Health in Discourse: Social Network and Text Analysis of Korean Skincare YouTubers

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1 Introduction

Korean skincare is a subcategory of Korean Beauty (K-Beauty) which has emerged as a global phenomenon, captivating beauty enthusiasts around the world with its innovative products, elaborate routines, and emphasis on achieving radiant, flawless skin. From 2016 to 2018, K-beauty grew in the U.S. market by nearly 300 percent, as American viewers and listeners of Korean pop and Korean dramas strived for the looks of Korean stars - including their makeup and their skin (Kim 2021).

Originating from South Korea, this skincare philosophy has garnered a cult following that transcends geographical boundaries and cultural barriers. Products that have gone viral include Cosrx's Snail Mucin Essence, Anua's Heartleaf Toner, I'm From's Rice Toner, Beauty of Joseon's Propolis Serum, Axis-Y's Niacinamide Glow Serum, Skin1004's Madagascar Centella Ampoule, and many more (Stylevana 2023).

In recent years, Korean skincare has become synonymous with meticulous skincare rituals, nature-based formulations, and an unwavering commitment to achieving a coveted complexion known as "**glass skin**." Glass skin is skin that is smooth, poreless, and translucent - like a piece of glass (Park and Hong 2021). Achieving this look entails a **10-step routine** consisting of two types of cleansers (oil and foaming), an exfoliator, a sheet mask, liquid or cream products (toner, essence, serum, eye cream), a moisturizer, and ending with sunscreen for the day and a sleep pack for the night (Kwon 2018). This contrasts with Western skincare which focuses on getting rid of any blemishes in a very short period of time; Korean skincare focuses on a softer but more healing approach of curing the skin barrier to fix the root of the problem (Micheli 2023). This emphasis on beauty and health from within resonates deeply with consumers who value a more holistic and nurturing approach to skincare.

Influencers on platforms like Instagram, YouTube, and TikTok play a pivotal role in shaping the narrative surrounding Korean skincare, offering a glimpse into their personal skincare journeys and sharing valuable recommendations with their followers. From skincare hacks to product hauls to before-and-after comparisons, these influencers serve as trusted guides and help spread awareness of practices and products (Straits 2018).

This study seeks to delve into the realm of Korean skincare influencers on YouTube through the lens of social network analysis and text analysis. What are the underlying mechanisms driving the spread and adoption of Korean skincare practices in the digital age? Through an exploration of network centrality metrics, token usage patterns, and interaction between the two, this study examines the evolving landscape of Korean skincare on YouTube and its impact on consumer behavior and cultural trends.

2 Background

2.1 Literature Review

Kwon (2018) finds that the Korean skincare ritual consists of individual self-care performances and that the products used are mythologized with a close affinity to nature. In the context of YouTube, these rituals find a natural platform for expression and dissemination. YouTubers engage in a form of performative skincare, showcasing their routines, techniques, and product recommendations to their audience. Moreover, the emphasis on nature means that many popular skincare products prominently feature natural ingredients sourced from the environment, such as snail mucin, propolis, and various botanical extracts.

The theoretical framework of parasocial relationships states that viewers can develop perceived interpersonal connections with media personalities, such as YouTube influencers (Perez 2021). The K-Beauty and skincare community on YouTube can be called a "network of desire" because public participation in the comments section builds new connections between extant desires and a wider network (Kozinets, Patterson, and Ashman 2016). Thus, content creators and viewers are linked through a cycle of performed consumption and consumed performance, and YouTube is the platform that facilitates this exchange of attention as a currency (Jodoin 2017).

Members who are sensitive to the latest trends and information and have a strong sense of collective sharing voluntarily participate and share knowledge and experiences with each other (Na, Kang, and Jeong 2021) in the comments section. Those who are perceived as more trustworthy and relatable tend to encourage the spread of K-Beauty trends and product acceptance among the community (Wang and Lee 2021).

This study is motivated by the fact that the intersection of social network analysis and text analysis within the realm of Korean skincare on YouTube is a largely unexplored research area. While the influence of Korean skincare practices and products is undeniable, substantial research has not been conducted on this phenomenon on YouTube. Understanding how Korean skincare influencers navigate and shape the YouTube ecosystem, including their network connection and linguistic patterns, presents a unique opportunity to unveil the underlying mechanisms driving consumer behavior, cultural diffusion, and attitudes of health in the digital age.

2.2 Hypotheses

The main research question is "How are Korean skincare practices and products accepted and diffused on YouTube?" I investigate three subquestions to answer this:

1. How do network centrality metrics of US-based Korean Skincare YouTubers predict viewership?
2. What tokens and hashtags are most common in titles and description boxes?
3. How do tokens interact with network position?

First, YouTubers who have a higher strength score are likely to have a greater sense of closeness with viewers and therefore higher viewership. In other words, strength is a statistically significant predictor of view count.

Second, tokens and hashtags about Korean beauty standards are the most popular. Specifically, I expect terms like "glass" and "glowing" to be among the most frequent tokens. These terms tap into beauty trends and are unique to the community, thereby leveraging the desire to achieve coveted beauty standards.

Third, tokens that relate to brands, ingredients, and skin-related concerns or aspirations positively correlate with network position. The more a YouTuber uses these buzzwords to optimize showing up in YouTube searches, the more likely they are to have a stronger influence in the network.

3 Methodology

3.1 YouTube Data

The `tuber` R package (SOod 2020) was used with the YouTube API to pull data from YouTube. The function `yt_search(term="korean skincare", type="video")` was used to obtain Korean skincare YouTube videos. Importantly, `yt_search` pulls both videos and Shorts. YouTube Shorts are videos that are less than one minute long. In general, Shorts attract more views and likes per view than regular videos but fewer comments per view (Violot et al. 2024). Therefore, how users interact with Shorts is systematically different than with a video. The `tuber` package does not contain any function that distinguishes between the two, so in order to identify YouTube Shorts, `get_video_details` was used to find the video length. Videos with a length of no more than 61 seconds (YouTube sometimes adds a second) were classified as Shorts.

