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Examining Racial Stereotypes in YouTube Autocomplete Suggestions

Eunbin Ha[1*], Haein Kong[1*], and Shagun Jhaver[1†]

Abstract

Autocomplete is a popular search feature that predicts queries based on user input and guides users to a set of potentially relevant suggestions. In this study, we examine what YouTube autocompletes suggest to users seeking information about race on the platform. Specifically, we perform an algorithm output audit of autocomplete suggestions for input queries about four racial groups and examine the stereotypes they embody. Using critical discourse analysis, we identify five major sociocultural contexts in which racial information appears—*Appearance, Ability, Culture, Social Equity, and Manner*. We found that the participatory nature of YouTube produces a multifaceted representation of race-related content in its search outputs, characterized by enduring historical biases, aggregated discrimination, and interracial tensions, while simultaneously depicting minority resistance and aspirations of a post-racial society. We call for innovations in content moderation policy design and enforcement to address existing racial harms in YouTube search outputs.

Keywords

Algorithm audit, algorithmic bias, content moderation, racial bias, search engine

Introduction

Autocomplete is a technical feature that facilitates the online search process by using the first few entered keywords to predict and offer users a set of query suggestions (Karapapa and Borghi 2015) (Figure 1). This feature, now ubiquitously available across all major search platforms, social media websites, and online marketplaces, is also available on YouTube,[1] the world's largest video-sharing platform. Autocomplete improves users' search experience by reducing typing by about 25 percent on average (Sullivan 2018). However, the algorithmic 'nudges' this feature offers have the potential to induce identity-based biases among YouTube searchers. This is because its autocomplete query suggestions are shaped not only by the inputting user's previous YouTube activities and location but also by the wider popularity of such queries and the content uploaded by YouTube creators, who often tend to be wealthy and White (Lennard 2015; Wang et al. 2018). Thus, YouTube autocompletes could incorporate the prevalent biases and stereotypes that some people hold and expose them to other users (Lin et al. 2023).

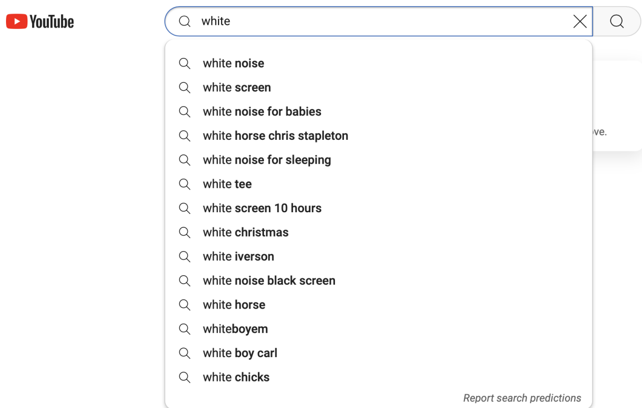

Figure 1. An example of YouTube's autocomplete function in action. Typing any keywords (e.g., "white") triggers a list of query options that users may select.

Such reproduction of stereotypes constitutes representational harm by narrowing demographic groups down to specific traits and exaggerating them (Leidinger and Rogers 2023). Negative stereotypes about oneself can influence one's well-being and productivity, whereas negative stereotypes about other groups can permeate public institutions and shape how society and policymakers treat those groups (Levy 2009). Roy and Ayalon (2020, p.1020) argue that the unsolicited suggestions offered by autocompletion induce "incidental learning," a "process of unconscious, unplanned absorption of contextual information," and are likely to influence users' short- and long-term beliefs and curiosity about different topics. Early investigations of Google autocompletion emphasized that autocompletion stereotypes, viewed and absorbed repeatedly, distort our worldview and perpetuate oppressive social relationships (Cadwalladr 2016; Noble 2018).

[1]Rutgers University, New Brunswick, United States
[*]Equal contribution.
[†]Corresponding author.

Corresponding author:
Shagun Jhaver, Department of Library and Information Science, Rutgers University.
Email: shagun.jhaver@rutgers.edu

[1]https://www.youtube.com/

Most prior research on autocomplete suggestions centers on algorithmic outputs from general-purpose search engines, especially Google Search (Al-Abbas et al. 2020; Baker and Potts 2013; Leidinger and Rogers 2023; Roy and Ayalon 2020). This research focus seems reasonable because Google Search has been the largest global search engine since the early 2000's.[2] However, the use of autocomplete to assist query inputs goes far beyond Google searching. For instance, YouTube, the platform we focus on in this study, has incorporated the autocomplete feature in its search function for many years. Indeed, if we count the number of searches made across all platforms, YouTube emerges as the second-largest search engine after Google (Smith 2020), offering all its results in a video format. While Google does not publicly describe the extent to which it uses the same data and algorithms to drive search autocomplete suggestions on Google and YouTube, official documentation suggests that YouTube autocomplete predictions are at least partly shaped by content specific to YouTube, including users' video watching history (YouTube 2025). However, YouTube autocomplete has attracted little scholarly attention, perhaps because of YouTube's public perception as a video-sharing platform rather than a search engine.

Unlike search engines, YouTube allows users to not just view, but also create content on its site (Wotanis and McMillan 2014). Prior research on YouTube's participatory culture has characterized it as a critical form of expression, "self-promotion, escapism, and utter play" (Boxman-Shabtai 2019). However, it is possible that YouTube's complex cultural fabric comprising both professional (i.e., traditional media) and amateur (i.e., independent individuals) content production (Boxman-Shabtai 2019) induces the types of biases that do not appear on search engines. At the same time, independent YouTubers have the potential to create and share content that counteracts traditional biases and influence search outputs in positive ways.

YouTube algorithms construct and shape content creators' visibility on the site's search and front pages as well as in features like autoplaying of 'related videos' (Bishop 2019). However, YouTube releases limited information about these algorithms to maintain a competitive advantage. This black-boxing of algorithmic governance makes accountability difficult (Reynolds and Hallinan 2024). Thus, there are growing concerns about how cultural producers, who must navigate the increasingly algorithmic nature of content distribution on YouTube, risk losing their visibility and income (Bishop 2019). Given YouTube's unique participatory culture and the uneven power relationship between content creators or searchers and the platform, Reynolds and Hallinan (2024) have called for examining YouTube algorithms' accountability in its specific platform environment. Responding to this call, we focus on YouTube's search algorithms.

Specifically, we explore what information YouTube users in the United States (U.S.) encounter through the search autocomplete suggestions. Since misinformation or limited information about racial groups, along with media stereotypes, can shape individuals' perceptions of race (Covington 2010), *we pose the following research question: what suggestions does the YouTube search feature provide to users exploring information about racial topics, and how may such suggestions shape users' understandings of race?* We focus on race here to extend prior conversations on the media's construction of race (Chen 1996; Squires 2014; Walters et al. 2024).

