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Anxiety, panic and self-optimization: Inequalities and the YouTube algorithm

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Abstract

This article will look to YouTube's algorithm to assess how such forms of mechanical decision-making can create a discriminatory visibility hierarchy of vloggers, favouring middle class social actors who make highly gendered content aligned with advertisers' demands and needs. I have selected entrepreneurial beauty vloggers as a case study for this article; beauty vlogging is defined as the demonstration and discussion of cosmetic use, often from a vloggers' own bedroom (Banet Weiser, 2017; Nathanson, 2014). This is a deeply entrenched genre on the site; beauty vlogging is a full-time job for some successful participants, and a source of pocket money for many more. Moreover, beauty vlogging is an effective illustration of how the YouTube algorithm causes the polarization of identity markers such as gender. Indeed, for female participants, I hypothesize that YouTube actively promotes hegemonic, feminized cultural outputs, created by beauty vloggers with significant embodied social and cultural capital. That is to say, for women on YouTube, the algorithm privileges and rewards feminized content deeply entwined with consumption, beauty, fashion, baking, friendships and boyfriends in the vein of the historical bedroom culture of the teenage magazine. A secondary hypothesis is that beauty vloggers' own understandings of YouTube's algorithmic processes are learned and embodied within their own practices, influencing modes of self-presentation, tone of voice, choice of content covered, words and sentence structures used. I argue that it is essential to situate all beauty vloggers' experience and content as specific to the platform of YouTube; it is their continued success on the YouTube platform that underwrites the value of their brands. In other words, even highly successful vloggers remain beholden to YouTube's technologies of visibility, they are not safe from the sovereignty of the algorithm.

Keywords

Algorithms, authenticity, beauty, entrepreneurship, inequality, symbolic violence, YouTube, Zoella

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Introduction

This article is concerned with YouTube's algorithm and aims to problematize how forms of mechanical decision-making can create a discriminatory visibility hierarchy of 'vloggers' (video bloggers), favouring content aligned with advertisers' demands and desires in ways that run contrary to participatory and open conceptions of the platform (Jenkins et al., 2013). I have selected entrepreneurial beauty vloggers as a case study for this purpose. Beauty vlogging is defined as the demonstration and discussion of cosmetic use on YouTube, often from a vlogger's own bedroom (Banet Weiser, 2017; Nathanson, 2014). This is a deeply entrenched genre on the platform, a full-time job for some successful participants and a source of pocket money for many more. Moreover, beauty vlogging is an effective illustration of how the YouTube algorithm influences the polarization of content along the lines of identity markers, such as gender. I argue that YouTube actively promotes hegemonic, feminized cultural outputs, created by beauty vloggers with significant embodied social and cultural capital.

In this article, I have utilized a political economy approach; political economy 'uncovers connections between ownership, corporate structures, finance, capital and market structures to show how economics affects technologies, politics, cultures and information' (Meehan et al., 1993: 105). YouTube is owned by Google, a profit-orientated company that produces audiences as commodities for advertisers. Furthermore, YouTube arguably follows the tradition of producing highly gendered commodity audiences through genres of media. Indeed, as television ratings company *Nielsen* produced rating reports proclaiming '*Where the Girls Are*', this article will argue that Google manufactures audiences in a way that polarizes majority female and male audiences on YouTube, in a response to advertisers' demands (Meehan, 2006: 317). Throughout this article, I will demonstrate that the YouTube algorithm privileges and rewards feminized content deeply entwined with consumption, beauty, fashion and baking, in an attempt to cultivate concentrated markets (McRobbie, 1991). Cultural content is highly gendered on YouTube. Of the 50 most '*subscribed to*' independent vloggers in the United Kingdom, 43 vloggers are male, producing content across diverse themes including gaming, football, technology, pranks, comedy, politics, news and sketch humour (SocialBlade, 2017). Of the seven channels run by female vloggers, two are produced by children under 18 years old (and their parents). These channels review toys and apps, with some comedy sketches. There is one female gaming vlogger in the top 50, and the remaining four are beauty vloggers who make an amalgamation of fashion, beauty, cosmetics and 'lifestyle' content. Not only do these statistics evidence a 'glass ceiling' of visibility for women making content on YouTube, as women make up fewer than 20% of the most subscribed to vlogging channels in the United Kingdom, they depict a clear gendered bifurcation of content on the platform. Turning to further analysis, data company TubularLabs identified the top 10 *most viewed* channels run by women in the United Kingdom in 2016 (Dryden, 2016). A majority of seven were beauty vloggers, alongside one gaming vlogger and two vloggers producing a combination of music, beauty and entertainment content.

As vloggers strive for visibility on the platform, their understandings of YouTube's algorithmic processes are learned and embodied within their own practices. Assumptions about algorithms can influence modes of self-presentation, tone of voice, choice of content covered, words and sentence structures used (Bucher, 2017). This article will argue that it is essential to situate all beauty vloggers' experience and content as specific to YouTube. Indeed, although many beauty vloggers host complementary textual blogs on their websites, and some have diversified their media portfolios, it is their continued success on the platform that underwrites the value of their brands.