A second dataframe for the comments under each video was built. Data on the comments were obtained with the `get_comment_threads` function. Observations where a YouTuber was the only commenter under themself were removed.

Table 1: Videos Data Dictionary

Variable	Type	Description
video_id	character	unique video ID
publishedAt	POSIXct	publishing time (yyyy-mm-dd hh:mm:ss)
channelId	character	unique channel ID
title	character	title of video
description	character	description box contents
channelTitle	character	title of channel
num_subscribers	numeric	number of subscribers
video_length	character	length of video in ISO 8601
video_length_s	numeric	length of video in seconds
Shorts	logical	whether the video is a Shorts or not
commentsExist	logical	whether comments are enabled
viewCount	numeric	number of views
likeCount	numeric	number of likes
commentCount	numeric	number of comments

Table 2: Comments Data Dictionary

Variable	Type	Description
video_id	character	unique video ID
channelId	character	unique channel ID
textOriginal	AsIs	list of comments under video
authorDisplayName	AsIs	list of commenter usernames under video
authorChannelId.value	AsIs	list of commenter channel IDs under video
Shorts	logical	whether the video is a Shorts or not

3.2 Edge List

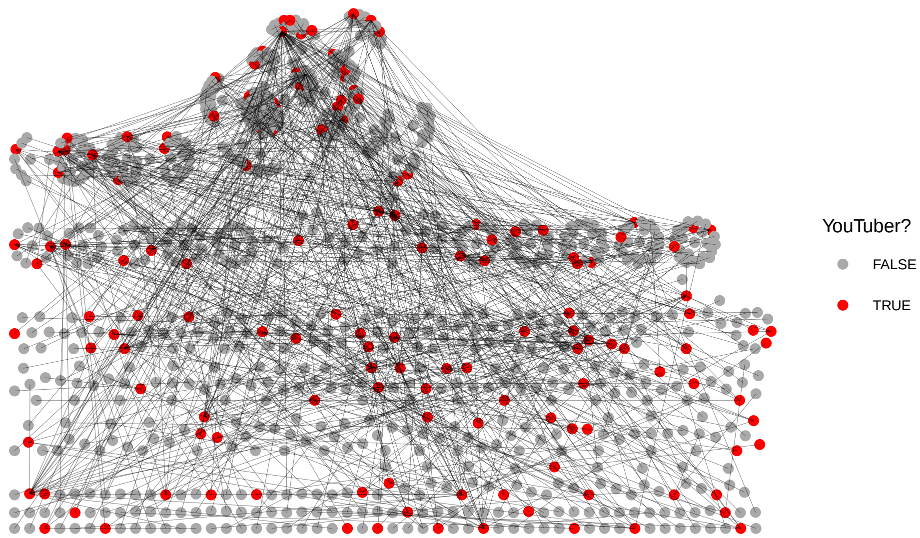
An edge list was created such that there is a connection between a YouTuber and a user if the user left a comment under the video. Only videos that are **not YouTube Shorts** were used. The number of times a user left a comment under a YouTuber (`num_comments`) was counted.

3.3 Network Graphs

Edges with `num_comments` at least 2 were filtered for. The graph is **undirected** because there is no meaningful difference between source (YouTuber) and target (Commenter) as some of the YouTubers are also commenters. Edges were weighed by `num_comments`.

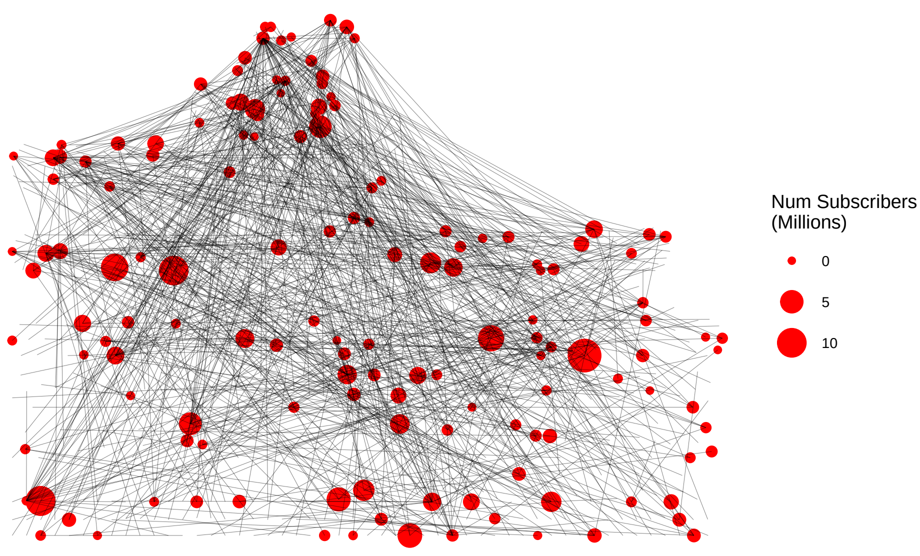
The network of YouTubers and Non-YouTubers is visualized below. Nodes are colored by whether a user is a YouTuber. Some YouTubers are at the center of highly clustered nodes while others are at the peripheries of the graph.

Network of YouTubers and Non−YouTubers



Next, the network of YouTubers is visualized below. Node size indicates the number of subscribers they have. Just because a YouTuber has many subscribers does not mean they are near the center of the network. However, YouTubers with a smaller number of subscribers tend to be near the peripheries.

