strategies and Influencer's Follower Size as Illustrated by Johnson-Neyman Floodlight Analysis

	Dependent Variable : Ln(Views + 1)											
Primary Predictors	**Expertise Alignment**			**Personal Life Topic**			**Cognitive Appeal**			**Affective Appeal**		
Follower Size (Continous)	1.011***	0.823***	1.105***	1.013***	0.800***	1.009***	1.026***	1.346***	1.656***	1.010***	0.490***	0.838***
Expertise-Aligned Content	0.059***	0.551***	2.224***									
Expertise Aligned Content*Follower Size		-0.034***	-0.152***									
Personal Life Content				-0.213***	-2.763***	-3.142***						
Personal Life Content * Follower Size					0.191***	0.212***						
Cognitive Appeal							0.222***	1.339***	1.522***			
Cognitive Appeal * Follower Size								-0.075***	-0.089***			
Affective Appeal										0.034***	-0.681***	-0.404***
Affective Appeal * Follower Size											0.056***	0.030***
Video Level Control												
Title length	0.004*		0.004*	0.004**		0.005**	-0.011***		-0.013***	0.002		0.004*
Pronoun in Title -I	0.003**		0.003**	0.003**		0.003*	0.006***		0.007***	0.002		0.002
Pronoun in Title -We	-0.014***		-0.013***	-0.014***		-0.014***	-0.009*		-0.009**	-0.015***		-0.015***
Pronoun in Title -You	0.016***		0.015***	0.016***		0.015***	0.014***		0.011***	0.015***		0.015***
Pronoun in Title -Shehe	-0.009		-0.009	-0.009		-0.01	-0.002		-0.001	-0.011		-0.011
Pronoun in Title -They	0.033***		0.030**	0.032***		0.032***	0.036***		0.036***	0.032***		0.032***
Hue	0.005***		0.005***	0.005***		0.005***	0.005***		0.005***	0.005***		0.005***
Warmhue_percentage	0.005***		0.005***	0.005***		0.005***	0.005***		0.006***	0.005***		0.005***
Saturation	-0.001**		-0.001**	-0.001**		-0.001**	-0.001**		-0.002***	-0.001**		-0.001**
Brightness	0.003***		0.003***	0.003***		0.003***	0.003***		0.002***	0.003***		0.003***
Brightness contrast	0		0	0		0	0		-0.000*	0		0
Intensity balance	-0.820*		-0.715	-0.788*		-0.797*	-0.745		-0.783*	-0.804*		-0.743
Color balance	0.565		0.451	0.533		0.539	0.543		0.602	0.547		0.475
Area diff	0		0	0		0	0		0	0		0
Color diff	0		0	0		0	0		0	0		0
Texture diff	64.098***		60.153***	65.120***		65.226***	59.837***		57.534***	64.150***		63.431***
Clarity	-0.001***		-0.001***	-0.001***		-0.001***	-0.001***		-0.001***	-0.001***		-0.001***
YouTuber Level Control												
Number of Videos Posted	-0.001***		-0.001***	-0.001***		-0.001***	-0.001***		-0.001***	-0.001***		-0.001***
Posting Frequency	0.012***		0.011***	0.012***		0.012***	0.011***		0.010***	0.012***		0.012***
Gender (Baseline: Male)												
Female	0.102***		0.107***	0.099***		0.096***	0.186***		0.186***	0.090***		0.084***
Race (Baseline: Other Race)												
Asian	0.226***		0.228***	0.208***		0.211***	0.261***		0.276***	0.202**		0.210***
Black	0.319***		0.298***	0.312***		0.313***	0.434***		0.442***	0.311***		0.287***
Mixed	0.682***		0.661***	0.669***		0.682***	0.690***		0.773***	0.646***		0.664***
White	0.268***		0.259***	0.252***		0.257***	0.323***		0.363***	0.240***		0.236***
Category (Baseline:Travel)												
Food & Drink	0.284***		0.338***	0.277***		0.278***	0.131***		0.121***	0.277***		0.253***
Beauty	-0.001		0.042	0.001		0.001	-0.071*		-0.121***	0.001		-0.013
DIY & Life Hacks	-0.565***		-0.576***	-0.571***		-0.569***	-0.675***		-0.678***	-0.576***		-0.578***
Health & Fitness	-0.371***		-0.371***	-0.366***		-0.362***	-0.508***		-0.485***	-0.361***		-0.369***
Fashion	-0.067		-0.088**	-0.076*		-0.074*	-0.116***		-0.089**	-0.076*		-0.075*
Tech & Design	0.483***		0.491***	0.458***		0.464***	0.355***		0.308***	0.470***		0.470***
R-squared	0.529	0.416	0.535	0.53	0.416	0.531	0.538	0.431	0.543	0.53	0.428	0.531
R-squared Adj.	0.528	0.416	0.534	0.529	0.416	0.53	0.537	0.431	0.542	0.53	0.428	0.53
N	16600	16600	16600	16600	16600	16600	16600	16600	16600	16600	16600	16600

