Exploring Inclusion in Snap Content

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Full Report

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In the current cultural climate, it is imperative for media organizations to understand whether the content they deliver to users represents the audience consuming the stories the company makes. In the case of social media companies, such as Snap, this is particularly important. Per Snapchat's internal information, the platform reaches 90% of U.S. teens and young adults (age 13-24), with 229 million daily active users globally. This means that Snapchat content reaches a U.S. audience that is more diverse across race/ethnicity, gender, and sexuality than previous generations. With its global platform, Snapchat users span cultural boundaries as well.

To understand the inclusion profile of Snapchat content, the Media Neuroscience Lab (MNL) at the University of California Santa Barbara, and the Annenberg Inclusion Initiative (AII) at the University of Southern California partnered with Snap. The goal of this partnership was to perform a first-of-its-kind analysis of Snapchat content. Pairing MNL's computational methods with AII's human assessment techniques resulted in a scalable procedure to reliably evaluate a large quantity of content in a relatively short amount of time. The outcome is a deeper understanding of how Snap's content reflects its audience with regard to gender, race/ethnicity, and other inclusion metrics.

This report presents our findings in four major sections: First, we provide overall key findings that span across all analyses and results. Subsequently, we deliver a detailed description of all analyses and results across two main content domains: (1) Snap Originals Content Analyses; (2) Snap Partnered Content Analyses. In each of these sections we break down results by gender, race/ethnicity, LGBTQ identity, and disability. Within the Snap Partnered Content Analyses, we share our findings from a hybrid and computational approach, combining AII's human coding with MNL's algorithmic evaluation. Next, we turn to a fully computational assessment of Snap Partnered Content videos conducted by the MNL, which provides insights into the structural representations of female and underrepresented characters within Snap narratives. We conclude our report with a description of methodological and algorithmic innovations provided by MNL and AII that extended beyond the contractual agreements, and with recommendations for future DEI research at Snap.

Overall Key Findings

Snap Originals

A total of 300 Snap Original episodes across 26 series were evaluated by human coders. This resulted in an analysis of 63 individuals who were hosts and talent and 726 speaking characters who appeared in the episodes assessed.

Gender Prevalence

Of the hosts and talent examined, 52.4% were male-identified while 47.6% were female-identified. Turning to speaking characters, 60.5% of the 726 speaking characters in Snap Original series were male-identified and 39.5% were female-identified. Thus, Snap Originals approached proportional representation with the U.S. population for gender among hosts and talent, but fell short for all speaking characters. Half of the series examined were gender-balanced, or featured girls/women in a minimum of 47.5% of all speaking roles.

Race/Ethnicity Prevalence

Of the hosts/talent in Snap Originals, 42.9% (n=27) were White/Caucasian, 7.9% (n=5) were Hispanic/Latino, 27% (n=17) were Black/African-American, 7.9% (n=5) were Asian, and 14.3% (n=9) were Multiracial/Multiethnic. None of the hosts/talent were American Indian/Alaska Native, Native Hawaiian/Pacific Islander or Middle Eastern/North African. However, more than half of the hosts and talent (57.1%) across Snap Original series were from an underrepresented racial/ethnic group.

In terms of speaking characters, 39% (n=277) were White/Caucasian, 9.3% (n=66) were Hispanic/Latino, 36.9% (n=262) were Black/African-American, 7% (n=50) were Asian, none were American Indian/Alaska Native, <1% (n=1) were Native Hawaiian/Pacific Islander, <1% (n=4) were Middle Eastern/North African, and 7% (n=50) were Multiracial/Multiethnic. In other words, 61% were underrepresented and 39% were White. These figures reveal that Snap Originals content exceeds proportional representation in its portrayal of underrepresented hosts and talent and speaking characters. In fact, 69.2% of all Snap Original series achieved proportional representation to the U.S. population, or featured speaking characters from underrepresented backgrounds in at least 35.9% of all speaking roles.

Race/ethnicity and gender were crossed to explore intersectional inclusion. White males comprised 20.6% of hosts and talent, white females were 22.2%, underrepresented males were 31.8%, and underrepresented females were 25.4%. Similar trends were observed for all speaking characters: white males were 22.7% of all speaking characters, white females were 16.2%, underrepresented males were 37.5%, and underrepresented females were 23.5%.

Every Snap Original series was examined to determine whether girls and women from specific racial/ethnic groups were depicted. All Snap Original series were missing Native or Indigenous girls and women. Additionally, nearly all series rendered MENA girls/women invisible and more than 60% excluded Hispanic/Latinas and Asian girls/women. While the percentage of series missing White and Black girls and women was equivalent, there were still over 40% of series that did not feature multiracial/multiethnic female-identified characters.

LGBTQ Prevalence

The LGBTQ-identification of each host/talent and speaking characters was evaluated. 6.3% or 4 of the hosts and talent in Snap Originals were LGBTQ, including one transgender host (Nikita Dragun). 8.1% of all speaking characters in Snap Originals were LGBTQ. These figures are on par with the 7.1% of U.S. adults who self-identify as LGBT, according to Gallup. Of the LGBTQ characters in Snap Originals, 58.6% were gay, 15.5% were bisexual, 13.8% were lesbian, and 12.1% were transgender.

Disability Prevalence

Only 1 host/talent across Snap Originals content was a person with a disability (Loren Gray, *Honestly Loren*). Of all speaking characters across Snap Originals, 1.4% had a disability. Of these 10 characters, 6 were male and 4 were female, and 6 were from underrepresented racial/ethnic groups. Less than one percent of all characters were shown with a physical disability.

Snap Partnered Content

We performed an analysis of Snap's 2021 Partnered Content. Snap Partnered shows were analyzed in a hybrid fashion by AII's human coders and MNL's computational pipelines to capture prevalence metrics on gender, race/ethnicity, and LGBTQ identity. We initially sampled 16,254 unique Snap stories randomly selected from datafiles provided by the Snap team. From this population of videos, there were 1,944 Snap Partnered content units with at least 1 *speaking or named* character that were extracted from across 636 channels and included within the hybrid evaluation procedure. This resulted in the human-based DEI evaluation of 7,572 characters.

Each individual character in the Snap Partnered shows was assessed for gender, race/ethnicity, and LGBTQ identity. The hybrid approach provides more conservative estimates on prevalence measures as compared to our computational pipelines. For the sake of ensuring reliability in reporting statistical estimates in our key findings, we default to the hybrid approach. Detailed comparisons between these two approaches are provided in subsequent sections.

Gender Prevalence

Of the 7,456 characters identified, 62.9% were male, 37.1% were female, and < 1% (n=9) identified as non binary. In comparison to the percentage of girls/women in the U.S. population (50.5%), Snap Partnered content is below proportional representation. Our findings on gender prevalence patterns suggest that approximately 1.7 male characters appear for every female character featured in Snap's 2021 Partnered content.

Additionally, female characters were more likely to appear in specific genre categories such as *Beauty*, *Fashion & Style*, *Animals*, *DIY & Crafts*, *Animation*, and *Parenting.* Female characters were least likely to appear in video content published across the majority of other genres. The identification of specific genre categories provide Snap with targeted areas for possible intervention.

Race/Ethnicity Prevalence

Across Snap Partnered content, a total of 7,245 individual characters were able to be evaluated for racial/ethnic identification. Based on U.S. Census categories, 65.5% of characters were White, 17.7% were Black/African-American, 5.2% were Hispanic/Latino, 5.7% were Asian, 4.3% were Multiracial/Multiethnic, 1.4% were Middle Eastern/North African, <1% were Native Hawaiian/Pacific Islander, and <1% were American Indian/Alaskan Native. Overall, 34.5% of all characters were from underrepresented racial/ethnic groups. Approximately 1.9 White characters appeared for every underrepresented character featured in Snap's 2021 Partnered content. In comparison to the percentage of underrepresented racial/ethnic groups in the U.S. population (39.9%), Snap Partnered content approached proportional representation, but still fell below.

Underrepresented characters were also more likely to receive equal, but not greater, representation in video content published from channels associated with the genres of *Sports*, *Beauty*, *Parenting*, *Travel*, and *General Satisfying.* Underrepresented characters were least likely to appear in video content published across the majority of other genres.

With respect to intersectionality, 41.1% of speaking characters were White males, 24.3% were White females, 21.7% were underrepresented males, and 12.9% were underrepresented females. Put differently, there were 3.2 White male characters for every underrepresented female character featured in Snap's 2021 Partnered content. Compared to White females, girls and women of color were outnumbered 1.9 to 1.

LGBTQ Prevalence

Of the 7,456 characters evaluated, 1.9% were identified as LGBTQ. Of the LGBTQ-identified characters, 46.5% identified as gay, 28.5% as lesbian, 9% as bisexual, and 16% were transgender. More than half of the LGBTQ characters (56.4%) were male while 43.6% were female. Snap Partnered content underrepresents LGBTQ characters In comparison to the percentage of U.S. adults who self-identify as lesbian, gay, bisexual, and transgender (7.1%) (Gallup, 2021).

Visual Portrayals and Structural Representations of UR Females

In the third section of our report, where we conduct advanced statistical modeling to evaluate the effects of unique demographic groups upon computational DEI measures of visual portrayal (on-screen appearance) and structural representation (networks within narratives), we find an interesting and consistent pattern with regards to underrepresented females. Underrepresented females, on average and as compared to White males, are *more* likely to be featured in narratives that focus on giving them greater screen time, increased singular shots, and substantial visual attention in general.

From a structural perspective, our findings further demonstrate that UR females, as compared to White males, are significantly *more* likely to be featured in narratives that position them in central and prominent roles. In other words, despite their exhibition of low prevalence patterns across Snap Partnered content, UR females as a demographic group seem to be featured in narratives in which they play a critical role. However, we do not make any conclusive inferences about the valence of such portrayals. There was no qualitative review of a selection of these Snap stories that could provide insight into whether these DEI metrics were reflective of meaningful narrative portrayals (e.g., journalistic contexts) or were simply limited to negative stereotypes (e.g., hypersexualization). Nonetheless, we do believe that our statistical modeling of computational DEI metrics provides a complementary perspective for the diagnostic evaluation of demographic specific narrative features that might be unconsciously salient within the creative processes of Snap Partnered content publishers.

The analyses of our computational DEI metrics also reveal a consistent gender and racial/ethnic homogeneity pattern. Specifically, we observe that characters from UR and female groups are also more frequently associated with *other* members of gender and racial/ethnic minority groups. One inference that could reliably be extracted from these findings is that Snap Partnered content publishers work on scripts that are frequently homogeneous in terms of their cast members' racial/ethnic and gender affiliations. While we believe that these findings may simply be a reflection of the type of narratives that are scripted and funded for production, we provide in this study a computational framework and a diagnostic toolkit for Snap Partnered content creators to use in their own work, push for increased awareness, and help chart the way towards greater on-screen and structural equity in representation across the entire Snap Partnered content ecosystem.