Network of YouTubers



3.4 Strength

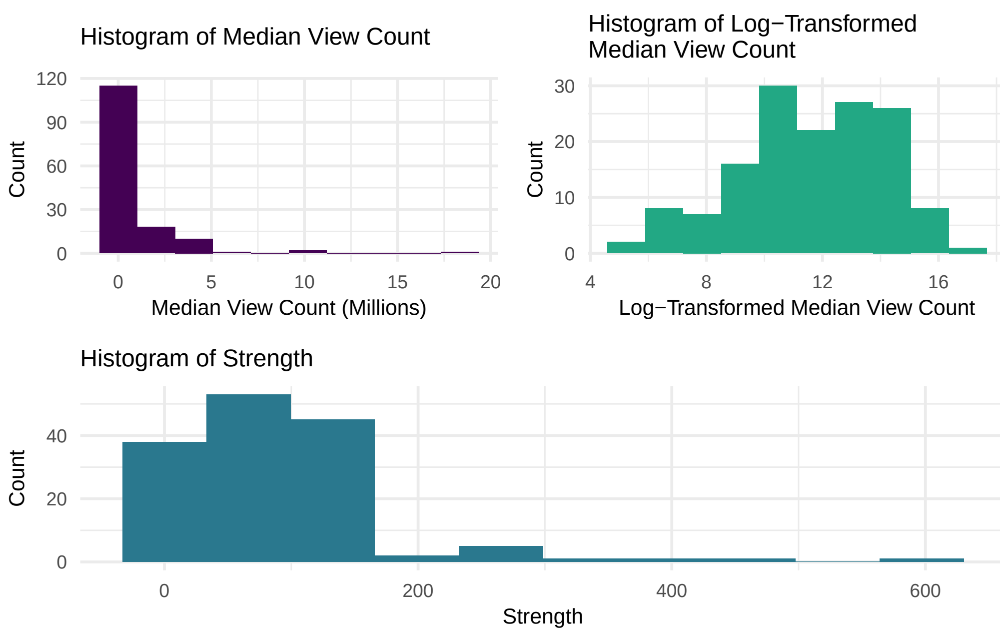
Strength centrality is the strength of a node in weighted networks. It is equivalent to the sum of weights assigned to the node's direct connections. Here, strength represents a YouTuber's influence or importance in the network.

3.5 Modeling

There are multiple videos from the same YouTuber in the video dataframe; each YouTuber has a strength score but some of them have multiple view counts. To avoid skewness, the median view count for each YouTuber was taken. The corresponding year of the video with the median view count was also taken.

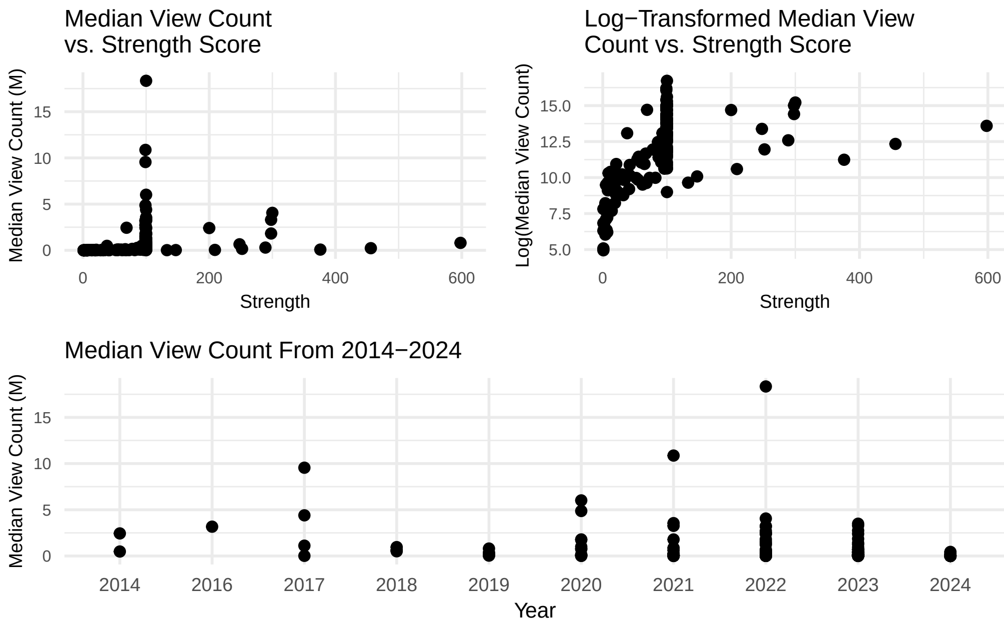
3.5.1 EDA

The distribution of median view count is heavily right-skewed. Log transforming it satisfies the normality condition. The distribution of strength is also very right-skewed. This aligns with expectations because it reflects the inherent nature of virality; fewer individuals achieve extreme levels of virality compared to the broader population.



YouTubers with a strength of 100 tend to have the highest median view counts, which is a bit surprising as it indicates the most influential YouTuber does not necessarily have the highest view counts. It is plausible that skincare enthusiasts value a breadth of opinions and perspectives, seeking input from multiple sources rather than solely relying on the recommendations of a single individual. As a result, while highly influential YouTubers undoubtedly hold significant sway within the skincare community, consumers may be inclined to explore diverse viewpoints, contributing to the distribution of views across a spectrum of content creators.

There is a positive but weak linear relationship between strength and log-transformed median view count. It appears to be a logarithmic relationship, but log-transforming strength would come at the cost of interpretability - a change in the approximated expected ratio of median view count is not very useful in practice. Therefore, strength will be kept as is.



Random effects are families of coefficients, usually associated with nominal categorical factors, that are assumed to follow some population distribution. Random effects are often assigned to factors that identify groupings in a data set. Here, `year` serves as a grouping variable that divides the data into distinct categories based on the year of observation. **Fixed effects**, as in typical linear models, are coefficients assumed to have a specific unknown value.