Self-presentation as entrepreneurial YouTube celebrities remains essential to vloggers' performance of celebrity in a wider sense: Zoella's series of teen books *Girl Online* centres on the life of a teenage vlogger, GraceVictory, recently hosted a BBC3 documentary predominately filmed through 'webcam' style segments in her bedroom, and Tanya Burr regularly features her own cosmetic line in her YouTube make-up tutorials. In other words, even highly successful beauty vloggers remain beholden to YouTube's technologies of visibility, they are not safe from algorithmically induced platform invisibility.

YouTube's algorithmic political economy

The political economy of YouTube's algorithmic design has material consequences for both audiences and aspiring beauty vloggers and actively determines and limits what is seen and consumed by viewers, and carves narrow pathways to success for entrepreneurial young women on the platform. The employed engineers who design and write the platform's algorithmic signals are the primary architects of content creators' visible cultural output. However, algorithms increasingly learn and self-sharpen, often causing unintended side effects and amplifying discrimination, refracting and sharpening classed and gendered bias (O'Neil, 2016). In one recent example, researchers uncovered a significant quantity of biased word pairs within Google News' algorithmic signals. Their research demonstrated that running the query '*man=computer programmer woman=x?*' returned the result '*woman=homemaker*' (MIT Technology Review, 2016). A similar result positioned 'nurse' as female, the binary opposite of the male 'doctor'. When the algorithm equates homemaker to woman within its search and recommendation function, this value system subsequently informs and manipulates relevant search results for users of Google News. It is perhaps pertinent to note that Google engineering workforce is majority male; as of March 2017, only 19% of those employed in tech roles are women (Google, 2017). However, equality legislation and common sense suggests it is unlikely this discriminatory output was explicitly designed for within the algorithm (after finding this result, technicians immediately attempted to correct the error). Rather, this is an instance in which pervasive societal bias present in news text has been intensified by algorithms, influencing the materiality of search results. A second example of an algorithmic instance of refracted bias, this time on YouTube, involves 'restricted view', a filter offered by the platform that hides 'potentially offensive' content (Hunt, 2017). A vlogger, Rowan Ellis, recently demonstrated that content she had tagged or titled with LGBTQ keywords including 'lesbian', 'gay' or 'LGBT' was hidden in restricted view. Her video on the subject prompted vloggers to check their content, unveiling similar results and fuelling the belief that queer content was deemed as 'potentially offensive'. Both examples of algorithmic bias in Google News' and YouTube's algorithms were exposed by accident. I argue that it is extremely likely there are many other similar instances of algorithmically sharpened and refracted bias on YouTube, waiting to be uncovered.

I argue that YouTube intentionally scaffolds videos consistent with the company's commercial goals and directly punishes noncommercially viable genres of content through relegation and obscuration. This mechanism of control is reminiscent of 'symbolic violence' defined as 'the violence which is exercised upon a social agent with his or her complicity' (Bourdieu and Wacquant, 1992: 167). Indeed, vloggers consistently negate a high degree of risk as the platform can, and does, punish noncompliance with loss of visibility. Recommended videos are selected by YouTube's 'black-boxed' algorithm, so called because YouTube 'provides little explanatory insight into the relative influence of the independent variables in the process' (Olden and Jackson, 2002: 135).

In this vein, the construction and materiality of algorithms are hidden from content creators, industry and researchers (Kitchin, 2016).

From YouTube's 2005 inception until recently, brands were hesitant to advertise on the platform. This reluctance is ongoing; YouTube has not yet turned a profit in 2017. Turow (2012) suggests fiercely competitive pricing from social media platforms, like YouTube, has re-ignited brands' nostalgia for controlling the themes and narratives of news and entertainment media. This desire is informed by Web 2.0's early reputation as a lawless 'Wild West'. Marketers nurse a legacy of concern, worried that their products sit next to illegal, inappropriate, sophomoric, amateur or copyright infringing videos on the platform (Snickars and Vonderau, 2009). Andrejevic (2009) predicted YouTube would attempt to extend their jurisdiction over the YouTube community, through rewarding those who complied with the demands of advertisers. In line with this prediction, YouTube implemented major algorithmic changes to increase the length and quality of visible videos on the site in 2012, causing many noncommercially viable channels to dramatically lose visibility (Jarboe, 2012). Moving away from valuing popular content such as 'skateboarding videos', these algorithmic changes dramatically shifted the aims and values of the algorithm. Instead of promoting videos attracting the most views, often with sensational content, the algorithm now valued good visual and audio quality, a refrain from sexual topics and profanity, and videos easily matched with branded content.

There is theoretically limitless specificity offered by YouTube's advertising platform. However, traditional demographics (class, gender and location) are foregrounded in promotional literature for YouTube's advertising application; 'YouTube has a variety of targeting options . . . You can target by *age*, *gender*, *location*, interests and more' (YouTube, n.d. 'Advertise'). This statement privileges age, gender and location targeting as primary selling points of YouTube's targeting services, arguably a turn from recent analysis of 'lifestyle branding' in which traditional demographics become secondary to highly specific market psychological segments (Turow, 2007: 103). Although Cunningham et al. (2016) assert that 'the new screen ecology is a space of unimagined scale and scope of flourishing online creativity and culture', I argue that the majority of diverse content is effectively hidden, as YouTube is invested in enabling and supporting branded investment (Cunningham et al., 2016: 388).

