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Influencer Management Tools: Algorithmic Cultures, Brand Safety, and Bias

Sophie Bishop

Abstract

This article explores algorithmic influencer management tools, designed to support marketers in selecting influencers for advertising campaigns, based on categorizations such as brand suitability, "brand friendliness," and "brand risk." I argue that, by approximating these values, tools reify existing social inequalities in influencer industries, particularly along the lines of sexuality, class, and race. They also deepen surveillance of influencer content by brand stakeholders, who are concerned that influencers will err and be "cancelled" (risking their investments in content). My critical framework synthesizes feminist critiques of ostensibly participatory influencer industries with close attention to critical algorithmic studies. This article provides an in-depth look at how brand risk and brand safety are predicted and measured using one tool, Peg. Through a "walk through" of this tool, underpinned by a wider industry ethnography, I demonstrate how value-laded algorithmic judgments map onto well-worn hierarchies of desirability and employability that originate from systemic bias along the lines of class, race, and gender.

Keywords

algorithms, bias, inequality, influencers, social media

Influencers are professional, independent, content creators working on social media platforms across genres including gaming, gossip, and beauty. Several conventions underpin influencer production across each of these verticals; a drive toward "authenticity," meaning personal and relatable self-branding; platform contingency, in which content is shaped according to the logics and conventions of social media platforms; and, finally, a curated and doggedly maintained intimacy with audiences. Despite these common threads, influencer cultures are rapidly developing and precarious; top creators and platforms rise and fall regularly, intermediary management models morph and change, working models and industry pay rates fluctuate and crash. Although influencer economies have been framed as participatory, creators across intersections of marginalized identity often suffer the consequences of this innovation and instability, through underpayment and platform obscuration.

It is essential to consider the role of intermediaries in shaping influencer economies. In moments of rapid industry development, industry stakeholders often attempt to stabilize uncertainty and risk. To this end, 380 new influencer marketing "solution" platforms and agencies entered the global market in 2019 and 2020 (Influencer Marketing Hub, 2020). What the industry calls marketing "solutions," hereafter referred to as *influencer management tools*, present analytics data and make algorithmic calculations designed to support marketers in selecting appropriate influencers for advertising campaigns, through subjective calculations about influencers' *brand safety* and *risk*. As a 2020 market research report noted, the "temperature [in this space] is high" (Forrester, 2020). Comparing the leading 12 tools in the market, the report observes that "all of the vendors have access to the same social media APIs; the differentiation comes in how this data is manipulated and presented to optimize marketers' workflows" (Forrester, 2020). In other words, tools draw from publicly available data. They create value through developing algorithmic recipes and creative data presentation. Through their respective *secret sauces* these tools promise to support marketers in stabilizing the influencer marketing industry.

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Influencer management tools use algorithms to categorize and process data, and predict outcomes—it is often implied that in doing so they position themselves as objective than humans. Yet, through their design and operation, influencer management tools present *subjective* calculations about the influencers who are most suitable for brand collaborations to marketing stakeholders through fuzzy inferences such as brand safety. So, as these inferences are used by brands, tools shape *which* influencers have access to these brand collaborations.

These decision-making processes and outcomes are urgently worth examining, as they scaffold employability in influencer ecologies. While an already fast-growing strain of creative work, influencers have been in particularly high commercial demand during COVID-19-induced social distancing, because of increases in social media consumption (most notably, Instagram and TikTok), and influencers' ability to independently produce advertorial content from domestic spaces (Taylor, 2020). Influencer marketing was valued at US$8 billion in 2020 (Influencer Marketing Hub, 2020). However, there are uneven relationships between brands and influencers, meaning this work is often highly laborious, under-compensated, and precarious (Caplan & Gillespie, 2020; Cotter, 2018; Duffy, 2017; Duffy & Hund, 2015; O'Meara, 2019). Alongside accounts of inequalities, a growing body of work is examining the political economy of rapidly changing influencer industry in practice (Abidin, 2017a; Abidin & Ots, 2016; Cunningham & Craig, 2018). Drawing from these bodies of work, I argue that it is thus worth probing how tools' methodologies and operations work in context, as 40% of brands use third-party tools to support their digital marketing campaigns (Influencer Marketing Hub, 2020). Thus, their inferences, hierarchies, and presentations directly inform which individuals are financially legitimized within influencer ecologies, and therefore who produces the content we see online.

In this vein, influencer management tools are designed deepen surveillance of influencer content by brand stakeholders who hope to monitor and hegemonize influencer behavior: 84% of marketers surveyed in Influencer Marketing Hub's 2020 report suggest that "brand safety" is a key concern when running influencer marketing campaigns (Influencer Marketing Hub, 2020). This finding is supported by a high level of mistrust surrounding influencers, frequently articulated by industry leaders. For example, L'Oreal's Chief Digital Officer, Cedric Dordain, told *The Drum* that "[L'Oreal] want more detail about the background of the influencers . . . From what they've posted in the past—not just on Instagram but on any social platform and any website or blog or forum" (Faull, 2018). In particular, L'Oreal is concerned about influencer behavior—Dordian offers the example of "nude pictures" as a key concern. A secondary concern is that of "fake followers"; *Wired* estimates that purchased followers or bots cost brands US$1.3 billion in 2019. Giving a keynote in Cannes in 2018, Unilever CMO Keith Weed called for increased transparency in influencer marketing, particularly citing concerns about "fakeness" and "dishonest practices" such as buying followers; he notes, "we need to take urgent action now to rebuild trust before it's gone forever" (Unilever, 2018). Influencer management tools are purchased by marketing stakeholders as a layer of surveillance to increase trust in the industry, as meaningful solutions to bad behavior and fraud. They are designed to rationalize the so-called Wild West YouTube economy, at the same time, they make it more difficult for those producing content not defined as "brand safe" to sustain income and opportunities.

