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Male or female gender-polarized YouTube videos are less viewed

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Abstract

As one of the world's most visited websites, YouTube is potentially influential for learning gendered attitudes. Nevertheless, despite evidence of gender influences within the site for some topics, the extent to which YouTube reflects or promotes male/female or other gender divides is unknown. This article analyses 10,211 YouTube videos published in 12 months from 2014 to 2015 using commenter-portrayed genders (inferred from usernames) and view counts from the end of 2019. Nonbinary genders are omitted for methodological reasons. Although there were highly male and female topics or themes (e.g., vehicles or beauty) and male or female gendering is the norm, videos with topics attracting both males and females tended to have more viewers (after approximately 5 years) than videos in male or female gendered topics. Similarly, within each topic, videos with gender balanced sets of commenters tend to attract more viewers. Thus, YouTube does not seem to be driving male–female gender differences.

1 | INTRODUCTION

Gender inequalities in society are an ongoing concern, particularly in careers (e.g., Mihăilă, 2016). Potential mass media influences include gender disparities in news reporting and journalism (in the UK: Howell & Singer, 2017; in Australia: North, 2016), stereotypes in advertising (Grau & Zotos, 2016; Tartaglia & Rollero, 2015), and stereotypes and other disparities on television (e.g., Sink & Mastro, 2017; see also UNESCO, 2012). Gender stereotypes can be attractive to advertisers because they encode easily understandable idealized narratives that products can be connected to (Goffman, 1979). For example, targeting toys at boys or girls has been a successful marketing strategy in Australia, but is facing resistance as attitudes change (Fine & Rush, 2018). One prominent theory argues that beauty-

related advertising tends to pressurize (relatively privileged) women to conform to appearance stereotypes in societies where a substantial proportion of women are employed (in the USA: Wolf, 1991; Stephens et al., 1994; see also Hirschman & Thompson, 1997). This extends to media types that are sustained by beauty-related advertising and create an environment conducive to beauty-related product sales (Wolf, 1991). Exposure to advertising has been shown to be effective in promoting a female thin body type ideal (e.g., Grabe et al., 2008). Young people consume less traditional mass media now, however, and increasingly replace it with the social web (e.g., in the USA: Schaeffer, 2019). The social web may work differently for gender since the presence of many amateur or self-employed content producers may give rise to different disparities or influences. There are also different gendering pressures online from algorithms (Bishop, 2019) and

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commenting audiences than there are offline from editors and publishers. As one of the world's most visited websites (second in January 2020: Alexa, 2020; third in April 2009: Alexa.com, 2009), YouTube is potentially the most powerful social web component and needs to be assessed for its contribution to the gender environment.

Since YouTube is free to join, sexism-based recruitment barriers to women in traditional employment do not apply except in professional channels. Nevertheless, there are complex systematic pressures within the site (Postigo, 2016). Women wishing to build careers as YouTube influencers (Hou, 2018; Marwick, 2013) may perceive the need to follow advertising revenue streams by creating marketer-friendly content in the form of beauty product reviews (in the UK: Bishop, 2018b, 2019). These are commercially desirable because word-of-mouth is important for these products, videos are a natural way in which to communicate the look of the product and demonstrate how to use them, and there are huge beauty and fashion markets (e.g., in France: Sokolova & Kefi, 2020). The belief that beauty product reviews can form part of a financially rewarding strategy on YouTube (in the UK: Bishop, 2018a; see also Marwick, 2018) can produce the side effect that increasing resources are devoted to produce high-quality interesting beauty content, pulling YouTube users away from the remainder of YouTube. Thus, YouTube may be creating a social pressure for female appearance conformity through the success of its high-quality beauty videos, but it is not clear if similar gendering trends operate throughout the site.

There are conflicting relationships with traditional Western gender stereotypes on YouTube. On the mainly positive side, successful U.S. comedian Jenna Marbles both leverages and confronts traditional gender roles (Wotanis & McMillan, 2014), natural hair vloggers promote an alternative identity and lifestyle for African American women (Neil & Mbilishaka, 2019), young English-speaking women have used YouTube to argue against rape culture (Garcia & Vemuri, 2017), a community of presumably mainly heterosexual adolescent male commenters on Minecraft game videos from the YOGSCAST Sjin YouTube channel engages with queer discourse (Potts, 2015), and Muslim women have posted video reactions to a Dutch anti-Islam video (Vis et al., 2011). YouTube can also be a safe space for people to express nonbinary genders and gender nonconformity (Day, 2018; Eckstein, 2018; Miller, 2019), opposing traditional binary gender stereotypes, and the head of YouTube has argued that advertising breaking gender stereotypes is more effective (Wojcicki, 2016). Conversely, comments on male or female intoxication in Italian videos reflect sexist stereotypes (Rolando et al., 2016), female broadcasters are more likely to be subject to

comment trolling (e.g., on Twitch: Todd & Melancon, 2019), criticisms of overweight people on YouTube can be sexist (e.g., Jeon et al., 2018), women are frequently sexualized in comments on fail videos (in the FailArmy channel: Döring & Mohseni, 2019), and videos can attract highly gendered audiences (e.g., for educational videos: Thelwall & Mas-Bleda, 2018; Thelwall, 2018). Different factors also seem to influence men and women to share videos (at least in Taiwan: Yang et al., 2010). Thus, YouTube is both a positive and a negative influence on gender stereotypes and its overall influence is unclear.

This article seeks clarity on the influence of the male-female gender divide and YouTube audience size by investigating the relationship between the topic of a video and the gender of its viewers. It adopts a unique perspective: while prior research on the influence of media gender portrayals has analyzed the prevalence of gender disparities and stereotypes (Howell & Singer, 2017) or the influence of stereotypes (e.g., Parent & Cooper, 2020), the current paper focuses on the number of viewers of male or female gendered content in comparison to less gendered content. It also assesses whether content for one gender (male or female) is more viewed. For purely methodological reasons, it does not assess the audience size for genderqueer content, which should not be assumed to fall somewhere on a spectrum between male and female (Whyte et al., 2018). Also for methodological reasons, it addresses commenter gender, which can be detected to some extent from user names, rather than viewer gender, which is unknown. The research questions address categories (nonoverlapping, user defined) and topics (overlapping, finer-grained, algorithmically derived) for data triangulation.