The sheer quantity of data now available on online platforms offers considerable opportunities for content manipulation, based on the detailed viewing habits of the desired audience. Online streaming services such as Netflix and Amazon produce video content directly based on their own consumer data. Netflix properties such as Orange is the New Black and House of Cards were developed using audience information retrieved from data mining, ultimately influencing directorial, generic, casting and writing decisions (Hallinan and Striphas, 2016). Every aspect of these shows was chosen for the strategic role they would play in attracting new audiences and subscribers. However, contrary to streaming services' concerned with production and distribution, YouTube is a platform, so called because YouTube ostensibly does not create media content. Distinct from more traditional terminology such as 'broadcaster' or 'network', the term 'platform' does not imply an active form of mediation. Indeed, the term 'platform' is often mobilized in tandem with emancipatory terminology, for example 'empowering' and 'open' (Gillespie, 2010: 357). However, although YouTube does not produce content, it does actively mobilize its algorithms to manipulate content creators towards cultural outputs that gain the attention of desirable audience segments and demographics (Gillespie, 2015). Thus, YouTube can easily promote and relegate a significant proportion of its channels through simple algorithmic tweaks. This practice is cheaper and more responsive than producing television shows and movies.

To facilitate algorithmic compliance, YouTube provides creators' access to an online Creator Studio, delivering convenient analytics software and guidance. Through the Creator Studio, vloggers are encouraged to carefully monitor and manage their views, comments and subscriber fluctuations to maximize their financial gains and social capital on YouTube. Data are displayed in colourful charts, and participants receive regular notifications pertaining to their performance. Andrejevic suggested that analytics software is deployed by YouTube as a mechanism of control, arguing that 'the congealed result of [vloggers'] own activity is used to channel their behaviour and induce their desires. Such is the goal of the "analytics"-based forms of marketing anticipated by the interactive economy' (Andrejevic, 2009: 421). Indeed, analytics software additionally displays the accumulation of advertising dollars each content creator has raised through the partnership programme. Users adhering to YouTube's strict community guidelines are now eligible to earn a percentage of advertising revenue, further encouraging the production of commercially viable content. Through analytics and algorithmic adherence, vloggers are required to perform 'visibility labour' as they work to strategically 'curate their self-presentations so as to be noticeable and positively prominent among prospective employers, clients, followers and fans' (Abidin, 2016: 5). Although Abidin suggests this form of labour is distinct from algorithmic forms of content optimization, I argue for vloggers to be noticed by 'prospective employers, clients, followers and fans' (Abidin, 2016: 5) requires being initially discoverable by YouTube's algorithm. Visibility labour thereby necessitates in-depth and timely comprehension of YouTube's algorithmic changes, likely obtained through regularly reading trade journals and annual attendance at industry conventions, mostly held in media centres in the Global North such as Los Angeles, London and New York (Duffy, 2015). For entrepreneurial vloggers, algorithmic understanding will shape their practice, a process I term algorithmic 'self-optimization'. I argue that if vloggers desire visibility then they ultimately are pushed towards complicity with YouTube's enigmatic algorithmic signals. Yet a significant degree of complex and time-consuming labour is required to understand how to create content that adheres to algorithmic requirements and avoids algorithmic punishment. Ultimately, success on YouTube is underpinned by algorithmic unpredictability; users are one misstep away from being relegated to obscurity by the algorithm, with little indication of what, when or why that could be.

There are two lines of enquiry in relation to algorithmic study: what algorithms *are* doing and what content creators *think* an algorithm is doing, that is to say, how YouTubers believe the YouTube recommendation algorithm operates and how perceptions of its value systems are consciously or unconsciously incorporated into vlogging practices. Bucher terms this phenomenon 'the algorithmic imaginary', which 'is not to be understood as a false belief or fetish of sorts but, rather, as the way in which people imagine, perceive and experience algorithms and what these imaginations make possible' (Bucher, 2017: 31). Of course, there is significant overlap between the function of an algorithm and the interpretation of its functionality by platform users. It is ultimately impossible to divorce the two as they flow in a loop; practice continuously informs the algorithm, and the algorithm shapes practice. In this vein, this study is concerned with both the mediated interpretations of YouTube's algorithms and the functionality of YouTube's algorithmic signals by drawing lines between widely published accounts of YouTube's algorithmic values and the analysis of beauty vloggers' performance of algorithmic optimization.