This article considers the role of one algorithmic influencer management tool in shaping the influencer marketing ecology, and platformed creative economy. Through examining this tool, I seek to understand how value-laded algorithmic judgments can map onto well-worn hierarchies of desirability and employability, originating from systemic bias along the lines of race, sexuality, and gender. To do this, I draw from a 3-year ethnography of the "messy web," meaning the porous mix of offline and online spaces relevant to the influencer industry (Postill & Pink, 2012). I examined White Papers, About Us pages, terms and conditions, marketing and press guidance, podcasts, trade press coverage, and conference presentations between 2017 and 2020. My ethnography is augmented by a focused walkthrough of a UK-based influencer marketing tool called Peg (2014). Peg uses historical data from influencer profiles and campaigns to generate scores representing influencer appeal, risk, and employability. I negotiated full access to this tool for 1 month, conducting my walkthrough in 2019.

This article opens by synthesizing feminist critiques of influencer industries with close attention to critical algorithmic studies. Then, I map the role of intermediaries in influencer industries, outlining how a developing rotation of stakeholders shapes this growing strain of the creative economy. The context for commercial definitions of "brand safety" is then explored, leading to a sharper overview of how commercial strains of social injustice have been sustained by algorithmic software across industries. Following this, I outline my methodological approach—a blend of digital ethnography of industry practices with a focused "walkthrough" of Peg. I introduce Peg's vision and governance, positioning the tool within the wider milieu of influencer management software. Finally, I conduct a technical walkthrough of Peg. I provide an in-depth examination of Peg.co's "Statistics" tab, as it generates algorithmically predicted audience demographics data and the "Brand Safety" tab, which surveills influencers' use of profanity, audience backlash, and their press coverage. Ultimately, I argue that by approximating analytics, and calculating subjective values such as "brand safety," influencer management tools reify existing social inequalities in influencer industries, particularly along the lines of sexuality, gender, and race. This is important as influencer industries have been heavily critiqued for their narrow representation of women and under-compensation of LGBTQ+ creators and creators of color. As platforms become more saturated with content, it is essential to ask who precisely can afford to participate in production, shaping information and culture that we can access to as audiences.

The Influencer Within Branded Cultures

Influencers blend everyday personal content with marketing communications producing "advertisements written in the form of an opinion editorial and deeply intertwined. . . with everyday lives as lived" (Abidin, 2016, p. 89). Originating from ostensibly do-it-yourself (DIY) media practices in the mid–late 2000s, influencer economies have gradually formalized. Proto-influencer practices included mum bloggers founding advertising networks (Lopez, 2009), strategically using hyperlinks to build communities of cross-promotion and commercial engagement (Rocamora, 2012), and fashion bloggers attending runway shows to lend "hipster credibility" to high-fashion houses (Pham, 2011, p. 12),

Those previously identified as bloggers supplement or supplant blog content with Instagram, the channel for the *commodified everyday* in fashion and beauty verticals (Hund & McGuigan, 2019). The wider influencer ecology also includes beauty YouTubers, who integrate product placement into cosmetic reviews (Hund, 2017; Jerslev, 2016) and now TikTokers, who are are the latest platform-dependent creators to ink deals with brands such as Proctor and Gamble Indeed (Stein, 2020). Influencers across social media platforms comprise a significant link in beauty industries' public relations strategies.

Influencers are "entrepeneural labourers," who, like other creative workers experience the individualized pressures and risks of irregular and piecemeal (un)employment (Neff et al., 2005). Precarity is heightened by double-layered surveillence or "visibility labour," a mandate to attain fans and followers while curating commercial attention within a saturated attention economy (Abidin, 2016). Influencers must be agile, platform-ready, and contigent—or, ready and responsive to platform policies and algorithmic changes (Nieborg & Poell, 2018).

Many users are aware of the visibility platforms engender. They adapt their content or privacy settings to manage the "imagined surveillence" of their profiles (Duffy & Chan, 2019); they develop strategies to negotiate platform functions, for example, to facilitate newsfeed visibility (Bucher, 2017). As professional platform users, influencers conduct research on industry trends and use their findings to piece together engaged approaches to gain and sustain visibility (Bishop, 2019). Keeping their industry embeddedness in mind, it is likely that many influencers are aware of influencer management tools. Indeed, the legal template for a Social Media Influencer Letter Agreement (or contract) asks influencers to agree that "you understand that we will be monitoring your Posts" (Thomson Reuters, 2020b). Creators are thus likely aware of surviellence, yet, we will see that they have little recourse over the data it produces. The lopsided nature of these relationships will be explored in more detail later. For now, it is important to recognize that influencers are dependant on platforms and other intermediaries within influencer marketing ecologies, rendering them alienated from their production.

Influencer Intermediaries

Influencer economies are commerically viewed as a confusing, under-regulated, and messy Wild West. Thus, a growing number of intermediaries advertise their ability to streamline and professionalize the relationships between marketers and influencers. Intermediaries include full-service "social talent" agencies—which are functionally akin to traditional talent agencies, brokering deals for a proportional fee (Abidin, 2017b; Abidin & Ots, 2016; Hutchinson, 2017); loose "collectives" that matchmake influencers with brands, charging membership fees (Stoldt et al., 2019) and Multichannel Networks (MCNs), thus far the most researched influencer management models. MCNs aggregate channels, sell advertising, and cross-promote talent and content, particularly for YouTubers (Cunningham et al., 2016). Each of these influencer management organizations fit Bourdieu's definition of "cultural intermediaries," in that they function to "divulge legitimate culture" in new cultural economies, in this case to reticent brands who should "have no need to be alarmed" as "they can recognize the 'guarantees of quality' offered by their moderately revolutionary tastemakers, who surround themselves with all the institutional signs of cultural authority" (Bourdieu, 2000, p. 326). Those who develop algorithmic influencer management tools sell expertise in influencer industries to reassure brands who are nervous in working in these new and risky ecologies.