Importantly, the autocomplete feature not only provides information but may also contribute to the propagation of racial stereotypes. *We perform an algorithmic output audit of YouTube autocomplete suggestions regarding four racial groups—Whites, Blacks, Asians, and Hispanics—to surface such stereotypes.* At the same time, we also attend to positive representations of racial minorities and attempts to counteract racial stigmas in these autocomplete suggestions.

Background and Related Work

Racial Stereotypes

Since the 1950's, significant changes in America's political and social landscape have made racial discrimination illegal and rendered overt racial prejudice socially unacceptable. In response to these broad shifts, social scientists have examined how racial stereotypes have evolved in tandem. Recognizing these changes is crucial in intergroup relations research since shifts in stereotypes are often seen as a necessary prerequisite to reducing prejudice and fostering more positive intergroup interactions.

Since Whites have long constituted the majority of the U.S. population, there exists a cultural tendency toward White ethnocentrism that contributes to shaping Whites positively and other racial groups negatively (Maykovich 1972). Specifically, US racial stereotypes often manifest as placing Whites and Blacks at the top and bottom of the racial hierarchy, respectively, with other ethnic minorities, such as Asians or Hispanics, in between these extremes (Song 2004).

Historically, Blacks or African Americans have been negatively stereotyped with respect to a variety of sociocultural characteristics, including their personality, hygiene, and criminal conduct. Messages from mass media and political communications often reinforce these stereotypes (Hurwitz and Peffley 1997). Some scholars maintain that these distorted perceptions of Blacks are rooted in slavery (Lintner 2004) and Christian mythology (Miller 1995). Whatever their origin, such racial stereotypes are dangerous because empowered non-minorities can exploit them to justify their privilege and continue to perpetuate harm and discrimination against 'others.' For instance, racial segregation in the U.S. was historically based on biased perceptions about Blacks' personalities, intelligence, and appearance (Lintner 2004).

Asians or Asian Americans, often described as a 'model minority,' are stereotyped as being intelligent, hard-working, and academically and economically accomplished (Lee et al. 2008; Trytten et al. 2012). While this model minority stereotype could be perceived as positive, Lee et al. (2008) argued that it can conceal the diversity among Asians, rouse interracial tensions, and discourage Asians from disclosing their problems and seeking assistance. In addition to the model minority stereotype, Asians have a long history of being marginalized in the U.S. Chen (1996) showed that

[2] https://www.britannica.com/topic/Google-Inc

the physical appearance of Asian male immigrants in the nineteenth century and the work they engaged in were often caricatured to build feminized and infantilized images; the mass media at that time reinforced this image by portraying them as wearing feminine clothes or engaging in housework (Chen 1996). Further, the U.S. mass media has often portrayed Asian women as exotic, submissive, and quiet (Paner 2018).

Another US minority, Hispanics, tend to be categorized as a single group despite their heterogeneous and complex ethnic roots (Nelson and Tienda 2014). They were typically described in early Western films as highly emotional and violent individuals with untidy features, aka the 'El Bandido' stereotype (Berg 2002). This stereotype has gradually evolved into the image of undocumented immigrants, contributing to racist discourses that portray them as criminals who are potentially threatening to American lives and jobs (Pérez Huber and Solorzano 2015).

Our work extends this prior understanding of racial stereotypes. We examine their *current state* in the U.S. through the lens of how each racial group is described in YouTube autocomplete algorithm's suggestions. We aim to identify the perpetuating racial stereotypes reinforced by this culturally influential online platform and highlight recently emerging stereotypes. In doing so, we also bring attention to the algorithmic biases.

Algorithmic Bias, Search Critiques, and Algorithm Audits

As digital platforms grow, systems designers rely on algorithms to determine what information to present to whom. These algorithms and the interfaces created for them can signal the quality and relevance of different search results and shape people's perceptions of topics of societal importance (Kay et al. 2015). However, both algorithms and interfaces can exhibit biases in their representation of information. While there is no universally agreed-upon definition of *algorithmic bias*, researchers from various disciplines have addressed its different manifestations. In social science, scholars tend to focus on how algorithmic bias perpetuates social discrimination and affects social equity.

The research presented here can be placed within the broader critique of algorithmic biases in content moderation, though we focus on search feature outputs rather than AI-assisted regulation of potentially inappropriate social media posts (Jhaver et al. 2019). Specifically, this article aligns with approaches that aim to assess the extent to which search outputs are: problematic; characterized by offensive, stereotypical, inappropriate, and discriminatory terms; and/or racist (Rogers 2023). Unlike these approaches, we also document how the search outputs serve to dismantle racist stereotypes. Our method of probing YouTube's search feature with specific queries could be positioned alongside approaches like algorithm audits (Sandvig et al. 2014) and ethical hacking practices that search for vulnerabilities (Roberts 2019).

Prior research has shown algorithmic biases in the operation of search engines regarding what they index, what they present to specific users, and—most relevant to our work—how their autocomplete suggestions reinforce social discrimination (Kay et al. 2015). For example, Baker and Potts (2013) showed that Google search produces a higher number of negatively stereotyped autocomplete suggestions for searchers with Muslim, Jewish, Gay, or Black identities. Lin et al. (2023) collected autocomplete predictions from three leading search engines—Google, Bing, and Baidu—and showed disparities in their toxicity scores with respect to gender, race, and sexual orientation. Leidinger and Rogers (2023) showed that autocompletes from Yahoo, another general-purpose search engine, include a large number of negative stereotypes for Latinos, e.g., portraying them as stupid and loud.

Our work contributes to this line of research by examining the prevalence of racial biases in YouTube search autocompletes. While prior studies have primarily focused on only the text of autocomplete suggestions (Al-Abbas et al. 2020; Baker and Potts 2013; Leidinger and Rogers 2023; Roy and Ayalon 2020), we analyze autocomplete texts in conjunction with the video results for each suggestion. This helps us present a more nuanced understanding of how YouTube users' interactions with its search feature may influence their perspectives. Our work is the first to deploy *critical discourse analysis* (CDA) in addition to inductive analysis to uncover not only how language and discourse practices of autocompletes reflect problematic socio-cultural norms but also how they reinforce hegemonic whiteness and racist ideologies.

It is possible that biased queries entered by users, in turn, could be influencing the autocomplete algorithm to produce stereotypical outputs. However, given the black-box nature of autocomplete algorithm, the extent to which this happens remains unclear. Some recent evidence suggests that the impact of search volume on autocomplete suggestions may be lower than is generally assumed and, in some instances, prior user queries may not feature at all in certain suggestions (Graham 2022). Thus, we largely focus in this article on the audit of autocomplete outputs rather than on inferring how biased user queries could influence the production of stereotypes in autocompletes.