Method: Reverse engineering the algorithm

I have chosen to approach this research question firstly through critically examining a published 'reverse engineering' of the algorithm. As noted, the YouTube algorithm is 'black boxed', thus studying

YouTube's algorithmic process introduces methodological challenges. Kitchin (2016) introduces reverse engineering as one methodological starting point for critically examining algorithms:

> by examining what data are fed into an algorithm and what output is produced it is possible to start to reverse engineer how the recipe of the algorithm is composed (how it weights and preferences some criteria) and what it does. (Kitchin, 2016: 24)

In other words, reverse engineering is undertaken by inputting controlled data onto a platform and closely monitoring algorithmic output. A large-scale reverse engineering of the algorithm has been recently undertaken by Gielen and Rosen (2016) of the popular YouTube industry journal *TubeFilter.com*. They conducted a year-long examination of a collection of videos on Frederator, an independent cartoon channel with 1.25 million subscribers.

It should be noted that reverse engineering (and particularly a secondary analysis) introduces many methodological issues. Firstly, Gielen and Rosen (2016) have asserted that there are some data points their analysis could not determine, including the influence of user viewing history and behaviour on YouTube's recommendation algorithm. Secondly, the YouTube algorithm is altered regularly, quickly rendering research irrelevant. Finally, it should be noted that platforms such as YouTube and Google are constantly running their own user testing, and thus, there is no certainty that the version of the site made visible to any one individual is consistent with the interface experienced by other users (Gillespie, 2014; Kitchen, 2016). However, I argue that these concerns are countered when the critical bifurcation between questions of what an algorithm *does* and what users *think* it does is revisited. In this vein, Gielen and Rosen's account is notable not only because it was widely publicized in industry journals and podcasts but also because a version was presented at the YouTube sponsored convention *VidCon* in Los Angeles, a convention with high levels of attendance from prominent content creators and their management teams. It can be reasonably inferred from the public nature of this presentation, aimed directly at content creators and industry, that their algorithmic interpretation and recommendations will be folded into practice. Using an online ethnographic approach, I have underpinned my analysis of this 'reverse engineering' with examples of vlogging performance. There is scope for further research on the gendered bias of YouTube's algorithms pertaining to individual algorithmic interpretation and practice. A wider sample of YouTube channels, and interviews with vloggers, would support an extension of research into inequalities embedded into YouTube's algorithms.

In the following section, I will consider three algorithmic signals that researchers claim shape video recommendations and stratify search rankings on YouTube. Firstly, I will consider *session starts*, *ends and duration*. This algorithmic signal refers to a *viewing session*, the platform's terminology for video consumption within a linear period, as one may watch subsequent television programming on one particular channel. The viewing session comprises 85% of time-sensitive algorithmic signals, with the other 15% pertaining to *upload frequency*, how regularly videos are published on a YouTube channel. Secondly, I will look at keywords and tagging practices, the descriptive labels applied to a video by a given vlogger. Keywords and tagging are one of three textual algorithmic signals, the other two being video titles and descriptions. Keywords and tagging are of particular interest to this article, as implementation of keyword optimization tactics has been identified by YouTube as a site of algorithmic abuse or manipulation. Prior to 2012, video tags were visible on the YouTube interface, displayed prominently below each video. However, in 2012, tags were hidden by the platform to discourage users from emulating the tags of popular videos. A post from YouTube in 2012 states:

> tags no longer appear on this page – this isn't a bug, but a change that went out this week. Having them on the watch page, in some cases, gave users an opportunity to abuse tags by copying them from other videos. (YouTube Help Forum, 2012)

Although tags are hidden, they are findable for those able to sort through basic code, stratifying accessibility. An analysis of tagging patterns offers insight on a supposedly 'hidden' YouTube affordance. Lastly, I will analyse automatically generated closed captioning (CC) text and how this is weighted as an algorithmic signal. Through Google's CC software, all spoken word on the site is automatically translated into keywords that are used to aid relevancy and search rankings on the video-sharing platform. However, this translation software is riddled with errors, favouring crisp and clear spoken English and discriminating against regional accents. Algorithmic signals that have fallen outside of the scope of this article include social algorithmic weightings, such as the volumes of comments, shares and likes garnered by vlogging channels. These cultures of audience response as an algorithmic value would benefit from further research.

YouTube session starts, ends and duration

Gielen and Rosen (2016) assert session starts, ends and duration are the second most influential algorithmic signal in YouTube's recommendation and search algorithm ranking. They state:

> 'Session Starts' is essentially how many people start their YouTube viewership session with one of your videos. 'Session Duration' is how long your content keeps people on the platform as they are watching your video, as well as after they've watched your video. 'Session Ends' relates to how often someone terminates a YouTube session while or after watching one of your videos. This is a negative metric to the algorithm. (Gielen and Rosen, 2016)

In short, the YouTube algorithm favours videos that maintain viewers' attention, leading to lengthy viewing sessions that are comprised of videos recommended by the platform's interface or an automatically generated playlist. Videos are promoted through their relevance to the original video; in other words, they are matched through similarities in their video genre and theme. I have argued that the majority of visible young women promoted by algorithmic signals on the YouTube platform in the United Kingdom produce make-up and fashion content (SocialBlade, 2017). In this vein, visible female vlogging playlists echo this pattern of content creation. Curly hair tutorials link to curly hair tutorials, and smoky eye demonstrations follow videos related to smoky eyes (Banet-Weiser, 2016).

