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‘Running to the Comments’: Examining the Cross-Platform Elasticity of Comment-to-Like Ratios Across Instagram and TikTok

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Abstract

Audience engagement in the form of comments and likes has long been known to influence the visibility of content creators, but little has been discussed in the ways that these interaction ecologies diverge between platforms. Using poetry posts surfaced from Instagram and TikTok’s search results as a case study, this paper utilises a regression model to compare the elasticity of growth for comment-to-like ratios between platforms. Results demonstrate that for low-engagement posts, Instagram’s ratios are higher, but those on TikTok scale at a much faster rate once posts gain more traction. The paper discusses comment strategies that content creators may use to leverage this information in an economy where attention grows scarce and social proof is increasingly more valuable.

Keywords: platforms; poetry; engagement metrics; comment ratios; content creators; social media

1. Introduction

It has been nearly a decade since the genre of Instapoetry established itself as a mainstream literary phenomenon, a moment crystallised when Rupi Kaur—often dubbed ‘Queen of the Instapoets’ (Carlin, 2017)—was featured at the top of the New York Times Bestseller list. Through strategic platform visibility tactics, Kaur and other poets like atticus, R.M. Drake, and Nikita Gill professionalised affective practices, curating aphorisms on romance, loss, and self-empowerment at an accelerated rate to achieve prominence in the always-demanding Attention Economy. The viral new genre, widely celebrated for its accessibility and critiqued for its perceived aesthetic genericity, served as a case study of the increasing industrialisation of platform-native art forms, revealing that enigmatic algorithmic systems have simply recalibrated barriers of value and visibility even as they claim to demarginalise creative voices.

As platforms evolved, so too did these professional-amateur poets. While many of the original Instapoets consolidated their success through print publication, sustaining a minimal platform presence to promote their latest Amazon edition or live performance, newer poets have needed to extend their voices across TikTok, X, Discord, Reddit, and more to gain a wider reach. Though platform poetry has proliferated, however, so too have the pressures shaping its production, ranging from increasingly opaque algorithmic governance to the recent influx of LLM-generated content. These compounding forces demand a new resilience from social media poets who are reframing their artistic personas whilst employing a broader repertoire of professional strategies to maintain relevance, from ‘stitching’ collaborations with other artists to re-establishing authorial ‘manifattura’—anything that

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makes their work appear more distinct. In addition to reverting to past literary traditions of rhetorical aurality and imagery, these most recent digital creators are also more skillfully involving their audiences, whose very participation continually shapes the living artefact that is a posted poem. While it has long been understood how social media production is dependent upon prosumers' participatory culture (Jenkins et al., 2015), it is important to note that the visibility of audience engagement, in which 'wreaders' (writer/readers) directly co-produce a continual 'reality in metamorphosis' (di Rosario, 2009, para 62), has increasingly impacted platform poetry's reception and reach. Genette's original foundation that public mediated epitext is also core to the original authorial product (Genette, 1997, p. 351) holds true with platform poems, where all the paratextual elements that frame the original product—such as the metrics of likes and comments—do not simply evidence the audience's general reception, but directly influence the poem's ability to receive future promotion (Penke, 2023, p. 36). Indeed, their prominent placement directly below or on top of each post categorises them as *'an essential part of the poem'* (Berens, 2019), which further influences the post's developing value.

It is unclear whether the first wave of Instapoets gave such weight to audience engagement as a collective part of their poems—indeed, microcelebrity poets such as Kaur, Atticus, Gill, and many others made it a point to neither follow nor interact with other users, whether their audiences or each other, as if to prove their own exclusivity (Knox, 2024). Now, however, the new generation of platform poets—as well as other creators—have reestablished the importance of interacting with their followers, where the ever-visible audience interactions not only signal the success of the original post or the friendly authenticity of the poster (Schouten et al., 2019; Abidin, 2015) but encourage additional engagement and reach through parasocial relationships (Labrecque, 2014). As it is 'in the creators' best interest to engage an audience that will continue to watch future videos, which can be done by actively promoting the creation of relationships with that audience' (Ferchaud et al., 2018), the comments accumulated by a post increasingly become one of the most valuable ways of assessing one's current and future public standing. Indeed, in environments where much of platforms' behaviours and resulting analytics appear insurmountably hard to understand or predict, the comment section may seem like the one outlet that creators can attempt to control, since both they and their audiences can engage with one another directly.

Yet despite this appearance, the truth is that platforms are not neutral environments that allow for such 'free' speech. In addition to governing which audience responses are promoted at the top of the feed and which remain buried (Liang et al., 2025), which are categorised as 'quality' comments and which are hidden as 'spam' (Ambhore, 2023), complex algorithms also utilise overarching engagement metrics to determine which posts feature on platforms' explore pages—which directly determines which creators get seen and which remain invisible. It is not merely that audience engagement metrics incite platforms to disseminate users' content more broadly, however, (Germano et al., 2026), which in turn drives further interaction on account of the weight of social proof (Huang et al., 2025). Rather, recent research increasingly demonstrates that platforms' individual digital architectures and their varied heuristics directly impact developing critical communication practices (Bossetta, 2018, p. 474; Dekker et al., 2025; Masciantonio et al., 2026). Even users' 'shared perceptions of culture, news, and politics' (Bossetta, 2018, p. 477) are inextricably tied to divergent algorithmic rankings of certain content over another.

This diversity is not necessarily bound to precise affordances either; in fact, there is a sense that platforms have increasingly become conglomerates, 'everything apps' or 'super apps' (van der Vlist et al., 2024) with their polymediated functions offering some versions of options for still photos, short-form videos, messaging, live feed, and instant shopping on virtually every space. Instead, it has been repeatedly observed that what is shifting are

audiences' forms of meaning-making and use practices (Boczkowski et al., 2018, p. 247; Matassi & Boczkowski, 2021, p. 214), wherein individuals are now specifically 'exploit[ing] the affordances within the composite structure of polymedia in order to manage their emotions and relationships' (Madianou, 2014, p. 671). Users not only swing between utilising platforms at different times for different purposes (Tandoc et al., 2019, p. 22), but shape their behaviours of posting, reacting, and interpreting content according to intricate constellations of what they collectively perceive to be 'acceptable' within each social space (Boczkowski et al., 2018, p. 255).

Take Instagram and TikTok, for instance, which happen to be some of the largest platforms for poetic distribution. In some ways, they may superficially resemble each other in their operations as mobile-centred, visual apps that allow creators to design and disseminate user-generated content (Turvy, 2025). The two platforms even appear to offer overlapping technical affordances, down to the names and symbols of user reaction haptics (such as the heart icon to 'like' or the ribbon icon to 'save'). Despite somewhat similar available functionalities and interfaces, audiences have come to particularly associate Instagram as a space that is both highly stylised and polished, designed to construct a certain presentation of one's identity to the public and private eye (Boczkowski et al., 2018; Masciantonio et al., 2026). TikTok, on the other hand, is seen as a space for the new *algorithmised* self as opposed to the traditional networked self, since users are more interested in 'experience[ing] content on its own, estranged from its source' (Bhandari & Bimo, 2022, p. 8), rather than sharing a constructed version of themselves with 'IRL' friends, family members, and acquaintances. The asymmetrical cultures surrounding both creator-audience relationships as well as inter-networked relationships can be directly linked to the manner that different platform logics push algorithmic discovery and circulation (Bhandari & Bimo, 2022), which in turn re-affects users' perceptions and behaviours of connectedness and communication towards and within these platforms (Taylor & Chen, 2024). In their critical cross-platform framework surveying the norms of several social network sites, Masciantonio et al. demonstrate that not only are there distinctive affordances or 'perceived possibilities or constraints' between Instagram and TikTok, with Instagram having mixed persistence and medium visibility versus TikTok's high persistence and high visibility, but that these also impact the socio-cultural contexts as sustained by audiences (Masciantonio et al., 2026, p. 4). For example, the norms of interactions for Instagram, with content majorly conforming to 'positively valenced social interactions, art, or travelling', include a high reciprocity of engagement, likely because users pictured their audiences not just as public but including private family and friends as well (Masciantonio et al., 2026, p. 5). On TikTok, where content was predominantly categorised as 'entertainment escapism, self-expression or archiving', reciprocity of interaction was much more moderate (Masciantonio et al., 2026, p. 5), likely because the platform is paradoxically viewed as a giant spread of public content moderated by the private self—by the help of serendipitous algorithmic discovery.