Methods

Development of Input Search Queries

We began our inquiry by selecting the following four categories of racial groups: "White," "Black," "Asian," and "Hispanic." This selection was based on racial categories most frequently included in prior research on stereotypes or biases in search engine autocompletes and language models (Kirk et al. 2021; Leidinger and Rogers 2023). Next, we developed a series of input queries based on combinations of group indicators and verb phrases. We leveraged the synthetic patterns of input queries employed in previous autocomplete studies (Al-Abbas et al. 2020; Baker and Potts 2013; Roy and Ayalon 2020) to guide this query creation. We combined the following verbs—*is, are, does, do, can, should*—with racial group indicators in the form of declarative and interrogative sentences. Table 1 shows the group terms and synthetic patterns we used to structure our input queries. In total, we curated 84 input queries for each of the four racial groups through this process.

Category	Group terms	Synthetic patterns
White	White/Whites, White person/people, White man/men, White boy/boys, White woman/women, White girl/girls	Is a(an)/are [Group Terms] Does a(an)/Do [Group Terms] Can a(an)/Can [Group Terms] Should a(an)/Should [Group Terms] A(An) [Group Terms] is/are A(An) [Group Terms] can/can A(An) [Group Terms] should/should
Black	Black/Blacks, Black person/people, Black man/men, Black boy/boys, Black woman/women, Black girl/girls	
Asian	Asian/Asians, Asian person/people, Asian man/men, Asian boy/boys, Asian woman/women, Asian girl/girls	
Hispanic	Hispanic/Hispanics, Hispanic person/people, Hispanic man/men, Hispanic boy/boys, Hispanic woman/women, Hispanic girl/girls	

Table 1. The structure of input queries used to guide our data collection.

Data Collection

We collected data from July through August 2023 by gathering YouTube autocomplete suggestions for our input queries. Figure 2 shows an example of a YouTube search with a sample input query and its autocompletes; we collected such autocompletes for each query. We automated our data collection by developing Python scripts that simulated YouTube search querying actions. This automated process comprised three stages: 1) accessing the YouTube.com website, 2) entering an input query in the YouTube search box, and 3) collecting autocomplete results, if available, and storing them. We used Chrome as a web browser and accessed YouTube in incognito mode without logging in to any account to prevent the effects of personalization and browsing history. Our scripts opened and closed a new browser window for each query to ensure that the search history of other input queries did not influence the autocomplete suggestions for any single query.

Figure 2. Screenshot of a YouTube search for one of our input queries. It shows five of the autocomplete results we collected that correspond to the query.

We used a virtual private network to collect data from multiple locations in the U.S. to account for location-specific biases (Ribeiro et al. 2020). In particular, we collected YouTube autocompletes from five states: New Jersey, California, Georgia, Texas, and Washington. We conducted our data collection three times, each separated by a few days, to account for the temporal variations in algorithmic suggestions. Through these efforts, we attempted to build a geographically representative and temporally stable dataset of autocomplete suggestions across the U.S.

Analyzing the data samples from three different waves and five different states, we found minimal differences among them. We integrated these samples and removed duplicate results to create a combined dataset for further inquiry. While this step precluded prioritizing more geographically and temporally stable autocompletes, it allowed us to work with a more comprehensive set of suggestions. Examining the resulting dataset, we also noticed that some autocomplete suggestions were not related to the racial groups. Thus, we removed the irrelevant autocomplete suggestions based on whether the autocomplete refers to non-human rather than human subjects. After removing duplicates, our dataset consisted of a total of 241 unique autocompletes.

We describe more details of our data preparation process and descriptive statistics in the Supplemental Material.

Data Analysis

We used inductive analysis (Elo and Kyngäs 2008) to examine our data and extract concepts and categories that describe the underlying phenomena. Two authors conducted a bottom-up open coding process on the platform 'Dedoose' which allowed the authors to collaborate in real-time.

We began by developing a situated understanding of each autocomplete suggestion by examining about ten videos displayed as top search results when selecting that suggestion. This examination helped us recognize the contextual and cultural meaning of autocomplete suggestions, and we leveraged this nuanced understanding to develop our open codes. Since we were primarily interested in the autocomplete texts, we did not create open codes to describe the video content; instead, we created codes and memos that delineated the racial biases, tensions, and struggles suggested by the corresponding autocompletes and the sociocultural contexts in which they occurred. This careful, context-driven coding process was important because some of the autocomplete results were closely related to memes or video content in their corresponding search results. For instance, the autocomplete "when an asian is kidnapped" was related to comedy content created by an Asian YouTuber. Thus, it was important to search for and understand the situated meanings of autocompletes rather than interpret them in isolation. However, in many cases, the resulting videos did not directly relate to or provide any additional context for the autocomplete text; we suspect that in such cases, the autocomplete texts could have been influenced by the search patterns of YouTube users rather than the content of YouTube videos.

Then, we developed the common themes arising from our open codes and their corresponding autocomplete data by grouping similar codes into conceptual categories. At this point in the process, when any pre-existing categories seemed not to directly align with an emergent theme, we carefully considered whether to introduce a new category, revise an existing category, and/or create a subcategory. This process was iterative and we compared our emerging categories with one another and with the underlying data at each stage of our analysis. Some autocompletes represented miscellaneous contexts that did not warrant inclusion in or creation of a separate category; we excluded such autocompletes from further analysis. In total, we grouped 217 autocompletes into a two-tier category structure, where the main categories represented the overarching sociocultural contexts in which racial biases manifest, and the subcategories represented more specific discursive events within these contexts. The five main categories that emerged through this process included *Appearance, Ability, Culture, Social Equity, and Manner* (see Table 3).

Throughout the process of qualitative coding and categorization of autocomplete results, we incorporated *critical discourse analysis* (CDA). CDA is a systematic approach to examining a text, event, or discursive practice to identify how it originates from and is affected by power relations (Fairclough 1993). We employed this framework to analyze each autocomplete as concurrently a text (language produced in a discursive event), a discourse practice (the production, distribution, and consumption of a text), and a sociocultural practice (hegemonic struggles that ideologically shape a discursive practice) (Fairclough 1995). This meant that during data analysis, our focus was less on examining the lexical meanings of each autocomplete suggestion than on the hegemonic function the suggestion performed or indicated within the sociocultural practices represented by our five main categories. For many autocompletes, our attention to their corresponding video results helped us characterize their text production, consumption, and underlying hegemonic struggles. Using this approach, we aimed to identify various facets of each discursive event, thereby revealing particular power dynamics reflected in that event. We engaged in regular discussions about how the autocomplete suggestions in our data reproduce and legitimize social inequalities, and our coding sought to identify various forms of domination, biases, and resistance.