Deliverables, Extension, and Outlook

This project includes four phases and five deliverables (phase 1/workflow design report; phase2/staffing and training report; phase 3/midterm report; phase 4/preliminary final report; phase 4/final report). With the submission of this final report, MNL and AII have provided all contractual deliverables. In addition to the contractual deliverables, MNL and AII have produced the following extensions:

- Development of the Measuring and Tracking Inclusion (MTI) online platform, a full workflow platform for extracting and sampling content, preparing content for coding, administering content coding across diverse coder groups, computational analyses of content, and the interactive reporting of content inclusion profiles
- New algorithms for the alignment of individual snaps into coherent “stories”
- Critical insights that can improve Snap's current content tagging procedures for future DEI studies
- Development and application of an innovative and previously unknown computational approach for the detection of LGBTQ identities
- Development and application of computer vision pipelines for the extraction of visual and structural representations of characters (e.g., are female characters central or peripheral in stories; beyond prevalence, how much “screen time” falls to UR characters)
- New algorithms for the reporting (and improvement) of content coding reliability

MNL and AII have generated novel and innovative solutions for pushing the envelope on classical and computational inclusion research. We would like to invite future research opportunities that take advantage of the extensively validated and purposefully designed infrastructure that MNL and AII have worked towards this past year in collaboration with Snap. Future collaborations may include:

- Provide an API provisioning for evaluating DEI metrics within Snap Partnered content on an almost real-time basis and at scale
- Provide an interactive inclusion reporting platform (MTI-Snap) specifically tailored for content-producers, Snap decision-makers, the public, and other stakeholders

Conclusion

The purpose of this study was to investigate inclusion in Snap’s 2021 Partnered content. Gender, race/ethnicity, LGBTQ identification, and characters with disabilities were evaluated for *speaking or named* characters across 26 Snap Originals series. Using hybrid procedures, we assessed gender, race/ethnicity, and LGBTQ identification across more than 7,000 characters in Snap Partnered content. The results provide an indication of where Snap’s content represents its users and where greater inclusion is needed.

Gender Parity is Elusive in Snap Content

Across both Snap Originals and Snap Partnered content, the portrayal of female-identified characters lags behind proportional representation. Snap Partnered content features slightly more female-identified characters overall (37.1%) than Snap Originals (30.5%). While the hosts and talent that Snap features in its original content is the closest to 50%, the data show that while girls/women may have *prominence* in some Snap content, there is room to grow when it comes to overall inclusion in smaller or more background roles.

Racial/Ethnic Representation Varies by Content Type

The portrayal of characters from underrepresented racial/ethnic groups differs across Snap content. In Snap Original content, both hosts and talent and speaking characters were more likely to be from underrepresented racial/ethnic groups than White. In other words, underrepresented characters were a majority of those appearing on screen in Snap Originals content. However, in Snap Partnered content, the reverse was true. Slightly more than a third (34.5%) of characters in Snap Partnered content were from underrepresented racial/ethnic groups, which is less than the 39.9% of the U.S. population that identifies as underrepresented.

Despite the findings for the prevalence of underrepresented characters overall, there are discrepancies for characters from specific racial/ethnic groups. In particular, Hispanic/Latino, Middle Eastern/North African, and Native/Indigenous representation are places where Snap under indexes compared to population figures. Additionally, increasing the representation of girls and women from these groups is an important way to bolster inclusion across content. Though Snap's Original series featured women of color in more than 20% of all speaking roles, there were series devoid of female-identified characters from specific racial/ethnic groups (e.g., Latinas, Native women, etc.). In Snap Partnered content, women of color were also outnumbered by White male characters by more than 2 to 1. While the results for racial/ethnic representation were encouraging, disaggregating the data reveals places for improvement.

Depictions of the LGBTQ Community and Characters with Disabilities are Rare

In terms of LGBTQ representation, the percentage of hosts/talent and all speaking characters in Snap Originals who were LGBTQ tracked against U.S. population estimates. Snap Partnered content, however, featured few LGBTQ characters. LGBTQ representation is an area where Snap can make clear gains, drawing on the practices it has used across its Original series.

Additional intervention is also needed for characters with disabilities. Although this metric was only evaluated for Snap Originals, very few characters were shown with a disability. This trend is consistent with larger patterns in the entertainment industry, which are also in need of change. Snap has focused on physical disability, which was represented less frequently than other forms of disability on screen. For this inclusion metric, Snap must consider other ways to introduce creators and channels that feature disability into its programming.

Overall, the results in this paper speak to the role that internal policy and content intervention can have to improve inclusion. For example, content that was more closely linked to Snap was more inclusive of underrepresented and LGBTQ characters. Female-identified characters were also more likely to be in prominent roles. This indicates that Snap's work with its internal teams has focused on ensuring a broad array of voices are present in its most high profile branded content. This also shows how Snap can leverage its influence as a platform to increase inclusion in Partnered content. Working with publishers, Snap can drive policy and practice to emphasize and improve metrics around representation.

Limitations

A few limitations must be noted, as with any research study. As with any study, the sampling method will influence the results. For Snap Originals, only one season of content was evaluated. Looking to other seasons might alter the findings slightly, particularly if other programming was launched or canceled. Similarly, the composition of the sample evaluated for Snap Partnered content could influence the results. However, the use of a randomized sample as done in this study should ensure that there is no sampling bias that would affect the outcome. Given these limitations, as well as the convergent findings across our human-coded and computational analysis, we have confidence that these findings reflect what users experience when they engage with Snap's content.

Final Notes

This paper recognizes the areas in which Snap is making progress in diversity and inclusion measures. Using the techniques outlined and with the empirical, theoretical, and methodological strength of the research teams, the groups examined the inclusion profile of social media content that reaches millions of users each day. As a result, the report reveals current inclusion gaps and areas of improvement for future Original and Partnered content. From the findings of this comprehensive analysis, Snap can continue to evaluate its content to determine how it aligns with external population data, and thus its user base. From there, Snap can focus its efforts on creating, supporting, and distributing content that represents the diversity of its users.

Detailed Analyses and Results

This report provides Snap with an analysis of gender and racial/ethnic representation in its content, including a breakdown by type of content where applicable. The analyses in each section were completed using the Measuring and Tracking Inclusion (MTI) Platform as developed for the project by the MNL team.

Snap Originals Content Analyses

This section of the report reviews the results of an analysis focused on Snap's 2021 U.S. Original Limited Series.[1] The Snap Originals were analyzed solely by AII's human coders to capture metrics on gender, race/ethnicity, LGBTQ identification and individuals with disabilities. The Snap Originals sample included 300 episodes across 26 series.[2]

There were three units of analysis identified in the evaluation. The first level was *hosts and talent*, which included individuals noted by Snap as "starring" in each series.[3] The second was every *speaking or named character* in each episode of the series evaluated. Once a speaking character was identified, they were evaluated across a series of measures, including gender, race/ethnicity, LGBTQ identification, and whether the character had a disability.[4] The results serve as a way to validate Snap's internally collected demographic data concerning the percentage of speaking characters who are BIPOC, LGBTQIA+ and people with visible disabilities. The third unit of analysis was the *program* or series as a whole.

Below, the results are presented by inclusion indicator (i.e., gender, race/ethnicity, LGBTQ, disability). Throughout the section, only differences of 5 percentage points or greater were deemed significant. This approach is consistent with previous work from AII and serves to ensure that trivial differences (1-2%) are not overstated. The letter "n" is used to denote sample size for each analysis.

Gender

We assessed gender identification (male, female, non binary) in Snap content. A total of 63 ***hosts and talent*** were evaluated in Snap's 2021 U.S. Originals Limited Series. Of those, 52.4% (n=33) were male and 47.6% (n=30) were female. None identified as non binary.

Table 1
Gender Identity of Characters Across Snap Originals

Measure	Male	Female
Hosts & Talent	52.4% (*n*=33)	47.6% (*n*=30)
All Speaking Characters	60.5% (*n*=437)	39.5% (*n*=285)

A total of 726 unique ***speaking characters*** were evaluated in Snap's 2021 U.S. Originals Limited Series. 60.5% (*n*=437) were male and 39.5% (*n*=285) were female. Only 1 character was non binary. In comparison to the percentage of girls/women in the U.S. population (50.5%), Snap Originals series fall below proportional representation.

The gender composition of speaking characters across three program types was evaluated in Snap Originals: scripted, unscripted, and documentary series.[5] Female-identified speaking characters were most likely to appear in unscripted series (44.3%, *n*=142), followed by scripted series (36.8%, *n*=35), and docuseries (35.2%, *n*=108).

Another way to evaluate the inclusion profile of Snap content is to move from assessing individual characters to evaluating whether Snap programs achieve gender balance. Gender balance was defined as a series that featured girls/women in 45.7% or more of all speaking roles.[6] Examining gender in this way provides a disaggregated view of the data and illuminates whether a few programs with a higher percentage of girls/women might tilt overall percentages toward gender parity. Overall, 13 of the 26 series examined, or 50% of series overall, featured gender balance. Thus, fully half of Snap Original series featured female-identified characters in proportion to the U.S. population. Additionally, 15 out of the 26 series featured at least one female host and/or talent. Of those 15 series, 10 were gender balanced.

The results in this section show that Snap Originals content approaches proportional representation for gender among hosts and talent, but falls short for all speaking characters. While half of the series were gender-balanced, this also means that 13 of Snap's Original productions did not feature women in nearly half of all on-screen roles. Scripted and docuseries were the areas where women were least likely to be featured, which provides targeted areas for Snap to take action. In the next section, we examine the representation of race/ethnicity in Snap Original content.

Race/Ethnicity

Based on the U.S. Census, we analyzed the race/ethnicity (i.e., White/Caucasian, Black/African American, Hispanic/Latino, Asian, Middle Eastern/North African, American Indian/Alaskan Native, Native Hawaiian/Pacific Islander, Multiracial/Multiethnic) of speaking or named characters in each series and assessed the prevalence of underrepresented racial groups in comparison to white characters.

Of the ***hosts and talent*** associated with Snap Originals series, 42.9% (n=27) were White/Caucasian, 7.9% (n=5) were Hispanic/Latino, 27% (n=17) were Black/African-American, 7.9% (n=5) were Asian, and 14.3% (n=9) were Multiracial/Multiethnic. None of the hosts/talent were American Indian/Alaska Native, Native Hawaiian/Pacific Islander or Middle Eastern/North African. Overall, 57.1% (*n*=36) of hosts and talent were from underrepresented racial/ethnic groups, which is significantly more than the percentage of underrepresented individuals in the U.S. population (39.9%).