Although the remuneration structures and contractual obligations for each intermediary model diverge, most connect influencers with commercial opportunities and offer a spectrum of support (e.g., with production and branding), in exchange for a percentage of influencer income. In turn, intermediary organizations promise brands *increased control* over content and messaging by disciplining and narrowing cultural production to limited commercially recognizable genres. Such commodifying practices have long histories across cultural production. Modeling agents identify talent based on commercial "types," including light-skinned commercial Black models who the "Midwest can relate to" (Wissinger, 2012, p. 134); record labels smooth and discipline a plurality of "Latin music" into a commercially recognizable genres like "salsa" (Negus, 1999). It is thus relevant that many intermediary models specialize in "popular channels that align with specific consumer 'verticals'" (Lobato, 2016, p. 357). Influencer management *tools* similarly claim to "surface hot talent in narrow verticals" (Forrester, 2020), which also map onto traditionally gendered genres, for example, sport, beauty, and fashion, or video gaming.

It is relevant that the automation of intermediaries often functionally narrow assessments of commerciality. For example, the introduction of the automated sales-tracking tool "BookScan" in the early 2000s shaped literary editors' purchasing decisions. As data became more comprehensive, poor sales records followed authors like "bad credit scores," reducing their viability in the industry (Childress, 2012, p. 613). Similarly, the arrival of "hard data" from music sales tracker Soundscan reshaped understandings of commercial music genres, and prompted significant investment in country music due to the growth of "suburban markets" (Negus, 1999). Through search and monitoring functions, influencer management tools make and recommend influencers that align with popular, commercial themes and genres.

Influencers are commercially valuable for their authenticity—in which their self-brands are hinged on consistent performance of amateurism and relatability (Duffy, 2017). Authenticity is both desirable and risky; that influencers may be simply *ordinary people* stokes brands' concerns about the unpredictability of their behavior. However, a particular performance of authenticity *has many crossovers with* definitions of brand safety; that is, it is consistent, virtuous, and glamarous, peppered with carefully managed "pourous" glimpses to acceptable mess of the everyday (Abidin, 2017a). Diagnoses of this style of authenticity dovetail with the intersectional inequalities that suffuse growing creative online economies. Duffy (2016, 2017) convincingly demonstrates how perceptions of authenticity in influencer industries is distributed alongside privilege and nepotistic access to creative networks. The boundaries here are narrow; a mandate to visibility also directly harms women through gendered behavioral policing and harassment (Duffy & Hund, 2019). Oh and Oh (2017, p. 699) argue that "white perspectives and bodies" are "commercially favoured" on platforms like YouTube, for example, racist stereotypes are common in popular vlogs. Gaunt (2015, p. 247) demonstrates Black girls' self presentations are "decontextualised" and ultimately "stigmatized" on YouTube. Speaking within a broader context, Noble (2018) argues that "racism and sexism are part of the architecture and language of technology" (p. 9). These perspectives underpin my theoretical framework; influencer ecologies hinge on carefully performed identities that are not neutral.

The following two sections underpin my critical analysis of influencer management tools. First, I examine the historical context of concerns about *brand safety*, and second, how bias informs algorithms and automated decision-making processes.

Brand Safety

Brands have historically funded media through paid advertising. In so doing they desire to influence content and reward production that is "noncontroversial, light and non-political" as this sustains a '"buying mood"' (Bagdikian, 1997, p. 113). Sustaining *brand safety* is thus a priority for content producers desiring to attract advertising dollars. Practically, brand safety is a positive reproduction of a brand's ideals, an avoidance of controversy, and a circumvention of sex, violence, and profanity (Fahey, 1991). As the *same* advertisers who have a long history of funding network media fund the influencer ecology, an avoidance of the aforementioned "big three" animates the search for influencers to sponsor. Particularly in marketing industries, diagnosis of brand safety has particularly haunted celebrities hired to represent brands (Pringle, 2004). They subject representatives to a disciplining "corporate gaze," mandating that they channel and convey brand values (Wissinger, 2012, p. 131). The following section outlines several contextualizing examples of how such assessment sits alongside marginalization; of women, people of color, and LGBTQ+ people.

First, the surveillance of *sexuality* has been particularly salient for women within promotional cultures. A cultural fixation with girls as being *at risk* dovetailed with young women being established as a consumer group. Since this moment in the early 1990s, girls' potential became socially positioned as something to be closely watched and managed, particularly, alongside *moral concerns* about "juvenile delinquency, nihilism, and antisocial attitudes" (Harris, 2004, p. 24). A much-studied example of this cultural preoccupation with girls at risk, is Miley Cyrus, whose wholesome Disney Channel tween brand shifted to a twerking, nude-posting, sexualized adult in the late 2000s.

The media attention (or obsession) surrounding this moment linked Cyrus' sexualized turn with *risk*, positing that girls would emulate her behaviors in ways that would cause them psychological or reputational damage (Vares & Jackson, 2015). Importantly, Cyrus then became a brand *risk*. She was described being dropped from a Walmart deal and the animated film Hotel Transylvania during this time. Female influencers are similarly dogged by questions about their suitability as role models; assessments are located in good/bad binaries. Beauty influencer Zoella is a regular target of such coverage; her ability to be a role model is frequently raked over by press. She was determined as "racy" by the *Daily Mail* for posting a Snapchat story featuring a hint of underwear (Kelly, 2016), "greedy" by the *Mirror* for her merchandise pricing (Mulroy, 2017), and the launch of her ghost-written book was charged with causing "declining literacy rates" among children in *The Guardian* (Williams, 2017). This representation of Zoella is symptomatic of a media framework that exclusively frames young women as good or bad role models.