Results

Our analysis generated five main categories representing distinct contexts in which we observed racial biases: *Appearance, Ability, Culture, Social Equity, and Manner*. Under these five main categories, we identified a total of 13 subcategories (Table 3).

Figure 3. A YouTube video suggested by the autocomplete "how often should a black man wash his hair."

Appearance

Personal Hygiene. This category is notable because only Blacks were subject to autocompletes related to personal hygiene. These autocompletes referenced Black people washing their hair or beard ("how often should a black man wash his hair," "how often should a black woman wash her hair," "how often should a black man wash his beard") and shaving ("should a black man shave everyday"). The resulting videos featured creators presenting their shower or shaving routines, e.g., Figure 3 shows the preview of a video resulting from the suggested autocompletes, which contains advice for preventing white flakes in hair.[3] Another autocomplete asked, "do black people get lice." It is possible that these autocompletes reflect highly sought-after searches by Black people for the information needed to take care of textured hair. However, these questions are raised only for the Black group, raising the possibility that they reflect the racial stereotypes of Black people having poor hygiene. Historically, a deep-rooted racial stereotype maintained that dark or non-white skin was associated with uncleanness (Brown 2009); indeed, this stereotype served as a rationale for racial segregation in the U.S. (Lintner 2004). These YouTube autocompletes suggest that the negative stereotypes about Blacks' hygiene still persist.

Skin Tone. Similar to 'Personal Hygiene,' Blacks were the main subjects of autocompletes in the 'Skin Tone' category. Autocompletes related to skin tones included "can a black person become fair." These bleaching-related autocompletes reflect both an interest in lighter skin and the implicit negative view of darker skin (Hunter 2011). We observed no autocompletes related to the action of changing natural skin tones for other races. Other autocompletes show how Black skin is perceived as unique and distinct from other races. Examples include autocompletes asking about the need for Black people's skin protection ("should black people wear sunscreen," "do black people get sunburn") and changes in their natural skin tones ("can black people blush," "can black people tan"). These results suggest both an otherization and a general lack of awareness about Black skin characteristics. However, some videos for these autocompletes showed

[3] https://www.youtube.com/watch?v=CZCuI4x1sUc

Main category	Subcategory	Description	% (n)
Appearance	Personal Hygiene	The activity of cleaning the body and maintaining a good appearance	3 (6)
	Skin Tone	The skin color originating from racially different genetic factors	5 (10)
Ability	Talent	One's abilities for artistic or physical performances	22 (47)
	Financial	One's abilities to purchase goods or services	2 (4)
	Intellectual	One's abilities to learn and study	2 (4)
Culture	Cultural Heritage	Conventional cultural elements of one society with a shared identity	21 (45)
	Ethnic Humor	The humor based on racial, ethnic, or national stereotypes	13 (28)
	Language	How someone communicates verbally	6 (12)
	Relationships	How people interact and connect with each other	9 (19)
Social Equity	Diversity/Inclusion	Practices of embracing socially diverse groups of people	2 (5)
	Racial Justice	Pursuit of fighting against injustice toward a certain racial identity	10 (22)
Manner	Aggression	Antisocial and violent traits	5 (11)
	Inappropriate Behavior	Being idle or behaving in a socially inept way	2 (4)

Table 2. Categories of racial stereotypes that emerged in YouTube autocomplete suggestions. % and n refer to the percentage and number of autocompletes belonging to each subcategory in the analyzed data, respectively.

creators dismantling stereotypes about Black skin, e.g, in one such video,[4] a Black creator applied blush to her skin.

Ability

Talent. Our analysis revealed racial stereotypes associated with talent in music, dance, and sports that mainly addressed White and Black groups. For White groups, the autocompletes related to their artistic talent included both positive ("white girl can rap," "white girl can sing") and negative ("white people can't dance") elements. Regarding physical talent, several autocompletes reflect stereotyped perceptions that Whites are not as athletic as Blacks ("white men can't jump," "white boys can't dance"). Indeed, the videos that such autocompletes guided users to related to a 1992 sports comedy movie called "White Men Can't Jump," which leverages the widely held stereotype that Black race is a positive indicator of physical ability (Felson 1981). Autocomplete suggestions linked to this movie's title decades after its release date suggest a cultural appetite to mock or stereotype White athletes as being inferior in their physical performance.

Similarly, most autocompletes for Blacks referenced their artistic or physical ability in both positive ("black people can dance to anything," "black man can sing") and negative ("black man can't dance," "black man can't play basketball") terms. Notably, we found some autocompletes related to Blacks' exceptional athletic abilities ("are black people more athletic"), which aligns with the previously reported stereotype (Biernat and Manis 1994) that Blacks are athletically superior to Whites. Those who did not meet such expectations were negatively stereotyped. For example, the autocompletes "black man can't dance," or "black man can't play basketball" reflect a stereotype that Black people should be good at dancing or basketball naturally, and the resulting videos mock Blacks who are not good dancers or sportsmen. In sum, these findings show that YouTube autocompletes reflect racial stereotypes based on widely held beliefs about the relationships between race and physical abilities.

Financial. Only Blacks were subjects of autocompletes that belonged to financial ability. All autocompletes here were associated with a lack of financial resources and acumen, which reinforces poor Blacks as the representative public image of poverty. Interestingly, this is consistent with how network TV news and weekly news magazines have historically grossly overrepresented Blacks in their portrayal of poor people as a whole (Gilens 1996). Autocompletes in this category reflected the stereotype that Blacks cannot purchase or own expensive products, such as fancy cars or clothes ("black man cannot own g wagon," "black woman can't buy a dress," "a black man can't have a suitcase").

While these results superficially reinforce the long-standing stereotypes of Blacks as poor, some video results for these autocompletes counter this stereotype. For example, the top video result for "black woman can't buy a dress" portrays a White shop assistant and manager treating a Black woman attempting to buy a bridal gown at a shop differently than they treat a White woman buying a gown (Figure 4).[5] This video undermines the stereotypical attitudes toward Black people regarding their financial ability (it also critiques the assumptions of criminality and poor hygiene associated with Blacks). Similarly, resulting videos for other autocompletes about financial ability dismiss the assumption that Black people are poor by explicitly showing that Black people can and do own expensive products. This shows that in some cases, users who review and watch the search results may get exposed to video content that helps diminish negative stereotypes of Blacks regarding financial ability.