Table 2
Race/Ethnicity of Characters Across Snap Originals

Race/Ethnicity	Hosts and Talent	Speaking Characters
White	42.9% (*n*=27)	39% (*n*=277)
Black/African American	27% (*n*=17)	36.9% (*n*=262)
Hispanic/Latino	7.9% (*n*=5)	9.3% (*n*=66)
Asian	7.9% (*n*=5)	7% (*n*=50)
Middle Eastern/North African	0	<1% (*n*=4)
American Indian/Alaskan Native	0	0
Native Hawaiian/Pacific Islander	0	<1% (*n*=1)
Multiracial/Multiethnic	14.3% (*n*=9)	7% (*n*=50)

Turning to ***speaking characters***, 39% (n=277) were White/Caucasian, 9.3% (n=66) were Hispanic/Latino, 36.9% (n=262) were Black/African-American, 7% (n=50) were Asian, none were American Indian/Alaska Native, <1% (n=1) were Native Hawaiian/Pacific Islander, <1% (n=4) were Middle Eastern/North African, and 7% (n=50) were Multiracial/Multiethnic. Of the speaking characters featured, 61% (*n*=433) were from underrepresented racial/ethnic groups. In other words, there were 1.6 underrepresented characters in Snap Originals for every White character who appears on screen. Moreover, the percentage of underrepresented speaking characters in Snap Original content outpaces the U.S. population.

Table 3
Underrepresented Status of Characters Across Snap Originals

Measure	Hosts and Talent	Speaking Characters
White	42.9% (*n*=27)	39% (*n*=277)
Underrepresented	57.1% (*n*=36)	61% (*n*=433)

Similar to gender balance, we were also interested in the percentage of programs featuring proportional representation of underrepresented characters. To achieve proportional representation, programs had to meet or exceed a threshold of presenting underrepresented characters in at least 35.9% of speaking roles. Overall, 69.2% (*n*=18) of the Snap Original series evaluated met this criteria. There was only one program that did not feature any underrepresented speaking characters in the sample.

In addition to examining race/ethnicity and gender separately, we explored intersectional representation in Snap Originals series. By crossing these two indicators it was possible to understand the prevalence of men and women of color in Snap Originals.

Table 4
Percentage of Characters by Underrepresented Status and Gender

Measure	Hosts and Talent	Speaking Characters
% of white males	20.6% (*n*=13)	22.7% (*n*=161)
% of white females	22.2% (*n*=14)	16.2% (*n*=115)
% of underrepresented males	31.8% (*n*=20)	37.5% (*n*=266)
% of underrepresented females	25.4% (*n*=16)	23.5% (*n*=167)

Of all ***hosts and talent***, 20.6% (n=13) of speaking characters were white males, 22.2% (n=14) were white females, 31.7% (n=20) were underrepresented males, and 25.4% (n=16) were underrepresented females. Overall, 22.7% (*n*=161) of ***speaking characters*** were white males, 16.2% (*n*=115) were white females, 37.5% (*n*=266) were underrepresented males, and 23.5% (*n*=167) were underrepresented females. These figures are striking, as roughly 30% of the U.S. population is comprised of white males, 30% are white females, 20% are underrepresented males and 20% are underrepresented females. Thus, Snap Original series over index against these figures for both underrepresented male- *and* female-identified hosts and talent and speaking characters.

Another metric related to intersectional identity is *invisibility* of girls/women from underrepresented racial/ethnic groups. Similar to proportional representation, we evaluated how many programs did not feature any girls/women from each racial/ethnic group. Table 5 presents the number and percentage of programs without even one speaking or named female-identified character from these groups.

Table 5
Invisibility of Female-Identified Characters Across Snap Original Series

Series	White	H/L	Black	Asian	AI/AN	NH/PI	MENA	Multi
# missing females who are…	6	18	6	16	26	26	23	11
% missing females who are…	23.1%	69.2%	23.1%	61.5%	100%	100%	88.5%	42.3%

Note: Rows do not total to 100%. Table should be read as 69.2% or 18 series do not feature one Hispanic/Latino girl or woman. H/L=Hispanic/Latino, AI/AN=American Indian/Alaska Native, NH/PI=Native Hawaiian/Pacific Islander, MENA= Middle Eastern/North African, Multi=Multiracial/Multiethnic

As shown in Table 5, every Snap Original series was missing Native or Indigenous girls and women. Additionally, nearly all series rendered MENA girls/women invisible and more than 60% excluded Hispanic/Latinas and Asian girls/women. While the percentage of series missing White and Black girls and women was equivalent, there were still over 40% of series that did not feature multiracial/multiethnic female-identified characters. This analysis demonstrates that while the overall percentage of girls and women of color in Snap Original content may reach proportional representation, not every series advances the representation of women of color.

In terms of race/ethnicity, Snap Originals content exceeds proportional representation in its portrayal of underrepresented hosts and talent and speaking characters. This is also true when it comes to intersectional representation on screen in Snap Original content. While these findings reflect Snap's commitment to showcasing underrepresented talent, there are places where growth is needed. For example, the percentage of Hispanic/Latino characters remains below U.S. population figures. Snap Original series did not feature any women from Indigenous backgrounds, and only a handful of series featured Middle Eastern/North African girls and women. Addressing these disparities will ensure Snap's leadership in representation is inclusive of all groups.

LGBT

This section explores the prevalence of LGBT-identified individuals in Snap Original content. Hosts/talent and speaking characters were evaluated for information on romantic attraction, including overt references and more implicit cues.

Table 6
LGBT Identification of Characters Across Snap Originals

Measure	Hosts and Talent	Speaking Characters
% of non-LGBT hosts and talent	93.7% (*n*=59)	91.9% (*n*=658)
% of LGBT hosts and talent	6.3% (*n*=4)	8.1% (*n*=58)

In 2021, 6.3% (n=4) of ***hosts and talent*** were LGBT-identified. Of the four hosts and talent that identified as LGBT, 75% (*n*=3) identified as gay and 25.0% (*n*=1) were transgender. None were lesbian or bisexual. The single transgender host was Nikita Dragun, a transgender woman, starring in Season 2 of *Nikita Unfiltered*.

Pivoting to ***speaking characters***, 8.1% (n=58) of speaking characters identified as LGBT. Of the speaking characters that identified as LGBT, 58.6% (*n*=34) identified as gay, 15.5% (*n*=9) identified as bisexual, 13.8% (*n*=8) identified as lesbian, and 12.1% (*n*=7) were transgender.

According to research by Gallup, the percentage of U.S. adults who self-identify as lesbian, gay, bisexual, transgender in 2021 is 7.1% which is comparable to Snap Originals.[7] However, while Gallup notes that one-fifth of GenZ respondents identified as LGBT, in Snap Originals content, 12.5% of adult characters ages 20 to 39 were LGBT. While overall there is a match, looking at the data by age demonstrates that there is still room for Snap to grow in terms of LGBT representation.

Characters with Disabilities

The prevalence of characters with disabilities was assessed. Characters with any disability were assessed overall, and given Snap's focus on characters with physical disabilities, we included a specific examination of those characters as well.[8]

Table 7
Characters with Disabilities Across Snap Original Series

Measure	Hosts and talent	Speaking Characters
% with a disability	1.6% (*n*=1)	1.4% (*n*=10)
% with a physical disability	0	<1% (*n*=5)

Of all ***hosts and talent***, only 1 had a disability. Loren Gray from *Honestly Loren* was the only host and talent with a disability and she identified as female. Of those with a disability, none had a physical disability.

Of all ***speaking characters***, 1.4% (*n*=10) had a disability. Overall, 40% (*n*=4) of speaking characters with a disability were female and 60% (*n*=6) were male. Six characters with a disability were underrepresented, and none were LGBT. In terms of age, five characters with disabilities were young adults (age 20-39), two were children, two were teens, and one was age 40-64. The prevalence of characters with disabilities in Snap Originals content stand in contrast to the U.S., where people with disabilities comprise 27.2% of the population. Across entertainment portrayals, however, Snap Originals are consistent with broader trends in the low representation of characters with disabilities.

Of the speaking characters, <1% (*n*=5) had a physical disability. Of the five characters with a physical disability, four were coded as underrepresented and none were LGBT. Two characters with a physical disability were from *Reunited* and three characters with a physical disability were from *Hype School*. Overall, the results in this portion of the paper demonstrate that Snap Originals content is largely missing characters with disabilities. While this is consistent with larger representational patterns in entertainment content, this is one place that Snap can target for improvement.

The results from the Snap Originals analysis demonstrate that Snap content has notable areas where series feature inclusive voices. Snap Originals feature a greater percentage of hosts and talent and speaking characters from underrepresented racial/ethnic groups than the U.S. population. Additionally, Original series also track with population metrics when it comes to LGBT representation. Where Snap can continue to evolve representation is in the area of gender– particularly for women from specific underrepresented groups– and for individuals with disabilities. As we turn to explore a broader array of Snap's content, the findings in this section show that when Snap maintains a hand in production, its content does represent its audience in important ways.