The plot shows that the median view count varies by year, suggesting that there are systematic differences in median view counts across different years. However, there is also a notable difference in the amount of data available for each year, with fewer observations from 2014-2019 compared to 2020 onwards. This discrepancy in data availability could reflect underlying trends, such as the increasing popularity of YouTube over the years and the rising trend of K-Beauty content.

By treating `year` as a random effect in the regression model, the variability in median view count that is specific to each year can be accounted for. This approach allows the model to incorporate the unique effects of each year on median view count while also accommodating the variation in data availability across different years. The regression model is thus a **linear mixed model**.

3.6 Keywords

A keyword score was calculated by summing up the number of occurrences of base words (words that generally all videos about Korean skincare have), brands, ingredients, and skin-related concerns or aspirations in the video title and description box. The selection of these tokens was informed by domain knowledge of the Korean skincare industry. This score serves as a proxy for the emphasis placed by each YouTuber on these thematic elements in their content.

Note: Olive Young, Stylevana, and YesStyle are Korean skincare retailers (like Sephora). They sell products to international consumers of Korean skincare.

Table 3: Keywords Dictionary

Category	Tokens
Base Words	beauty, care, haul, korea, korean, products, review, routine, skin, skincare, step, tips, trend, trending, viral
Brands	anua, axis, beauty of joseon, cosrx, goodal, haruharu, i'm from, isntree, jart, laneige, ma:nyo, medicube, mixsoon, nature republic, numbuzin, oliveyoung, round lab, skin1004, skinfood, some by mi, sulwhasoo, stylevana, tocobo, torriden, yesstyle
Ingredients	aloe, ceramides, cica, centella, extract, fermented, galactomyces, ginseng, heartleaf, honey, hyaluron, infused, milk, mineral, mugwort, niacinamide, propolis, retinol, rice, snail mucin, tea, vitamin, volcanic, vegan
Skin	acne, aging, ampoule, anti, balancing, blackheads, booster, brightening, breakouts, calm, cleanser, cleansing, cream, depuffing, dermatologist, dewy, dry, exfoliator, firming, flawless, glass, glow, glowing, glowy, healing, hydrating, hyperpigmentation, mask, milky, moist, moisturiser, natural, nourishing, oil, oily, pads, pore, pure, redness, revitalizing, serum, smoothing, soothing, tone, toner, uneven, whitening

4 Results

4.1 LMM

The regression equation is

$$\begin{aligned}
\log(\text{med_viewCount}_{ij}) &= \beta_0 + \beta_1 \text{strength}_{ij} + \beta_2 \text{num_subscribers_millions}_{ij} + \text{year}_j + \epsilon_{ij} \\
j &= 1, \dots, 10 \text{ groups} \\
i &= 1, \dots, n_j \text{ samples in group } j
\end{aligned}$$

`num_subscribers` was scaled by a factor of one million. The model output is given below:

Table 4: Fixed Effects

	Estimate	Std. Error	t value
(Intercept)	10.8057091	0.5249214	20.585387
strength	0.0108825	0.0020739	5.247307
num_subscribers_millions	0.2497793	0.0878725	2.842519

Table 5: Random Effects

grp	var1	var2	vcov	sdcor
year	(Intercept)	NA	1.812453	1.346274
Residual	NA	NA	3.442851	1.855492

The t-values for `strength` and `num_subscribers_millions` are both above 1.96, indicating that they are statistically significant predictors of log-transformed `med_viewCount`. The variance for `year` is 1.812 and the standard deviation is 1.346.

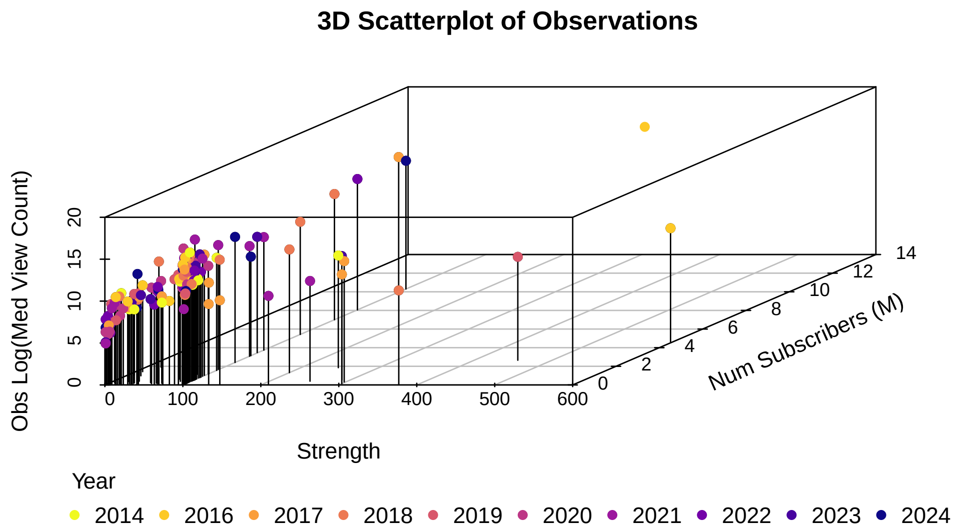
For every one-unit increase in `strength`, `med_viewCount` is expected to multiply by a factor of 1.011 ($e^{0.011} \approx 1.011$), holding all else constant. This means for a ten-unit increase in `strength`, we expect about an 11.6% increase in `med_viewCount` ($e^{0.011\times10} \approx 1.116$), holding all else constant. Similarly, for every one million new subscribers, we expect `med_viewCount` to increase by 28.4% ($e^{0.250} \approx 1.284$), holding all else constant.

The coefficients for each year are given below. Because `year` is a random effect, only the intercept estimates differ.