- RQ1: Are videos in primarily single gender (male or female) commenter YouTube categories or topics more viewed than videos in YouTube categories or topics that attract a more equal balance of males and females?
- RQ2: Are YouTube videos within a topic or category more viewed if they primarily attract one gender (either male or female) commenter rather than attracting a more equal balance of males and females?
- RQ3: Are YouTube videos within a topic or category more viewed if they predominantly attract female commenters rather than male commenters? Or is the opposite true?

2 | METHODS

The research design was to gather a large sample of mature videos and to compare the number of views they

attract with the gender of their commenters within and between categories and topics. The rest of this section describes how this was put into practice.

2.1 | Sample of videos

It is difficult to sample YouTube videos because there is no exhaustive list or method to generate a complete or random sample (Bärtl, 2018). Instead, YouTube's API (applications programming interface) provides samples in response to category requests or keyword searches, and these can be used to generate large nonrandom sets of videos across all YouTube's basic categories. Since keyword searches could be biasing, and the YouTube categories seem to be exhaustive, category searches were used to identify videos. The YouTube IDs of videos returned by category searches every 5 days for 95 days from December 29, 2015 and every day from April 4, 2015 for 30 days for a different project were used as the initial sample. While this is a biased set of videos, with more viewed videos than average and different sampling characteristics between categories (Foster, 2020), it at least provides a large sample of videos with a range of view counts and topics.

From the initial set of videos, the 55,365 initially posted between July 16, 2014 and July 15, 2015 were extracted. This date range was selected to give a substantial number of mature videos of a similar age, to allow relatively unbiased comparisons of their view counts. Over 4 years later in November–December 2019, the videos were searched in YouTube with the API to download their view counts and the most recent 100 comments and commenter usernames (for gender information). The YouTube API was called by a program (<http://mozdeh.wlv.ac.uk>) from Wolverhampton in the UK with a YouTube developer account login. The purpose of the YouTube API is to “incorporate functions normally executed on the YouTube website into your own website or application” (developers.google.com/youtube/v3/docs), so the results are not expected to be personalized to the searcher (the first author) although they might be customized for the UK market by prioritizing UK-relevant content.

In terms of video age, although older videos have more time to attract view counts (up to 23% longer: 5 years and 4 months against 4 years and 4 months), all videos have had a substantial amount of time to attract viewers. YouTube mainly recommends videos in their first year of publication (Foster, 2020), so older videos are less likely to be found through this route. Nevertheless, multiple factors influence the longevity of a video, including the primary methods by which it is discovered

(Figueiredo et al., 2011; Zhou et al., 2016). In addition, while some videos are inherently current, such as news or influencer “haul” reviews of new season fashions, others have longer term value, such as maths tutorials or home maintenance advice (Yu et al., 2015). Thus, given that there may be topic differences in the extent to which the view counts after 4–5 years reflect total views, there may be a second-order effect on the relationship between gender and view count if one gender's videos tend to attract more long-term views. This is a methodological limitation. Only the most recent 100 comments were downloaded as a practical step to avoid overloading the YouTube server with low value requests. Comments can be used to post an opinion on a video or to engage with conversation with other viewers (Bou-Franch et al., 2012). A small minority of video viewers comment, but their names can be used for a very approximate indication of viewer genders.

2.2 | Commenter genders

The YouTube API does not report the gender of video viewers or commenters, so this was estimated from the apparent gender of the commenters (the most recent 100 per video). The text of the comments is not analyzed: the commenters are exploited purely for the ability to infer their gender, as part of a video's audience. Although commenters are likely to be a gender biased subset of viewers, with the level of bias perhaps varying between topics (e.g., Thelwall et al., 2012), this seems to be the only source of large-scale gender information available. Gender was inferred from YouTube usernames, which is an indicator of the gender portrayed or performed by users through their chosen name rather than biological sex (which is irrelevant here). The names of the commenters were analyzed, split into two and the first part cross-referenced against a list of names from the U.S. census 1990 that were at least 90% male or at least 90% female, supplemented by Gender-API.com queries for missing names. The split was made at the first lower-to-upper case switch (e.g., at eT in MikeThelwall) or at the first digit (e.g., Mike99). Only names with at least three letters were used to avoid false matches from initials. Names not matching this list were discarded, as were multiple instances of the same commenter. For example, a video with 100 comments, including 40 for different female names, 10 with different male names and 50 unrecognized or duplicate names would be classified as 80% female. Videos with less than 30 gendered commenters were discarded because these may give an inaccurate impression of the overall proportion of female commenters. Nonbinary genders had to be ignored

because they are statistically rarer and there are no widely used naming conventions (e.g., nonCisMike, non-binaryMike) that would allow them to be identified from YouTube usernames. Trans users would be included with the gender aligned with their Twitter name, which would presumably be their chosen gender.

The above gender identification process makes errors (e.g., BritneyTopFanMike would be female rather than male) but these are rare because of the 90% threshold (<https://doi.org/10.6084/m9.figshare.5688622>) and weaken the statistical evidence rather than increasing the likelihood of false positives. It also enforces a binary divide whereas gendered behavior falls more on a spectrum, even for those identifying as male or female, and includes many genderqueer people. Nevertheless, the binarizing approach allows statistical analyses identifying male–female tendencies in the number of viewers of YouTube videos. There is a potential systematic source of bias in that one gender may be more likely to use obscure usernames, and the extent of this bias may vary between topics. For example, if younger males are more likely to avoid using their own name in their username and form a higher percentage of commenters on gaming videos, then the procedure used in this paper may underestimate the proportion of male commenters in the Gaming category.