Snap Partnered Content Analyses

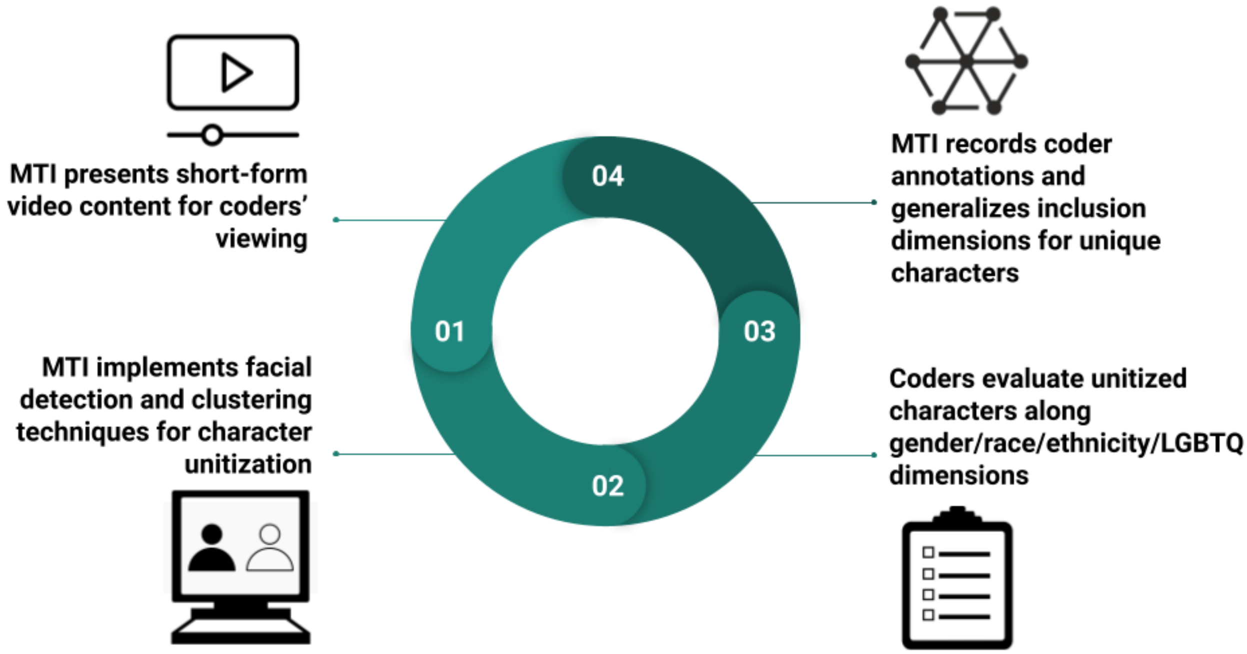
The second section of this report reviews the results of an analysis focused on Snap's 2021 Partnered Content. Snap Partnered shows were analyzed in a hybrid fashion by AII's human coders and MNL's computational pipelines to capture prevalence metrics on gender, race/ethnicity, and LGBTQ identity. Our initially sampled dataset included 16,254 unique Snap stories randomly selected from Looker datafiles as provided by the Snap team. From this population of videos, there were 1,944 Snap Partnered content units, with at least 1 *speaking or named* character, that were extracted from across 636 channels and included within the hybrid evaluation procedure. This resulted in the human-based DEI evaluation of 7,572 characters. Moreover, there were 12,569 Snap Partnered content units, with at least 1 *visually detected* character, that were extracted from across 1008 channels included within the computational evaluation procedure. This sample resulted in the computer-based DEI evaluation of 60,894 characters.[9]

Below, we first provide some essential and detailed background information for the conceptual understanding of how our hybrid and computational procedures independently, as well as synergistically, contributed towards the extraction of demographic prevalence patterns in this study. Next, our report expands and provides a more in-depth assessment of how emergent prevalence patterns from Snap Partnered content should be considered within the context of data scalability, sample representativeness, and comparative methodological strengths.

Measuring and Tracking Inclusion (MTI)

The hybrid evaluation procedure directed individual coders to the Measuring and Tracking Inclusion (MTI) Platform (https://inclusion.mnl.ucsb.edu/). This platform provides a standardized full-workflow capacity for the human annotation of inclusion metrics in audiovisual narratives. The workflow is shown in Figure 1, and allowed for human and machine coding to occur in one platform. Video content was provided to coders, along with computationally-derived images of uniquely identified characters.[10] Coders used the MTI-provided images and full videos to evaluate gender, race/ethnicity, and LGBTQ status for each character. Then, the decisions made by coders were used to generalize across the repository of images collected for each character and stored in the platform.

Figure 1. *General workflow for MTI's hybrid coder annotation procedures.*



Units of Analyses

There were 3 units of analysis identified. The first was the individual character. Human coding, as noted earlier, identified each speaking or named character appearing in a video. Computational metrics indicated each visually detected character in a video. Once a character was identified, demographic indicators including gender and race/ethnicity were assessed. LGBTQ identity was evaluated by humans or through story-level computational metrics. Human coding decisions were also used to validate fully computational methods for MNL.

The second unit of analysis was the program level, or the full video. The third unit of analysis was the Partnered channel level. At this level, one critical variable also evaluated was video genre. We used genre classifications as provided from Snap to evaluate whether our key outcome variables (gender, race/ethnicity, etc.) differed.[11] The Partnered channel level also allowed for global trends in proportional representation and invisibility to be examined. Below, the results from both evaluative procedures are presented stratified by an inclusion indicator (i.e., gender, race/ethnicity, and LGBTQ identity).

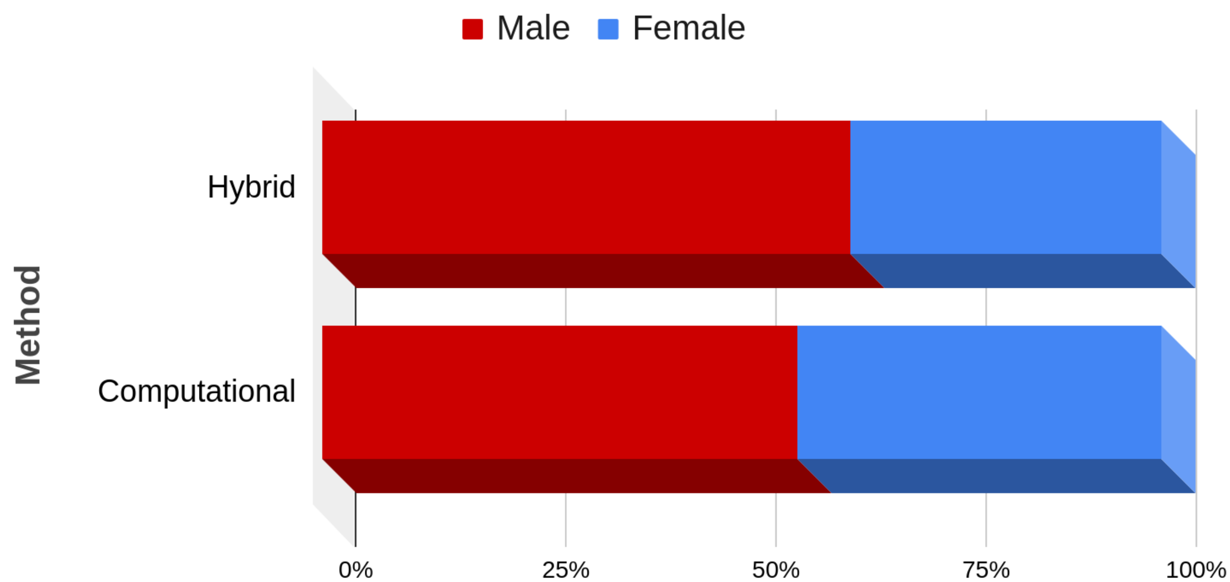
Gender

First, we assessed gender identification (male, female, non binary) in a hybrid fashion within Snap's 2021 Partnered content. A total of 7456 *speaking or named characters* were evaluated. Of those, 62.9% (*n*=4,688) were male, 37.1% (*n*=2,759) were female, and < 1% (n=9) identified as non binary. Second, we assessed gender identification (male, female) in a computational fashion within Snap's 2021 Partnered content. A total of 60, 894 *visually detected characters* were evaluated. 56.7% (*n*=34519) were male and 43.3% (*n*=26375) were female. As demonstrated in Table 8 and Figure 2, our findings on the prevalence of male and female characters find convergence and remain comparable across the hybrid and computational evaluative approaches. In fact, we observe only a 6.2% point difference between the two methodologies, i.e., the computational evaluative procedure underestimates the prevalence of male characters by -6.2% while it overestimates the prevalence of female characters by +6.2%, suggesting the existence of a significant gender prevalence bias. In other words, and assuming that the true frequency for male and female characters falls within this range, we can state that there are approximately 1.5 male characters for every female character featured in Snap's 2021 Partnered content. In comparison to the percentage of girls/women in the U.S. population (50.5%), Snap Partnered content falls below proportional representation. Additionally, we observe that Snap Partnered content features a lower percentage of girls/women than Snap Original series.

Table 8
Gender Identity of Characters Across Snap Partnered Content

Method	**Male**	**Female**
Hybrid	62.9% (*n*=4688)	37.1% (*n*=2759)
Computational	56.7% (*n*=34519)	43.3% (*n*=26375)
	-6.2%	+6.2%

Figure 2. *Gender prevalence patterns across hybrid and computational procedures.*

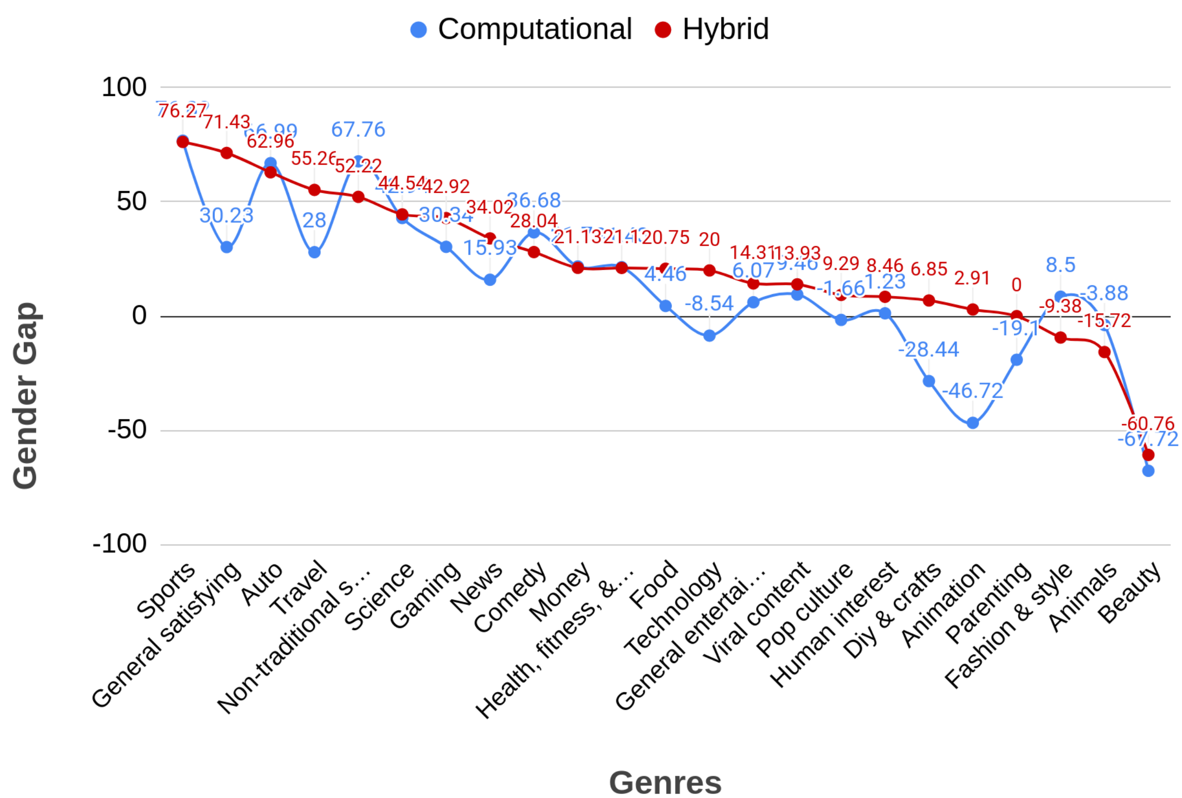


In addition to analyzing the overall prevalence of female and male characters across video content, their gender composition was further assessed as stratified along the 23 genre categories outlined in Table 18 in the Appendix section of this report. In order to contrast gender prevalence patterns as emergent from our hybrid procedures against the computational pipelines, we computed an additional gender gap metric which essentially reflects the percentage point difference between male and female characters *within* individual genre categories. In this manner, negative values indicate that the prevalence of female characters (as opposed to male characters) is higher while positive values indicate that the prevalence of male characters (as opposed to female characters) remains higher. We would also like to take the opportunity to emphasize here that the current taxonomical structure that Snap provides for genre classification remains conceptually ambiguous. For instance, distinctions between “Pop Culture” and “General Entertainment” or “Beauty” and “Fashion & Style” remain quite vague and thereby can influence policy relevant inferences that we can extract from the current analyses in substantial ways. Keeping this consideration in mind, we invite future opportunities for the creation of more streamlined taxonomic genre classification structures that would allow for more robust DEI comparisons.