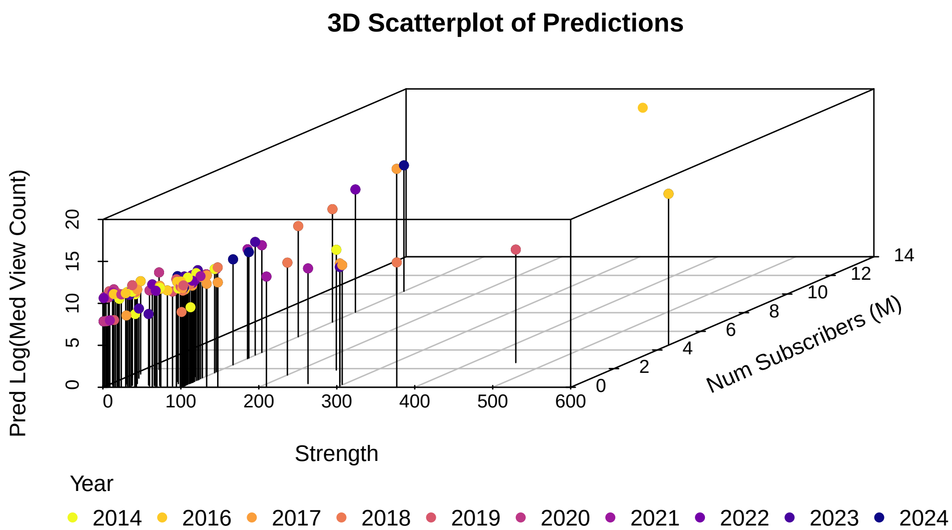
	year..Intercept.	year.strength	year.num_subscribers_millions
2014	11.800370	0.0108825	0.2497793
2016	11.853277	0.0108825	0.2497793
2017	11.341189	0.0108825	0.2497793
2018	11.167071	0.0108825	0.2497793
2019	10.302247	0.0108825	0.2497793
2020	11.516745	0.0108825	0.2497793
2021	10.611744	0.0108825	0.2497793
2022	10.878981	0.0108825	0.2497793
2023	10.744756	0.0108825	0.2497793
2024	7.840711	0.0108825	0.2497793

4.1.1 3D Scatterplots

3D scatterplots show the observed and predicted values. In general, as strength and/or number of subscribers increase, so does log-transformed median view count.

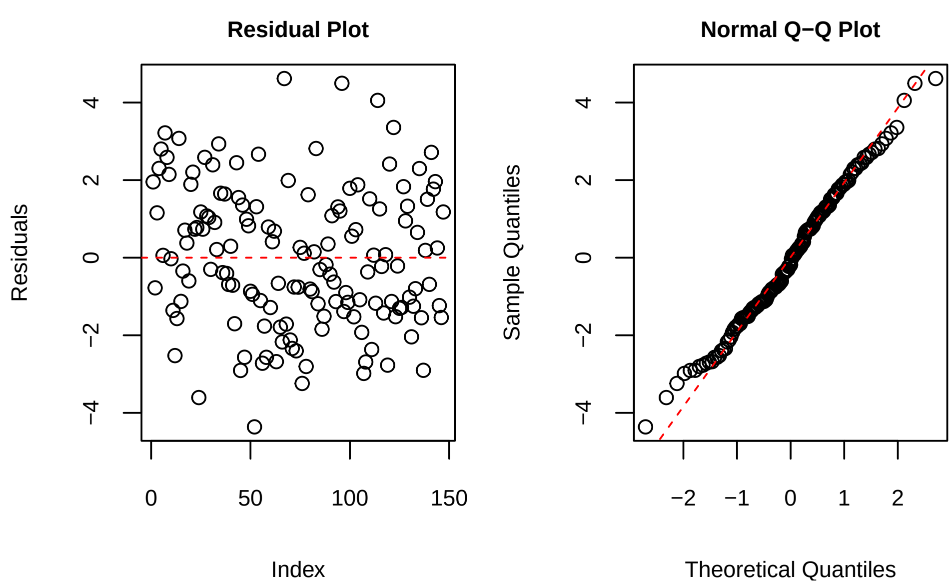


The 3D scatter plot for predicted values has an overall similar shape to the plot of observed values. However, there is a discrepancy for YouTubers with a strength score of 100: the model consistently underpredicts log-transformed view count. Thus, the model does not fully account for the disproportionate impact these YouTubers with a strength of 100 have on median view counts.