The monogender (commenter) proportion for each video was calculated as the proportion of male or female commenters, whichever is the larger, bypassing non-binary genders and users without an inferred gender. For example, if a video had 100 commenters, with 30 having a male name and 70 a female name then its monogender proportion would be 70% (the maximum of 30% and 70%). The higher the monogender proportion of commenters, the more the content of the video has attracted a single gender (male or female), at least in terms of commenters.

2.3 | Topics and categories

YouTube reports two content categorizations for most videos: an overall category (for all videos) and one or more topics (for some videos). Whereas users pick a category when they upload a video, the topics are algorithmically assigned by YouTube. There are more topics than categories, so they have the potential to give finer-grained information and were used in addition to the categories.

The 10,211 qualifying videos were organized into the 15 (nonoverlapping) YouTube categories, each of which had at least 30 videos. The videos were also organized into overlapping topics, with each video being assigned to all topics for which it had an associated label. Averages

for topics with few videos could be imprecise (in the sense of wide confidence intervals for the assumed population mean). To minimize the risk of the results being influenced by this, topics with fewer than 30 videos were deleted. The threshold of 30 was chosen in the absence of an evidence-based method as a common minimum sample size (e.g., Kar & Ramalingam, 2013; VanVoorhis & Morgan, 2007). This left 32 topics with a total of 17,860 videos, including duplicates. The 31 topics deleted included seven without any videos and 24 with between 1 and 28 videos.

As described above, the data collection includes a double selection for sample size. To illustrate, a video having at least 30 gendered commenters (see above) and with the category How-to & Style and topics Lifestyle, Food, Knowledge would be assigned to How-to & Style in the first set (categories) and both Lifestyle and Food in the second set (topics), but its Knowledge topic would be ignored because there were only 28 videos overall with at least 30 gendered commenters for Knowledge.

2.4 | Analysis

For RQ1 the average (geometric mean) number of views in each category and topic was correlated with the monogender proportion to assess whether topics or categories were more viewed if they tended to attract one of the genders investigated here. Geometric means were used for the view counts because the data was highly skewed. Spearman correlations were used rather than Pearson correlations for the same reason. For this, the average monogender proportion was calculated to assess the extent to which videos tended to attract the same gender. For a video with a proportion of female commenters f , its monogender proportion was f when $f > 0.5$, otherwise $1 - f$. Thus, the monogender proportion is always between 0.5 and 1 and is close to 1 if most commenters are male or if most commenters are female. The monogender proportion is therefore an indicator of gender imbalance.

For RQ2, Spearman correlations were calculated between view counts and the monogender proportion so assess whether videos appealing to a single gender tended to be more viewed.

For RQ3, Spearman correlations were calculated between view counts and the proportion of female commenters (within male and female commenters, ignoring unknown gender commenters) within each category and topic. This assessed whether videos that mainly attracted female (in comparison to male) commenters tended to be more viewed. Negative correlations would point to the opposite conclusion.

3 | RESULTS

The research questions are addressed for the YouTube categories first and then for the YouTube topics. A follow-up analysis is also reported for an issue raised by the results.

3.1 | View counts and commenter gender for YouTube videos by category

The average (geometric mean) view counts of videos in a category correlated strongly, negatively, and statistically significantly with the monogender proportion ($\rho = -0.582, p = .023, n = 15$), indicating that videos in binary gender-balanced categories tend to be more viewed. This negative correlation is mainly due to videos in the binary gender-balanced Music, Comedy, and Film and Animation categories being highly viewed (Figure 1).

Videos in all categories have, on average, 74% of commenters with the same gender, so gender imbalance is the norm for videos. How-to & Style has mainly female

commenters but includes some videos with mainly male commenters, giving it a high proportion monogender (Figure 2). The categories in YouTube vary from the strongly male Auto & Vehicles (94% male commenters) to the moderately female How-to & Style (78% female commenters) (Figure 2). Thus, there is extensive gendering between categories on YouTube, with only People & Blogs being close to gender-equal (52% female).

With the minor exceptions of News & Politics and Non-profits & Activism, videos within each category that are the most monogender tend to have the fewest viewers, with the correlations typically being moderate or strong (Figure 3). This suggests that attracting more gender diverse commenters can increase audience size. The opposite strategy of attracting a large audience with male or female gender-specific content seems to be less successful. In parallel with this, there is a tendency for videos in more male categories to attract a greater audience when they attract a greater share of females (e.g., the first four categories in Figure 3). Videos in the two female categories attract a larger audience when they have a greater share of males (e.g., the last two categories in Figure 3).