Intellectual. Intelligence-related autocompletes appeared for Asians and Blacks. In the U.S., Asians have historically been perceived as intelligent, hard-working, and pursuing high educational achievements (Trytten et al. 2012). Autocompletes such as "are asians smarter" reflect this model minority stereotype. Unlike Asians, Blacks have often been negatively stereotyped regarding their intellectual and academic abilities (Lintner 2004; Miller 1995). In line with this, we found autocompletes regarding Blacks' intelligence: "black people can't name one african country," and "black man can't say beginning." Videos for the first autocomplete show the lack of knowledge of some Black people about Africa, which suggests their ignorance of Blacks' historical or ethnic roots. The second leads to a video of a South

[4] https://www.youtube.com/shorts/tMkpBnmNy7o
[5] https://www.youtube.com/watch?v=XMcRS2-la3E

Figure 4. A YouTube video suggested by the autocomplete "black woman can't buy a dress."

African President, who is Black, repeatedly mispronouncing his words when attempting to say "in the beginning." These cases show how videos uploaded to YouTube position individual mishaps to denigrate racial groups under the guise of humor. YouTube's automated use of such content to build autocomplete suggestions further removes necessary context and can thus perpetuate racial stereotypes.

Culture

Cultural Heritage. Our analysis reveals that YouTube autocompletes reflect long-standing debates about *cultural appropriation*, described as "the use of one culture's symbols, artifacts, genres, rituals, or technologies by members of another culture" (Rogers 2006, p.476). We found that concerns about such appropriation appear in YouTube autocompletes related to several aspects of cultural heritage, such as cultural practices and culturally specific attire.

First, we found autocompletes that indicated appropriation of cultural practices, highlighting asymmetric power relations between racial groups. For example, several autocompletes related to White groups coopted indigenous Black cultures while belittling its native contexts (e.g., "white girl can dance african"). Other autocompletes revealed how White people could appropriate specific aspects of popular Asian culture, e.g., "can a white guy won [sic] an asian beauty pageant," "can a white person become a kpop idol." The keyword 'Black' elicited one autocomplete related to the adoption of Asian cultural elements ("can a black person become a kpop idol").

Second, autocompletes associated with culturally specific attire and beauty standards also indicated instances of cultural appropriation, where members of the majority group coopted traditional garments, hairstyles, or makeup practices of other minority groups. For example, autocompletes related to garments or hairstyles for White groups included traditional styles with deep origins in Asian or Black culture, e.g., "can a white person wear a kimono," "can a white person wear a durag," "can white girls get braids," and "can a white boy get waves" (Figure 5).[6] Additionally, we found instances of *blackfishing*, i.e., the practices of modifying one's appearances physically or digitally or using terms and language patterns linked to Ebonics for racial commodification (Stevens 2021, p.1). For example, we found autocompletes for White groups that included references to White people attempting to look like Blacks (e.g., "the white woman who turned black"). Some videos linked by these autocompletes displayed the television coverage of Martina Big, a German model who underwent a perma-tanning procedure to darken her skin color.

Figure 5. A YouTube video suggested by the autocomplete "can a white person wear a durag."

In contrast, for Asians and Blacks, autocompletes related to cultural attire rarely reflected acts of cultural appropriation toward other cultures. Instead, the autocompletes for Blacks were related to changing their natural hairstyle ("how can a black person get curly hair," "can a black man straighten his hair") or achieving a popular hairstyle or makeup ("how to do a black person's hair," "how to do a black person's makeup," "how to do a black man bun").

The autocompletes for Asians often included the term "Asian Baby Girl (ABG)" ("what is an asian baby girl," "what is an abg asian baby"). *Asian Baby Girl* is a slang term referring to "a young Asian woman who displays stereotypical traits, such as enjoying clubbing, wearing excessive makeup and tattoos, drinking bubble tea, wearing revealing clothes, etc" (Wiktionary 2023). Though the popularity of such language can subvert stereotypical images of Asian women as submissive or quiet, it also associates them with negative attributes, like aggression and violence (Wu 2023). Thus, autocompletes about ABG could increase awareness about the diversity of Asian women but, in doing so, risk generating new negative stereotypes about them.

In sum, our analysis reveals that YouTube autocomplete suggestions tend to be unidirectional, i.e., supporting ways that dominant racial groups (usually White) appropriate the cultural heritage of racial minorities but not vice versa.

Figure 6. A YouTube video suggested by the autocomplete "when an asian is bad at maths."

Ethnic Humor. Schutz defined ethnic humor as "humor directed at racial and nationality groups, denigrating alleged

[6] https://www.youtube.com/watch?v=gSZ8U64EL-Q

attributes of those groups" (Schutz 1989, p.167). Ethnic stereotypes or shared beliefs toward specific ethnic groups are the basis of such humor (Boxman-Shabtai and Shifman 2015). In our analysis, Asians have the largest number of autocompletes in this category. Most of these autocompletes led to content created by the Chinese-Irish comedian Steven He O'Byrne (12.3 million subscribers).[7] O'Byrne's videos usually parody Asian dads and mock East-Asian parenting stereotypes. For instance, the video content corresponding to the autocomplete "when an asian is bad at maths" shows O'Byrne portraying Asian parents who have a high expectation for their children's academic achievements and are harsh toward them when grades do not meet their standards (Figure 6).[8] Other autocompletes, like "when an asian is kidnapped," "when an asian is president," and "when an asian is your substitute," lead to videos with similar stereotypical images of Asians. While these videos presumably aim to generate clicks and their associated revenue through humor, they reproduce stereotypes by portraying Asians as alien or different and endorsing the 'model minority' myth, which characterizes Asian Americans as being financially and educationally more advanced than other minority groups (Lee et al. 2008).

Language. Language attributes (such as accents) tend to be understood as a strong indicator of ethnic categorization (Rakić et al. 2011). We found several autocompletes related to accents or speaking styles of each racial group. For example, the autocompletes for speaking styles included, "how to do a white girl voice," "how to do a white person voice," and "how to do a black man voice." Autocompletes for accents referenced the unique mode of pronunciation of certain racial groups ("black man can't pronounce," "what does an asian accent sound like," "all latino accents," "woman with spanish accent"). Videos resulting from such autocompletes often depicted individuals mimicking or mocking the voices and accents of other racial groups. This suggests that the multicultural aspects of U.S. languages are still being leveraged to otherize specific groups.

Relationships. Many autocompletes in this category highlight anxieties about interracial relationships. For example, some autocompletes reflect curiosity or potential worries about relationships between White women and people with darker skin ("do white girls like brown guys," "do white girls like latinos"). Similarly, many autocompletes referenced relationships between Black people and women from different cultures ("can a black man marry an arab woman"). These results often portray interracial relations as incongruous and reflect an unfavorable view of darker skin in the relationship contexts.

The most severe tension was found regarding the interracial relationships or marriages between White and Black individuals ("can't date a black woman until my grandpa died," "black people can't marry meme," "black people can't marry white people"). These results indicate that cultural remnants of the historical prohibitions of interracial marriage and fears around miscegenation persist (Pascoe 1991). There was only one result for Asians in this category: "asian men are bitter." Though seemingly unrelated to romantic relationships, the top resulting videos of this autocomplete had titles such as "Asian men are least desired." These videos depicted the struggles of Asian men with dating and pursuing romantic relationships, thereby perpetuating their historic feminization and infantilization (Chen 1996).