If a *viewing session* is terminated on a vloggers' video, this will negatively affect that channel's algorithmic ranking. This algorithmic signal is termed *session ends*. In short, if a viewer exits the platform during a given video, then the video and channel are punished with obscurity. YouTube incorporated this punishing algorithmic signal most likely because of the commercialization of the platform; if longer time spent on YouTube generates increased advertising revenue, videos that turn viewers off should not be promoted. YouTube's press page foregrounds a vast improvement in gross watch time, boasting 'on mobile, the average viewing session is now more than 40 minutes' (YouTube, n.d, 'Statistics'). In 2007, Burgess and Green argued that the crux of YouTube's community lays within its function as a social networking site, filled with short 'quotes' of content and reactions (Burgess and Green, 2007: 49). However, YouTube CEO Susan Wojcicki confirmed, in 2016, that YouTube's algorithm now rewards vloggers for keeping viewers on the platform, promoting longer sessions of related videos with commercial breaks (Winkler, 2016).

An algorithm valuing videos inspiring extended *viewing sessions* on YouTube arguably skews towards punishing diverse, riskier and original content that may accrue *session ends* more frequently. A simple thought experiment demonstrates one way that these algorithmic signals are perfectly placed for exacerbating and sharpening existing bias on YouTube. In the case of the example of 'gaming vlogging', it is a fact that there are far, far fewer visible female gaming vloggers in the United Kingdom than male (SocialBlade, 2017). One could explain this disparity through looking to numerous cultural factors, including the male-dominated nature of gaming audiences and a generic legacy of exclusion, harassment and misogyny within online gaming culture (Banet Weiser and Miltner, 2016; Chess and Shaw, 2015). However, this existing bias could also be sharpened and heightened by YouTube's *viewing session* algorithmic signals. Gaming fans who are less likely to appreciate content made by women, due to their own bias and values, may repeatedly quit a video produced by (and featuring) a woman. This could be a deliberate act of sabotage (which would echo the campaigns of abuse that have been waged against female gaming journalists) but is more likely simply a preference. This action repeatedly signals to YouTube's algorithm to demote that vlogger's channel, ensuring their content is obscured. If fans of gaming culture are more likely to be adverse to content made by women, then videos made by female gaming vloggers would therefore acquire higher than average *session ends* leading to a pattern of demotion by YouTube.

The *viewing session* has further implications for the beauty vlogging genre. Beauty YouTubers are often sponsored by brands to create themed advertorial videos on their channels. For example, prominent beauty vlogger *Zoella* publishes a seasonal 'Lush Haul' video, in which she talks her viewers through a 'haul' of products, from the cosmetic company Lush (Zoella, 2016a). This 'haul' consists of a significant quantity of valuable products, paid for by Lush or their hired Public Relations firm (Duffy, 2015). When a viewer begins their viewing session with a Zoella 'Lush Haul' video, YouTube's algorithms selects videos to automatically follow Zoella's. These videos are also Lush themed videos, mostly from other beauty vloggers. Notably, viewing session playlists promote channels with diffuse subscriber volumes, promoting the possibility of inclusion with such a playlist as a key opportunity for visibility. Indeed, viewing session playlists are recognized as a big break for prospective beauty vloggers; to follow a *Zoella* video would be financially rewarding even *without* the promised algorithmic bump. Sponsored videos are often not labelled adequately, creating a murky space in which paid-for advertising is looped with nonpaid vlog content, replicating and mirroring beauty vlogger branded content. For those who have not reached the levels of visibility required for sponsorship, the purchase of 'haul' products required to participate in this genre is expensive, with few guarantees a video will be featured in a playlist. The seasonality of this video genre additionally creates a pressure to keep up; for Lush (and many other brands), Zoella documents a fresh and breezy spring haul, festival fun summer haul, a warm and cosy autumnal haul surrounded by pumpkin kitsch and, of course, the crescendo of a Christmas Haul (often undertaken as part of 'Vlogmas', during which beauty vloggers post every day to maximize advertising revenue). Thus, it stands to reason brands may begin to exploit this algorithmic side effect; sponsoring one prominent YouTuber will inevitably lead to a much greater volume of content promoting their products, hoping to follow a sponsored video during a viewing session. Furthermore, YouTubers experience the persistent threat of *session ends* algorithmic punishment if their content is unappealing and should they feature fewer or outdated products, for example. This arguably leads to a financial and emotional pressure; vlogs have to keep up with spectacular consumption within the preceding videos in the watch session. This individualized economic pressure is not limited to beauty vloggers. Aspirational gaming vloggers must keep up with new games and hardware if they hope to compete with larger visible gaming channels, who are often gifted the new products or sponsored by their manufacturers.