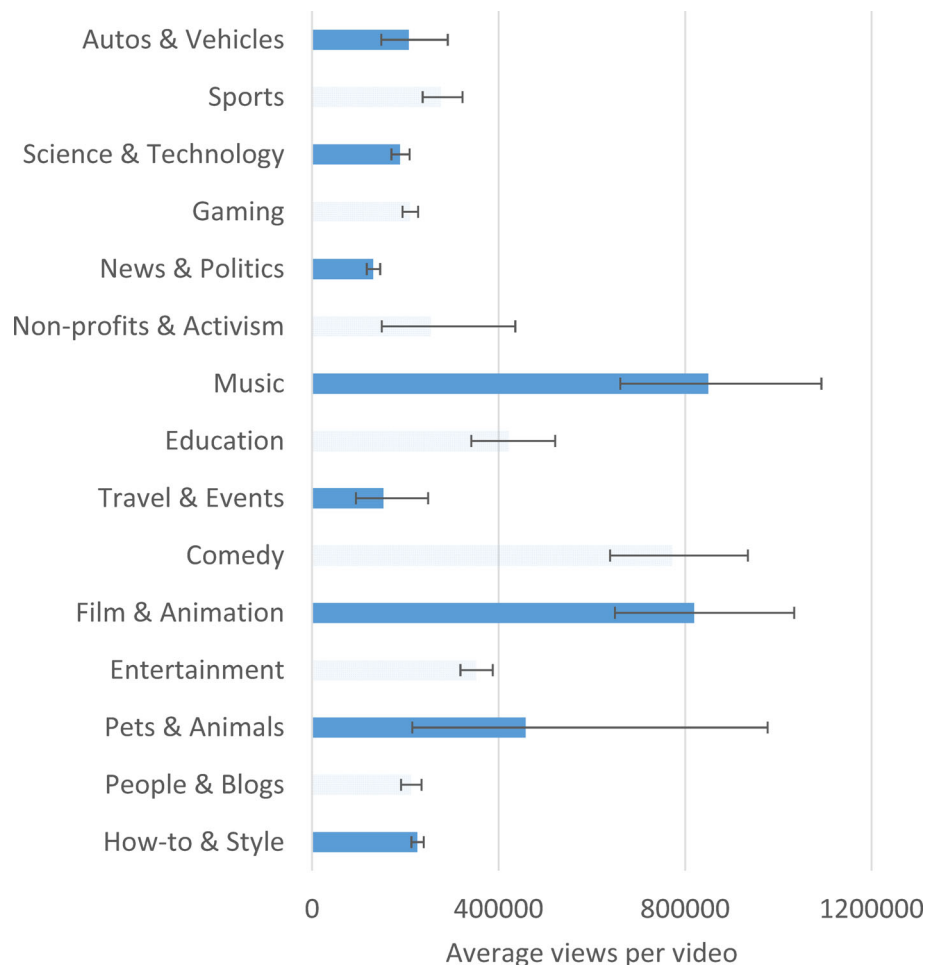


FIGURE 1 Average (geometric mean) number of views per video by YouTube category, ordered through increasing proportion of female commenters, with 95% confidence interval error bars. Qualification: at least 30 videos with at least 30 gendered commenters each [Color figure can be viewed at wileyonlinelibrary.com]

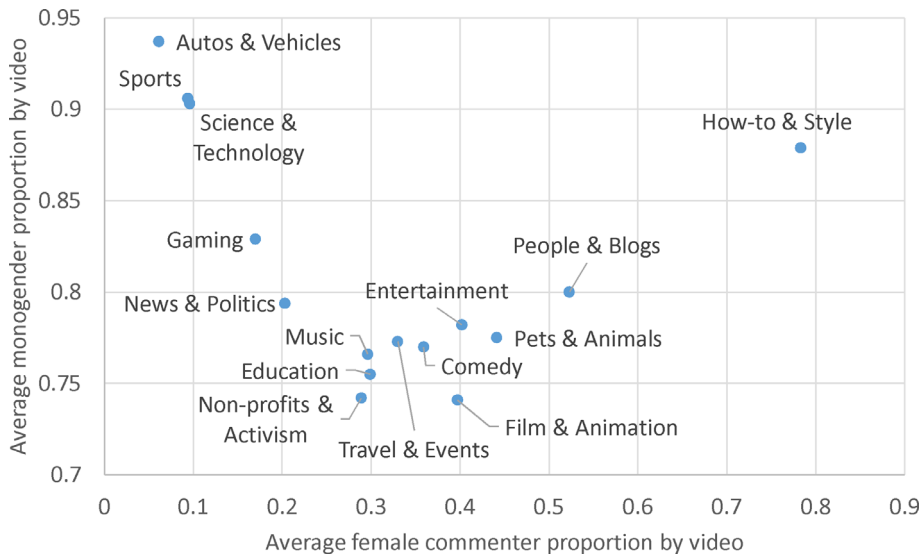


FIGURE 2 Average proportions of female and single gender (male or female) commenters by video in each YouTube category. Qualification: at least 30 videos with at least 30 gendered commenters each [Color figure can be viewed at wileyonlinelibrary.com]