Despite the fact that there has been core work that includes both Instagram and TikTok as part of a broad survey of several platforms' interaction dynamics, or even individual examinations of their user practices, there have been fewer studies directly juxtaposing these two platforms' metrical divergences in audience engagement as specifically affected by algorithmic norms, particularly through quantitative means. Alex Turvy's qualitative discourse exploration of TikTok and Instagram's unique sociotechnical environments is certainly a major step forward in distinguishing critical differences in platformic cultural production and reception between the two. Notably, Turvy observes that TikTok's algorithmic personalisation affordances create tensions in the possibility of establishing an "authentic" digital-born community. On the one hand, the emphasis on trend participation rather than prior networks could allow audiences to interact more organically, building

connections based on joint cultural interests and a 'shared symbolic vocabulary and a sense of insider knowledge that binds users together, even as the specific trends and challenges constantly evolve' (Turvy, 2025, p. 13). Nevertheless, the fact remains that these discovery and participatory functions are directly curated by algorithmic suggestions—a fact that audiences are indeed hyper-aware of, with many coming to treat it as a personified *entity or ego*, in place of previous networked friends (Bhandari & Bimo, 2022, p. 6). Thus, this challenges the idea of whether such communal interactive experiences could be truly authentic, if users are 'increasingly sorted into content-defined groups based on their engagement patterns rather than organic social connections' (Turvy, 2025, p. 13).

Turvy's findings are thus clearly quite relevant to this study in establishing a theoretical framework for the distinctions between Instagram and TikTok's audience interaction trends, and the subsequent effects upon users' reactions towards poetic movements across the platforms. However, the methods of this qualitative-leaning study focus less on precisely measuring the quantifiable trajectories of audience engagement and more on investigating the discourse released by platforms themselves: community guidelines, privacy policies, homepages, ToS conditions, and marketing statements. Though the study ultimately suggests that TikTok cultivation of shared experiences and cultural co-creation is specifically engineered around 'behaviorally defined microcommunities that are optimized for attention retention' (Turvy, 2025, p. 13), whereas Instagram is more 'curated and controlled... [for] niche communities' made of familiar connections and pre-existing preferences (Turvy, 2025, p. 15), Turvy ultimately notes that these observations rely heavily upon the corporations' mediated self-representation. As such, this potential limitation must be followed with more comprehensive analysis of both the diverging algorithmic logics and user practices themselves.

This comparative lacuna becomes even more pronounced when it comes to platform-poetry scholarship, as in-depth studies of platform poetry are usually subsumed together under the larger umbrella of Instapoetry, a genre that benefits both from its longer-established presence as a pop-cultural movement and its catchy portmanteau of the platform and genre. Subsequent studies on TikTok poetry do exist, such as Jeroen Dera's examination of readers' ideological discussions on the platform, but this paper does not focus on comparing the two platforms, other than mentioning that the 'accessibility of Instagram poetry (and TikTok poetry alike) runs the risk of being seen as a form of lowbrow culture not worth studying' (Dera, 2025, p. 26). In terms of distinctions, Dera helpfully notes that TikTok's poetic audiences only partially intersect those of Instagram, but only includes a couple of lines on the platforms' 'different orientations': namely that Instagram is more filter-friendly, leading to idyllic views of reality, whereas TikTok may offer more opportunities for 'authenticity' on account of its 'quirky' vibes (Dera, 2025, p. 27). This is understandable as Dera's particular emphasis is exploring successful practices of #BookTok and using them as guidelines for analysing TikTok poetry reels, but the fact remains that there is still a clear gap in research directly contrasting the engagement trends of audience interaction across the two platforms.

Imran Khan's thesis on 'Platform Poetry and Restorative Experience: Creator, Community and Catharsis' is perhaps the most critical in acknowledging cross-platform distinctions of poetic genres as a whole, along with exploring creators' own leverage of selves within the ecologies of individual platform communities. Within the thesis, Khan does discuss the importance of understanding platform-specificities in poetry published in a variety of spaces, from Tumblr to YouTube, noting how authors utilise cross-posting practices to articulate different sides of their identities to different audiences. However, as this work is more focused on accounting for the way that specifically bibliotherapeutic poetry is performed and received on platforms designed to profit from affective commerce, by examining the tensions microcelebrity selves face in building 'authentic' personas within

cathartic-solidarity communities, its scope does not emphasise measuring the rates that comments-to-likes accumulate on two distinct platforms.

It is also notable that both the above works are relatively small-scale and qualitative in their approach, whether through thematic analysis of three TikTok poets to examine readers' cognitive responses (Dera, 2025), or through a qualitative overview of how platform poets individually negotiate the ecologies of therapeutic well-being within their respective platform communities (Khan, 2024). This emphasis on more condensed qualitative work through case studies may be partly explained by the difficulty of conducting large-scale, quantitative comparisons on how audience engagement accumulates disparately on different platforms and how such diversity may in turn affect posts' visibility. Such comparative work is particularly challenging primarily because most platforms deliberately hide the mechanics of their recommendation systems.[1] Post-Cambridge Analytica privacy concerns are often given as an excuse, though the real reasons likely stem from 'economic rather than ethical motivations' (Bruns, 2019), given that platforms can now both protect their inner workings from competitors and charge hefty sums from academics legitimately seeking understanding. Scholars must either request access through an Application Programming Interface (API), which itself is time-consuming, expensive, and overwhelmingly limited even if it is granted (Tromble, 2021; de Vreese & Tromble, 2023), or else resort to more precarious means of scraping—a risky business as most platforms' Terms of Service have entirely banned automated scraping (Mancosu & Vegetti, 2020). Many researchers thus inevitably turn to various forms of manual collection to perform more succinct or constrained qualitative case studies (Joshi, 2024). While such methods do reap rich understanding of individual users' interactions, it becomes increasingly difficult to use these means to account for more extensive metrical engagement in the form of comments and likes.

Fortunately, there have been increasingly innovative digital methods of obtaining such data. By utilising the academically developed plug-in Zeeschuimer, it is possible to more readily collect large sets of public metadata from multiple platforms, which was previously largely inaccessible to both quantitative and qualitative scholars. Although the proprietary nature of what platforms choose to include in the 'public domain' means researchers still cannot precisely declare the exact weights of different engagement signals, it is possible to juxtapose large collections of surfaced posts and their associated public metrics, and in so doing, infer some unique patterns that distinguish the commentary tendencies of each platform ecosystem. In particular, one can compare the 'elasticity' patterns of these platforms, contrasting the levels of engagement to posts surfaced by set key terms. For this paper, 'elasticity' refers to the commensurate responsiveness of the increase in comments in comparison to the percentage change of likes. This type of juxtaposition is useful for comparative analysis of social media platforms because elasticity is not bound by specific units or diverse scaling. For example, posts that have increased from 5 to 10 likes versus 500,000 to 1 million likes have extraordinarily different raw values, even though the increase between them is proportionally identical. The fact that 'elasticity is dimensionless' (Udell, 2026) enables researchers to contrast the overarching similarities or differences in platform behaviours despite having superficially disparate, non-linear scales of measurement. In computational terms, elasticity can be modelled by log-log regression, where independent and dependent variables are altered logarithmically: the slope coefficient equates the percent change of the dependent variable correlated with a 1% increase in the independent variable (Rönkkö et al., 2022, p. 72). If there is an elasticity of 1, this demonstrates that comments grow proportionally to likes. For elasticities where values <1, this means that comments increase less proportionally than do likes, whereas those with values >1 have a higher proportional increase in comments as opposed to likes. These elasticities can be juxtaposed

across platforms to discover whether comments on either Instagram or TikTok tend to surpass, match, or decline when engagement, in the form of liking, subsequently increases.

With the critical access this tool affords, this paper therefore seeks to accomplish three objectives. The first is filling a methodological lacuna, utilising a regression model to compare the engagement metrics of platform poetry on Instagram and TikTok, and account for the ratios of posts' comments-to-like growth. The second is describing an empirical discovery: demonstrating that the elasticity results exhibited can reveal both divergent commentary ecosystems and even emergent distribution pattern variances between two seemingly similar platforms. And finally, this article aims to offer some practical contributions to content creators, in the ways they might apply these findings to boost their content and increase interactions with diverse audience engagement dynamics.