4.1.2 Diagnostics

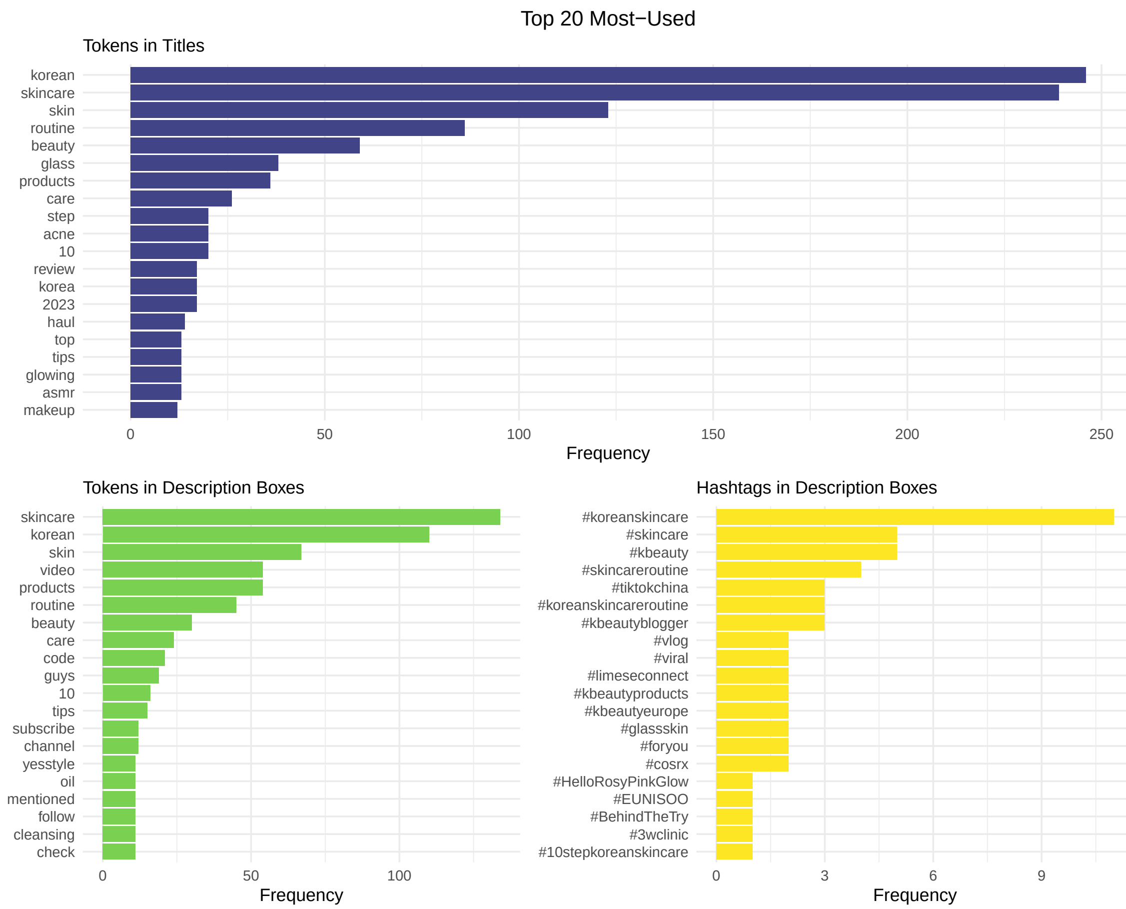
The residual plot shows a relatively constant vertical spread of the residuals. The errors are mostly homoscedastic. The Q-Q residual plot also shows that residuals largely follow a straight line, though there is slight tapering at the ends. Overall, the residuals are normally distributed. Therefore, the model is appropriate.



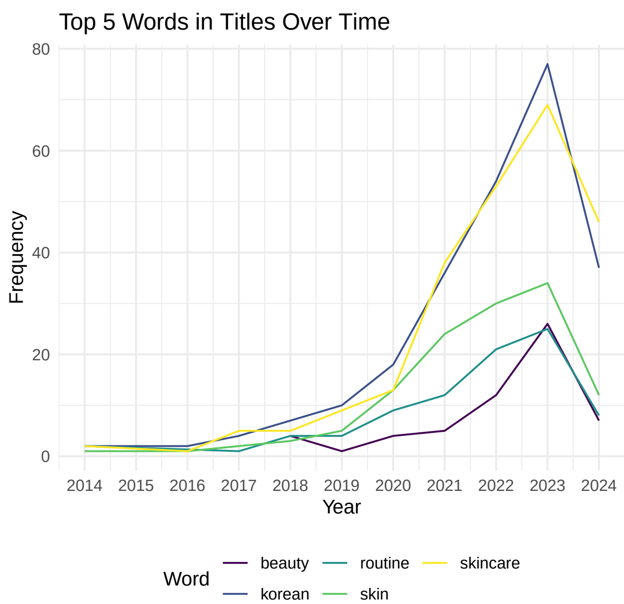
4.2 Text Analysis

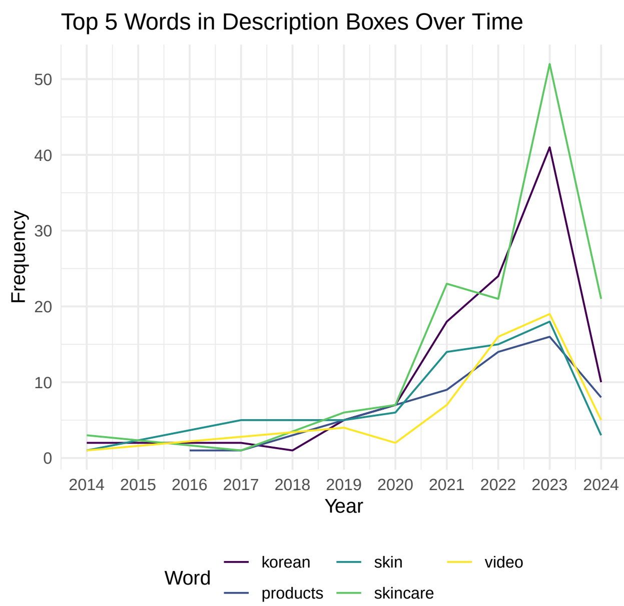
4.2.1 Top Tokens & Hashtags

The 20 most-used tokens and hashtags in titles and description boxes are shown below. "korean," "skincare," "skin," "routine," and "beauty" are the most used words across titles and description boxes. Cosrx is the only brand that appeared in the top 20 most-used hashtags in description boxes.