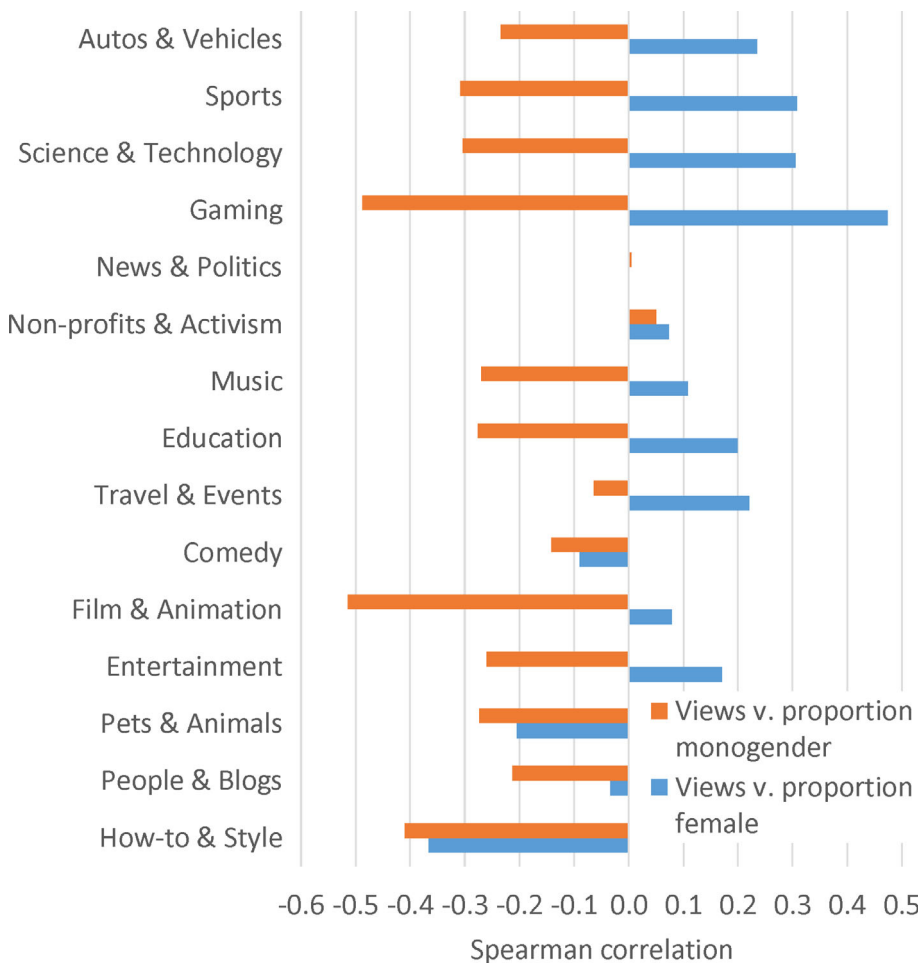


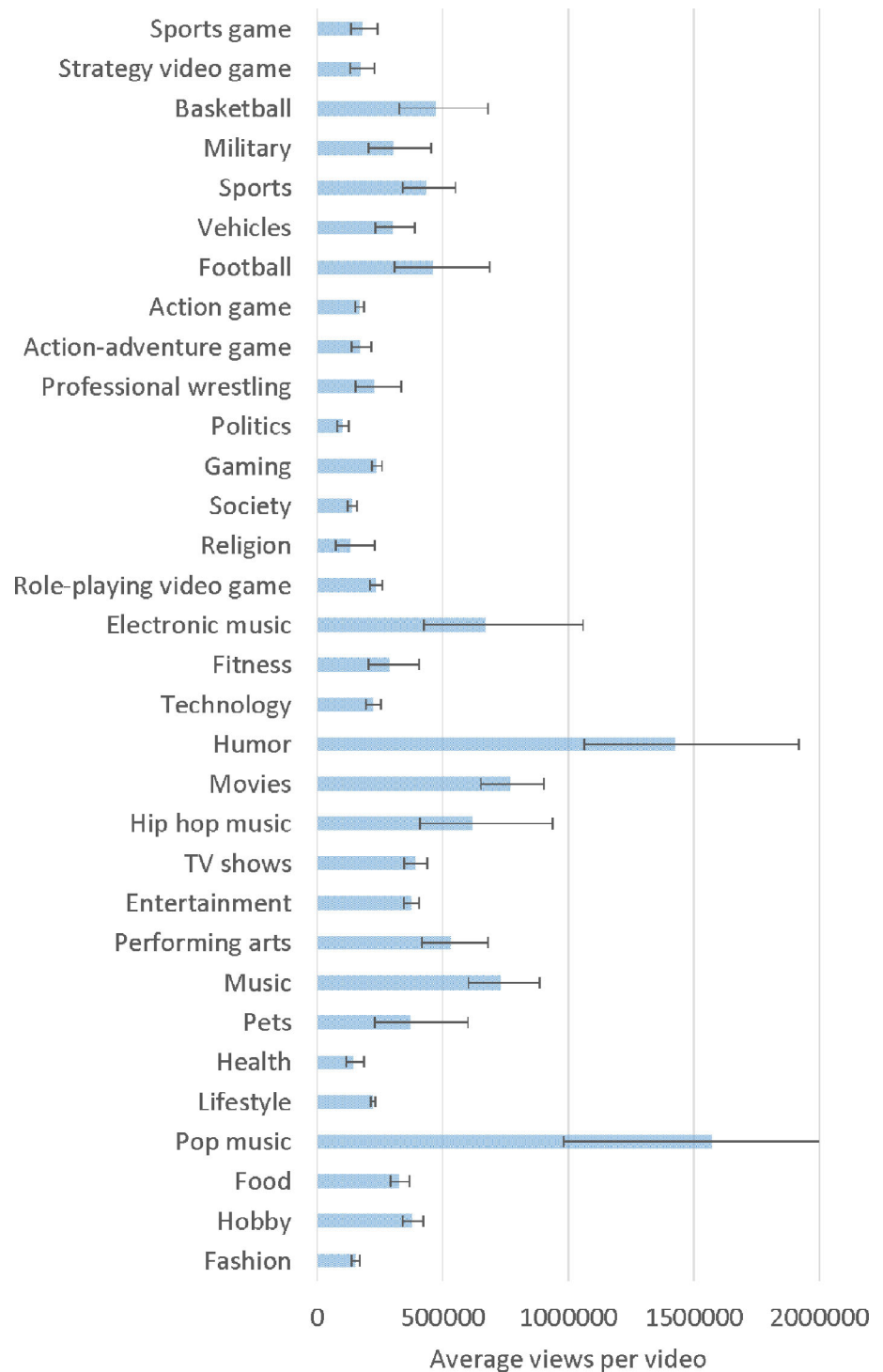
FIGURE 3 Spearman correlation between view counts and the proportion of female [or single gender] commenters on videos by YouTube category. Qualification: at least 30 videos with at least 30 gendered commenters each [Color figure can be viewed at wileyonlinelibrary.com]

3.2 | View counts and audience gender for YouTube videos by topic

The average (geometric mean) view counts of videos in a topic correlated strongly, negatively, and statistically significantly with the monogender proportion

($\rho = -0.433, p = .013, n = 32$), indicating that videos with male–female gender-balanced topics tend to be more viewed. This negative correlation is partly due to videos in the relatively male–female gender balanced Pop music topic being highly viewed (Figure 4).