Social Equity

Diversity/Inclusion. Whites, Blacks, and Hispanics had autocompletes associated with the issues of diversity and inclusion. Curiously, most of these autocompletes referred to the underrepresentation of racial minorities in popular culture ("can a black man be captain america," "is there a hispanic disney princess"; see Figure 7).[9] This reflects a cultural appetite for seeing racial diversity and encouraging inclusive casting decisions in mainstream media. While whitewashing has historically been salient in the entertainment industry, the percentage of White characters depicted on-screen has slightly declined in recent years, while the depiction of Asian characters has significantly increased (Smith et al. 2023). However, no notable changes have occurred in the prevalence of Black or Hispanic characters over the same period (Smith et al. 2023). Seemingly in response to these trends, YouTube autocompletes in this category reveal frustrations about persistent inequalities in the racial representation of Black and Hispanic character portrayals.

Figure 7. A YouTube video suggested by the autocomplete "is there a hispanic disney princess."

Racial Justice. We observed autocompletes in this category only for the White and Black racial groups. First, we found autocompletes that referenced 'White Lives Matter,' a racist counter-movement that emerged in response to the 'Black Lives Matter' movement ("do white lives matter one minute," "do white lives matter shorts") (Figure 8).[10] 'White Lives Matter' uses a variation of the Black Lives Matter core slogan to weaken the latter's message about addressing unwarranted police violence against Blacks (Goodman et al. 2023). The slogan 'White Lives Matter' appeared verbatim in YouTube autocompletes. Despite video results for the query 'White Lives Matter' displaying diverse voices and criticisms on contested topics, text suggestions of YouTube autocomplete itself were solely generated based on the messages of 'White Lives Matter,' and no analogous autocompletes were associated with 'Black Lives Matter' messaging. This indicates that the autocompletes curated by YouTube do not always balance perspectives from opposing sides of an issue and, in this case, give short shrift to the side combatting racial disparities.

One autocomplete indirectly reflected the perspective of Blacks on racial inequality: "can't keep a black man down,"

[7] https://www.youtube.com/@StevenHe
[8] https://www.youtube.com/watch?v=6lMpjmPiTWE
[9] https://www.youtube.com/watch?v=AQLUeshn3nE
[10] https://www.youtube.com/watch?v=GlMYUFDb8qg

Figure 8. A YouTube video suggested by the autocomplete “do white lives matter one minute.”

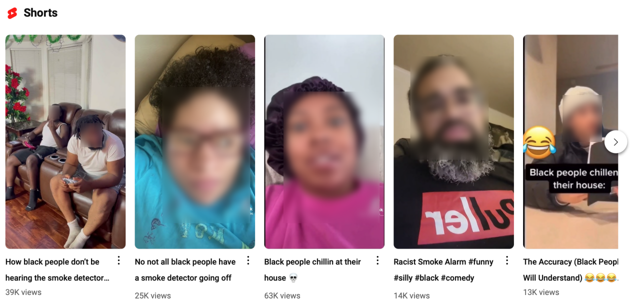

Figure 9. A series of YouTube shorts suggested by the autocomplete “black people can’t hear smoke detectors.”

a lyric excerpt from 2Pac’s song “Trapped,” which addresses police brutality and harassment faced by African Americans (Gaines 2022). This autocomplete and its resulting videos highlighted ongoing racial inequality and police brutality toward African Americans in the U.S.

Manner

Aggression. Our results reference perceptions of Blacks and Asians as being aggressive. Blacks had the highest number of autocompletes, which often described them as dangerous (“pretend there is a black man chasing you,” “run like a black man is chasing you”) or criminal (“a black woman is accused of shoplifting”). This aligns with long-held negative stereotypes of Black violence and aggression (Gilens 1996). We also found one autocomplete that suggests a desire to circumvent this stereotype: “every black man should have a latte.” While this does not relate to aggressive traits at face value, the top resulting video shows a Black stand-up comedian poking fun at the violence stereotype by recommending Black men hold a latte to appear ‘safe’ to law enforcement officials. Additionally, we found aggression-related autocompletes for Asians: “asian man goes crazy.” The top resulting video for this shows an Asian male game streamer screaming violently while playing games. Other videos show Asian men engaging in gun violence. While such aggressive images are typically not associated with Asian men in the U.S., these videos depict Asian men as not always docile and potentially violent.

Inappropriate Behavior. This category contains autocompletes that describe Black people as lazy or behaving inappropriately in social settings. One longstanding negative stereotype of Black people maintains that they are lazy, which is also posed as an explanation for other undesirable attributes, such as their disproportionate poverty (Gilens 1996). The autocomplete “black people can’t hear smoke detectors” depicts this stereotype; it led to videos that show Black people as being too lazy to change the low battery of smoke detectors even though their alarms kept sounding. Figure 9 presents a series of YouTube shorts that show how creators promote this stereotype via memes.

Several autocompletes describe Black people as lacking the self-control needed to behave appropriately in social settings. For instance, this category included “black man cant [sic] hold his laugh,” and “black man can’t stop laughing.” The resulting videos show instances where a Black man cannot refrain from laughing in a serious situation where laughter is clearly inappropriate.

Discussion

We began this study with the goal of examining the information that YouTube’s search feature provides to users seeking video content on race-related topics. As expected, we found the presence of racial biases and stereotypes in search autocomplete outputs, revealing the critical problems with search moderation. However, we also found that the participatory nature of YouTube has contributed to a more complex picture of race-based information in its search outputs, marked by desires for a race-neutral society, condemnations of historical oppressions, and curiosities about other races. We discuss these complexities below.

First, our analysis reveals that race-related autocompletes embody troubling stereotypes regarding Blacks’ personal hygiene, financial abilities, language use, aggression, and laziness. Many search outputs reinforce historical biases against Blacks (e.g., the poor Black, the ignorant Black, the criminal Black), show a lack of awareness about them, and perpetuate their otherization. While we found instances of negative stereotypes against Whites (e.g., regarding their athletic ability), they occurred less frequently than stereotypes against racial minorities. This asymmetry underscores the potential of search autocomplete feature to contribute to representational harm.