Table 6: Study 1 Results, Number of View as Dependent Variable

We replicate the analysis using views instead of likes, with Ln(Views +1) as a proxy for total video reach and attention. The results remain consistent: expertise-aligned content interacts negatively with influencer size (b = -0.152, $p < .001$), while personal-life-related content interacts positively (b = 0.212, $p < .001$). Similarly, cognitive appeal shows a negative interaction with influencer size (b = -0.089, $p < .001$), whereas affective appeal exhibits a positive interaction (b = 0.030, $p < .001$).

These findings highlight the critical need to align content strategies with the unique profiles of influencers. For small influencers, adhering to their domain expertise and prioritizing cognitive appeals, such as informative and analytical content, yields the greatest benefits in terms of engagement and popularity. Conversely, large influencers achieve higher success by sharing personal life stories that employ affective appeals, fostering relatability and emotional connection with their audience. To ensure the robustness of these conclusions, we conducted additional analyses using alternative operationalizations for each primary predictor (see results in Appendix D).

Building on these empirical insights, we will conduct a controlled lab experiment to validate these findings and uncover the underlying mechanisms driving the observed effects. Specifically, we propose that:

H5: *Smaller influencers are perceived as highly relatable and human-like but less credible, whereas larger influencers are seen as credible and brand-like but less relatable.*

H6: *Consistently posting expertise-aligned content strengthens perceptions of brand-like credibility, while sharing personal life-related content enhances perceptions of human-like relatability.*

H7: *Employing cognitive message appeals will reinforce brand-like credibility, whereas using affective message appeals will enhance human-like relatability.*

STUDY 2: Topic Selection - Expertise-Aligned versus Personal Life-Related Content

Study 2 examines the role of topic selection and its interaction with follower size in influencers' personal brand development. We propose that small influencers, often perceived as relatable human rather than credible brand, benefit from consistently aligning their content with their area of expertise. This strategic focus allow them to cultivate a more credible personal brand. In contrast, large influencers, who have already established significant brand-like credibility, may experience diminishing returns from strict adherence to expertise alignment. For these influencers, sharing personal stories and insights from their lives can foster relatability, humanizing their brand and strengthening emotional connections with their audience.

Method

Study 2 employed a 2 (small influencer vs. large influencer) × 2 (expertise-aligned content vs. personal life-related content) between-subjects design. As pre-registered (https://aspredicted.org/7589-4hv6.pdf), we requested 720 responses on Amazon Mechanical Turk and received 729 completed responses.

To enhance relevance and engagement, we created experimental stimuli across three distinct content categories: (1) fitness and workout guides, (2) fashion tips, and (3) tech product reviews. At the start of the study, participants ranked these categories based on their personal interest levels. They were then randomly assigned to view stimuli featuring either a small or large influencer in their top-ranked category. To minimize gender bias, all fictitious influencers were named Jordan Wilson, a gender-neutral name. Participants were presented with the following scenario: "Imagine you come across Jordan Wilson, a YouTube content creator with 5.5 million (vs. 5.5 thousand) subscribers. Jordan has been posting [fitness and workout guides/fashion tips/tech product reviews] since 2012 (vs. 2022), with over 500 (vs. 50) videos uploaded."

Participants were then randomly assigned to one of two conditions: expertise-aligned content or personal life-related content. In the expertise-aligned content condition, participants viewed a list of 10 video titles exclusively focused on the influencer's area of expertise (e.g., for the fitness category: "10-Minute Full-Body Workout: No Equipment Needed" or "Low Impact, High Results: 5 Simple Exercises"). In the personal life-related condition, the list included a mix of five expertise-aligned videos and five personal life videos (e.g., "Why I've Been MIA – Life Update & New Beginnings" or "A Day in My Life as a YouTuber: Behind the Scenes"). The complete content categories and corresponding manipulated titles are presented in Appendix F-1.