For each genre, we compared the gender gap metric as emergent from the hybrid approach and the computational evaluative procedure. As demonstrated in Figure 3, we observed good convergence between both methodologies across genre categories with 15 out of 23 genre categories exhibiting an approximate 10% point difference between the two methodologies.[12]

From evaluating broad trends, as illuminated via both our analytical procedures, we can conclusively determine that gender gap patterns remain definitively large in specific genres. For instance, female characters were least likely to appear in video content published from channels associated with the genres of *Sports* (including *non-traditional sports*), *Automobiles, Science,* *Gaming, News, Comedy, Money, Health & Fitness,* as well as *Viral Content*. On the other hand, female characters were most likely to appear in video content published from channels associated with the genres of *Beauty, Fashion & Style*, and *Animals*. It should also be noted here that our computational pipelines, that assessed a much larger and more representative sample as compared to the hybrid datasets, further suggest that female characters are also likely to appear more frequently in video content published from channels associated with the genres of *DIY & Crafts*, *Animation*, and *Parenting*.

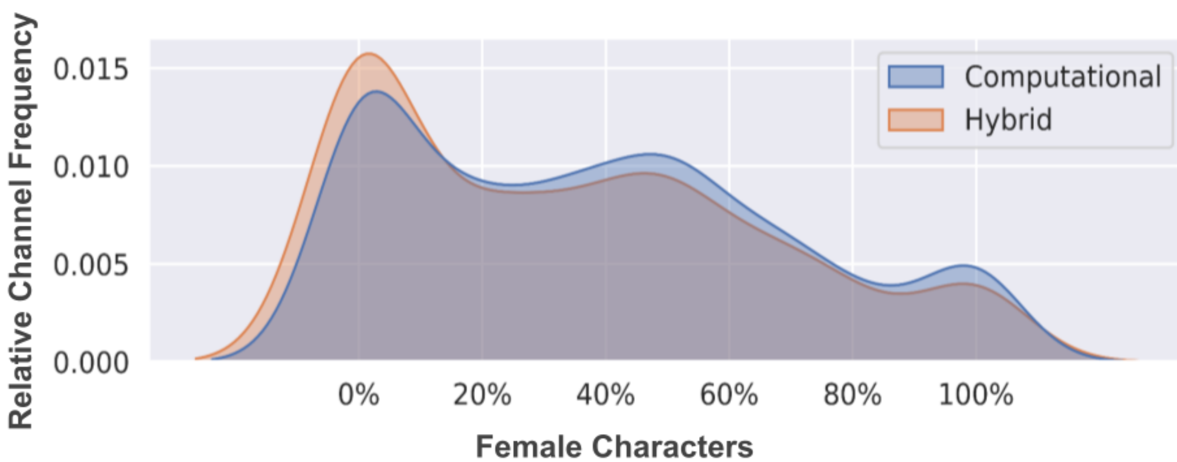
Figure 3. *Computational and hybrid assessed gender gap patterns across genre categories. Positive values indicate greater male representation. Negative values indicate greater female representation. Values close to zero indicate equal representation.*



In line with our analyses conducted in the previous section on Snap Originals, another way to evaluate the inclusion profile of Snap Partnered content is to move from assessing individual characters to evaluating whether Partnered channels as a whole achieve gender balance. Content appearing across a total of 636 Partnered channels was evaluated. We defined a gender-balanced Partnered channel as one that featured girls/women in at least 45.7% of character roles. Examining gender in this way provides a disaggregated view of the data. It also illuminates whether gender parity is influenced primarily by a small selection of channels featuring a higher percentage of girls/women.

Within the hybrid approach, we observed that 237 of the 636 channels examined, or 37.3% of channels overall, featured gender balance. Similarly, within the computational evaluative procedure, we observed that 413 of the 1008 channels examined, or 41.0% of channels overall, featured gender balance. Thus, we find converging evidence that less than half of Snap Partnered channels featured female characters in proportion to the U.S. population. In fact, and as is distinctly noticeable in Figure 4, there is relatively a higher number of channels that exclusively focus on emphasizing the presence of male characters in contrast to channels that exclusively focus on emphasizing the presence of female characters. This channel induced gender disparity within Snap Partnered content, as is convincingly revealed via the combination of hybrid and computational methodologies, can therefore be argued to explain the differences in gender prevalence patterns that we have previously observed in the aggregate.

Figure 4. *Female character prevalence distributions across Snap Partnered channels.*



Race/Ethnicity

Next, we analyzed the race/ethnicity (i.e., White/Caucasian, Black/African American, Hispanic/Latino, Asian, Middle Eastern/North African, American Indian/Alaskan Native, Native Hawaiian/Pacific Islander, and Multiracial/Multiethnic) of *speaking or named characters* in a hybrid fashion within Snap's 2021 Partnered content. This racial/ethnic taxonomical structure was adopted from the U.S. Census. Human-based evaluation of race/ethnicity was not applicable for and/or could not be determined for 327 characters. These were mostly non-human agents and therefore removed from the statistical analyses reported below which resulted in a total of 7245 *speaking or named characters* being evaluated for race/ethnicity prevalence patterns. As highlighted in Table 9, of the total characters evaluated within the hybrid procedure, 65.5% (*n*=4742) belonged to the White racial/ethnic demographic while 34.5% (*n*=2503) were from Underrepresented groups. Table 10 and Figure 5 provide additional breakdowns for racial/ethnic minority characters indicating that 17.7% (*n*=1281) were Black/African-American, 5.2% (*n*=380) were Hispanic/Latino, 5.7% (*n*=409) were Asian, 4.3% (*n*=310) were Multiracial/Multiethnic, 1.4% (*n*=102) were Middle Eastern/North African, 0.2%

(*n*=15) were Native Hawaiian/Pacific Islander, and 0.1% (*n*=6) were American Indian/Alaskan Native.

Table 9
Underrepresented Status of Characters Across Snap Partnered Content

Measure	Hybrid	Computational	
White	65.5% (*n*=4742)	65.3% (*n*=39794)	-0.2%
Underrepresented	34.5% (*n*=2503)	34.7% (*n*=21100)	+0.2%

In a likewise manner, a total of 60, 894 *visually detected characters* were evaluated with our computational pipelines. Again, as highlighted in Table 9, of the total characters evaluated within the computational procedure, 65.3% (*n*=39794) identified as White characters while 34.7% (*n*=21100) were predicted as being part of UR racial/ethnic groups. Computationally derived racial/ethnic breakdowns for *visually detected characters* are further provided in Table 10 and Figure 5 suggesting that 17.0% (*n*=10351) were Black/African-American, 2.2% (*n*=1316) were Hispanic/Latino, 4.8% (*n*=2905) were Asian, 7.8% (*n*=4738) were Multiracial/Multiethnic, 1.8% (*n*=1080) were Middle Eastern/North African, and 1.2% (*n*=710) were American Indian/Alaskan Native. As discussed in the previous sections, there were an extremely low number of Native Hawaiian/Pacific Islander characters and datasets from previous research that could aid efforts in the computational identification of this racial/ethnic category were also limited. We were regrettably unable to include these characters in our computational evaluation procedures.

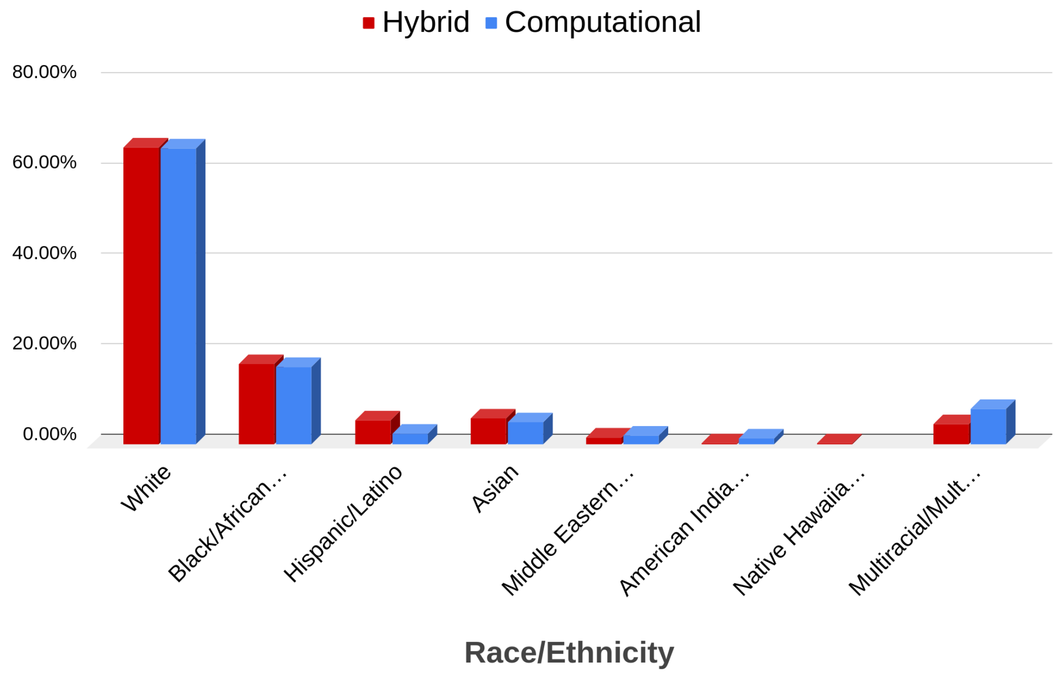
Despite this important limitation, our findings on the prevalence of White and UR characters find remarkable convergence and remain equivalently comparable across the hybrid and computational evaluative approaches with only a 0.2% point difference along this specific inclusion dimension between them. Additionally, and as demonstrated in Table 10, deviations between the two methodologies for evaluating White, Black/African-American, Asian, and Middle Eastern/North African character prevalence patterns remain < 1% (0.2%, 0.7%, 0.9%, 0.4%). We do observe relatively larger percentage point differences, albeit < 5%, when establishing the prevalence of Hispanic/Latino, American Indian/Alaskan Native, and Multiracial/Multiethnic characters (3.0%, 1.1%, 3.5%) indicating that there is sufficient opportunity for improvement in making existing computer vision prediction pipelines more sensitive towards the robust classification of these racial/ethnic minority groups. Given that the complexity involved in determining race/ethnicity from visual cues remains non-trivial and that such groups exhibit relatively low frequencies across multiple mass media formats, we believe that future research should incorporate multimodal approaches (textual, visual, and auditory) for the robust identification of characters belonging to these specific demographics.