FIGURE 4 Average geometric mean number of views per video by YouTube topic, ordered through increasing proportion of female commenters, with 95% confidence interval error bars. Qualification: at least 30 videos with at least 30 gendered commenters each [Color figure can be viewed at wileyonlinelibrary.com]



YouTube topics vary from strongly male Sports game (92% male commenters) to moderately female Fashion (81% female commenters) (Figure 5). Thus, the extensive gendering between categories on YouTube extends to topics. Lifestyle (55% female) is the closest to gender-equal at the video level but Pop music has, on average, the least gendered videos. Videos in nearly all topics have, on average, 75% of commenters with the same gender, so gender imbalance is the norm for videos. Pop music is an outlier,

with 57% female commenters and videos having 68% of commenters with the same gender (Figure 5). This is therefore the most gender-mixed YouTube video topic. This is perhaps surprising given the presence of gender stereotypes in some genres (Frisby & Behm-Morawitz, 2019). Fitness, technology, lifestyle, and fashion all have relatively high monogender proportions, suggesting that they each encompass male-oriented and female-oriented videos (e.g., separate male and female fitness workouts).

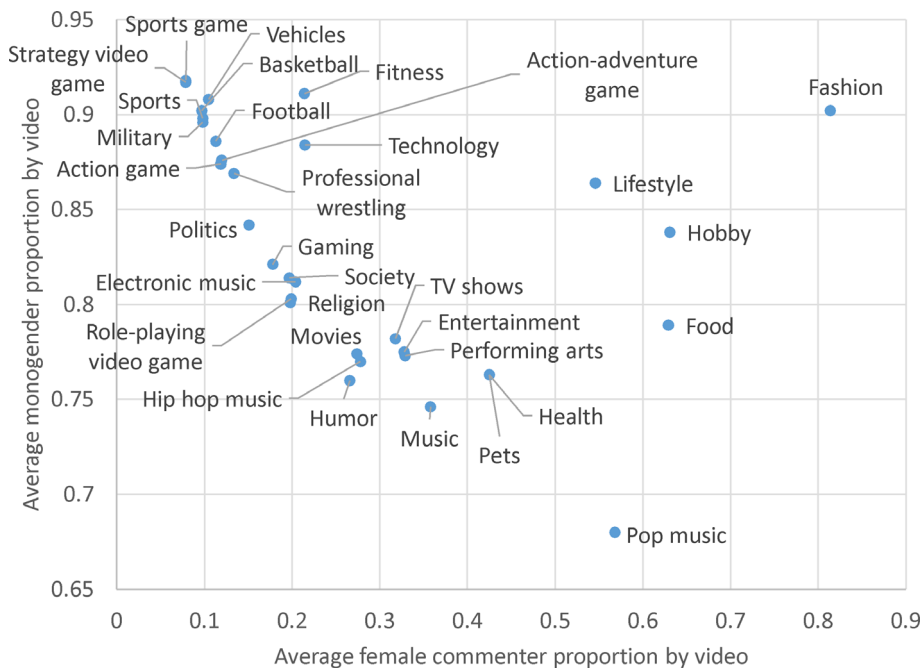


FIGURE 5 Average proportion of female and monogender (male or female, whichever is the larger) commenters on YouTube videos by associated topic. Qualification: at least 30 videos with at least 30 gendered commenters each [Color figure can be viewed at wileyonlinelibrary.com]

As for categories, with the minor exceptions of military, religion, and fitness, videos from each topic that are the most monogender tend to have the fewest viewers, with the correlations typically being moderate or strong (Figure 6). This again suggests that attracting more gender diverse commenters can increase a video's overall audience. Videos in the most male categories tend to have a greater audience when they attract a greater share of females (e.g., 13 of the first 14 categories in Figure 6). Videos in the five female categories have more viewers when they attract a higher share of males (the last two categories in Figure 5). Topics in Figure 6 that seem to be anomalies in terms of the overall trend for categories were investigated to find possible explanations.

- **Military:** The tendency for videos with a higher share of female commenters to be less watched was due to an inappropriate classification for a single video (out of 35), with by far the highest proportion female for the category (0.45, compared to 0.26 for the second most female, which was a WW1-themed supermarket advert). The misclassified video was tagged, "Society, Religion, Military" but was on religion, "How To Be Born Again WITH POWER - T.B. Joshua Sermon." Its only relationship to the Military topic seemed to be the term *power* and the camouflage-style shirt of the preacher.
- **Religion:** The tendency for videos with a higher share of female commenters to be less watched was due to the most viewed videos in this category being news about religion rather than being religious, and attracting a male audience for their military, news, and politics themes. The most viewed video was, "The