Such coverage is apparently concerned that young female celebrities may *poorly influence* their *young audiences*—placing them in opposition to morality, chaste sexuality, conservative dress, healthful consumption behaviors (McRobbie, 2009). Industry texts call on brands to monitor influencers to "protect their reputations" (Callahan, 2017). The legal firm Thompson Reuters advises brands to add a "Morals Clause" to their contracts "to give the advertiser the right to terminate the agreement for acts by the talent that might reflect negatively on the advertiser." The behaviors that may violate such a clause are vague and unclear; they are listed as "moral turpitude" or "to offend public morals" (Thomson Reuters, 2020a). The application of this may be broad—recall that L'Oreal's influencer background checks involve vetting for "nude pictures" (Faull, 2018).

Brand safety is raced. Blackness specifically has been bound up with risk in cultural industries (H. Gray, 2004; Saha, 2018). Within music industries, record labels distance themselves from rap as a genre due to associations with "profanity, violence, and misogyny" (Negus, 1999, p. 94). The marketization of rap is suffused with racist anxieties about its potential to travel to different markets and endure through time; thus, rap and other "raced" music genres receive minimal investment from mainstream record labels (Negus, 1999). Generically, diverse Black musical acts are often stereotyped and marketed as "Urban" (Balaji, 2009). On television, broadcasters have historically avoided shows that were "perceived to appeal only to black people"; a small number of Black-cast shows were considered to have "crossover appeal" if they were "*safe* for white consumption" (Fuller, 2010, p. 290). Advertisers' comfort levels have been a key factor in political economic decision-making; cable channels partially or fully funded by subscription models could take *risks* by purchasing Black content. These brief examples demonstrate an important precedent for advertisers' racist perception of risk and safety, which have contributed to limited representations and distribution of Black content on social media platforms.

As the "mainstream," White audiences are "the ideal subjects of consumerism and representation" (H. Gray, 2005, p. 95). In each of the examples cited here Black audiences remain a commercial market, but one that is economically and culturally valued as niche. Similar practices of narrowcasting play out in influencer economies as Black influencers are hired for fewer commercial campaigns, or function as "tokens" to signal diversity (Dodgson, 2020). Black influencers are paid drastically less than their White colleagues, and are more likely to be approached and hired by smaller brands addressing Black audiences, for example, natural haircare (Carman, 2020). These factors contribute to real visibility and pay inequality, which is augmented by platforms' racialized practices such as YouTube's "Supporting Black Creators" initiatives. These functionally raise visibility in certain contexts, but have arguably done little to improve Black creators' economic positioning on the platform, as Black creators are still avoided by advertisers.

Finally, until the mid-1990s advertisers avoided association with homosexuality; Fahey (1991) demonstrates how advertisers routinely withdrew from media depicting homosexual themes, and brands rarely hired LGBTQ+ spokespeople (Ragusa, 2005). Although LGBTQ+ consumers have been identified as a lucrative niche market, this market is constructed as "white, male, professional, urban with an abundance of good taste and discretionary income" (Sender, 2004, p. 8). Sender argues that this conservative picture of gay consumers does not accurately reflect the diversity of LGBTQ+ people in addition to eradicating any relationship with overt sexuality. Brand safety involves navigating between "business interests and political risk" (Sender, 2004, p. 98) transmorphing identity into what is contained, sexless, and sanitized. More recently, YouTube has been criticized for designating everyday LGBTQ+ YouTubers' content as non-brand safe, reducing commercial opportunities and income (Alexander, 2019). In 2019, some of those affected brought legal action against the platform, claiming both automated systems and human reviewers tagged videos using terms such as "gay," 'bisexual' or "trans" as unsuitable for advertisers. Herein, brand safety skews toward discrimination of marginalized peoples. The following section demonstrates how this trend is often extended by algorithmic tools used for influencer hiring decisions.

Algorithmic Management

Algorithms are fetishised for their "objectivity" in this case, are "formulaic with an identified function or role that determines the steps and the processes that are employed" (Willson, 2017, p. 5). Algorithmic software is increasingly introduced to manage datasets (often groups of people) who are viewed as unruly, messy, or risky. By using algorithmic influencer management tools, brands hope to make the glut of user-generated content produced by influencers manageable and monetizable. In so doing, however, they reify existing social inequalities. This is because algorithms are "embedded in old systems of power and privilege" (Eubanks, 2018, p. 178). They classify individuals while giving little insight into their processes, or how to address instances of misclassification. Indeed, it is no coincidence that influencer management tools draw from colonial discourse in framing influencer ecologies as a "Wild West" to be stabilized and managed. As Benjamin (2019, p. 8) points out, such technological solutions often "hide, speed up or even deepen discrimination." Long social histories of discriminatory decision-making are baked into engineering practices, training datasets, and underscore patterns in predictive algorithmic modeling.

Algorithms "judge similarity and probablity" and use "categories to discipline action" (Ananny, 2016, pp. 102–103). They predict outcomes without understanding intention and context. Indeed, algorithms act on "measurable types," assigning users identities and categories "directed towards operability and efficiency, not representative enactness" (Cheney-Lippold, 2017, p. 50). As this article's analysis sets out, measurable types such as brand safety can only be an *approximation*, relying on coded definitions of safety and risk, which run alongside intersections of discriminatory decisions and oversights.

Algorithms are often advertised with small margins for error, yet, even small errors can have significant implications. Gillespie (2018) provocatively queries what is an acceptable rate of "false positive" in categorization and prediction; "when it comes to culture and expression, even a few false positives can be a real concern, depending on whether these errors are idoscyncractic or systemic" (p. 104). As this article demonstrates, so-called errors particularly harm Black users, in addition to those along intersections of marginalized identity. Critical scholars argue that these "errors" are often designed for; that raced inequality is "fundamental to the operating system of the web" (Noble, 2018, p. 10). And indeed, we know that it is those who are intersectionally marginalized in society that are, systemically, targeted and affected by algorithmic discrimination. There are multiple examples from 2020 alone; Twitter systematically cropped out Black faces in image preview, TikTok looped White creators (and excluded those of color) through its content-filtering algorithm. Epps-Darling (2020) defines the frequency of moments of algorithmic prejudice as "technological microagressions," demonstrating how Black users' experiences of technology are consistently animated by systematic discrimination. In the limited scope of this article, I deepen insight into *how* this exclusion happens, specifically in influencer economies by examining how influencer management tools extend the exclusion of "Black digital practioners" from the "capitalist economies of social media" (Brock, 2019, p. 215).