Regardless of these limitations, our findings generate robust insights for the current study and indeed suggest the existence of a marginally significant racial/ethnic prevalence bias across Snap's 2021 Partnered content. In other words, and assuming that the true frequency for White and UR characters falls within the reported ranges, we can state that there are approximately 1.9 White characters for every UR character featured in Snap's 2021 Partnered content. In comparison to the percentage of Underrepresented racial/ethnic groups in the U.S. population (39.9%), Snap Partnered content falls below proportional representation.

Table 10
Race/Ethnicity of Characters Across Snap Partnered Content

Race/Ethnicity	**Hybrid**	**Computational**	
White	65.5% (*n*=4742)	65.3% (*n*=39794)	-0.2%
Black/African American	17.7% (*n*=1281)	17.0% (*n*=10351)	-0.7%
Hispanic/Latino	5.2% (*n*=380)	2.2% (*n*=1316)	-3.0%
Asian	5.7% (*n*=409)	4.8% (*n*=2905)	-0.9%
Middle Eastern/North African	1.4% (*n*=102)	1.8% (*n*=1080)	+0.4%
American Indian/Alaskan Native	0.1% (*n*=6)	1.2% (*n*=710)	+1.1%
Native Hawaiian/Pacific Islander	0.2% (*n*=15)	Not Assessed	-
Multiracial/Multiethnic	4.3% (*n*=310)	7.8% (*n*=4738)	+3.5%

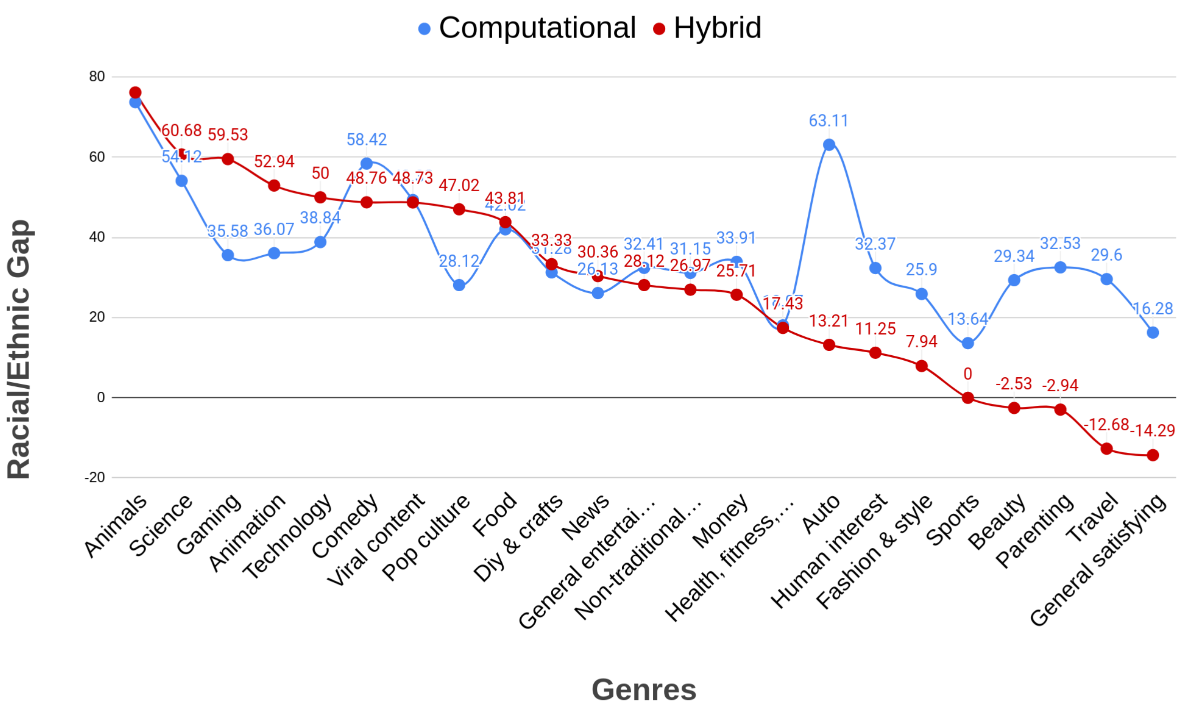
Figure 5. *Racial/ethnic prevalence patterns across hybrid and computational procedures.*



Similar to the analyses as outlined in the previous section, in addition to analyzing the overall prevalence of White and UR characters across video content, their racial/ethnic composition was further assessed as stratified along the 23 genre categories. In order to contrast racial/ethnic prevalence patterns as emergent from our hybrid procedures against the computational pipelines, we computed an additional racial/ethnic gap metric which essentially reflects the percentage point difference between White and UR characters *within* individual genre categories. In this manner, negative values indicate that the prevalence of UR characters (as opposed to White characters) is higher while positive values indicate that the prevalence of White characters (as opposed to UR characters) remains higher. For each genre, we compared the racial/ethnic gap metric as emergent from the hybrid approach and the computational evaluative procedure. As demonstrated in Figure 6, we observed good convergence between both methodologies across genre categories with 14 out of 23 genre categories exhibiting an approximate 10% point difference between the two methodologies.[13]

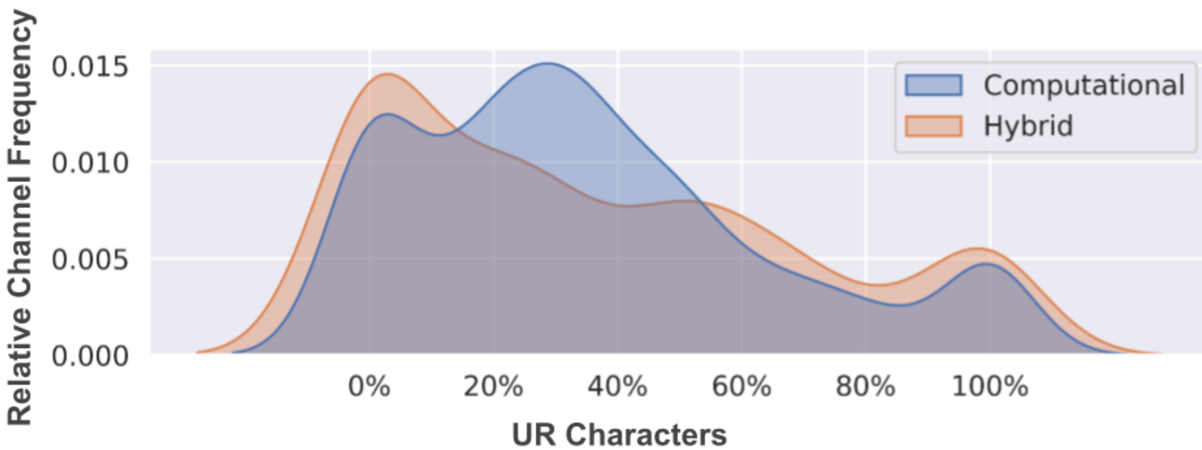
From evaluating broad trends, as illuminated via both our analytical procedures, we can conclusively determine that racial/ethnic gap patterns do remain definitively large across genres regardless of percentage differences observed between the methodologies. Notably, UR characters were least likely to appear in video content published from channels associated with the genres of *Animals, Science, Gaming, Animation, Technology, Comedy, Viral Content, Pop Culture*, and *Food*. On the other hand, UR characters were more likely to receive equal representation in video content published from channels associated with the genres of *Sports* (but not including *non-traditional sports*), *Beauty*, *Parenting*, *Travel*, and *General Satisfying*. It should also be noted here that our computational pipelines, that assessed a much larger and more representative sample as compared to the hybrid evaluative procedure, further suggest that the racial/ethnic gap as observed across genre categories remains generally consistent around a threshold approximately less than that we would expect for proportional representation.

Figure 6. *Computational and hybrid assessed racial/ethnic gap patterns across genre categories. Positive values indicate greater White representation. Negative values indicate greater UR representation. Values close to zero indicate equal representation.*



Finally, and in line with our previous channel level analyses, we were interested in evaluating what proportion of Snap Partnered channels achieved racial/ethnic balance. Within this analytical framework, a racial/ethnic balanced Partnered channel is defined as that which features UR groups in at least 35.9% of character roles. Thus, as before, examining race/ethnicity prevalence patterns in this way provides a disaggregated view of the data and illuminates whether or not overall percentages on racial/ethnic parity are influenced primarily as a function of a small selection of channels featuring a higher percentage of UR characters. Within the hybrid evaluative procedure, we observed that 270 of the 636 channels examined, or 42.5% of channels overall, featured racial/ethnic balance. Similarly, within the computational framework, we observed that 414 of the 1008 channels examined, or 41.1% of channels overall, featured racial/ethnic balance. Thus, we again find converging evidence that less than half of Snap Partnered channels featured UR characters in proportion to the U.S. population. As can be distinctly observed in Figure 7, there is relatively a higher number of channels that exclusively focus on emphasizing the presence of White characters in contrast to channels that exclusively focus on emphasizing the presence of UR characters. This channel induced racial/ethnic disparity within Snap Partnered content, as is convincingly revealed via the combination of hybrid and computational methodologies, can therefore be argued to explain the differences in race/ethnicity prevalence patterns that we have previously observed in the aggregate.