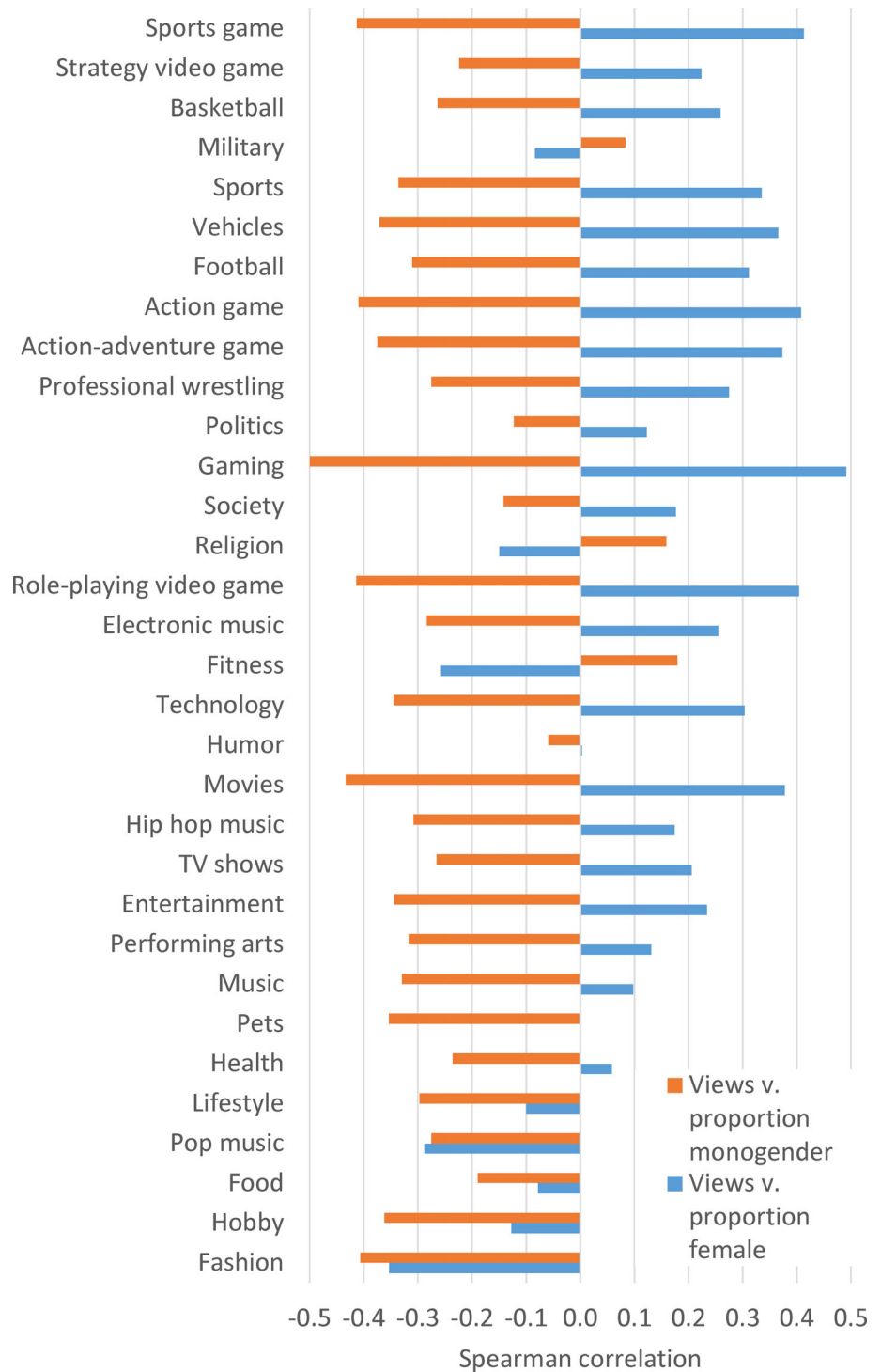
Spread of the Caliphate: The Islamic State (Part 1)," with 95% male commenters. Many news videos about various aspects of religion (e.g., "RWW News: Robertson: Adult Films Lead To Demonic Possession," "The Harlem Globetrotters teach Pope Francis how to spin a basketball on his fingers") attracted relatively male audiences and were more viewed than religious videos, such as "What Is Living The Torah Lifestyle?" (60% female commenters).

- **Fitness:** The tendency for videos with a higher share of female commenters to be less watched was due to an audience size dichotomy between male-oriented fitness videos (e.g., "Cooking A High Calorie Meal w/Kali Muscle," 90% male commenters, 17 m views, humorous) and female-oriented fitness videos (e.g., "5 Tips to FIT | Starting Your Healthy Lifestyle," 94% female commenters, 92 k views, serious), with the male subset being more viewed.

3.3 | Beauty-related videos

Since the results pointed to gendering not occurring overall in YouTube, beauty-related videos were investigated to identify the role of gender for these since beauty vloggers are known to be subject to gendering influences (Bishop, 2018a). Although YouTube has a Beauty topic, none of the videos in the collection were classified with this tag. Instead, video titles were searched to produce a subset of 500 videos including the term "beauty" in their titles, and with the most commenters classified for

FIGURE 6 Spearman correlations between view counts and the proportion of female [or single gender] commenters on YouTube videos by associated topic. For example, for Society, there is a small positive correlation between the proportion female and the number of views (more female commenters associate with more views), whereas there is a small negative correlation between the monogender (male or female) proportion and the number of views (more commenters of the same gender [male or female] associate with less views). Qualification: at least 30 videos with at least 30 gendered commenters each [Color figure can be viewed at wileyonlinelibrary.com]



gender. The video titles were manually checked to remove videos that were about beauty pageants, music, or anything except personal human physical beauty. The 500 Beauty videos all had at least 42 gendered commenters. The commenters were 95.5% female, on average. Only one video had mostly male commenters (47%, “Beauty Hacks: Fail or Holy Grail? ♥ Charcoal Teeth Whitening | Ellko”). Beauty videos mostly give advice on personal beauty products or their application.

Nearly all the 500 beauty videos were tagged with the Lifestyle topic. Overall, Lifestyle videos have a slight majority of female commenters (Figures 3) but are more viewed when they have a higher proportion of male commenters (Figure 4). This seems to be due to the inclusion of popular male-oriented issues within the general Lifestyle topic. For example, the five most viewed videos (>6 m views) with only male commenters were, “How To Pick Up Milfs!,” “How To Make An Electrical Arc

Furnace,” “World’s Greatest Drag Race 4!,” “People You Hate At The Gym,” and “Corsair Gaming K70 RGB Keyboard vs Razer Blackwidow Chroma – Comparison Review.”

To test for beauty videos being more viewed than comparable Lifestyle videos targeted at females, all 2,605 Lifestyle videos with at least 80% female commenters (to exclude male or broadly male–female gender balanced topics) and at least 30 gendered commenters were extracted and classified as being beauty-related (630: containing the term “beauty” in the title and about personal physical beauty) or not. A two-sample *t* test was run to check which set had the most views (after taking the log of the views to remove the skewing in the data). The results showed that the nonbeauty videos had statistically significantly more views (geometric mean average 214,472 vs. 115,061, $p = .024$).