Keywords and tagging

Keyword and tagging practices are manually undertaken by all vloggers; the platform requires users to attach multiple tags to their video to assist the algorithm in sorting genre determination, establishing search relevancy and grouping linked content (Gielen and Rosen, 2016; Snickars and Vonderau, 2009). Common beauty vlogging tags typically relate explicitly to the themes of the video and include 'make-up tutorial', 'smoky eye', 'skincare routine' and 'make-up haul'. Research has evidenced similar algorithmic exploitation across social media platforms; for example, users label YouTube videos with 'XXX, Porn' to accrue traffic (Kessler and Schafer, 2009: 283), Facebook users tag their statuses with brands to push them up in algorithmic rankings (Gillespie, 2014), and Instagram users aspirationally copy and paste hashtags from their favourite influencers (Abidin, 2016). YouTube and Google are attempting to retire tagging practices through developing visual and semantic search, as tags are seen to be easily exploitable and have been removed from the platform interface (YouTube Help Forum, 2012). Moreover, YouTube is invested in countering attempts to falsely tag videos, supporting the myth of platform objectivity. However, for vloggers, visibility is integral; tagging practices must follow popular patterns of search. Although ostensibly hidden from the YouTube interface, video tags remain findable for those able to sort through YouTube's basic code, further stratifying algorithmic optimization by temporal and educational privilege. YouTubers with technical expertise, who are therefore privy to tagging discourse, are free to copy and paste entrepreneurial tags from their favourite popular vloggers. Entrepreneurial use of tags is hereby important to focus on, as a clear example of algorithmic optimization stratified by inequality. Tags are symptomatic of YouTube genres, and in turn, genres on YouTube are indicative of hegemonic and normative tagging patterns.

To illustrate these points, I analysed the latest video from all 39 vloggers managed by prominent UK digital talent agency GleamFutures (2016), 28 of whom are women and 11 are men. I isolated tags utilized by male and female vloggers to demonstrate the highly gendered nature of tagging practices, as stabilized across prominent content creators. For women, the overwhelmingly most popular tags utilized were 'make-up', 'tutorial', 'routine', 'beauty', 'fashion', 'skin', 'drugstore' and 'cardio'. Contrastingly, for male vloggers, the top tags were 'funny', 'muscle', 'building', 'challenge', 'daschund' and 'Halloween'. Furthermore, the commercial nature of the women's tags is evidenced with brand names including 'Neutrogena', 'Bourjois', 'ASOS', 'Rimmel' and 'L'Oreal' featured prominently. Tags determine and support genre formation on YouTube through informing search and recommendation algorithms' patterns of related key words, and these tags are influenced by and influence gender norms on the platform and within society. Tags form 'algorithmic identities' of those creating and consuming such genres, their interests and their generic identification (Cheney-Lippold, 2011). The stabilized identity of the popular female vlogger, symbolized by the domineering 'make-up' tag, is reminiscent of the teenage magazine and the 'consensual totality of feminine adolescence' in stark contrast to the diversity of male hobbies (McRobbie, 1991: 84). Furthermore, content outside of the beauty vlogging genre also utilizes highly gendered tags and keywords. The two most popular female comedian vloggers on YouTube, Superwoman and Jenna Marbles, riff off the 'how to' genre, often utilizing keywords and tags pertaining to cosmetic and make-up use. Superwoman's most viewed video, with over 22 million views, is 'How Girls Get Ready' and includes the tags 'high heels', 'nails' and 'smoky eye' (iiSuperwomanii, 2013). Jenna Marbles' most popular video with 65 million views is entitled 'How To Trick People Into Believing You're Good Looking' which includes the tags 'how to', 'make-up' and 'cosmetics' (JennaMarbles, 2010). Although these videos are clearly parodies of beauty vlogging, their utilization of keywords and tags has positioned them for visibility within the beauty vlogging genre, leading to significant traffic and views.

Furthermore, beauty vloggers making noncosmetics-based content consistently utilize tags related to beauty and make-up. For example, a recent video, entitled 'Apple Crumble Cupcakes', shows hugely popular beauty vlogger Zoella baking cupcakes in her kitchen (Zoella, 2016b). In the video, Zoella does not mention cosmetic use or beauty products, yet the video tags used are beauty and cosmetic related; the tags are as follows: 'zoella, zoesugg, zoe, sugg, british, vlogger, beauty, cosmetics, fashion, lifestyle, make-up, how to, hair, collaboration, tutorial, chat, chatty, vlogs, Brighton' (Zoella, 2016b). Having recently moved away from cosmetic and tutorial-based videos into more diverse content, Zoella demonstrates the value of being 'findable' in make-up-related searches. For the self-learning algorithm, this tagging practice will relate feminized content such as baking, to commercialized make-up and cosmetic content. This could easily contribute to YouTube generically intertwining 'baking', 'lifestyle' and 'make-up' in the vein of teen magazines and their remit that 'all girls want to know how to catch a boy, lose weight, look their best and be able to cook' (McRobbie, 2009: 69). Self-learning algorithms arguably link such content together using tags, establishing a genre consisting of traditional feminized labour. Likewise, beauty vlogger Tanya Burr's 'How to Bake a Chocolate Loaf Cake' video includes tags such as 'cute', 'Topshop' and 'dress' (TanyaBurr, 2016). Furthermore, beauty vlogger Estee Lalonde's 'Health and Fitness Update' video is tagged with 'fashion', 'cute outfits', 'natural make-up' and 'eye make-up' among myriad fashion and beauty-related tags (Estee Lalonde, 2016). As so much entrepreneurial female vlogging content is tagged with diverse keywords, arguably in an attempt to increase 'findability', the algorithm is likely to self-develop a conception of generically related feminized labour such as lifestyle, baking, fashion and make-up. The algorithm is invested in sketching out the shape of a genre and the algorithmic identity of those within it, although further research is needed to determine how this affects the visibility of individual users of the YouTube platform.