The dependent variable, influencer popularity, was measured using two items ($\alpha = .885$): "How interested are you in watching Jordan Wilson's content?" on a 7-point Likert scale (1 = Extremely uninterested, 7 = Extremely interested), and "How likely are you to subscribe to Jordan Wilson on YouTube?" on a 7-point scale (1 = Extremely unlikely, 7 = Extremely likely).

To examine the proposed mechanism, we included two questions: Based on the influencer description, participants responded to: "YouTubers can be perceived on a spectrum from a relatable personal entity to a credible, professional brand. Where would you place this influencer?" (1 = Relatable personal entity, 7 = Credible professional brand). Based on the video list, participants answered: "To what extent do these videos make the influencer appear more like (1) a relatable personal entity or (7) a credible professional brand?" Demographic data, including gender and age, was also collected.

Results

Likelihood to View and Subscribe. We conducted a two-way ANOVA to examine the effects of influencer size (large vs. small) and video topic (expertise-aligned content vs. personal life-related content) on participants' likelihood of viewing the video and subscribing to the influencer. Both influencer size and video topic were included as fixed factors. The analysis revealed a significant main effect of video topic, expertise-aligned content significantly increased influencer popularity relative to personal-life content (M_{expert}= 4.60 vs. $M_{personal}$ = 4.33; $F(1, 725) = 6.07$, $p = .014$, $\eta^2 = .008$). However, no significant main effect emerged between large and small influencers (M_{large} =4.55 vs. M_{small} =4.39; $F(1, 725) = 2.05$, $p =.153$, $\eta^2 = .003$). Importantly, as hypothesized, the interaction between influencer size and video topic was significant ($F(1, 725) = 33.98$, $p <.001$, $\eta^2 = .045$). Participants were more likely to view and subscribe to content from small influencers when the content aligned with their expertise, as compared to content related to personal life ($M_{expertise*small}$ =4.85 vs. $M_{personal*small}$ =3.92, $F(1, 725) =34.343$, $p < .001$). In contrast, participants were more likely to view and subscribe to content from large influencers when the content was related to personal life, as compared to expertise-aligned content ($M_{expertise*large}$ =4.36 vs. $M_{personal*large}$ =4.73, $F(1, 725) =5.67$, $p = .001$).

Human vs. Brand Perception. To investigate the underlying mechanism, we analyzed how participants perceived influencers on a spectrum ranging from a relatable human entity to a credible brand entity. Participants rated large influencers as significantly more like credible, professional brands (M_{large} = 4.73, significantly above the mid-point of 4 on a 7-point scale), while small influencers were rated as more relatable human entities (M_{small} = 3.38, significantly below the mid-point of 4). An independent t-test confirmed that this difference in perception between large and small influencers was significant ($t(727) = 11.37$, $p < .001$). Additionally, participants viewed influencers as more brand-like when their videos were consistently aligned with their expertise. The expertise-aligned video list led to higher ratings of the influencer as a credible, professional brand (M_{expert} = 4.45, significantly above the mid-point of 4), whereas the video list with personal life-related content made influencers seem more like relatable human entities ($M_{personal}$ = 2.98, significantly below the mid-point of 4). This difference in perception between the expertise-aligned content and personal life-related content was also significant ($t(727) =11.37$, $p < .001$).