In this paper, I explore how measuring bins of like metrics for posts (N = 7332) varies greatly between Instagram and TikTok, two platforms that have often been compared to each other for their technical affordances and participatory creative cultures (Hendrikse & Limniou, 2024; Turvy, 2025). When key terms are searched across 3 datasets, elasticity regression analysis repeatedly shows a steeper correlation between comments and likes on TikTok as opposed to Instagram. Although new, low-engagement Instagram posts appear to show higher ratios, these ratios of visibility exponentially scale faster on TikTok than on Instagram once a post reaches a certain level of virality of 10 k likes. The search results also consistently displayed that TikTok surfaced comparatively fewer low-engagement posts, instead exhibiting posts that had already begun accumulating traction in terms of likes and comments. Instagram's distributions were more varied, with a more niche, genre-related term actually displaying more results from new, low-engagement posts, but with broader, generic terms dominated by higher-reaction posts. Regardless of the search term, however, it was evident that comment growth relative to likes was definitively higher on TikTok for every one of the datasets.

This suggests that although the act of commenting is important on both platforms, content creators on Instagram—or at least those creating similar posts to those in these case studies—must be more strategic in the ways they cultivate discursive engagement. Whilst this paper has particularly examined platform poets, filling this methodological gap of cross-platform elasticity will enable researchers to apply the findings in other fields, uncovering more examples of how audiences' interactions are being used to push or bury content in an economy where visibility continuously becomes harder to obtain.

2. Materials and Methods

One of the most critical tools utilised for the following data collection was the academically developed Firefox plugin 'Zeeschuimer', which was created by the Digital Methods Initiative at the University of Amsterdam (Public Data Lab, 2023) to safely collect large sets of publicly available social media data. Its semi-manual nature, wherein only open-access information is collected through the researcher's own account—as opposed to automatic scraping of the entirety of hidden metadata—enables scholars to comply with ToS conditions (Bellingcat GitBook, 2026). In this case, Zeeschuimer functioned as a digital notetaker, accounting for the like-counts and comment-counts of posts across Instagram and TikTok's search pages, before packaging this data into an NDJSON file that could be readily exported into a CSV and analysed via a Jupyter notebook (7.4.2).

This access to such large numbers of poems and their correlated metrics enabled me to track extensive quantities of posts categorised by key search terms, and explore divergent surfacing patterns in the ways that platforms display posts with certain engagement metrics. Although Zeeschuimer has been utilised in innovative contexts thus far, from exploring reactions to vaping practices (Jung et al., 2024) to tracking influencer marketing practices

(Annabell et al., 2026), it has never, to this author's knowledge, been used to collect data through cross-platform search results in order to distinguish their engagement elasticity.

Therefore, this study also addresses a methodological gap as well as a conceptual one, by analysing macro-level engagement patterns of surfacing and scaling for posts (N = 7332) across two platforms, before discussing direct implications for content creators strategising how to increase their reach through engagement. While the inquiry will offer broad applications for anyone working within the digital creator economies, it will also afford a new quantitative focus on platform poetry that has never been undertaken, as most previous work has either overviewed the often-affective nature of the poems as a whole, or examined individual case studies of Instapoets' behaviours, rather than directly comparing metrical patterns of cross-platform genres.[2]

For this investigation, two platforms have been selected for juxtaposition—Instagram and TikTok. This is in part because the largest movements of poetry are currently broadcast on these spaces, but also because their interface architecture and affordances for engagement, including the icon shapes of hearts for 'liking' and speech bubbles for 'commenting', are at least externally similar. In fact, this apparent resemblance has contributed to scholars often lumping the poetic movements on each platform together, with only superficial allowances that Instagram is a bit edgier for its 'polished', curated aesthetic (Udescu, 2025), or that TikTok is 'nicer' (HalfTheStory, 2025; Harper, 2022) for its 'messy, campy, chaotic' vibes (Dera, 2025). While deeper, qualitative explorations are needed to expose the issues of such generalised assumptions, this paper will focus instead on examining the quantitative divergences in engagement growth on each platform, and note some emergent patterns of how the two platforms distribute content correlated with like-counts and comment-counts. Comments and likes, in addition to being readily available for collection through Zeeschuimer, also represent opposite ends of the scale in terms of most and least amounts of 'effort' in terms of engagement. Likes indicate a passing interest, as they do not require additional steps of saving or sending a link elsewhere. Comments, in contrast, represent the most 'discursive' form of metrics, as they involve more time in crafting a response, particularly as they are more liable to public scrutiny. Such conditions result in fewer comments overall, but these concise texts hold greater analytical value because of the deliberative cognitive effort required to produce them (Ciunova-Shuleska et al., 2024; Swani & Labrecque, 2020). Comparing the overall ratio of comments to likes for key search terms—in this case, 'tiktokpoetry', 'poetry', and 'poetrytok' on TikTok, alongside 'instapoetry', 'poetry', and 'poetsofinstagram' on Instagram—selected because they represent the most widely used discovery terms for poetry on each platform—could indicate whether either space endorsed more 'transactional' or 'discursive' interaction, or whether the divergence was more nuanced.[3]

To obtain a sufficiently large dataset for assessing the commentary propensity ratio in each search term, approximately 1200 posts per term (N = 7332) were collected on each platform,[4] sequentially gathered as they appeared through the search interface at the time of extraction. Using fresh researcher accounts, commonly referred to as sockpuppet accounts, that underwent a rigorous neutralisation training period before and during collection was key in minimising the effect of personalised algorithms on the content that emerged during collection.[5] Collection took 14 weeks between late December 2025 and early March 2026, partly because recording needed to occur on varying weekdays and weekends with 'cool-off' periods to look at nonpoetry-related topics in between, but also due to unforeseen platform restrictions in decreasing the number of new posts available for collection, and the occurrences of duplicates presented on the 'For You'/'Explore' pages, which needed to be removed before analysis.[6]

The large NDJSON text files collected by Zeeschuimer were then converted through Python-scripted Jupyter notebooks (7.4.2) into flattened CSV datasets for greater ease of metric computation and deduplication. This enabled calculation of the precise comment-to-like ratio, indicating the density of more discursive engagement relative to lower-effort endorsements. Before measuring these proportions, the notebooks were set to exclude posts with 'hidden' like counts, a feature unique to Instagram, to avoid skewing ratios.[7] The engagement levels were then summarised with median values rather than averages, which can often be swayed by a few viral outliers with atypical like counts.

Following this initial cleaning stage, it was critical to account for diverging visibility scales between TikTok and Instagram by grouping the posts in terms of like-count ranges, or 'bins'. On affective platforms, it has been observed that participation paradigms divergently influence how audiences respond, with engagement such as comments and likes 'distinct in the degree of expression', though all haptic possibilities may be visible at any point in time (Tenenboim, 2022, p. 4). As such, posts that gain more engagement typically increase in comments and likes simultaneously, but not in a one-to-one scale, as likes require more effort, mentally as well as physically (Bucher, 2012). Thus, posts with a modest range of likes may also have a modest range of comments, but their ratios would still be substantially higher than that of posts with extremely large like-counts. For example, a post with 1000 likes and 170 comments yields a higher comments-to-likes ratio than a post with 1.2 million likes and 300 comments, despite the latter receiving more absolute engagement. This made it necessary to also utilise a log-to-log regression to rescale raw counts between platforms' comments-to-likes ratios to avoid misrepresentation from a few viral outliers. The model $\log(\text{comments}_i + 1) = \beta_0 + \beta_1 \text{TikTok}_i + \beta_2 \log(\text{likes}_i + 1) + \beta_3[\text{TikTok}_i \times \log(\text{likes}_i + 1)] + \varepsilon_i$ calculates the rate at which comments tend to increase as likes grow, and whether posts on either platform proportionally generated more comments than the other. As the results will demonstrate, this explanatory strategy made it possible to detect broad differences in how platforms exhibited posts as correlated with their engagement patterns, as well as how comment interactions increased relative to like counts across both platforms.