Method

Industry and scholars position algorithms as black boxes, where the inner workings of algorithmic systems are deliberately or pragmatically obscured (Pasquale, 2015). Often the fetishization of the complexity of algorithms is a "red herring, a piece of information that distracts from the other" (ref). There are no guarantees that cracking open the *black box* will reveal secrets or make the roots of bias or discrimination visible in algorithmic systems (Ananny & Crawford, 2018). Even scrutinizing code often cannot reveal how algorithms are always constructed by, and in tandem with, humans. Rather, for Bucher there is a methodological opportunity in studying the ancillary content that surrounds algorithms and their formations. This includes "press releases, conference papers on machine learning techniques . . . media reports, blog posts" in addition to other available texts and resources (Bucher, 2018, p. 61). A dataset is generated that can be analyzed ("taken apart") and "interpreted and shaped" according to the researcher's own frameworks (A. Gray, 2003).

Informed by this approach, my methodology involves gathering background information about influencer management tools, including White Papers, About Us pages, marketing and press guidance, podcasts, trade press coverage and conference presentations between 2017 and 2019. This process was guided by a broader ethnography of the UK influencer marketing industry. Second, I negotiated full access to Peg for 1 month, and used the "walkthrough method," combining Science and Technology Studies and Cultural Studies approaches to systematically analyze Peg's "technological mechanisms and embedded cultural references" (Light et al., 2018). I walked through the Peg platform as a brand, interrogating its features, options and guidelines. The walkthrough method offered a guiding approach to support thickly describing and analyzing Peg's interfaces, scenarios of use, political economic factors and governance, technical features, tone, symbolic representation, and interface.

Despite the clear limitations of being unable to reveal how influencer management tools work, the multisited approach employed in this article can demonstrate how they are conceived, sold, and embedded within marketing industries. I offer valuable insight into how data intermediaries are being wielded to make decisions in growing datafied marketing industries. My method focuses on how influencer management tools can integrate bias, and amplify and sustain discrimination for workers within influencer industries. As a start, I briefly overview Peg's vision, operating model, and governance.

Peg

Peg was founded in 2014 and is run by a small team in London, UK. The tool is marketed and sold directly via their website, which prominently displays the logos of recognizable companies who have employed the software, such as L'Oreal, Google, and Lego. These logos appear next to testimonials from public relations (PR) agencies and a positive review (dotted with stars) from industry watchdog "Influencer Marketing Hub." The site's clean, polished aesthetics, and testimonials are comparable with the homepages of many B2B promotional services. However, Pegs strives toward legitimization by association with prominent brands is worth noting when considering their positioning in influencer marketing industries. Although creator economies are often categorized as disruptive or divergent from "mainstream" media and advertising spaces, in practice, influencer marketing is often shaped by association with the very same actors who are long-time funders of these industries. Through their website, Peg underscores this point through their emphasis on their alliance with mainstream promotional cultures.

There is no price point publicly available for Peg. Rather, users can request a product demonstration by submitting their name, job title, company name, and phone number. Submitting a Gmail address returns an error code, prodding users to instead submit a *work email*. This implies "*serious enquiries only.*" On completion of this form, a message informs the user that "we will be in touch shortly"—in other words "don't call us, we'll call you." For this project, I negotiated access to Peg through my networks, but at different times attempted to sign up for free trials for other influencer marketing software. In each instance, I inputted my job title (Lecturer) and my employer (King's College) to forms on their websites. My requests to CreatorIQ and Traackr went unanswered, while

Mavrck and Upfluence invited me to book a request to have a demo call. Influencer marketing software is tightly gatekept—you are not guaranteed the advertised free trial, rather, you are vetted via Zoom call. Imagined users are legitimate stakeholders within closed PR industries. Influencers, then, cannot view how they are presented to brands, or correct inaccuracies, often as they simply cannot enter the software. This ultimately alienates further from their own representation and data, particularly in relation to weighty algorithmic judgments made about them.

Influencers do have the option to partner with Peg to provide the software with accurate data. If they do not sign up to the Peg partnership, they will be automatically listed on the software, but with Peg's algorithmically approximated metrics. Further research is required into influencers' awareness of management tools. However, reflecting on the sheer volume of software entering the market, it is clear that even if they are very aware, verification with each one would be time-consuming. There are, however, shortcuts available for some. Talent agents often forge partnerships with influencer software providers—for example, Peg has partnered with elite UK digital talent manager GleamFutures to batch approve their clients' data. These deals give the upper hand to influencers with talent managers, ultimately calcifying inequalities as those with representation are often White, middle-class, and commercially attractive (Bishop, 2018).

Any influencer who verifies with Peg grants the software access to all of their personal data available through the API, "including but not limited to measurements of user activity, geographics and demographics, video view counts and ratings, traffic sources and user device type and operating systems" (Peg.co, 2019a). What is perhaps more important is that they also grant Peg

> creation and unlimited use and disclosure of data which combines or aggregates
>
> (wholly or in part) the Creator Data with other data or information, or otherwise
>
> adapts the Creator Data, to such a degree that it cannot be identified as originating
>
> or deriving directly from the Creator Data, cannot be reverse-engineered such that it can so be identified, and is not capable of use substantially as a substitute for the Creator Data. (Peg.co, 2019a)

Even providing Peg with access to your YouTube account, and thereby giving them the opportunity to verify data, the software will continue to make algorithmic calculations that cannot be "reverse engineered." These subjective calculations (which are explored in the discussion to follow) are calculated in obscure ways—intermeshing YouTube with many other data points that can be gathered without creator authorization or consent.