Additional Exploration. We conducted additional analysis to explore whether the observed effects held across different audience and influencer categories. The predicted interactions were significant for both male ($F(1, 379) = 8.081$, $p = .005$, $\eta^2 = .021$) and female ($F(1, 326) = 31.55$, $p < .001$, $\eta^2 = .088$) audiences. For small influencers, both male and female participants were more likely to view and subscribe to content when it was aligned with the influencer's expertise, rather than content related to personal life (male audience: $M_{expertise*small} = 4.75$ vs. $M_{personal*small} = 3.81$, $F(1, 379) = 18.50$, $p < .001$; female audience: $M_{expertise*small} = 5.00$ vs. $M_{personal*small} = 4.06$, $F(1, 326) = 18.47$, $p < .001$). In contrast, for larger influencers, the effects varied by audience gender. For male participants, the advantage of expertise-aligned content diminished but did not reverse; there was no significant difference between personal life-related and expertise-aligned content ($M_{expertise*large} = 4.33$ vs. $M_{personal*large} = 4.27$, $F(1, 379) = .074$, $p = .785$). For female participants, the effect reversed: personal-life content outperformed expertise-aligned content for large influencers ($M_{expertise*large} = 4.44$ vs. $M_{personal*large} = 5.24$, $F(1, 326) = 13.32$, $p < .001$). These results suggest that female audiences place greater value on personal connections than brand-like credibility when engaging with established creators, compared to male audiences.

To further investigate whether these interactions held across different influencer categories, we segmented the data by content type. We focused on three categories: tech product reviews (predominantly male audience: N = 292, 24.0% female), fitness content (more gender-neutral: N = 258, 46.5% female), and fashion tips (primarily female audience: N = 179, 78.2% female). The predicted interactions were significant across all three categories: tech product reviews ($F(1, 288) = 10.34$, $p = .001$, $\eta^2 = .035$), fitness/workout guides ($F(1, 254) = 16.32$, $p < .001$, $\eta^2 = .060$), and fashion tips ($F(1, 175) = 8.99$, $p = .003$, $\eta^2 = .049$). However, pairwise comparisons revealed distinct patterns for each category. For small influencers, across all three categories, participants were more likely to view and subscribe to content when it aligned with the influencer's expertise, as compared to content related to personal life. The effect was strongest for small influencers in the tech product review category ($M_{expertise*small} = 4.73$ vs. $M_{personal*small} = 3.77$; $F(1, 292) = 13.24$, $p < .001$) and fitness/workout guide category ($M_{expertise*small} = 5.00$ vs. $M_{personal*small} = 3.89$; $F(1, 258) = 19.86$, $p < .001$), but was attenuated for fashion tips influencers ($M_{expertise*small} = 4.83$ vs. $M_{personal*small} = 4.24$; $F(1, 175) = 3.82$, $p = .052$).

However, for large influencers, the effects differed by category. In both the fitness/workout and tech product review categories, the advantage of expertise-aligned content diminished but did not reverse; there was no significant difference between personal life-related and expertise-aligned content for large tech product review influencers ($M_{expertise*large}$ = 4.08 vs. $M_{personal*large}$ = 4.32, $F(1, 292)$ =.83, p = .364) and large fitness/workout influencers ($M_{expertise*large}$ = 4.48 vs. $M_{personal*large}$ = 4.81, $F(1, 258)$ =1.61, p = .205). In contrast, for large fashion tips influencers, the effect reversed: personal-life content outperformed expertise-aligned content ($M_{expertise*large}$ = 4.63 vs. $M_{personal*large}$ = 5.31, $F(1, 175)$ =5.24, p = .023).

Discussion

The findings from Study 2 highlight the critical interplay between an influencer's follower size and video topic in shaping audience intent to view and subscribe. For small influencers, who are often perceived as relatable individuals, consistently aligning content with their area of expertise enhances their professional appeal, compensating for their relatively lower credibility. In contrast, for large influencers, who are already regarded as credible and well-established brands, the benefits of strict expertise alignment diminish. Instead, sharing relatable personal experiences alongside expertise-aligned content emerges as a more effective approach, enabling them to foster emotional connections with their audience while reinforcing their existing professional credibility. We further suggest that influencer size not only moderates the effectiveness of content strategies but also interacts with audience gender and content domain to shape engagement outcomes. Specifically, female audiences and viewers of fashion-related content tend to place greater value on personal connection and relational authenticity than on brand-like credibility when engaging with established influencers. This effect is less pronounced among male audiences and in content domains such as tech or fitness.

Study 3: Message Appeal - Cognitive vs. Affective

Study 3 explores how different message appeals interact with follower size to shape audience interest in viewing and following, as well as their perceptions of the influencer. We hypothesize that cognitive appeals are particularly effective in enhancing the popularity of smaller influencers, who are often perceived as relatable human entities and may need to actively establish credibility and demonstrate competence. In contrast, affective appeals are more effective for large influencers. With their credibility already established, large influencers use affective content to humanize their brand and maintain audience engagement.