3. Results

The findings of this study revealed some consistent trends in terms of engagement, though these were not completely uniform in their distribution across platforms. The first paired datasets, comparing the search results for 'instapoetry' and tiktokpoetry', demonstrated that the ratio of comments to likes was highest in posts with lower levels of engagement, and such ratios declined as like counts increased. This correlates with aforementioned studies demonstrating that even though viral posts get more engagement overall, likes increase more quickly than do comments, which require more labour (Ciunova-Shuleska et al., 2024; Bucher, 2012). Moreover, liking not only serves as a 'default engagement mechanism' on account of its reduced cognitive demand, but because it has a lower 'social risk' (Anderson et al., 2026, p. 52). This is particularly significant as posts increase in visibility, as the social risk of having one's comments publicly observed and judged also increases. Thus, it was unsurprising that as posts increased in visibility, the comments-to-likes ratios declined as well. What was notable, however, was that the rate of this decline diverged distinctly between the two platforms, as shown in Figure 1A–C.

In the bins with low engagement levels (<100 likes), the Instagram posts collected for the search term 'instapoetry' displayed much higher medians of comment-to-like ratios (0.171, N = 361), in contrast to the TikTok posts for the term 'tiktokpoetry' (0.124, N = 36). This gap narrowed in the 100–999 like bin, before then reversing completely in the 1 k–9.9 k like bin. From this point onwards, the comment-to-like ratios of TikTok posts consistently exceeded those of Instagram. For example, in the 100 k–999 k bin, the median comment-to-

like ratio for 'instapoetry' posts was 0.0045 (N = 36), whereas 'tiktokpoetry' posts had a ratio of 0.0074 (N = 217). This shift suggests that during data extraction of the first set, not only did Instagram typically display more posts with lower visibility (and a 'higher' ratio of comments to likes) than did TikTok, but that once TikTok posts reached 1000 likes or more, comments began *increasing* at a rate higher than Instagram's. Similar trends occur for both Dataset B and C, where Instagram started initially higher in comments-to-like ratios, but this switched around the 1000–10,000 threshold, although it is noticeable that for Dataset B (search term 'poetry' for each platform) the ratios are lower overall for both platforms.

Figure 1A	like_bin	IG median (comments/like)	IG N	TT median (comments/like)	TT N
0	1–99	0.170732	361	0.124144	26
1	100–999	0.034483	277	0.022059	43
2	1k–9.9k	0.010172	261	0.012115	74
3	10k–99.9k	0.005368	158	0.007195	164
4	100k–999k	0.004546	36	0.007434	217
5	1M+	NaN	0	0.006060	32

Figure 1B	like_bin	IG median (comments/like)	IG N	TT median (comments/like)	TT N
0	1–99	0.125000	117	0.030303	51
1	100–999	0.038172	132	0.017045	65
2	1k–9.9k	0.008333	349	0.010374	160
3	10k–99.9k	0.005381	564	0.006577	358
4	100k–999k	0.004299	292	0.005290	336
5	1M+	0.004144	8	0.004844	40

Figure 1C	like_bin	IG median (comments/like)	IG N	TT median (comments/like)	TT N
0	1–99	0.097561	104	0.054795	153
1	100–999	0.026104	133	0.012490	84
2	1k–9.9k	0.008436	284	0.010098	141
3	10k–99.9k	0.003782	322	0.006010	342
4	100k–999k	0.003173	163	0.005323	378
5	1M+	0.005632	6	0.004930	77

Figure 1. (**A**) Bin Ratios of Comments to Likes for Dataset A ('tiktokpoetry' vs. 'instapoetry'). (**B**) Bin Ratios of Comments to Likes for Dataset B ('poetry' vs. 'poetry'). (**C**) Bin Ratios of Comments to Likes for Dataset C ('poetrytok' vs. 'poetsofinstagram'). In these sets, 'IG' stands for Instagram and 'TT' stands for TikTok.

Although the bin-level comparison revealed an overall inverse trend in comment-to-like ratios, it did not fully display how engagement evolves across platforms, in part because it did not show the precise rate at which comments increase relative to likes on either Instagram and TikTok. This number was also difficult to assess from raw counts alone, as both likes and comments were highly skewed by a small number of very viral posts.

To address this, the relationship was then modelled on a logarithmic scale, which can compare orders of magnitude or engagement elasticity, rather than just taking raw values at face value (Tian et al., 2024). This rescaling makes it possible to examine how quickly comments grow as posts increase in overall traction, rather than simply comparing the end total metrics of likes versus comments. The model, presented below, also allows the

relationship to differ by platform, capturing both baseline differences and differences in growth rates.[8]

$$\log(\text{comments}_i + 1) = \beta_0 + \beta_1 \text{TikTok}_i + \beta_2 \log(\text{likes}_i + 1) + \beta_3 [\text{TikTok}_i \times \log(\text{likes}_i + 1)] + \varepsilon_i$$

With Instagram acting as the reference category, the coefficient β_1 represents the difference in baseline comment levels between TikTok and Instagram, while β_2 stands for the rate at which comments increase alongside likes on Instagram. Importantly, β_3 represents the additional change in this rate for TikTok relative to Instagram, allowing the two platforms to scale differently as posts become more visible. Accordingly, the Instagram slope is represented by β_2, while the TikTok slope is represented by $\beta_2 + \beta_3$. For this first dataset, ($N = 2198$), using Ordinary Least Squares Regression through Python's library *statsmodels* resulted in a strong overall model fit between likes and comments, which represent the dominant contributors to comment volume ($R^2 = 0.830$). But while comments increase for both platforms simultaneously to likes, there is a statistically significant distinction between their scaling rates ($p < 0.0001$). The model indicated that Instagram's slope was 0.4792, while TikTok's slope was $0.4792 + 0.2801 = 0.7593$, a notably sharper increase (See Figure 2).

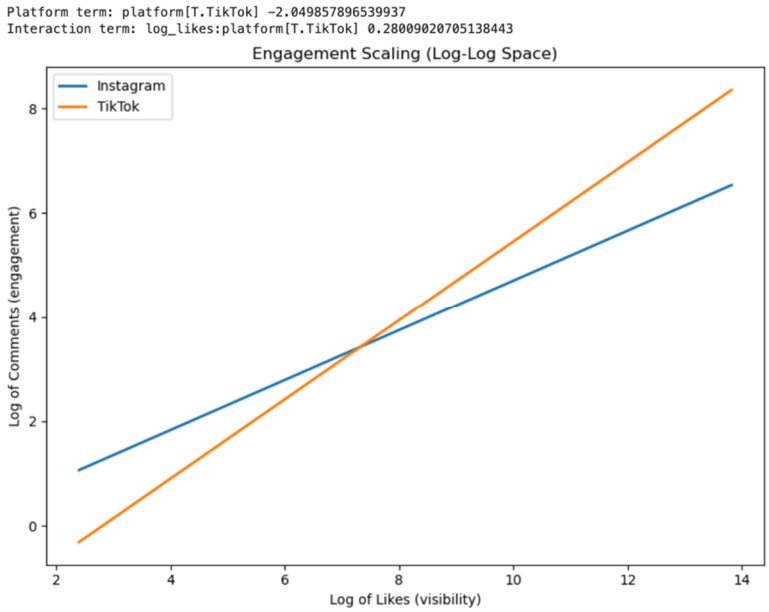


Figure 2. Scaling of Engagement between Instagram and TikTok for Dataset A.

This divergence becomes even clearer as the posts increase in total traction. The quotient of the slopes demonstrates that TikTok comments scale substantially more than on Instagram, about 1.58 times faster (see Figure 3). This is to say that on Instagram, if likes were to double, then there would be approximately an 39% increase in comments ($2^{0.4792}$) whereas on TikTok there would be about 69% increase in comments ($2^{0.7593}$).

Although Figure 2 clearly demonstrates the different slopes of growth, it is easier to detect proportional visibility patterns when utilising a semi-log plot, which denotes the exact numbers of comments against a logarithmic scale of likes. As Figure 3 shows, at lower-visible posts that already have fewer comments and likes, there is minimal difference between Instagram and TikTok. However, as posts receive more engagement, around the 10,000-like threshold, the platforms begin to converge, with TikTok exponentially accumulating more comments relative to Instagram's growth in comments. This divergent scaling rate clearly portrays that for Dataset A, posts that increase in traction will have an incrementally higher rate of comment growth on TikTok in comparison to that of Instagram.