Closed captioning and auto-generated closed captions

In various updates since 2009, YouTube has automatically generated translated spoken word and sound into closed captioning for every video uploaded to the platform. Closed captions (CC) were initially launched by YouTube in the name of increasing accessibility for deaf and hard of hearing viewers. However, the platform has since announced this capability has greatly increased search functionality. The CC text generated is submitted both to YouTube's own search engine and to third parties such as Google (Gielen and Rosen, 2016). Ellcessor is critical of commercial CC practices, arguing that this can impede the experience of closed captioning for deaf and hard of hearing users; 'online captioning initiatives . . . have numerous goals, including the production of metadata for search engine optimisation, and they do not clearly serve the needs of deaf and hard-of-hearing audiences' (Ellcessor, 2012: 333). CC text, as utilized in search, is demonstrative of YouTube's attempt to extend search capability to content *within* videos. Google and YouTube are also developing visual search capability, although this has thrown up many discriminatory issues, including a widely publicized example of Google's photo app labelling two black women as gorillas (Kasperkevic, 2016). Visual search is not yet included in YouTube's search or ranking algorithms. However, text translated by YouTube from spoken word *is* widely used to assign relevancy to search queries and to select related videos to be recommended and promoted by the YouTube algorithm. Keywords are picked out of spoken text and matched with users' search queries.

Videos with CC text matching widely search terms will be pushed up in algorithmic rankings, yet this reward is experienced unequally by social actors of different social class. Words spoken in regional accents are misassigned or designated unrecognizable. Bourdieu describes the significant function of accent in determining social class and authority, arguing 'accent [functions] as an index of authority' (Bourdieu, 1977: 653). Indeed, this hierarchy is calcified within search recognition software designed and utilized by YouTube. Employment and social mobility operate within the sphere of the language market; accent inescapably stratifies participation in the social world, opportunity and class mobility, not least for those in media work. Skeggs asserts:

> The media as an institution can produce symbolic violence against the working classes. It is these different market values (themselves historically developed from the division of labour, from resistance to it, from struggles against exploitation and delegitimacy) that may give local cultural value to certain dispositions [accents] but which have little trading value on the markets that matter for economic survival. (Skeggs, 1997: 12)

When spoken word is translated by software, those with strong regional accents are disadvantaged in YouTube's attention economy; they are often translated into nonsensical words and subsequently are less likely to be matched up with search terms or recommended following related videos. In this vein, there are very few visible beauty vloggers with regional accents. To evidence this disparity, I turned to Barnsley-based vlogger PollyanneB, using her video 'Smokey Eye using the Urban Decay Naked 2 Pallette!' as an example (PollyanneB, 2016). The video is mistranslated in its entirety. During her demonstration, Pollyanne states: 'that just starts us off with a really nice base. I am kind of wanting to do a gradient eye, I think with eyeliner, so I will start in the inner corner with a lighter shade and go to the outer corner with a darker shades'. This statement is translated by auto-CC as near nonsensical: 'in a really nice day, I kind of wanted to do a gradient I think with lineup so I'm going to kind of stop in a conical I should go out into darker shade'. This section is symptomatic of the misrecognition of key words and terms in the entire video, including primary terms likely to be searched for on the platform, such as 'gradient eye', 'lighter shade' and 'base'.

Ellecssor (2012) observes that Google Voice translation (utilized by YouTube) has been available online since 2007, with little advancement, arguably betraying Google's priorities for this service and demonstrating a slim probability of improvement in the near future. She posits: 'neither deaf nor international audiences are being well served by these error ridden translations, but the production of some textualised content is better than having none for Google's corporate purposes' (Ellecssor, 2012: 343). Closed caption automation rarely performs perfectly, yet vloggers with 'standard English' accents such as Zoella and Tanya Burr are mistranslated far less regularly. Indeed, for these beauty vloggers, the CC software correctly translates almost all spoken words in the majority of the videos sampled. The degree of misrecognition is ultimately dependent on clipped and clear speech patterns; therefore, media training can overcome the 'negative effects' of an unrecognizable accent. Press outlets have pointed out that popular beauty vlogger Zoella had a noticeably broader West Country accent prior to being signed by talent agency GleamFutures, who have assumedly facilitated this transition (Vogue, 2014). Furthermore, subtitles themselves can be manually overridden and corrected within the YouTube software, yet this process is labour-intensive for a 10-min spoken video, and beauty vloggers with commercial and agency support will be able to draw from this.