Method

Study 3 employed a 2 (small influencer vs. large influencer) × 2 (cognitive appeal vs. affective appeal) between-subjects design. the study was conducted in a university lab in the Northeastern United States, undergraduate students participated in exchange for partial course credit. As pre-registered (https://aspredicted.org/bjqc-6m8b.pdf), data collection continued for five weeks, and we received 694 completed responses.

First, participants were then randomly assigned to view stimuli featuring either a small or large influencer. The scenario was "Imagine browsing YouTube and coming across Alex's Kitchen, a content creator with 5.5 million (vs. 5.5 thousand) followers who has been posting over 500 (vs. 50) videos on food tasting, cooking, and baking since 2012 (vs. 2022)."

Next, participants were randomly assigned either cognitive or affective appeal conditions and viewed a list of 5 recent videos posted by Alex's Kitchen. In the cognitive appeal condition, "Blind Comparison: Evaluating Premium vs. Budget Ingredients for Optimal Outcomes", "A Comprehensive Step-by-Step Guide to Crafting Chocolate Chip Cookies", and "The Science of Baking: How to Calibrate Your Oven for Best Performance". In the affective appeal condition, examples of videos titles were "Gourmet or Garbage: Can Pricey vs. Cheap Ingredients Fool My Taste Buds?", "Grandma's Chocolate Chip Cookies Recipe — Will They Be as Sweet as the Memories?", and "My Oven Hates Me! Join Me as I Try to Fix My Epic Baking Fails". The complete content categories and corresponding manipulated titles are presented in Appendix F-2.

The dependent variable, influencer popularity, was measured using two items ($\alpha = .847$): "How interested are you in watching Alex's Kitchen's content?" on a 7-point Likert scale (1 = Extremely uninterested, 7 = Extremely interested), and "How likely are you to subscribe to Alex's Kitchen on YouTube?" on a 7-point scale (1 = Extremely unlikely, 7 = Extremely likely).

To examine the proposed mechanism, we included two questions: Based on the influencer description, participants responded to: "YouTubers can be perceived on a spectrum from a relatable personal entity to a credible, professional brand. Where would you place this influencer?" (1 = Relatable personal entity, 7 = Credible professional brand). Based on the video list, participants answered: "To what extent do these videos make the influencer appear more like (1) a relatable personal entity or (7) a credible professional brand?" Demographic data, including gender and age, was also collected.

Results

Likelihood to View and Subscribe. We conducted a two-way ANOVA to examine the effects of influencer size (large vs. small) and appeal (affective vs. cognitive) on participants' likelihood of viewing the video and subscribing to the influencer. Both influencer size and message appeal were included as fixed factors. The main effect of message appeal on influencer popularity was not significant ($M_{affective}$ =3.98 vs. $M_{cognitive}$ =3.85 ; $F(1, 690) = 1.78$, $p = .182$, η^2 .003). However, participants were more likely to view and subscribe to content from larger influencers compared to smaller influencers (M_{large} =4.10 vs. M_{small} =3.72; $F(1, 690) = 14.86$, $p < .001$, $\eta^2 = .021$). Importantly, as hypothesized, the interaction between influencer size and message appeal was significant ($F(1, 690) = 33.82$, $p < .001$, $\eta^2 = .047$). Participants were more likely to view and subscribe to content from small influencers when their videos used cognitive rather than affective appeal ($M_{affective*small}$ =3.50 vs. $M_{cognitive*small}$ =3.95, $F(1, 690)=10.01$, $p = .002$). In contrast, participants were more likely to view and subscribe to content from large influencers when their videos used affective rather than cognitive appeal ($M_{affective*large}$ =4.46 vs. $M_{cognitive*large}$ =3.75, $F(1, 690)=25.64$, $p < .001$).

Human vs. Brand Perception. To investigate the underlying mechanism, we analyzed how participants perceived influencers on a spectrum ranging from a relatable human entity (1) to a credible brand entity (7). Participants rated large influencers as significantly more like credible brands (M_{large} = 4.34, significantly above the mid-point of 4 on a 7-point scale), while small influencers were rated as more relatable human entities (M_{small} = 3.03, significantly below the mid-point of 4). An independent t-test confirmed that this difference in perception between large and small influencers was significant ($t(692) = 11.36$, $p < .001$). Additionally, participants viewed influencers as more like a credible brand when their videos used cognitive appeal ($M_{cognitive}$ = 4.74, significantly above the mid-point of 4), whereas affective appeal made influencers seem more like relatable human entities ($M_{affective}$ = 2.87, significantly below the mid-point of 4). This difference in perception between the cognitive and affective conditions was also significant ($t(692) = 15.83$, $p < .001$).