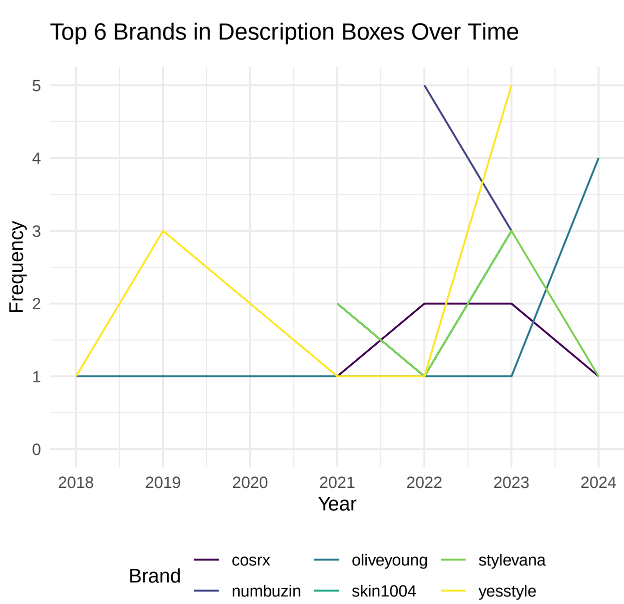


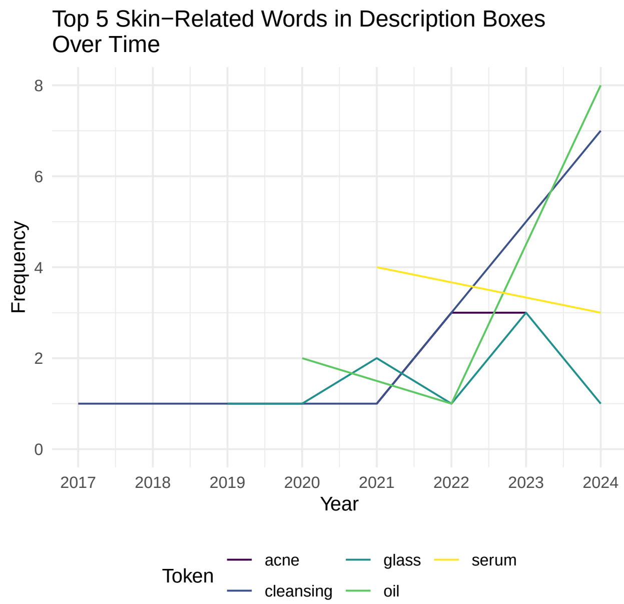
The time plots below show the top 5 words in titles and description boxes over time. There is a drop from 2023 to 2024 because 2024 is not over yet, so the **frequencies in 2024 do not reflect the entire year**. Both "korean" and "skincare" have consistently been the most popular tokens in titles and description boxes. However, the tokens "video" and "products" appear more regularly in description boxes whereas "routine" and "beauty" appear more regularly in titles.





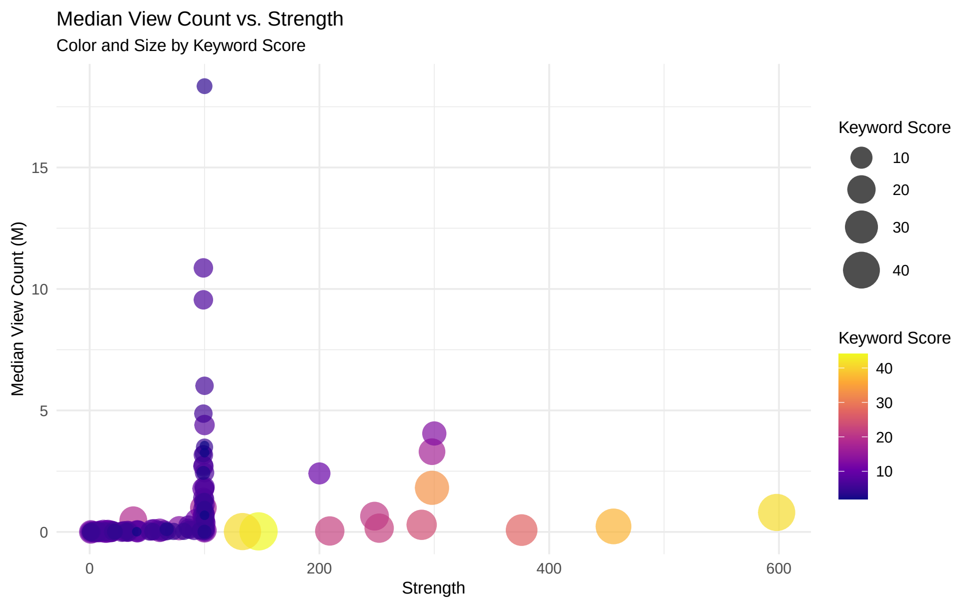
The time plots below show the top 6 brands and top 5 skin-related tokens in description boxes over time. Interestingly, the plots do not start until 2018 and 2017, respectively, indicating that Korean skincare brands and skin-related trends did not make their way into the mainstream Western skincare YouTube community until 6-7 years ago. There were not enough occurrences of ingredients to make a meaningful plot. Cosrx was popular in 2022 and 2023 while Numbuzin peaked in 2022. YesStyle saw popularity before the other 2 retail brands though Olive Young has been gaining more popularity recently. Oil and cleansing are the two most frequent skin topics in 2024 so far. This likely reflects the trend of using cleansing oil as part of double cleansing (Balagam 2024). Glass skin peaked in 2023 while acne has been a consistent concern in 2022 and 2023.