We found that both mainstream media and user-generated content contribute to the production of racial stereotypes in YouTube search outputs. Notably, we observed that YouTube search amplifies distorted racial views that appear in mainstream entertainment media by reproducing titles or dialogues from existing media content (e.g., “white men can’t jump”). On the other hand, amateur YouTube creators, seemingly driven by the platform’s commercial logic (Boxman-Shabtai 2019), also contribute to racial stereotypes, often delivering them in the form of *ethnic humor* and memes. Curiously, we found that such ethnic humor is sometimes delivered by creators belonging to racial minorities (e.g., Steven He O’Byrne), presumably to gain an audience by propagating stereotypes about their own race with impunity.

Besides racial stereotypes, we also identified traces of interracial tensions through various ways of cultural appropriation, anxieties around interracial relationships, and concerns about persistent underrepresentation in the media.

These insights reflect contemporary racial dynamics in the U.S. and suggest shifting terrains of racial discord, visibility, and exclusion that warrant further inquiry.

Balanced against the above problematic trends, we found that YouTube search outputs reproduce some creators' attempts to dismantle racial stereotypes, often through deploying humor (e.g., "every black man should have a latte."). However, such dismantling often occurred only after viewing the videos in the corresponding search results; in many cases, the autocomplete text alone—short, decontextualized, and hyper-visible—perpetuates racial biases (e.g., "black woman can't buy a dress," "white lives matter"). We observed discursive events that showed a repudiation of racial inequalities and hopes for a post-race society (e.g., "is there a hispanic disney princess"). We also found potential attempts at promoting positive representations of racial minorities (e.g., "black people can dance to anything"), seeking practical information about one's own race, and genuine curiosities about other races. Additionally, we found depictions of struggles and inequalities faced by racial minorities (e.g., "asian men are bitter," "can't keep a black man down"). Thus, the user-generated content that drives YouTube serves to produce search outputs that go beyond racial stigmas and reveal the ideological messiness of the participatory culture (Khan and Malik 2022).

Our results highlight ethical concerns about the potential 'nudge effects' of autocomplete suggestions on YouTube users. Graham (2023) noted that autocompletes can be biased in ways that might not be clear on an individual level but become apparent when evaluating a larger sample. Our analysis reveals evidence of similar *aggregated discrimination* in race-related queries on YouTube. For example, we find that while Black struggles to combat oppression are diminished, e.g., through the removal of references to "Black Lives Matter" in autocomplete suggestions, "White Lives Matter" continues to feature in these suggestions despite its known associations with hate groups.

Examining the relative prevalence of different themes in our data, we note that skin tone, which serves as an explicit marker of race, appeared much less frequently than other categories like culture and ability in search autocompletes. This aligns with prior findings by Walters et al. (2024) on race-related Facebook memes, where explicit depictions of race and appeals to racism appeared much less frequently than implicit appeals to forward a racist agenda. This suggests a need to attend to traditionally palatable rhetorics of racism rather than just overtly racist speech on digital platforms.

Building on our findings, we recommend a careful development of moderation policies and practices for the ethical deployment of search autocomplete tools. As Rogers (2023) points out, search platforms should take actions that exceed mere 'quiet patches' of infamous autocompletions highlighted by journalists and researchers—they must institute overarching mechanisms that proactively detect and regulate problematic suggestions. Like many AI-based technologies (Rai 2020), autocomplete feature does not inform users how it generates specific outputs and why they embed identity-based biases. Such lack of information allows search platforms to avoid taking the full ethical responsibility for problematic suggestions, even in cases when they result from machine learning biases rather than prior search queries or creators' contributions. Therefore, we call for greater transparency regarding autocomplete sources and algorithms to facilitate a more precise attribution of problematic suggestions.

This study has some limitations. We observed an under-representation of Hispanics in our analysis of autocompletes. However, it is possible that this result is influenced by other terms referring to the "Hispanic" race (e.g., "Latino," "Mexican") being used colloquially more often than similar counterparts (e.g., "Caucasian," "African-American") for other races. Future research on autocomplete audits should also collect queries using such colloquial terms. Our arguments about the influence of autocomplete biases on users would benefit from further engaging with the duality of how aggregated user behaviors and audience cues, in turn, feed into autocomplete outputs. While we attempted to obtain a temporally stable and geographically representative dataset, the YouTube platform constantly updates its search autocomplete suggestions, thus limiting the study's generalizability. Although outside the scope of the current study, future research would benefit from a systematic comparison of search autocompletes (and their associated biases) on Google and YouTube sites and examining the reasons behind those differences.

Conclusion

This article has presented the first systematic analysis of racial stereotypes in YouTube's search autocomplete outputs, addressing a major gap given YouTube's cultural significance and its role as the second-largest search engine. Our thematic framework highlights asymmetric representation of different racial groups, evidence of harmful stereotypes, and hegemonic counter-struggles. We call for greater transparency and reform in content moderation to counteract identity-based harms enacted by search outputs.

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Examining Racial Stereotypes in YouTube Autocomplete Suggestions

Supplemental material

This document includes additional information on data preparation and descriptive statistics of the dataset.

Data Preparation

As part of our data preparation and preliminary analyses, we first conducted a comparative review of the collected autocomplete datasets. We analyzed data from all five US states collected three times to identify inter-location differences between autocomplete results. We used the data of New Jersey as a reference category because it had the highest number of autocomplete results compared to other states. Over 85% of YouTube autocomplete results were consistent between New Jersey and the other four states: Texas (97.32%), Georgia (95.54%), California (91.67%), and Washington (86.61%).

Given this high consistency, we determined to employ all the extracted data for data analysis after removing the duplicate autocomplete results from three different waves and five different states. This process of integrating datasets and removing the duplicates was carried out in three stages described below.

In the first stage, we integrated the data. We consolidated data extracted in three different waves for each state into one dataset per state, resulting in five datasets representing the five states. Then, the five datasets based on states were further merged back into one combined dataset (n=534). Accordingly, we obtained one unified dataset across three different waves and five different states. We tagged each autocomplete in our data with a racial category corresponding to the input query that produced that autocomplete. Thus, the dataset comprised four racial categories. Figure 1 presents an example of autocomplete results for a few queries of the racial category 'White' in our dataset.

1	Input Query	Autocomplete Result
2	Can a White	can a white person wear a kimono
3	Can a White	can a white person wear dreads
4	Can a White boy	can a white boy be goated with the sauce
5	Can a White boy	can a white boy get dreads
6	Can White girls	can white girls get braids
7	Can White girls	can white girls wear wigs
8	Can White people	can white people get dreads
9	Can White people	can white people get waves

Figure 1. Examples of autocomplete results for the racial category "White."

In the second stage, we processed our data to exclude the autocomplete suggestions that did not refer to race. For example, for the group terms relevant to "White" and "Black" races, several autocomplete results refer to the term as a color rather than a race. Thus, we used the following criteria used by Baker and Potts (2013) to refine our dataset: whether the autocomplete suggestion refers to human subjects rather than non-human subjects. As a result, the dataset resulted in a total of 301 race-related autocomplete results.