The cat's cradle of data points used here has particular implications when Peg also takes pains to abscond their responsibility as an intermediary, stating plainly in their Terms and Conditions that "we are not your agent, advisor or consultant." This smoothes over Peg's link in the influencer marketing chain—although they have automated some of the key activities of a talent agent (such as advertising and vetting clients for jobs and opportunities), they maintain that they are simply a platform—a neutral term that glosses over their role in decision-making and advisory work (Gillespie, 2010). Indeed, Peg's presentation is heavily invested in neutrality, particularly through their investment in data—which Nic Yeeles has called "99% accurate" (Ghosh, 2016). Many questions spring from this statement—how can a subjective quality like brand safety be predicted accurately? Who does this accuracy serve? The following section will examine two key features of Peg—the "Statistics" tab, as it generates algorithmically predicted audience demographics data and the "Brand Safety" tab, which surveills influencers' use of profanity, audience backlash, and their press coverage. I explore how each section functions, and how each section may contribute to inequalities within influencer industries.

The Statistics Tab

The statistics presents a consolidation of metrics for *any influencer*. Through colorful graphs, it presents an account of influencers' YouTube subscribers, Instagram followers, and a calculated average of their views and likes. Under this tab, Peg also presents influencers' audience information including demographics: audience gender, age, and location. This provision is remarkable as the data are ostensibly accessible through private platform provided analytics, only available to content owners. Peg automatically generates demographics data for *any and all* content creators, approximated based on Peg's "own algorithms" (Ghosh, 2016). If influencers verify with Peg, these data will be matched with YouTube data. However, as we saw earlier, these data are meshed with a mix of other data points. Although this hard numeric data is fetishized as objective and by the tool it is pulled from a number of obfuscated sources, stretched, and molded according to Peg's designs, without the understanding or intervention of those who it is supposed to represent.

Predicted demographics data serves two functions. First, brand representatives can easily search a wide range of influencers based on their desired audience demographics. This feature emphasizes that media continues to be funded based on its ability to capture and package desirable audiences (Ang, 1991). Second, demographics information as presented by Peg can be part of a secondary process of verification. Industry standards dictate that demographics data are currently provided to brands by influencers themselves, accessible through platform analytics for content owners. Due to reliance on the self-presentation of analytics, fraud in this space is a key concern among marketing stakeholders;

Unilever CMO Keith Weed stated the importance of "increase[ing] transparency in the influencer space" (Stewart, 2018). Peg mirrors this language, stating that their tool is driven "by real results not vanity metrics" (Peg.co, 2019b). The value of verification data is consistent with research that demonstrates the importance of demographics data to advertisers (Bivens & Haimson, 2016; Turow, 2011).

To take one example within the statistics tap, Peg clearly provides an "Audience Gender" breakdown; a stable, binary percentage of "men" and "women" are communicated through a pink and blue pie chart. There is no information about how these gendered audiences are calculated; whether they are pulled from YouTube (whose own accuracy has been questioned) or augmented using other data sources. Research has shown that algorithmically approximated demographics categories such as "gender" are dynamically created, and continuously and automatically categorized online. We can and should question their veracity; Cheney-Lippold (2017) notes, "it's 'measurable types' universality of allowable wrongness that shape our experiences online, contributing metrics presented as measured 'truths'" (p. 65). To refer to Cheney-Lippold's example, Google's search behavior data are inferred by how they behave—meaning they are categorized by stereotypes that configure online experience. Similarly, Bivens (2017) demonstrates that (despite offering over 57 custom gender options) binary demographics data are so crucial to advertisers on Facebook, that the platform "computational re-[classifies] custom gender selection on the user interface back into what amounts to a binary" (Bivens, 2017, p. 893). Again, this example shows that normative assessments of online behavior supersede the gender identities that individuals claim for themselves. These works demonstrate the value of automatically generated binary data for marketers. Peg.co's provision of verifiable statistics is designed to fact-check influencers' and platform-provided analytics. There is no evidence that they successfully measure material identity. Rather, the availability of data supersedes accuracy, as it is demanded by marketers.

Peg: Brand Safety Tab

Peg uses machine learning algorithms to approximate a Safety Score out of 100, made up of three other scores: a Family Friendly rating measuring "bad language and profanity," an Audience Consistency score representing influencers "consistent reception from their audience," and a Controversy Free score measuring whether influencers are "covered negatively in the press or associated with controversial topics" (Peg.co, 2019a). The following section will analyze the presentation of these micro-scores, and how discrimination across intersections of marginalized communities can become baked into the macro Safety Score in Peg.

Family Friendly measures instances of profanity (termed "Naughty Words") in an influencers' video metadata (titles and tags) and spoken words using language processing. The Peg dashboard presents a color-coded breakdown of *all historic* Naughty Words uttered by an influencer in *any published video*. Instances are totaled over a YouTube lifetime; gaming vlogger Pewdiepie has used Naughty Words in 108 videos, beauty vlogger Zoella has used them in 17. The severity of the language is categorized using a traffic light system; "Piss," "crap," and "damn" are coded green. Orange words include "arse," "dick," and "vagina." Words coded in red include severe profanity such as "fuck" and "shit," but also racist slurs. The implied parity here is jarring from a functional perspective, even without ethical issues; brand backlash from an influencer exclaiming "fuck" is unlikely to equal that of the use of a (directed or undirected) racist slur. A guide to the values informing confusing judgments is missing: what makes "tit" orange and "boob" green? What contributes to the medically correct term "vagina" being coded orange, the same categorization as "whore" and "ass"? Naughty Word categorizations matter because stakeholders do not have access to information on *how* words are categorized and *why*. Hundreds of influencers' spoken words are categorized are then streamlined into the Family Friendly score, which then have a significant impact in overall Safety Score. These categorizations are used to select influencers and distribute income and opportunities.