The nine most viewed female-oriented Lifestyle videos were not in the beauty set, although three were arguably personal beauty-related, “FROZEN ELSA GLITTER GLOBES How to Paint Elsa Anna Olaf 3 Disney Snow Domes,” “Morning Routine (10 DIY Ideas, Makeup, Healthy Recipes),” “Rainbow Loom! DIY 5 Easy Rainbow Loom Bracelets without a Loom (DIY Loom Bands),” “30 Last-Minute DIY Halloween Costume Ideas!,” “DIY: Make Eyeliner Out of Colored Pencils!,” “How To Be A Girl | MyLifeAsEva,” “DIY Toothpaste Blackhead Remover Test \\ إزالة الرؤوس السوداء تظللخ,” “DIY Galaxy Slime – Man Vs. Pin – Pinterest Test #40,” “DIY Mermaid Barbie Mini Doll The Pearl Princess Custom Craft Disney Little Mermaid Inspired Video.” A possible explanation for the lower view counts for beauty-related lifestyle videos is that they may target females under about 25, whereas other female-oriented videos may attract a wider range of ages and therefore have a larger potential audience. Thus, despite the statistical results above, it is possible that bloggers in the age range 18–25 that talk about their interests get more views for their videos if they focus on beauty than on other common lifestyle interests for their age range, as they believe (Bishop, 2018a).

There were many beauty videos amongst the set with the fewest comments, including “May 2015 Beauty Favorites + GIVEAWAY” and “Drugstore Haul-Beauty Sale @ Walmart!,” both with 3 k views, showing that not all beauty videos attract large audiences. Thus, another possible explanation for the statistical result is that the beauty market is saturated on YouTube so that a small proportion of beauty videos can be very successful.

4 | DISCUSSION

The results are limited by the factors mentioned in section 2. In particular, the videos are not random

samples and have unknown sample selection bias, the genders are estimates with unknown commenter self-selection bias, and the topic/category assignments are imperfect. The view counts relate to approximately 5 years after the videos were posted, disadvantaging categories with longer-term appeal. In addition, the topics and categories are quite broad and mask some gender-specific categories, such as beauty as a topic. The audience size (views) for a video is likely to be influenced by the unknown extent to which YouTube has promoted it to users, for example, through suggested views; the results are U.S.-centric due to the gendering algorithm; and the YouTube recommendation algorithm changes over time. Recommendation algorithms can be complex (Hallinan & Striphos, 2016) and therefore difficult to account for directly.

The results concern commenter gender proportions rather than the more important issue of viewer gender proportions. While the commenter gender proportions may be used as rough estimates for viewer gender proportions, it is likely that male and female viewers comment on videos at different rates, so the estimates are likely to be biased overall. As mentioned above, the level of bias may vary between topics. This may occur as a second order effect, as discussed in section 2, or due to gender conformity pressure. For example, females or males might secretly enjoy watching some opposite gender oriented content without wishing to participate through comments. Conversely, they might feel more willing to comment on some types of opposite gender oriented content to give an alternative perspective, such as to call out sexism or just to interact with opposite genders. Nevertheless, it seems reasonable to cautiously accept the commenter female/male gender proportions as rough estimates of female/male viewer proportions in the absence of concrete evidence of bias.

The results suggest that the overall gendering tendency in YouTube, if any, is towards the creation of content that attracts both males and female commenters. This applies to both the choice of topic/category and videos within each topic/category. This agrees with a YouTube message on gendering in advertising (Wojcicki, 2016). While the obvious attraction of generating content for both males and females is doubling the potential audience, away from YouTube, gender-specific merchandise dominates some consumer product types (e.g., clothes, beauty/personal grooming) and so male–female gender balanced appeal is not a universal advantage. On YouTube, the previously found importance of the highly gendered topic of beauty in lifestyle vlogging for attracting a female audience (Bishop, 2018b, 2019) therefore seems to be an exception. It is nevertheless an important exception, given the influence that body image can

have on the happiness of young people. The findings do not show why videos targeting either males or females tend to be less popular. For example, the underlying cause could be the working of the YouTube algorithm or viral sharing patterns rather than intrinsically lower appeal or value.

The results echo to some extent a previous study of gender differences in book reading, which found that readers appreciated gendered aspects of books, even when in nongendered or opposite gender genres; thus, an author of mystery novels might attract more female readers by adding a romantic subplot (Thelwall, 2019). On YouTube, highly successful content creators in many categories might be adding elements to attract both males and females, irrespective of main target audience.

The results suggest that direct marketing tie-ins are not always critical to YouTube because second most viewed category, Humor (Figure 4), does not have a substantial product connection, other than comedy videos and TV shows. In contrast, video games have a large market and an obvious sales connection with YouTube videos of people playing or reviewing them. Thus, while an advertising connection can help YouTube topics become more professional and hence more viewed (Bishop, 2018b, 2019), videos can be viewed without this direct connection. Many of the humor videos were professionally produced, however, and presumably get revenue for general advertising or age-specific advertising.

5 | CONCLUSIONS

In societies in which gender disparities in many areas of life persist, such as employment, the finding that YouTube does not seem to be a systematic gendering influence, other than for the previously found pockets of beauty-related content, seems to be positive. For YouTubers, this suggests that creating content with aspects that appeal to multiple genders is likely to help with audience building more often than not. This article was unable to investigate nonbinary (Miller, 2019) or trans (Miller, 2017) gendered content.

Despite videos appealing to both males and females tending to be more viewed (after approximately 5 years) between and within categories and topics, videos in many YouTube topics are viewed primarily by males (e.g., Sports game) or females (e.g., Fashion) (Figure 4). This may therefore reflect gender differences in society rather than promoting them. Hence, YouTube can be a source of evidence of gender differences in interests even if it is not a source of evidence of macro-level influences on gender difference trends.

More directly, the suggestion that videos attracting both males and female commenters (and perhaps also viewers) to be more viewed seems to be the first large-scale evidence of the relationship between binary gendering and audience size in a media context. The finding that videos that are mainly attractive to one gender (male or female) tend to be less viewed (albeit within a subset of relatively highly viewed videos) provides useful practical information for content producers in addition to those seeking to understand how the media influences perceptions of gender.

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