Figure 7. *UR character prevalence distributions across Snap Partnered channels.*



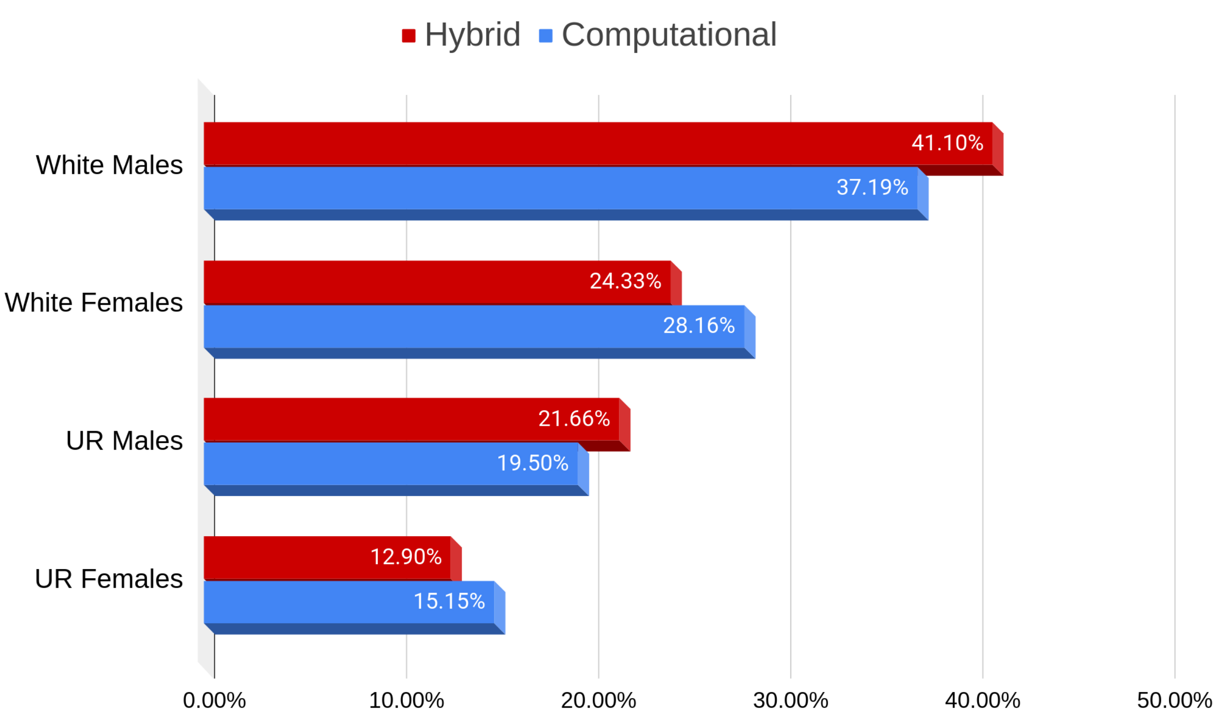
Intersectionality

In line with our analyses reported in the section for Snap Originals and in addition to examining race/ethnicity and gender separately, we explored intersectional representation in Snap Partnered channels. By crossing these two indicators it was possible for us to understand the prevalence patterns of men and women of color in Snap Partnered content. As highlighted in Table 11 and Figure 8, of the total characters evaluated within the hybrid procedure, 41.1% (*n*=2973) of speaking characters were White males, 24.3% (*n*=1760) were White females, 21.7% (*n*=1567) were UR males, and 12.9% (*n*=933) were UR females. Furthermore, and reflecting quite similar demographic prevalence patterns, of the total characters evaluated within the computational procedure, 37.2% (*n*=22645) of visually detected characters were White males, 28.2% (*n*=17149) were White females, 19.5% (*n*=11874) were UR males, and 15.2% (*n*=9226) were UR females. Additionally, and as demonstrated in Table 11, deviations between the two methodologies for evaluating White male, White female, UR male, and UR female character prevalence patterns remain < 5% (3.9%, 3.9%, 2.2%, 2.2%). These results provide robust convergent validity for the adoption of our two methodologies and suggest the existence of a significant gender and racial/ethnic prevalence bias across Snap's 2021 Partnered content. In other words, and assuming that the true frequency for characters that belong to each demographic group falls within the reported ranges, we can state that there are approximately 1.32 White male characters for every White female character, 1.91 White male characters for every UR male character, and 2.39 White male characters for every UR female character featured in Snap's 2021 Partnered content. In addition, we can further extrapolate that there are approximately 1.44 White female characters for every UR male character, and 1.86 White female characters for every UR female character. Finally, we also find evidence that there are approximately 1.29 UR male characters for every UR female character featured. In summary, our intersectional analysis of Snap's 2021 Partnered content emphasizes significant gender prevalence biases both within and across racial/ethnic categories and demonstrates that characters featured within these narratives are predominantly White males. These are followed by White females who are in turn followed by UR males. We find converging evidence that UR females exhibit the least frequent prevalence patterns.

Table 11
Percentage of Characters by Underrepresented Status and Gender

Measure	**Hybrid**	**Computational**	
White Males	41.1% (*n*=2973)	37.2% (*n*=22645)	-3.9%
White Females	24.3% (*n*=1760)	28.2% (*n*=17149)	+3.9%
UR Males	21.7% (*n*=1567)	19.5% (*n*=11874)	-2.2%
UR Females	12.9% (*n*=933)	15.1% (*n*=9226)	+2.2%

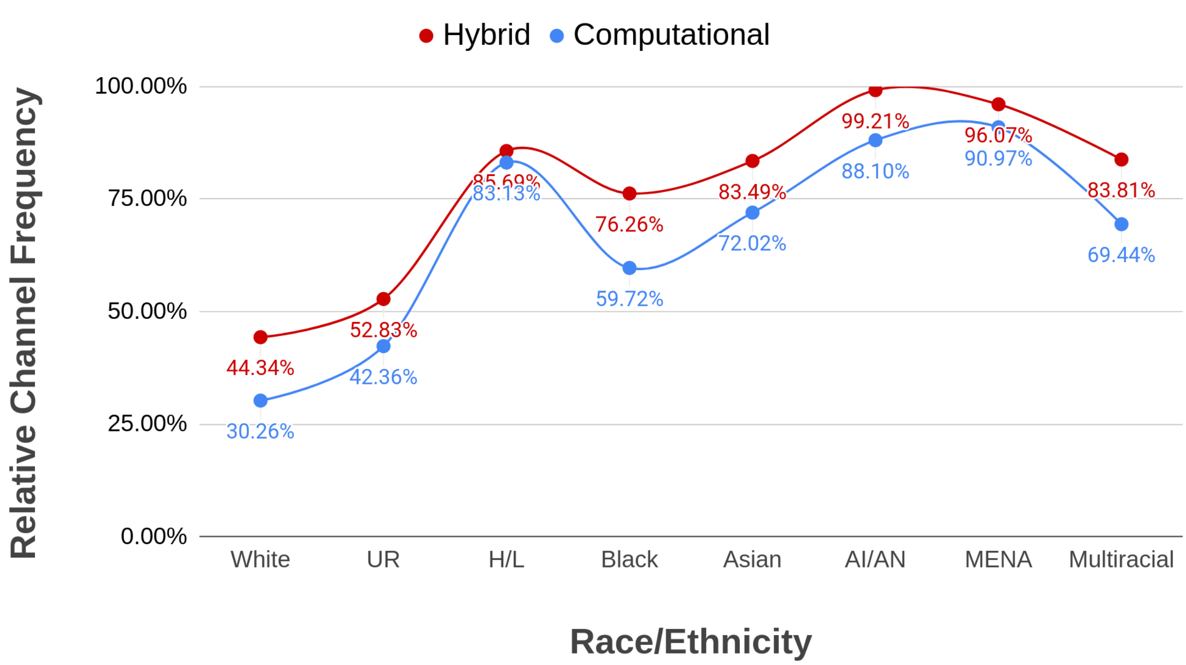
Figure 8. *Demographic prevalence patterns across hybrid and computational procedures.*



We further extend our previous analyses on intersectional identity and focus on the *invisibility* of girls/women from underrepresented racial/ethnic groups. Similar to proportional representation, we evaluated how many programs did not feature any girls/women from UR racial/ethnic groups. As demonstrated in Figure 9, our hybrid approach and computational procedure exemplified quite comparable trends for this specific inclusion metric.[14]

As illuminated via both our analytical procedures, we find converging evidence suggesting that female invisibility patterns do remain definitively dominant across Snap Partnered content. We assume that the true frequency for channel induced female invisibility, as pertaining to each demographic group, falls within the reported ranges, yet, we threshold as the lower-bound our computationally derived statistics for evaluating Snap Partnered channels along this dimension as we believe these are more robust measures for the female invisibility metric. Accordingly, our findings demonstrate that at least 30% of Snap Partnered channels were missing White girls and women while at least 40% of Snap Partnered channels rendered UR girls/women invisible. In particular, 70 ~ 90% of Snap Partnered channels rendered Native, Indigenous, Hispanic/Latinas, MENA girls/women, Asian, and Multiracial girls/women invisible. We further observed that 60% of Snap Partnered channels did not feature Black girls/women. These findings corroborate the aggregate demographic prevalence patterns that we assessed at the character level in the previous analysis. The current analysis further, and conclusively, demonstrate that a majority of Snap Partnered channels are not producing content with the inclusive purpose of highlighting female characters, and especially those that are of color.

Figure 9. *Percentage of Snap Partnered channels that were missing Female characters.*



LGBTQ

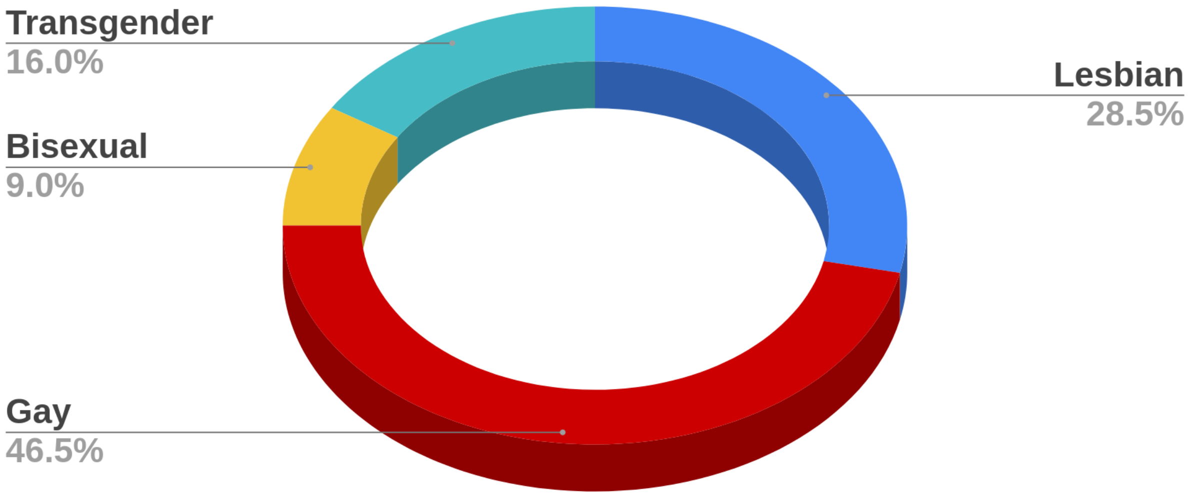
As mentioned in the beginning of this section, we conducted the assessment of LGBT character prevalence across Snap Partnered content on two different levels. First, and in line with the standardized hybrid evaluative procedures that were utilized for the assessment of gender and race/ethnicity, we implemented the same protocol for providing statistical estimates on the LGBT status of the total 7456 *speaking or named characters* as unitized within our sample. These characters were evaluated for information on romantic attraction, including overt references and more implicit cues. Second, and in line with our collaborative decision to ensure sensitivity with regards to making identity-related predictions using computational approaches, we explored the prevalence of LGBTQ-related content across 12559 Snap Partnered stories. Due to technical limitations in processing 10 specific stories, this sample resulted in 10 stories fewer than the broader computational sample.