Algorithms cannot measure context, and cannot attend to experiences sustained intricate intersections of race and gender identity within social and cultural life. Writing on content moderation has highlighted contextual challenges for commercial platforms, for example, Facebook notably flagged 1972 Pulitzer Prize winning photograph Napalm Girl for child nudity (Gillespie, 2018). The following section outlines two comparable examples of complexity which shape the classification of safety on Peg. The decontextualized analysis of language to measure for brand safety works against minority communities because tools are designed to read decontextualized language through a heteronormative and White lens.

First, the word "queer" is coded as a green Naughty Word. While queer does have roots as a homophobic slur, it is a term used widely in activism and LGBTQ+ communities, in addition to within deconstructivist theory to recognize that sexualities are "unstable, fluid and constructed" (Gamson, 1995, p. 392). So, one may identify as queer, partake in queer activism, or discuss queer theory. In many of these contexts, queer can be an everyday or academic identifier, and is used by YouTubers to align content with LGBTQ+ communities and audience.

My walkthrough revealed that several high-profile LGBTQ+ influencers have been identified by Peg for their use of "queer" as a Naughty Word, including A List YouTubers Ingrid Nilsen and Tyler Oakley—decreasing their Family Friendly scores. Tyler Oakley's YouTube series "Stories of Queer Resilience" is flagged by Peg for the use of the word "queer" as brand unsafe. This series, however, features celebrities that have long attracted advertising partnerships such as Olympic Skier Gus Kenworthy, the face of hair care Head and

Shoulders. The classification of words such as "queer" as brand unsafe punishes creators who use it by lowering their safety score, reducing their visibility in tools' search functions, and making them less likely to be complements of the ongoing YouTube demonetization of LGBTQ+ content outlined in the literature review. However, while YouTube's proprietary algorithms are black-boxed, Peg's dashboard makes the commercial punishment associated with use of LGBTQ+ terminology explicit. This adds a layer of confirmation that can be useful to research and activists uncovering the LGBTQ+ bias.

The second example of contextual complexity involves "ni**er," a term coded red. Peg identifies that KSI, a Black British vlogger, has used "n**ger" three times in one video, contributing to his low Family Friendly score of three. The video is a parodic music video featuring KSI's family humorously rapping about KSI's recent successes. A line rapped by KSI's mum includes the word "n**ger" in the style of many popular rap artists; the shock of a middle-aged woman performing typical street lyrics adds to the gag. It is clear that "n**ger" is a word with hugely complex etymology. For many, but not all, it "takes on a completely different complexion when uttered by someone who is Black in contrast to someone who is white" but the word is ultimately "contingent, changeable and context-specific" (Kennedy, 1999, pp. 91–94). Indeed, context is central, but is not represented through the Peg scores. For comparison, Pewdiepie is a White gaming vlogger who has featured "c**n" six times and "n**ger" twice, in one case during a parodic "hip hop" dance. Like KSI, Pewdiepie *also* has a "family-friendly" score of 3. In both cases outlined, it is individuals in minority groups who are penalized for *reclaiming* words that have historically been used against them. In a saturated influencer marketplace, small differences in Safety Scores may have significant impact on income. It is important, therefore, to understand how judgments ignore the contradictory nature of culture, in a way that may impact and harm historically marginalized groups.

Audience Consistency: This score measures whether influencers are "receiving a consistently good reception from their audience," by measuring like to dislike ratios on YouTube videos (Peg.co, 2019a). This ratio is visualized in a graph, dipping into an angry red Backlash Zone if a video receives more "dislike" votes than "like" votes for the YouTube channel's average. The area is illustrated with a red exclamation point, signaling a hazard.

Although the like/dislike ratio is designed to approximate creator scandals, it actually measures an audience's tolerance for creator behaviors. For example, gaming vlogger Pewdiepie's use of anti-Semitic language has been widely profiled, yet he has high audience consistency score of 9/10. He only dips into the Backlash Zone on a video entitled "WHY I DON'T LIKE MARVEL MOVIES." Similarly, Impaulsive, the podcast hosted by controversial vlogger Logan Paul, has an audience consistency score of 8/10, never dipping into the Backlash Zone, despite Paul hosting far right commentator Alex Jones on the podcast in April 2019. During the podcast Jones (who was banned from YouTube in 2018) discussed conspiracy theories and called Megyn Kelly a "goddam lying whore" (Impaulsive, 2019). According to Peg.co, this video is brand safe.

Indeed, influencers whose brands are *built* on being controversial tend to have very consistent like/dislike ratios, a positive metric for Audience Consistency and their overall Safety Score. In many mainstream online spaces hate speech, misogyny and racism are not only present but performed as *pleasurable*. Phillips (2015) points out that trolls who regularly visit 4chan, an androcentric platform sharing Pewdiepie's audience, "enjoy racist expression" (p. 96). There is evidence of a wider normalized "networked racialised hostility" within YouTube comments (Murthy & Sharma, 2019, p. 209). There is institutionalized racism in social life, and within social media platforms, as spaces where social life is lived and produced. The above discussion demonstrates how discrimination and bias leak into influencer management tools, and what they can tell us about the political economy of influencer industries. An unsurprising finding, perhaps, is that the Backlash Zone would suggest that brands are concerned with how audiences may react to videos, rather than the pursuit of social justice.

Measuring audience consistency as a factor in brand safety also has implications for victims of racist, sexist, sustained online attacks. These campaigns are part of "toxic technocultures," which exploit social media platforms as a "channel of coordination and harassment" (Massanari, 2017, p. 333). In this vein, marginalized users suffer the "risk of visibility," as their online presence is weaponized, mocked, and harassed in an attempt to silence them (Massanari, 2018, p. 1).