Finally, the closed captioning algorithmic signal arguably leads to formulation and organization of speech as algorithmically recognizable (Gillespie, 2014). The knowledge that closed captioning functions as an algorithmic signal is widely published and presented, and practice is likely reshaped accordingly. Popular vloggers are noticeably employing ‘keyword stuffing’ in their speech; keyword stuffing is a search engine optimization practice involving the determination of popular keywords using analytics software and inserting these words into a website, to be read by search engines. Zappavigna (2015: 1) terms similar practice on Twitter ‘searchable talk’ as users select hashtags to aggregate topics and themes with the intention of being easily searchable for a target audience. Indeed, as closed captioning text is translated into written text, enunciating keywords ensures that they are readable text for a search engine. This practice is visible in a recent ‘Primark Haul’ video by Zoella (2016c). Zoella shows her audience a rotation of products, ostensibly purchased on a recent jaunt to a clothing shop. In this video, Zoella holds up each item and carefully and crisply pronounces key words. She includes description of the seasonal change: ‘autumn transitional dress’, ‘the true spirit of Autumn’ and ‘more of a Winter item’, a practice that ensures readability for searchable seasonal keywords. Zoella describes the style, length and colour of each and every one of her purchases in search engine ready discursive patterns. She holds up a ‘navy midi dress’, a ‘striped maxi dress’, ‘black, flat ankle boots’ and a ‘burgundy corduroy pinafore’. She organizes her video carefully, beginning with dresses and methodically moving on to various trousers, shoes and accessories, readying and grouping together keywords for a search engine crawler to neatly sort and process. The entrepreneurial beauty vlogger must learn to form their speech in this particular way; YouTube surveils micro-actions of vloggers and rewards those employing advertising speak. In addition to a harmony of algorithmic signals, this bears increased responsibility on microperformances of the self; the actor must learn and master technologies of entrepreneurship and employability as they speak in keywords. Despite the calculated pronunciation, vloggers simultaneously perform a degree of authenticity throughout their videos; in Zoella’s (2016c) Primark Haul Video, two dogs (pugs, naturally) are in the room with her and they bark and interrupt her as she begins the video. She attempts to adjust the light density several times, while the dogs have a fight on the bed in the background. This ‘blooper real’ (scored by plodding ‘comedic’ music) functions as an authenticity marker, to underscore the home-made quality essential to the vlogging brand (Banet-Weiser, 2016). However, these transgressions are cut together and rolled out at the start of the video; bloopers do not hinder the processing of keywords. Tellingly, there is no dog barking when Zoella crisply describes her ‘Primark autumnal patterned shirt’ (Zoella, 2016c).

Conclusion

To conclude, I argue that YouTube’s algorithmic practices and published speculation contribute to stratification by class and gender on the video-sharing platform. The mobilization of *viewing session* algorithmic signals suggest that YouTubers who do not fit within an existing genre will be punished. This excludes channels outside of popular genres in playlists and actively demotes channels if users end a *viewing session* with a given video. Furthermore, through *viewing sessions*, YouTube’s algorithmic signals actively encourage entrepreneurial vloggers to create commercial content for free, as they hope to follow prominent vlogging videos in playlists. Such algorithmic self-optimization by beauty vloggers is reminiscent of the entrepreneurial conspicuous consumption and 'hope labour' (Kuhne and Corrigan, 2013: 1).

The seemingly naturally gender segregated genres formulated on YouTube are structured and maintained by algorithmic signals. Through the algorithm, the YouTube platform guides female content creators towards commercially recognizable feminized content, rewarding complicity with visibility and punishing diverse or less lucrative video themes. Like 'Soap Operas' created as vehicles for domestic advertising in the 1950s, beauty vlogs provide mechanisms for feminized commercial messages, foregrounded by YouTube through its algorithmic signals (Meehan, 2006). I argue that platforms are invested in affording *some* users' self-optimization tactics. Such a practice ultimately helps assist ranking and recommendation algorithms; while rewarding, the utilization of popular tags in algorithmic signals promotes and strengthens participation barriers akin to a digital divide and additionally stabilizing gender inequality. Furthermore, this article has argued that weighting closed captioning as an algorithmic signal has little to do with improving experiences for deaf and hard of hearing YouTube users and rather is invested in creating metadata for search. Closed captioning further excludes YouTubers with regional accents, as their videos are translated into nonsensical text.

It is vloggers who go against algorithmically recognized genres, or who lose viewers in a single video, that are actively punished by the platform. Such an environment creates a fear of obscurity underpinning the attention economy of the site. In this vein, further research on the affects of algorithmic signals would be beneficial. A larger-scale algorithmic reverse engineering centred on polarized gendered genres would aid a wider understanding of YouTube's algorithm, as would interviewing vloggers and their management about motivations and intentions for their content. This article has formed an emerging argument that runs contrary to discourses of openness, democracy or participation on YouTube (Cunningham and Craig, 2016). I maintain YouTube's algorithm ultimately rewards hegemonic and normative performances of femininity, in line with the desires and needs of brands and advertisers.

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