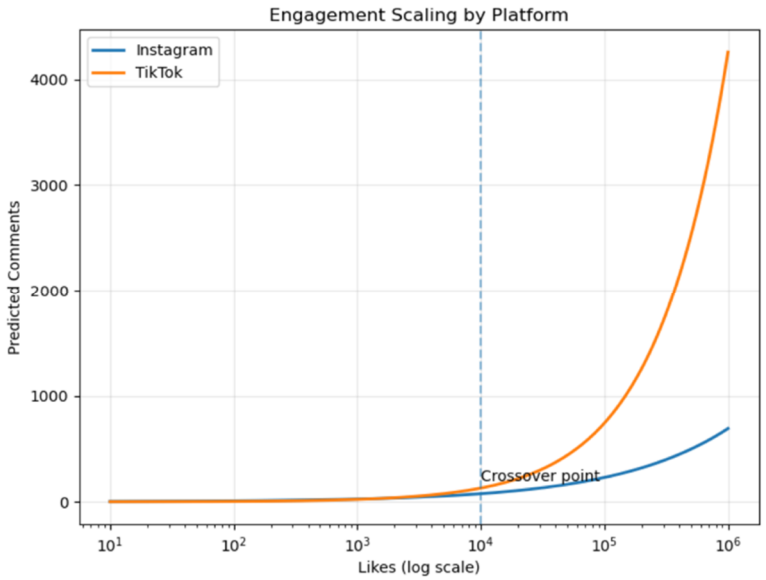


Figure 3. Semi-log Plot of Scaled Engagement between Instagram and TikTok for Dataset A.

When the same model was applied to the search terms 'poetry' across both platforms (Dataset B), as well as 'poetsofinstagram' versus 'poetrytok' (Dataset C), the overarching trend remained the same. In both datasets, comment-to-like ratios decreased as the posts' visibility increased, and the resulting number of comments was still much higher across TikTok posts in comparison to Instagram. Nevertheless, the span of this divergence was not as large as Dataset A, with TikTok scaling at 1.22× (Dataset B) and 1.24× (Dataset C) as Instagram respectively. This exhibits that although TikTok continuously demonstrates a greater percentage of comments-to-likes at higher visibility points than does Instagram, the level of impact changes depending on the individual dataset. In particular, posts that are more genre-specific and thus have more 'defined' poetic forms (e.g., 'tiktokpoetry' or 'instapoetry') display a greater divergence between platforms, as opposed to broader terms ('poetry)' or more specific, folksonomy-based tags ('poetsofinstagram' or 'poetrytok'), which display a less steep divergence.

4. Discussion and Implications

From this study, we can come away with some key conclusions. First, in all six datasets across both platforms, it was confirmed that engagement with platform poems consistently reflects typical audience behaviours on platforms, wherein low-effort likes accumulate more quickly than high-effort comments (Rides et al., 2025; Wang & Sundar, 2022). What was unique, however, was the fact that the rates at which these likes and comments grew was quite different dependent on their platform. On Instagram, comment-to-like ratios were initially higher than those on TikTok, at least until they reached the 1 k–9.9 k bin of likes. Then, across all datasets, this relationship switched as like-counts reached towards the 10 k mark. On Dataset A, comparing the genre-tags of 'instapoetry' to 'tiktokpoetry', it was clear that scaling was particularly stronger on TikTok. An increase in comments by 69% (TikTok) in comparison to 39% (Instagram) is no small variance—and again, this was comparing the elasticity if likes were to only double. Although these gains were slightly less strong for the other datasets, the fact that comments still scaled 1.22x and 1.24x faster on TikTok was surprising, particularly considering the fact that communities associated with poetry have been established far longer on Instagram.

It was also notable that organising posts into 'like-bins' revealed some emerging trends in the types of posts that each platform brought to the forefront of the selected search terms.

On TikTok, it was clear across all datasets that the platform did not surface as many posts in the low-engagement categories, with relatively small numbers of posts in the 1–99 and 100–999 like bins. This changed, however, for all three search terms, once posts started to increase in traction, as there were increasingly more posts exhibited which had in between the 1 k–9.9 k range and even higher numbers of posts between the 10 k–999 k range. By the time posts had reached 1 million likes, numbers had tailed off again, majorly because there are not as many poetry-related posts that have reached this extent of virality. Nevertheless, the fact that this trend was consistent for the search terms across all datasets suggests that TikTok is a platform that continuously promotes virality, and will boost posts that its algorithm views as already performing well in engaging audiences. This is of course a bit of an ouroboros, since it is the algorithm's governance that allows a post to be seen and interacted with by audience members in the first place, but the implication that content creators can draw is that once a post is starting to attract attention, it is crucial to cull further engagement as much as possible, in hopes that the post will be more likely to be displayed in the top results for a related search term.

While content creators are of course looking to encourage both likes and comments, it has been demonstrated that TikTok's platform ultimately weighs comments over likes, so users should particularly strategise to increase this form of engagement. Quality comments with replies are especially given more weight, with videos in the 'top 10 percent of distribution' having approximately '4.5 times more comment replies per thread than videos with average performance' (Ruaro, 2026). In fact, it has been observed that if a post has not gained 'several comments within the first 30 to 60 min after posting' (Ruaro, 2026), it is likely to have a downward trajectory in views, as the algorithm will limit featuring it on the FY page. Therefore, creators looking to gain more visibility should not only respond to any commentors in timely manner, but utilise overlay text, captions, and responses that are more likely to increase further replies such as questions or playful hooks (Mishra, 2025), of course dependent on the theme and tone of the post as well as the intended audience.

Although the TikTok datasets reveal incrementally more comment growth than the Instagram sets once posts hit a certain number of likes, and TikTok's algorithm appears to circulate more posts with higher traction than those with lower engagement for the selected search terms, this does not at all mean that Instagram is a platform that *punishes* accumulating audience engagement, in either the form of comments or likes. In fact, the bins from Datasets B and C depict that there are more higher-engagement posts featured as a whole, with the platform surfacing multiple posts in the 1 k–9.9 k like category and even more so in the 99 k like category, though this trend tailors off in the 100 k+ bins. Uniquely, however, Dataset A reveals an opposite trend, where the highest number of posts is in the 1–99 like bin (N = 361) and the 100–999 like bin (N = 277), with post numbers decreasing in each further category. What could be the meaning for the discrepancy here?

At this point, it is helpful to recall the search term for each dataset, when analysing the numbers of posts that appeared within each set. For Dataset A, the term 'instapoetry' is associated with 5.8 million posts. Whilst this is a sizable number, it is comparatively small to the 20.1 million posts correlated with 'poetsofinstagram' (Dataset C) and 93.7 million posts correlated with 'poetry' (Dataset B). Although more studies could be conducted to confirm this pattern, the sheer variation between these posts' quantity suggests that on Instagram, when results have been overwhelmed with content, the algorithm is more likely to suggest posts that are already gaining audience traction, whereas a smaller body of posts for a particular topic allows new, lower-engaged posts to have more visibility. The quality of the terms could have some significance as well, as the broad subject term 'poetry' and even the more community-oriented term 'poetsofinstagram', are still quite general, encompassing not only Instapoets but anyone tagging a poem in any style, from

any time period, that they have happened across—even if they did not write it themselves.[9] 'Instapoetry', in contrast, has definitely come to be more associated with a certain genre with a recognisable look or style, and functions as an 'in-the-know' phrase of anyone familiar with this contemporary movement. From this, we may infer that creators who are able to find a more niche (though still popular) avenue with which to align their content may also find more success in attaining visibility if they are just starting out, but further studies must be conducted to confirm whether this niche-specific trend of discoverability holds true for other genres as well.

It is also important to acknowledge that throughout this study, nothing has been said about the quality, format, or composition of these comments on either platform. On both Instagram and TikTok, pictorial responses like emojis and memes also count as 'comments', and while these forms of audience interactions have unique significance in themselves, it was necessary to treat them equivalently when counting the comment totals for the regression analysis. This was partly a consequence of the extraction tool used for collection; although Zeeschuimer is able to retrieve metrical content, such as posts' numbers of comments and likes, it currently does not support the option to extract the comments themselves, at least on Instagram. On TikTok, comments can be collected by a different toggle on the plug-in, but this requires manually scrolling through each post and individually un-nesting each response. Not only was this unfeasible for a collection of over 3600 TikTok posts, when some posts had tens of thousands of comments and nested replies, but it would still be impossible to account for non-static image responses like gifs or memes, since resulting NDJSONs and CSVs can only capture textual/Unicode content.