In the last stage, we eliminated the autocomplete results that were produced multiple times. For example, the result "how often should a black man wash his hair" was generated from the input queries "Should a Black," "Should a Black man," and "A Black man should." In such cases, following prior research (Al-Abbas et al. 2020; Baker and Potts 2013; Roy and Ayalon 2020), we removed duplicates and counted them as one result. Through this process, we obtained YouTube autocomplete results for the four racial groups without any duplicates. This led to a dataset of 241 unique autocomplete results on which we conducted our qualitative analysis.

During this analysis, we further refined the dataset by removing autocompletes that belonged to the miscellaneous category, i.e., that were not included in our final two-tier category structure. As a result, our final dataset consisted of 217 autocomplete results.

Descriptive Statistics

We calculated descriptive statistics for different datasets in our analysis. First, we calculated the number of generative input queries (i.e., queries returning at least one autocomplete suggestion related to racial groups) based on the dataset (n=301) that includes duplicate autocompletes (Table 1). We observed differences in the number of generative input queries across racial groups. Whites and Blacks had the most generative input queries, followed by Asians and Hispanics. We also counted non-generative input queries, which refers to the queries that *do not* generate any autocompletes regarding each racial group. We found large differences in the number of such input queries across racial groups. Surprisingly, 77 out of 84 (91.6%) input queries did not generate any relevant autocompletes for Hispanics. Similarly, approximately 80% of the input queries for Asians did not generate relevant autocompletes. Lastly, both White and Black categories had similar results—about 58% of the input queries did not generate any autocompletes.

Category	# of Generative input queries	# of Non-generative input queries
White	36	48
Black	35	49
Asian	17	67
Hispanic	7	77

Table 1. Descriptive statistics of generative and non-generative input queries.

Table 2 presents the racial distribution in our dataset after the removal of duplicate autocompletes (n=241). Our result shows differences in the number of autocompletes across different racial groups — 'White' group had the highest number of autocompletes (n=99), followed by the 'Black' group (n=95). This number dropped substantially for the Asian (n=37) and Hispanic (n=10) groups. This suggests that videos with Whites and Blacks are more visible, and the content including them is more likely to be recommended on this platform compared to Asians and Hispanics. This shows that YouTube under-represents minoritized racial groups in its autocomplete suggestions.

Category	# of Autocompletes
White	99
Black	95
Asian	37
Hispanic	10

Table 2. Racial distribution in our dataset after removal of duplicate autocompletes (n=241).

Table 3 (on page 3) shows the racial distribution for the number of autocompletes in each subcategory following our qualitative analysis (n=217). These results show that many categories disproportionately represent specific racial groups. For example, only Blacks have autocompletes that belong to *Personal Hygiene*, *Financial*, and *Inappropriate Behavior* categories.

Note that YouTube's autocomplete system does not strictly follow the exact syntactic patterns of input queries. Instead, it seems to generate suggestions based on broader associations between keywords. As a result, some of our collected data included autocomplete suggestions that do not include the original query patterns from which they were derived. Table 4 (on the last page below) lists cases where this occurs and that we present as examples in our main manuscript. This helps clarify the connections between our input queries and their corresponding outputs.

Main category	Subcategory	White % (n)	Black % (n)	Asian % (n)	Hispanic % (n)
Appearance	Personal Hygiene	-	100 (6)	-	-
	Skin Tone	10 (1)	90 (9)	-	-
Ability	Talent	72 (34)	26 (12)	2 (1)	-
	Financial	-	100 (4)	-	-
	Intellectual	-	75 (3)	25 (1)	-
Culture	Cultural Heritage	78 (35)	16 (7)	7 (3)	-
	Ethnic Humor	21 (6)	18 (5)	61 (17)	-
	Language	25 (3)	42 (5)	17 (2)	17 (2)
	Relationships	47 (9)	37 (7)	11 (2)	5 (1)
Social Equity	Diversity/Inclusion	40 (2)	40 (2)	-	20 (1)
	Racial Justice	36 (8)	64 (14)	-	-
Manner	Aggression	-	82 (9)	18 (2)	-
	Inappropriate Behavior	-	100 (4)	-	-

Table 3. The proportion of racial groups for each subcategory in our final dataset (n=217).

Racial Group	Autocomplete Result	Input Query
White	how to do a white girl voice	Does a White girl
	how to do a white person voice	Does a White person
	do white lives matter one minute	Do Whites
	do white lives matter shorts	Do Whites
	that is a white man's luxury	Does a White man
	can a white guy won [sic] an asian beauty pageant	Can a White
		Can a White boy
	the white woman who turned black	A White woman is
	white men can't jump	White men can
	white boys can't dance	White boys can
	white people can't dance	White people can
Black	pretend there is a black man chasing you	Is a Black man
	how to do a black person's hair	Does a Black person
	how to do a black person's makeup	Does a Black person
	how to do a black man bun	Does a Black man
	how to do a black man voice	Does a Black man
	how can a black person get curly hair	Does a Black person
		Can a Black person
		A Black person can
	can't date a black woman until my grandpa died	Does a Black woman
		A Black woman can
	can't keep a black man down	Does a Black man
		Can a Black man
	how often should a black man wash his hair	Should a Black
		Should a Black man
		A Black man should
	how often should a black woman wash her hair	Should a Black
		Should a Black woman
		A Black woman should
	how often should a black man wash his beard	Should a Black man
	black woman can't buy a dress	A Black woman can
	a black man can't have a suitcase	A Black man can
	run like a black man is chasing you	A Black man is
	every black man should have a latte	A Black man should
	black man can't pronounce	Black men can
	black man can't dance	Black men can
	black man can't play basketball	Black men can
	black man can't say beginning	Black men can
	black man cannot own g wagon	Black men can
	black man can't stop laughing	Black men can
	black man cant [sic] hold his laugh	Black men can
	black people can't marry meme	Black people can
	black people can't marry white people	Black people can
	black people can't name one african country	Black people can
	black people can't hear smoke detectors	Black people can
Asian	what does an asian accent sound like	Does an Asian
	what is an asian baby girl	Is an Asian
	what is an abg asian baby	Is an Asian girl
	when an asian is bad at maths	An Asian is
	when an asian is kidnapped	An Asian is
	when an asian is president	An Asian is
	when an asian is your substitute	An Asian is
	asian man goes crazy	An Asian man is
Hispanic	is there a hispanic disney princess	Is a Hispanic
	all latino accents	A Hispanic should
	woman with spanish accent	A Hispanic girl should

Table 4. This table lists autocomplete suggestions and the input queries they derived from for cases where the suggestion did not contain the input query. This highlights that YouTube's autocomplete generation does not strictly follow the exact syntactic patterns of input queries.