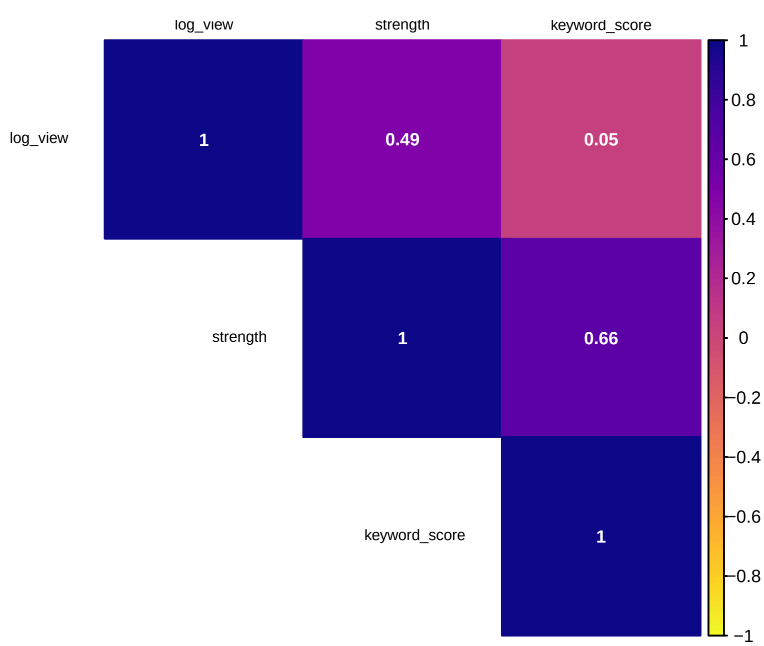


4.2.2 Token & Strength Interaction

The bubble plot below shows that keyword score tends to increase as strength increases. However, there is not a strong relationship between keyword score and median view count. The YouTubers with the highest median view count seem to have a moderately low keyword score of around 10. Perhaps targeting keywords over spamming as many buzzwords as possible leads to better search engine optimization or discoverability.



The correlation matrix plot below confirms that keyword score is not strongly correlated with log-transformed median view count. However, it is positively correlated with strength.



5 Discussion

The results of this study shed light on the acceptance and diffusion of Korean skincare practices and products on YouTube.

First, strength is a statistically significant predictor of log-transformed median view count. This means the influence or importance of US-based Korean Skincare YouTubers plays a role in determining their viewership. YouTubers with higher levels of influence within the network have more views, likely due to their perceived authority or credibility within the Korean skincare community on YouTube.

Second, commonly used tokens such as "korean," "skincare," "skin," "routine," and "beauty" reflect the overarching themes and topics discussed by content creators. The presence of specific tokens like "routine," and "beauty" in titles suggests a focus on content type or desired outcomes, while tokens like "video" and "code" in description boxes may indicate additional information or promotional content. "glass" was indeed the most popular non-base word token. The temporal analysis shows that there is a lag in Korean beauty trends in the U.S. This suggests a gradual diffusion process rather than an abrupt introduction; Korean skincare practices gradually permeate Western beauty culture over time.

Third the positive correlation between keyword score and strength suggests that YouTubers with higher levels of influence tend to incorporate more domain keywords into their content. However, the lack of a strong correlation between keyword score and median view count indicates that simply having a higher keyword score does not necessarily translate to higher viewership. This finding underscores the importance of quality content and engagement strategies beyond keyword optimization in attracting and retaining viewers.

5.1 Limitations

`yt_search` failed to retrieve data from 2015 which is strange because a quick YouTube search indicates there are videos about Korean skincare in 2015. This limitation may introduce a bias towards more recent data and potentially overlook important trends or patterns in the earlier years.

The use of median view count as the primary outcome measure may result in loss of information, particularly when multiple videos are released by the same YouTuber. Median view count is a less useful response variable than just view count; it would be more practical to predict the view count on a new video given strength, number of subscribers, and year.

While linear mixed models were chosen for their interpretability, exploratory data analysis revealed a logarithmic relationship between log-transformed median view count and strength. The decision to not explore models with log-transformed strength may have overlooked potentially important nuances in the data.

Lastly, the results from the year 2024 pose a temporal limitation, as the year is currently ongoing. They do not fully capture the dynamics of the entire year.

6 Conclusion

Through exploring network centrality metrics and token usage patterns, this study aimed to examine the evolving landscape of Korean skincare on YouTube and its impact on consumer behavior and cultural trends. Network centrality metrics, such as strength, significantly predict viewership while the analysis of token usage patterns highlighted the prevalence of keywords related to Korean beauty standards, reflecting the unique language and discourse within the community.

While network centrality metrics and token usage patterns play a role in shaping the visibility and influence of Korean Skincare YouTubers, other factors such as content quality, engagement with the audience, and broader trends in the skincare community also influence viewership. This underscores the importance of a holistic approach to content creation and engagement strategies for YouTubers and brands alike.

These findings hold implications for both YouTubers and brands seeking to leverage YouTube influencers for marketing purposes. For YouTubers, understanding the factors that contribute to network strength and viewership can inform content creation strategies aimed at maximizing engagement and visibility within the YouTube community. For brands, identifying influencers who not only possess large subscriber bases but also occupy influential positions within the network, as quantified by strength, may offer greater potential for effective product promotion and brand exposure.

Overall, these findings contribute to a deeper understanding of how Korean skincare practices and products are embraced and disseminated within the YouTube ecosystem, highlighting the multifaceted nature of content creation and audience engagement in this niche.

6.1 Future Work

Further exploration of understanding Korean skincare practices and their dissemination on YouTube are discussed below.

Exploring a log transformation of strength as a predictor variable could potentially offer a more nuanced and accurate representation of the data. Similarly, including more data from earlier years, particularly from 2014 to 2017, could also provide valuable insights into the evolution and trajectory of Korean skincare content on YouTube over time. Future research could also expand upon the findings of this study by conducting text analysis on the comments section, gaining valuable insights into audience engagement.

Additional research on the effect of the Hallyu wave (a term for the popularity of South Korean pop culture) on the spread of Korean skincare practices could be conducted. For instance, how do influential figures, such as K-pop idols promoting glass skin beauty standards, contribute to the adoption and diffusion of Korean skincare practices? This could offer intriguing insights into the intersection of pop cultural trends and digital media influence.

Following the example of Bail (2016), who combined natural language processing and network analysis to analyze how cultural bridges shaped public discourse about autism spectrum disorders on Facebook, a similar approach could be applied to analyze how cultural bridges and online interactions shape discussions and perceptions surrounding Korean skincare practices on YouTube.

These research endeavors can deepen understanding of the interplay between digital media, cultural influences, and skincare practices, ultimately shedding light on the broader phenomenon of cultural and health dissemination in the digital age.

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