The inability to organise the six datasets according to the types of comments, categorised as purely text-based, purely emoji-based, purely gif- or meme-based, or even as a combination of all of these, does pose an important limitation on the study. The elasticity patterns that have been observed here describe differences in the aggregated volume of comments relative to growth in like-counts, and therefore do not convey any substantive distinctions in the length, depth, or 'discursive' nature of individual audience responses. Such deeper divergences in the content, as well as the composition of audiences, or even the specific affordances of individual platforms, could all be pertinent to explaining why these patterns have occurred. For instance, it could be highly relevant to the juxtaposition if one platform afforded a larger library of memes, gifs, or ready-made emoji combinations over the other in terms of available user responses, since these instantly available responses required less physical (if not cognitive) labour to use in contrast to typing out a traditional text-based comment. Platforms still include all comments as part of the accumulated 'comment count', regardless of whether users write a 5-paragraph text response or leave a single heart emoji—the latter of which may be discursively viewed almost as equivalent to the default 'heart' reaction, yet which is still ultimately counted as another 'comment'. If TikTok offered greater ease for users to respond in this more minimalist type of commenting, it could plausibly contribute to the faster acceleration of comment growth on TikTok in comparison to the growth of comments on Instagram, though it still would not explain why the ratio trend inverses between the two platforms once there is a significant increase in likes past the 10 k mark.

There are, however, other complex factors that may offer context for these patterns without necessarily explaining them in full, one of these being the role of user norms that both emerge from—but then subsequently shape—platform environments. For example, users' general awareness of platform stereotypes in terms of social networks might affect their willingness to publicly post comments. Instagram, as established in the earlier theoretical framework, has historically been more associated as a place for users to utilise their 'genuine' offline identities, and maintain pre-existing social ties with their relatives,

friends, and acquaintances. Therefore, users could be less willing to comment on Instagram, particularly if they are aware that the individuals they know 'IRL' ('in real life') could potentially see and judge the responder's public comment. TikTok, on the other hand, more readily promotes pseudonymous identities leading to much looser networks of connection; in many cases, users are more likely to engage in asymmetrical, parasocial creator-audience interactions rather than reciprocal communication with their existing friends and acquaintances (Bhandari & Bimo, 2022, p. 8). This platform atmosphere could mean that users feel safer about their comments being exposed to a larger audience, and less fearful of the social impact of having real-world acquaintances hold them accountable to their words—thus potentially contributing to the comparative decline of comments on Instagram versus TikTok once a post begins to get a large amount of traction and algorithmic visibility by surpassing the 10 k mark of likes.

This effect of platform awareness on audience behaviours can be seen even more overtly in the practice of comment-ratioing on TikTok, where users deliberately attempt to manipulate engagement in response to perceived algorithmic dynamics. Comment-ratioing occurs when audiences exhibit their disapproval of a post or a creator by collectively ensuring that a user response gets more reactions, replies, and traction than the original post. Because TikTok does not display comments in straightforward chronological lists but foregrounds those already getting interaction (TikTok Help Center, n.d.), these highly visible top-level comments can quickly establish further cycles of engagement from those 'running to the comments'. Preliminary research by the author suggests not only that the platform is more stable than Instagram at keeping a single, popular comment at the top of the feed, but that users are keenly aware of this algorithmic proclivity, using their knowledge to shape how future viewers interpret the original post and contribute to further ratioing behaviours. Incidentally, one of the 'best practices' commentors advise includes using traditional comments over images, as the algorithm tends to privilege text-based content over sole-emojis, gifs, and memes when ordering the feed. This could be simply because text-based retorts, questions, and sarcastic quips are more likely than images to engender further textual debate. Regardless of the precise rhetorical form, however, users have been observed to directly urge others to post 'higher-quality', detailed textual comments and avoid emoji-only responses to gain further replies. It is also common for users to directly challenge readers to 'comment or like' below a particular response, turning ratioing into a participatory game and compelling even relatively passive readers to contribute to the contest within the nested replies. Critically, users attempting to defend the original poster still reinforce the visibility of a critical top-level comment by replying within its thread, thereby contributing further traction to the comment they are attempting to contest.

Instagram, on the other hand, does not initially appear to support the trend of comment-ratioing in quite the same way. Although it started ranking comments algorithmically rather than chronologically in early 2025, preliminary field observations indicate more volatility in the viewing conditions of which comments are prominently displayed across feeds. The platform also provides users with different controls over comment and like visibility, such as the ability to hide comments and like-counts, which directly alters the effectiveness of ratioing as a visible participatory tactic. This divergence in algorithmic curation of comment ranking and visibility, together with users' awareness and reactions of such platform conventions, may therefore offer important context for platforms' divergent scaling of comment accumulation that takes place as likes increase.

Within this discussion of limitations, it is also important to acknowledge that none of these platform-level dynamics can be considered in isolation of the individual poetic content itself, the reputation or established persona of individual creators, and the impacts this milieu has upon their collective audiences. A politically divisive TikTok poem dis-

cussing civil unrest, for example, may be more likely to incite adversarial practices such as comment-ratioing in ways that an aphoristic Instapoem on budding romance does not. These divergences may increase when one moves outside of the genres of platform poetry altogether, where the topics and domains of entertainment, current affairs, technology, or operate according to very different participatory norms. Taken together, platform interface affordances, user engagement cultures, algorithmic progressions, content characteristics, and audience compositions can all offer plausible contexts for the observed differences in comment-to-like scaling. However, none of these elements as yet can be retrospectively evidenced by the present data to be the single root cause of the elasticity trends identified here.

What the present study does demonstrate is that different cross-platform patterns do exist, patterns that are statistically distinguishable within the datasets examined. Whilst there are still limitations on concluding the multi-layered reasons for these scaling distinctions, these do not diminish the value of the current study but establish opportunities to further explore them through more targeted qualitative analysis. One productive next step would be to more deeply examine identical content across platforms, as opposed to broader distributions of surfaced posts according to selected search terms. In concurrent research, the author is using qualitative discourse analysis to study individual poems cross-posted to Instagram and TikTok, alongside the metrics and content of their most highly ranked comments. Restricting analysis to identical posts reduces variation introduced by content and creator differences, allowing platform-specific audience behaviour and comment visibility to be examined more directly. Such an approach may help clarify whether differences in comment accumulation arise from the composition and formatting of comments themselves, or from diverse algorithmic ranking practices, organic audience norms, perceived social risks, and other platform-specific dynamics. The present study therefore provides an initial depiction of large-scale movements of engagement, whilst subsequent qualitative analysis can investigate the contexts through which these patterns are produced, for both individual posts and comments themselves as they increase in visibility on either platform. Future exploration must also be conducted to confirm whether these trends consistently hold true for other fields besides platform poetry, once it is established that the scales of audience engagement are not completely random but exhibit consistent elasticity across different platform ecosystems.

5. Conclusions

It has long been known that platforms are not neutral, blank slates where users may freely post, but intricate ecospheres that regulate how users generate, receive, and disseminate content. Navigating these terrains, whether as a researcher or a creator, can be extremely difficult, especially for large platforms like TikTok and Instagram, which despite using superficially similar paratextual features, often operate as black boxes that obscure how these latent components work beyond their interface. Using computational means to capture broad-scale metrical relationships between comments and likes, however, offers insight into how these frameworks of prominence actually function in practice, including for social–cultural artefacts that have been predominantly studied by qualitative means, such as platform poems. This is not to suggest that such methods are deficient, but rather prove that accessing large amounts of metadata through innovative tools such as Zeeschuimer can pioneer new convergent parallel approaches for combining quantitative and qualitative explorations.