Additional Exploration. We conducted additional analysis to explore whether the observed effects held across different audience. The predicted interactions were significant for both male ($F(1, 323) = 10.82$, $p = .001$, $\eta^2 = .032$) and female ($F(1, 358) = 26.11$, $p < .001$, $\eta^2 = .068$) audiences. For small influencers, male participants were significantly more likely to view and subscribe to content when it uses cognitive rather than affective appeal (male audience: $M_{cognitive*small} = 3.77$ vs. $M_{affective*small} = 3.24$, $F(1, 323) = 6.18$, $p = .013$). This effect held but become less pronounced for female audience ($M_{cognitive*small} = 4.06$ vs. $M_{affective*small} = 3.69$, $F(1, 358) = 3.73$, $p = .054$). In contrast, for larger influencers, male participants were significantly more likely to view and subscribe to content when it uses affective rather than cognitive appeal ($M_{cognitive*large} = 3.85$ vs. $M_{affective*large} = 4.28$, $F(1, 323) = 4.66$, $p = .032$). This effect become more pronounced for female audience ($M_{cognitive*large} = 3.58$ vs. $M_{affective*large} = 4.60$, $F(1, 358) = 27.21$, $p < .001$). These results suggest that, compared to male audiences, female audiences tend to place greater value on affective appeals and comparatively less on cognitive appeals.

Discussion

The findings of this study highlight the interplay between appeal type and influencer's follower size, providing evidence for the differential effectiveness of cognitive and affective strategies. As hypothesized, smaller influencers benefit significantly from cognitive appeals, as this type of content enhances perceptions of competence, a critical factor in establishing a credible brand identity. Conversely, larger influencers achieve greater success with affective appeals, which foster relatability and strengthen audience connection by humanizing their established brand. These results underscore the importance of aligning content strategies with an influencer's position along the spectrum from relatable human entity to credible professional brand.

GENERAL DISCUSSION

The rise of social media has fundamentally transformed personal branding, creating new avenues for individuals to build their online presence and cultivate meaningful connections with their target audiences. This study explores the complex dynamics of personal brand-building in the digital age, focusing specifically on the content creation strategies employed by social media influencers.

Utilizing a mix-method approach, including BERTopic modeling, AI-driven feature extraction, and regression analysis on a large dataset from YouTube (16,600 posts from 63 content creators in seven distinct categories), alongside two experimental studies, we demonstrate how influencers at different follower size can strategically develop their personal brands through tailored content strategies. Our findings suggest that small influencers, often viewed as more human and relatable, may struggle to establish themselves as credible brands due to the lack of inherent social proof. In a saturated digital landscape where consumers are overwhelmed by content, employing expertise-aligned content and cognitive appeals to build brand-like reliability is essential for small influencers to stand out from the crowd. However, as influencers grow their following and gain credibility, they encounter a different challenge: the need to preserve their human connection with their audience. Large influencers benefit from sharing personal life stories and using affective appeals to maintain a human-like connection, carefully balancing professionalism with approachability.

By illustrating how the optimal mix of topic selection and message appeal shifts as influencers scale their following, this research enriches both theoretical discussions and practical applications.

Theoretical Contributions

First, while previous research has primarily focused on how brands can collaborate with influencers and maximize the effectiveness of sponsored posts (e.g. Hughes et al. 2019; Rizzo et al. 2023; Rizzo et al. 2024), we extend the influencer marketing literature by identifying how influencers themselves can strategically craft their content to effectively grow their personal brands. As personal branding represents a natural extension of traditional branding practices, our study highlights the importance of applying branding principles to the evolving landscape of personal branding. A unique dilemma in personal branding lies in the interdependent relationship between an influencer's personal and professional personas (Fournier and Eckhardt 2019). Our research underscores the need for an integrated approach, bridging the gap between humanized appeals and strategic brand-building efforts, including topic selection and message appeal. This approach allows influencers to balance their personal identity with brand qualities, offering a more holistic view of personal brand-building.