Beauty influencer Scarlett London felt the consequences of this risk, when an Instagram advertorial for mouthwash became the center of trolling swarm in late 2018. In the advert, London lies on a blanket decorated with her own image, surrounded by 20 heart-shaped balloons and strawberry pancakes (that on closer inspection suspiciously appear to be folded corn tortillas). While excessive, the image utilizes standard tropes of Instagram glamor. However, it was screenshotted and Tweeted with the caption "fuck off this is anyone's normal morning" (Nathan, 2018), retweeted 20,000 times and picked up by the *Daily Mail*, amplifying the swarm and causing further backlash. The public critique of London's image was couched in concerns about social media's influence on self-esteem and mental health. However, this discourse drew on sustained critiques against highly visible young women—that London was vain, opportunistic, and fake. Crucially, Peg identifies that Scarlett London dips well into the Backlash Zone for this period, reducing her Safety Score and likely affecting income and opportunities for brands using Peg. Backlash is uneven: women and people of color are more vulnerable attacks that diminish an Audience Consistency score and overall Safety Score, both used by brands make recruitment decisions.

Controversy Free: This score measures whether influencers are "covered negatively in the press or associated with controversial topics" (Peg.co, 2019a). A scrollbar displays thumbnails of all press coverage of a given influencer. Coverage is categorized by "positive," 'negative, or "very negative." Peg allows users to view media coverage by recent or by "top outlets," which include (UK publications) *The Sun*, the *Daily Mail*, *The Telegraph*, and the *Independent*. Although *top outlets* imply some editorial distinction, these outlets frequently engage in misogynistic reporting, particularly taking aim at young and visible women to benefit from their highly visibility and large fanbases (Gies, 2011; Vares & Jackson, 2015).

The uneven attention toward the actions of young women is normalized within press and society more broadly; it means that female influencers will always be at increased risk of "negative" or "very negative" press attention, feeding into (decreasing) their overall Peg Safety Score. On the contrary, controversial vlogger's PewDiePie's press coverage was categorized as near-exclusively positive in Peg. Although articles similarly focused on how much PewDiePie earned (e.g., "meet the man making $4 million a YEAR from his bedroom"), such affirmation was uncoupled with the critique of PewDiePie's exploitation or vanity levied at feminized vloggers such as Zoella.

Conclusion

In many cultural contexts, but particularly in the United Kingdom, creative work has been enthusiastically heralded as a pathway for entrepreneurship and social mobility. It is those at intersections of social inequalities that are most harmed by these trends. The valorization of creative work normalizes forms of precarious, individualized employment alongside a reduction in workers' rights and social protections. The hyper-individualized nature of online content creation complements the UK government's decimation of creative industries funding during ongoing austerity. Promises of creative success are now channeled toward social media platforms, who exacerbate mythologies of the lucrative and participatory nature of contingent production. For example, the UK Media Trust now offers "vlog training" for young people, post-16 Colleges advertise courses in vlogging and content creation and Ronan Harris, VP of Google UK, sits on the UK Government's Creative Industries Council—which is responsible for identifying skills shortages and distributing funding. In critical media industry studies, it is important to attend to the specific ways that the mythological power of creative work translates to the uneven distribution of employment opportunities.

Influencer management tools make up one part of the ecology of intermediaries that work to forge inequalities in influencer economies, by selling diagnoses of brand safety which further entrenches longstanding hierarchies in influencer industries. Through their marketing as *objective software*, influencer management tools are used to shore up decisions made by intermediaries, such as talent agents and brand liaisons. They justify selection processes that exclude marginalized influencers, harming them economically, as those with lower scores are less likely to be hired by brand. Brands using Peg include Lego, L'Oreal, and EA Games; 40% of *all brands* use similar software. Thus, scores likely impact the financial sustainability of the YouTube channels run by marginalized creators, which thereby shapes the gendered and raced representation on YouTube. In so doing, influencer management tools make a profit—the types of exploitation here are multifaceted.

Peg, alongside other influencer management software, is very invested in promoting their complex data science, which sustains their legitimacy as experts and intermediaries. Such promotion fits with big data's "mythology" of "truth, objectivity and accuracy" (Boyd & Crawford, 2012, p. 663). Peg define their algorithmic processes in opaque and humerous copy, for example, "sponsored content [is] directed using clever sciency stuff," boasting their tool is "jam-packed with advanced features, AI algorithms and machine learning models" (Peg.co, 2019a). They harden fuzzy and subjective concepts such as *brand safety*, but in so doing encode decontextualized language through a heteronormative and White lens. Influencer markets are intensely saturated; estimates put the number of YouTube channels at 37 million, approximately 2,200 channels have 1 million subscribers. Decisions about who to hire are bound up with risk. Like Bookscan and Soundscan in publishing and music industries, intermediaries such as brand representatives and talent managers use automated tools to sharpen and justify decisions, which in practice are based on a number of subjective feelings and

These uses of AI could be intentionally or accidentally weaponized, particularly as the science behind them is knotty with high proportions of false positives, and imperfect training data. Claims to expertise legitimize the endorsements made by influencer management tools; we should attend to which influencers they validate and promote, seemingly supported by *metrics* and data. Moreover, it is important that there is a historical precedent for sociocultural discrimination against women, people of color and LGBTQ+ people in promotional ecologies. Understanding this context should give us pause before diagnosing issues as simply *algorithmic* errors.

Although influencer management tools rapidly enter the market, they can exit just as fast. For example, they alter their algorithmic processes, are shut down or purchased—thus *how they work* is broadly inaccessible to researchers. My multisited approach to researching these tools presents a start, to show how software is being used to distribute employment opportunities within influencer economies. More research is needed into how algorithmically enlivened software works, how they are involved in the distribution of work, and how they are imagined and used within marketing industries.

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