In this particular case, accessing an extensive number of posts and associated likes and comments was key in juxtaposing the separate engagement ecologies of Instagram and TikTok, demonstrating that although there are certainly many external similarities between the two, audiences do not necessarily engage in the same way or at the same rate. Utilising

a regression model between the post ratios, when divided into bins, demonstrated that even though Instagram had superficially higher ratios when posts had minimal likes and comments, the rate at which posts gained comments while simultaneously accumulating likes became much higher for TikTok, at least once a post had gained a certain level of traction. The number of posts surfaced for TikTok results in each dataset also demonstrated that this platform tends to exhibit content that has already proven it can gain such traction. On Instagram, the level of engagement associated with post search distributions were a bit more varied between datasets, although this variance could likely be accounted for the fact that the search term Dataset A was far more niche than those of the other two, and thus there were more posts displayed which had not yet gained much engagement in either likes or comments. Regardless of this divergence of individual result compositions, it is clear that the overall elasticity patterns remained consistent across the datasets, demonstrating that although both platforms grow in likes more quickly than comments, TikTok's comment growth scales more quickly than Instagram, particularly as posts edge towards virality.

The results of these findings do not mean that content creators juggling either or both platforms need to view one as inherently more conducive to comments, but acknowledge that the ecologies of audience engagement—along with potential platform-specific tendencies to surface some posts over others—can be quite divergent. It can be exhausting and overwhelming to remake content for multiple platforms, which is why so many creators have resorted to simply re-using the exact same content (Ma et al., 2023), even using tools like Hootsuite, Buffer, Repurpose.io to automatically post for them (Ranganathan, 2024). However, not only is it true that platforms are increasingly punishing creators for resorting to these tactics—after all, they are built to be 'walled gardens' that retain users on their own sites (Flonk & Garvey, 2025; Neels, 2024)—but it is also apparent that audience engagement behaviours can fluctuate between platforms. Therefore, it is recommendable that creators potentially develop new content between Instagram and TikTok, or at the very least, strategise which kinds of text and tools to coax genuine comments from audiences, rather than mere reactions. Timing could also be strategic as well, with TikTok posts requiring a more rapid response to demonstrate to the algorithm that a post has the potential of attracting more engagement, whereas Instagram posts could benefit from the creator returning to old replies, rekindling attention on a post when the comments have begun to dry out. Utilising questions, quips, or other types of stimulating responses may also be helpful to gain further interaction on either platform, as opposed to affirmational replies of gratitude or motivation (Deolankar et al., 2024), which are often more likely to close rather than extend a comment thread.

This last difference could be especially pertinent within platform poetry, where some topics naturally invite diverse types of response. Broadly aphoristic or traditionally romantic poems often lend themselves to inciting supportive or affirmational responses, whereas poems that are more politically contentious, socially polarised, or simply more niche in nature can be more likely to spark further debate and discussion. This implies that some of the scaling trends observed in this dataset may be in part due to the varying thematic composition of platform poems, especially the divergence between the sets for comprehensive search terms and more genre-specific terms.

These contexts can have major impact on creators, who are already expected to wear so many different hats as entrepreneurs, marketers, editors, artists. Platform poets in particular may grapple with the increasing labour of not only having to produce increasingly participatory forms of their art, engaging in all the parasocial practices that make their content more visible in an already glutted visual economy, but having to now distinguish alternative commentary-and-response practices on different platforms, including those such as comment-ratioing. While there are numerous factors that could contribute to some

cross-posted poems exploding in engagement on one platform over another, it is essential to take into account different audiences' hypermediated awareness of platform conventions, and the discursive cultures that evolve as users attempt to exploit, resist, or negotiate these constraints.

By quantitatively identifying clear trends occurring for large search terms associated with platform poetry, this study thus lays the foundation for more targeted qualitative work that specifically analyses examples of where comments-to-likes scale higher on either platform. Such exploration requires different methodologies of examination, since Zeeschuimer does not extract comments on Instagram, and only affords constricted opportunities on TikTok. In a co-current study, this author is therefore utilising traditional qualitative discourse analysis to manually collect the metrics of the top-ranked comments for cross-posted poems, selected in a manner that reduces variation introduced by style, content, and creator differences, and then conduct sentiment analysis of these comments. This approach would allow more direct investigation into the ways that algorithmic comment ranking shifts between platforms, as well as the impact of these environments upon subsequent audience reactive cultures and practices, such as comment-ratioing.

Regardless of the further avenues for investigation, however, they do not alter the broader conclusion demonstrated by this study: that the success of platformed content cannot be contributed to creators alone. Both platforms and audiences are formidable actors, contributing to a post's discoverability and potential for future reach. In spaces where attention is the rarest form of commodity, engagement metrics have become the concrete evidence that any piece of content, including a poem, is worth a few seconds of viewing time. Whether or not this form of evaluation based is *justified* or *desirable* is another matter, but in the current ecologies of social media, it is crucial that more researchers start 'running to the comments'—as well as their ratios.

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Institutional Review Board Statement: Ethical review and approval were not required for this study. The analysis used publicly available social-media engagement metadata and was limited to anonymous, aggregated numerical measures, including like and comment counts at the public posting-level. No identifying information was accessed or analysed by the researcher, and no attempt was made to identify individual users. In accordance with UK GDPR and Information Commissioner's Office guidance, anonymous information that does not relate to an identified or identifiable individual falls outside the scope of per-sonal-data regulation.

Informed Consent Statement: Not applicable

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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Conflicts of Interest: The author declares no conflicts of interest.

Notes

[1] Aiger et al.'s quantitative study on the ways that scientific information is communicated across TikTok, Instagram, and YouTube (Aiger et al., 2026) is critical in showing that measures of content's metrical success can vary substantially between domains. However, this paper predominantly juxtaposes the quantities of multiple engagement types within a large body of scientific disciplines, measuring the total sums of engagement relative to audiences' polarity towards posts, rather than this current study's focus on the precise ratios between the specific metrics of likes and comments.

[2] Camilla Holm Soelseth's study on Scandinavian Instapoetry (Soelseth, 2023) is a key exception to these more common approaches, as her study utilises visual network analysis (VNA) to explore the co-currences of hashtags and the distribution of associated posts. This larger scale use of topological mapping to determine ecologies across diverse Instagram communities would be

fascinating to apply in a cross-platform comparison. However, its dataset of hashtags at the time (N = 24,072) might be less readily feasible today, particularly since platforms as a whole—especially TikTok—have been moving away from utilising hashtags to establish folksonomies.

[3] At the beginning of the study, searches from the public logged-out view, as well as a freshly made researcher account, both revealed that typing titular genre terms into the platform's corresponding search bar—'instapoetry' for Instagram and 'tiktokpoetry' for TikTok—also suggested other popular terms below these first results, including 'poetry', 'poetsofinstagram' and 'poetrytok' amongst other trending posts. These are not static trending terms for either platform, and change depending on what users are currently interested in. Notably, at the initial collection in December 2025, the second top result for TikTok poetry was 'tiktok bad poetry', and the third result was 'tiktok deep poetry'. As of 29 April 2026, the most trending term related to TikTok poetry is now actually 'tiktok poetry cringe'. Despite the striking observations that could be made about these terms, the fact that they contained words that were already highly polarised in sentiment ('bad', 'deep', or 'cringe') meant that it was necessary to select more neutral terms for the other 4 datasets, to avoid skewing the types of posts that might surface, and to ensure comparability across the two platforms.

[4] There is not a single, prescribed size-threshold for social media datasets, as these depend entirely on individual research aims and objectives. While scholars diverge in their preferred number of datapoints, usually depending on whether their study is more quantitative or more qualitative, it has often been agreed that extremely small samples may 'yield inconclusive or potentially misleading results', while an extremely expansive sample can 'waste resources and detect trivial effects that are statistically significant but clinically negligible' (Gan, 2025). Particularly when accounting for the breadth of social media behaviours for billions of users globally, collecting these 'large amounts of data are becoming a standard feature for representing civilization around the world' (Rahman & Reza, 2022). Larger samples will show more variations in social media topic distributions and network patterns within these 'live labs', though the fact remains that 'access to behavioral data at a scale inconceivable to many social scientists' can also introduce new ethical challenges (Ellison & Boyd, 2013). As this study is the first of its kind, it was appropriate to select a number that may appear 'arbitrary in size but what might be considered reasonable for the field' (Andrade, 2020). In this case, the original intended sample size of 7200 posts enabled a large enough collection to provide stable descriptive statistics, whilst the use of bins afforded more precise numbers notwithstanding the influence of extreme outliers. Since Zeeschuimer manually collects posts in sets of 16–24 per scroll, this total number of distinct posts sometimes organically exceeded the target of 1000 per collection. These minor variations did not significantly affect the results however, because the collection sets were large enough to attain data saturation, so that assessing 1200 versus 1224 posts per set did not affect the comment-to-like ratios, but accumulated together provided a comparatively large basis to observe the regression analysis. When examining multiple regression, it has been established that it is better to rely on the model complexity and the effect magnitude rather than minimum, 'rule-of-thumb' thresholds (Green, 1991). Taking into account three predictors and approximately 1200 posts per dataset, a sensitivity analysis reveals that, assuming the conventional significance threshold of $\alpha = 0.05$, and 80% statistical power, it would be possible to distinguish a total effect of about $f^2 = 0.009$. As this is much smaller than Cohen's standard $f^2 = 0.02$ for a 'small' effect, this would signify that current samples for these datasets were sensitive enough to observe relatively modest relationships. The actual regression results, including $R^2 = 0.830$ and a significant platform-by-likes of ($p < 0.0001$), further support the adequacy of the sample, demonstrating the estimated difference between the ratio slopes of the two platforms.