Second, while past research has extensively explored how brands can select influencers based on follower count to maximize campaign effectiveness (Gu, Zhang, and Kannan 2024; Leung et al., 2022; Wies, Bleier, and Edeling 2023), our findings extend beyond this metric by adopting an influencer-focused perspective. Rather than prescribing whether influencers should focus on expertise-aligned topics or share personal life stories, use cognitive or affective language, we reveal that content strategies must adapt as an influencer's follower base expands. As influencers progress in their careers, they must continuously adapt their content to meet the shifting expectations of their expanding audience. This dynamic approach underscores the importance of modifying strategies over time, as content that resonates in the early stages of growth may lose effectiveness as influencers scale their reach.

We contribute to a deeper understanding of influencers' content creation strategies by refining two critical elements: topic selection and message appeal. Our research identifies two distinct content approaches, topic alignment and cognitive appeals, which are particularly effective for small influencers. These strategies enhance brand-related credibility by showcasing expertise and reliability, helping smaller influencers differentiate themselves in a competitive market. While prior research has emphasized the positive effects of expertise, information-rich content, and professional credentials on brand attitudes and purchase intentions (Hughes et al., 2019; Lou & Yuan, 2019; Packard & Berger, 2021), our findings suggest the presence of expertise saturation. This occurs when an overemphasis on expertise leads to diminishing returns for larger influencers, as their audience seeks more relatable and emotionally engaging content. For large influencers, we suggest that personal stories and affective appeals become increasingly important, enabling them to sustain audience engagement and foster emotional connections. By addressing this gap, our research offers insights on how influencers can balance professional credibility with personal engagement as their audience grows.

Practical Implications

Our findings provide actionable insights for influencers, agencies, and brands in tailoring content strategies based on an influencer's follower size. For small influencers, the primary recommendation is to focus on creating content that closely aligns with their domain expertise. This approach helps establish credibility and relevance, both of which are critical for building an initial follower base. Additionally, employing cognitive appeals, characterized by logical, rational, and informative content, can further enhance their perceived expertise and professionalism. As influencers grow their audience, a strategic shift becomes essential. For large influencers, the emphasis should transition to fostering relatability by sharing personal stories and experiences. Leveraging affective appeals, such as emotional, entertaining, and interactive content, enables these influencers to maintain a strong emotional connection with their audience, ensuring sustained engagement and loyalty.

This research also offers valuable insights for influencer agencies and Multi-Channel Network (MCN) companies. When pairing influencers with brands, ensuring a strong brand-influencer fit is particularly critical for small influencers. Unlike large influencers, who often benefit from their broad reach and established social proof, small influencers rely more heavily on their credentials and alignment with the brand's values and message to resonate with audiences. In contrast, large influencers, due to their widespread influence and established reputation, have greater flexibility in the brands they can partner with, as their reach often compensates for a less precise fit. Moreover, offering training programs that teach influencers how to effectively communicate their expertise and relate to their audience can be valuable. This includes workshops on crafting compelling narratives and make informed decision on content strategies.

The insights gained from this research not only inform influencer practices but also provide valuable guidance for brands seeking to optimize their influencer partnerships. It is insufficient to base collaboration decisions solely on follower count. Brands should assess how well an influencer's content strategy aligns with their growth stage. Sponsored posts by small influencers may come across as more genuine, but they might be perceived as lacking the depth of expertise large influencers offer. Collaborations with small influencers can include product reviews, tutorials, or explainer videos, reinforcing the credibility of both the influencer and the brand. In contrast, large influencers might share relatable personal experiences or host interactive events with fans, making the content feel less promotional and more like a shared experience. Tailoring partnerships in this way can lead to more effective campaigns and stronger audience resonance. Moreover, long-term partnerships should be flexible, allowing influencers to shift between cognitive and affective appeals based on their audience size and evolving market positioning.

Application of Emerging Research Methods

By integrating BERTopic for quantifying expertise alignment and applying generative AI for nuanced content analysis, we demonstrate the potential of these emerging tools and offer a notable methodological contribution to marketing research.