[5] Studies show that Instagram and TikTok's recommendation algorithms can adapt to user behaviours and interaction with the feed extremely quickly, within minutes if not seconds in the case of TikTok (Siles, 2024; eBell, 2025). Therefore, these accounts were initially used to browse a wide range of non-poetry related tags within the For You feed, such as #health, #travel, #food, #history, #sports, in order to reduce risk of algorithmic bias. Previous studies, such as Boeker and Urman's investigation of personalisation factors on TikTok, have demonstrated that utilising sockpuppet accounts with 'posts [picked] randomly or based on predefined sets of hashtags' reduces the number of personalised posts that TikTok's recommendation system serves to users (Boeker & Urman, 2022, p. 2305). Whilst this particular study did not account for Instagram, Meta's own discussion of its content suggestion patterns reveals something similar: sources are 'sources are derived implicitly based on a user's activity across Instagram and are then ranked based on similar factors... for extremely new users, we typically get them started with popular media items and then adapt our parameters based on their initial response' (Mahapatra, 2020). Therefore, by searching multiple, seemingly unrelated tags, I sought to avoid the personalised, tailored, and therefore narrowed offering of content that results from both Instagram and TikTok's recommendation systems. Additionally, throughout this preparatory stage, each post was viewed for no more than three seconds before being scrolled away, to avoid training the algorithm in a certain direction (Mishra, 2025); indeed, not only does watching a video longer than others as a whole generally influence the kinds of recommendations of TikTok's algorithm produces, but also 'the longer one watches the stronger it influences the algorithm' (Boeker & Urman, 2022, p. 2304). No direct interactions were made, such as following, liking, sharing, commenting, or even opening the post fully, since this kind of active engagement, particularly, following and liking, have also been noted to cause users' feeds to surface similar faster content than did the feeds of control users (Boeker & Urman, 2022, p. 2305). The accounts were then logged out and left inactive for approximately three days before the same browsing procedure was conducted with different non-poetry tags. After repeating this process over a two-week

period, the accounts were approximated to be more sufficiently neutralised to introduce the primary research content, as informal checks of the subsequent feeds did not reveal the results for a search term as predominating over another. For example, in the above example of a sock-puppet account that searched the terms '#health, #travel, #food, #history, #sports', there was roughly the same number of posts related to the topic of health as opposed to history. It is important to note, for methodological transparency, that such a technique is still best-effort approximation as opposed to guaranteed control. In Mousavi et al.'s case study of TikTok video explanations, wherein the platform offers explanations as to why users are suggested certain content, it was discovered that even for sockpuppet accounts using a 'No Engagement (NE) Configuration', for 42.67% of the videos TikTok still offered an 'explanation' of *Liking*, *Commenting*, or *Sharing*, to justify the platform's suggestion, despite that the sockpuppet accounts in these category did not engage in any form of liking, commenting, or sharing during their 15 s watch times (Mousavi et al., 2024, p. 1114). The fact that there was mixed accuracy in terms of TikTok's generic engagement explanations led the researchers to conclude that the platform's 'transparency efforts are not fully compliant with the DSA regulation,' (Mousavi et al., 2024, p. 1120) which is to say that until large platforms disclose more precise information about their recommendation systems, it is hard to ascertain with higher accuracy the level of personalisation of posts surfaced for given search terms. Nevertheless, although it is impossible to absolutely guarantee the elimination of algorithmic personalisation, the triple strategy of looking up random search terms unrelated to poetry, the limitation of watch-time to 3 s, and the absence of user engagement, did ultimately appear to produce FYPs and Explore pages that suggested a balanced set of non-poetry-related content.

[6] As both platforms typically displayed 300–337 posts for a given search term, I originally sought to collect this number of posts every three days, with additional days in between each session to browse non-poetry related terms and return the algorithm to a more neutral baseline. Once each metadata extraction via Zeeschuimer had been completed, the plug-in was deactivated until the next collection period. While this method allowed for efficient collection of large datasets, it is important to note that the extraction process itself also revealed the instability of platform discovery systems. The prior exploratory searches I conducted in the fall of 2025 for broad terms such as 'instapoetry' initially produced a relatively extensive chronological mix of posts, ranging from highly visible influencers to amateur poets with minimal engagement, a vast sampling that was key in revealing just how diverse content categorised as 'instapoetry'. However, after the completion of the first TikTok dataset in early 2026, I observed that suddenly the same set of posts were appearing repeatedly for the search term within short scrolling intervals, suggesting that the methods of algorithmic ordering had been altered on Instagram. In many cases, identical posts, with duplicated metrics and comments, would arbitrarily reappear every few dozen entries, despite no interaction having taken place. In one example, a poem on 'lost love' that featured a distinctive dying rose background received exactly 63 likes and 10 comments. This same post appeared multiple times within the feed during a single collection session. This evolving pattern, which appeared specifically on the desktop version of the interface (no matter which browser was used), meant that scrolling over the feed would generate many repeated posts alongside newly surfaced content. Since the process now involved reviewing a much higher number of posts in sequence, extraction of the Instagram datasets was conducted more slowly than initially anticipated. In some cases, when scrolling extended large stretches of posts, the feed would occasionally lag or stop loading entirely, and collection would need to continue during the next session. Later in the collection, on the second set of poems gathered for the key term 'poetry', TikTok began presenting a similar problem, where certain reels were pushed repeatedly, despite the fact that they were never clicked ror opened. Unlike Instagram, however, where duplicates tended to appear after an initial bout of scrolling new content, these repeated TikTok posts appeared intermittently throughout the whole collection process. Whereas the Zeeschuimer plug-in automatically discounted duplicates for Instagram, it did not do the same for Tiktok. As a result, approximately 1900 posts had to be extracted for each set in order to obtain roughly 1200 unique entries. On account of these workarounds and the need to deduplicate these posts via Jupyter Notebook, the entire collection process took longer than originally planned, ultimately requiring 14 weeks in total.

[7] Instagram claims this option is to help audiences focus on 'content' (Instagram, 2021), though it also works for users who are fearful of showing they have too few or too many likes on a post. When users enable this setting, the platform exhibits only two named users, hiding the total public count-like under an aggregated category labeled 'others'. Regardless of whether a thousand or a million users liked the post, the metadata still only displays and records the posts as having exactly 3 likes. Whilst such behaviours were still relatively uncommon, as most users seek to exhibit rather than hide their popularity in the form of like-counts, these infrequent exceptions would drastically skew averages of engagement ratios. For example, a post with 46 comments but a recorded like-count of '3' (e.g., 'liked by User 1, User 2, and 'Others') yields a comments-to-likes ratio of 15.33, a disproportionately inflated rate relative to a more typical ratio of 0.0048.

[8] Note that where i indexes posts, $TikTok_i$ is an indicator variable equal to 1 if post i is from TikTok and 0 if post i is from Instagram, and ε_i is the error term (Cano, 2026, June 27).

[9] 'Poetry' is a particularly generic search term, since it encompasses posts made by those who are not even attempting to share poetry for seemingly 'altruistic' reasons. It has been evidenced clear that there are many users who will use 'click-bait' tags to poems in order to sell a product, from fair-trade coffee to yoga classes (Knox, 2024). Therefore, it is no wonder that this term is

associated with such a large number of posts, which edges out the possibility of less-established posts achieving visibility when the algorithm is already overwhelmed.

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