Our approach to text feature extraction leverages the Generative Pre-trained Transformer (GPT) API in a conversational mode to semantically analyze YouTube video titles. Unlike traditional methods that rely on keyword extraction or pre-labeled datasets (e.g., LIWC, emoLex, or VADER), generative AI allows for more dynamic and adaptable content analysis, breaking free from rigid, predefined feature sets. This overcomes many of the limitations of keyword-based or dictionary-driven tools, which often fail to capture semantic depth, context shifts, or creative language use in real-world data like YouTube titles. The flexibility offered by generative AI enhances not only the specificity of the analysis but also facilitates the discovery of hidden patterns and themes that might otherwise be overlooked. It enables greater adaptability in selecting variables tailored to specific research questions and improves accuracy, as demonstrated by our rigorous validation process. As generative AI continues to evolve, this method holds great promise for future research, offering the potential for even deeper insights into consumer engagement and digital content dynamics.

In addition, our use of the BERTopic model for clustering video titles enables the exploration of latent semantic similarities and dissimilarities, capturing subtle nuances in language and context. This method provides richer insights into how expertise alignment manifests in digital content, allowing us to identify intricate connections between video topics and influencer expertise. Unlike more rigid clustering techniques, BERTopic combines BERT embeddings with dynamic topic modeling to capture both subtle semantic relationships and distinct thematic variations between titles. This allows us to group videos based on their underlying thematic connections, even when their surface-level language differs significantly. By analyzing these latent semantic patterns, we uncover how video content aligns with influencer expertise and relates to their personal lives, identifying relationships that might not be apparent through traditional keyword-based clustering methods. BERTopic's ability to detect thematic shifts and context nuances enables us to refine our understanding of expertise alignment and provides a robust methodological framework for future studies aiming to analyze large volumes of digital content in a more sophisticated, context-aware manner.

Directions for Future Research

The focus on YouTube as a specific platform offers valuable insights, but it also highlights the need to explore whether our findings apply across other social media contexts. YouTube's unique content structure, user interaction patterns, and recommendation algorithms—especially its emphasis on long-form video content—shape how expertise alignment and content dynamics unfold. These platform-specific features, such as visual engagement, search functionality, and algorithm-driven content discovery, may influence the outcomes in ways that differ from platforms with shorter-form content or other media formats. Additionally, YouTube's monetization model, audience retention metrics, and subscription-based engagement may lead to dynamics distinct from platforms focused on short-form or text/image-based content.

Future research has the opportunity to extend these findings by examining how similar dynamics play out across other platforms. For example, platforms that prioritize short-form content like TikTok and Instagram Reels, live-streaming platforms like Twitch, or audio-based platforms like Spotify (for podcasts) could present different engagement patterns. Each of these platforms has distinct mechanisms for user interaction and content consumption, which could yield further insights into the role of expertise alignment in influencer success. Exploring text-based platforms such as Twitter and LinkedIn, image-focused platforms like Instagram and Pinterest, or mixed-format platforms like Facebook could also reveal how different mediums impact influencer-audience engagement. By broadening the research scope to include a variety of platforms and content formats, future studies can enhance the generalizability and applicability of these findings across the evolving digital content landscape.

While our study captures a snapshot of content strategies for influencers, it does focus primarily on video views and likes as the dependent variable. We acknowledge that this may appear as a limitation, as it does not account for the specific content elements of the videos themselves, such as content quality, scene changes or acoustic appeal. However, our focus on video views is a justifiable and practical approach to understanding the drivers of influencer's success at the attention stage, given the complexity of influencer content and the broad scope of our study. Future studies could complement this approach by delving deeper into content-specific features to provide a more comprehensive understanding of engagement.

Future research should employ longitudinal studies to track individual influencers over time, providing a more granular understanding of when and why they shift their content strategies. By following influencers through various growth stages, researchers could identify key transition points, such as follower milestones, changes in engagement metrics, or shifts in content formats, that drive strategic adjustments. Additionally, longitudinal research could investigate the influence of external factors, such as platform algorithm updates, changes in monetization policies, or shifts in audience preferences, on the evolution of content strategies. This approach would offer a deeper understanding of the factors driving strategy shifts, providing a more detailed view of the influencer lifecycle and allowing researchers to distinguish between short-term adjustments and long-term strategic pivots. Furthermore, this type of study could explore the sustainability of different strategies across different influencer growth trajectories, offering practical insights into how influencers maintain or scale their success over time.

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