Within the hybrid evaluative procedure, and as referenced in Table 12, we observed that 1.9% (n=142) of speaking or named characters identified as LGBT. Of the LGBT-identified speaking characters, 56.4% (*n*=79) further identified as male while 43.6% (*n*=61) identified as female. Moreover, and as demonstrated in Figure 10, of the speaking characters that identified as LGBT, 28.5% (*n*=41) identified as lesbian, 46.5% (*n*=67) identified as gay, 9.0% (*n*=13) identified as bisexual, and 16.0% (*n*=23) were transgender. Within the hybrid sample, we also observed the presence of 1 gay transgender & 1 lesbian transgender character.

Table 12
LGBT Identification of Characters Across Snap Partnered Content

Measure	Hybrid
non-LGBT speaking characters	98.1% (*n*=7170)
LGBT speaking characters	1.9% (*n*=142)
Male-identified LGBT speaking characters	56.4% (*n*=79)
Female-identified LGBT speaking characters	43.6% (*n*=61)

Figure 10. *LGBT character prevalence patterns as measured within the hybrid procedure.*



Within the computational evaluative procedure[15], and as referenced in Table 13, we observed that 5.7% (*n*=111) of Snap stories, as assessed within the hybrid sample, featured LGBTQ-related content. We found similar LGBT prevalence patterns within the larger and more diverse computational sample. In particular, we observe that only 4.2% (*n*=529) of Snap stories featured LGBTQ-related content. For an extended triangulation of the above results, we additionally observed that, as assessed within the hybrid sample, 3.5% (*n*=70) of Snap stories featured LGBT-identified characters. In summary, our findings on the prevalence patterns of LGBTQ identity across Snap Partnered content remain convergent across both methodologies and suggest the existence of a marginally significant prevalence bias *against* this particular demographic. As referenced in the previous section on Snap Originals, according to research done by Gallup, the percentage of U.S. adults who self-identify as lesbian, gay, bisexual, and transgender in 2021 was 7.1%. In other words, our analyses reveal that a majority of Snap Partnered stories are not producing content that emphasizes the representation of the LGBTQ identity in a proportional manner.

Table 13
LGBTQ Identification of Content Across Snap Partnered Content

Measure	**Hybrid**	**Computational**	
Stories featuring non-LGBTQ content	94.3% (*n*=1833)	95.8% (*n*=12030)	+1.5%
Stories featuring LGBTQ content	5.7% (*n*=111)	4.2% (*n*=529)	-1.5%
Stories featuring LGBT characters	3.5% (*n*=70)	Not assessed	

Visual Portrayals & Structural Representations

The third section of this report reviews the results of an analysis focused on Snap's 2021 Partnered content. Snap stories were analyzed in an entirely computational fashion by MNL pipelines to capture metrics on visual portrayals and structural representations of gender and race/ethnicity. The Snap Partnered sample included 12569 stories across 1008 channels.

We examined the unique effect of demographic status, i.e., UR female, UR male, and White female, on characters' visual portrayals. It should be noted here that the effect of a particular demographic upon an individual visual portrayal measure was considered with respect to the differential effects upon the same measure as observed from White males. In other words, inferentials drawn from the statistical models we computed below considered White males as the reference demographic category for purposes of comparison.

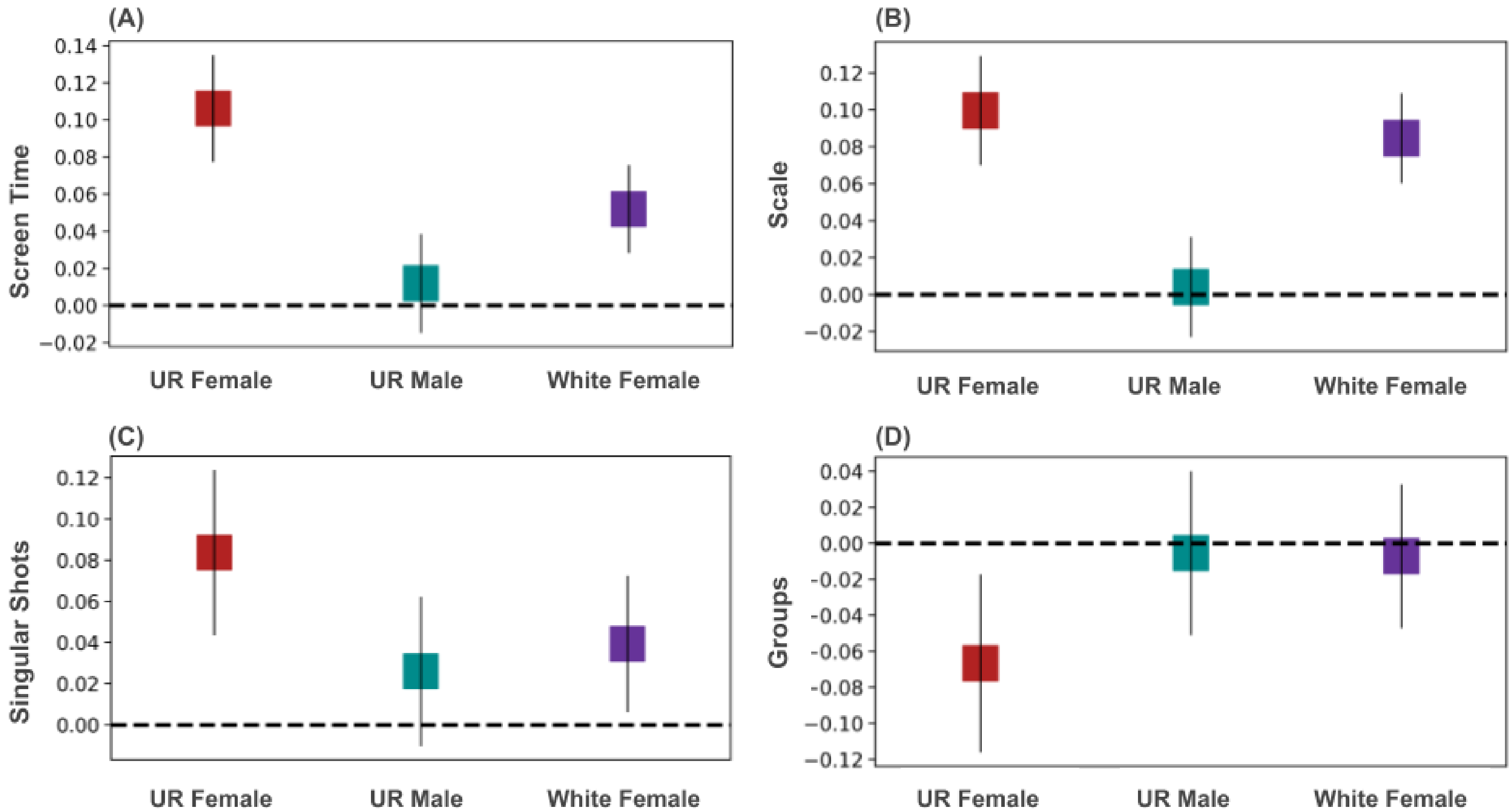
Analytical Approach

We assumed non-independence between the Partnered channels publishing content and the outcome variables of interest to this study. In other words, in addition to character demographics, we assume there to be random variability across the Partnered channels characters are featured in. For instance, certain Partnered channels might be significantly associated with a greater probability of emphasizing our visual measures while others might be significantly associated with a lower probability. Therefore, to robustly account for the nested nature of our data, character-specific demographic variables (first level) that are nested within unique Partnered channels (second level), we relied on Multilevel Linear Models (MLMs) to test the effect of individual demographic categories on different indices of visual portrayal measures. We applied *Bonferroni* correction within each model for multiple-comparison correction and accordingly report below only *p-values* and *confidence intervals* obtained after adjustment.

Visual Portrayals

As demonstrated in Figure 11, we found a consistent pattern emergent with regards to the visual portrayals of UR female characters in Snap Partnered content. Interestingly, UR females are represented with significantly greater screen time ($\beta = .106$, $p = .00$), i.e., the standardized average amount of time they appear within a narrative, as compared to White male characters. Moreover, upon comparing the standardized parameter estimates' confidence intervals for screen time between UR females (95% CI [.083, .130]), UR males (95% CI [-.010, .034]), and White females (95% CI [.033, .071]), we observed that UR females also received significantly greater screen time as compared to UR males and White females. Similar patterns emerge when assessing the effects of demographic status upon scale, i.e., the standardized average amount of facial prominence they receive within a narrative. UR females are indeed represented with significantly greater scale ($\beta = .100$, $p = .00$) as compared to White male characters. Moreover, our pairwise comparisons suggest that UR females receive significantly greater scale (95% CI [.075, .124]) as compared to UR males (95% CI [-.018, .026]) but demonstrate no significant difference when compared to White females (95% CI [.065, .105]). Likewise, UR females (95% CI [.075, .124]) are represented with significantly greater singular shots (β = .084, p = .00), i.e., the standardized average amount of time they appear alone within a narrative, as compared to White males. However, we do not find additional pairwise differences between UR females and other demographic groups for this visual portrayal measure. Additionally, and consistent with the pattern of strong visual attention within narratives for UR females, we observe that UR females are also significantly less likely, and only as compared to White males, to appear on-screen within group like structures (β = -.067, p = .001), i.e., the total number of *additional* characters present within a single frame, thereby corroborating our earlier findings on increased scale and singular shots.

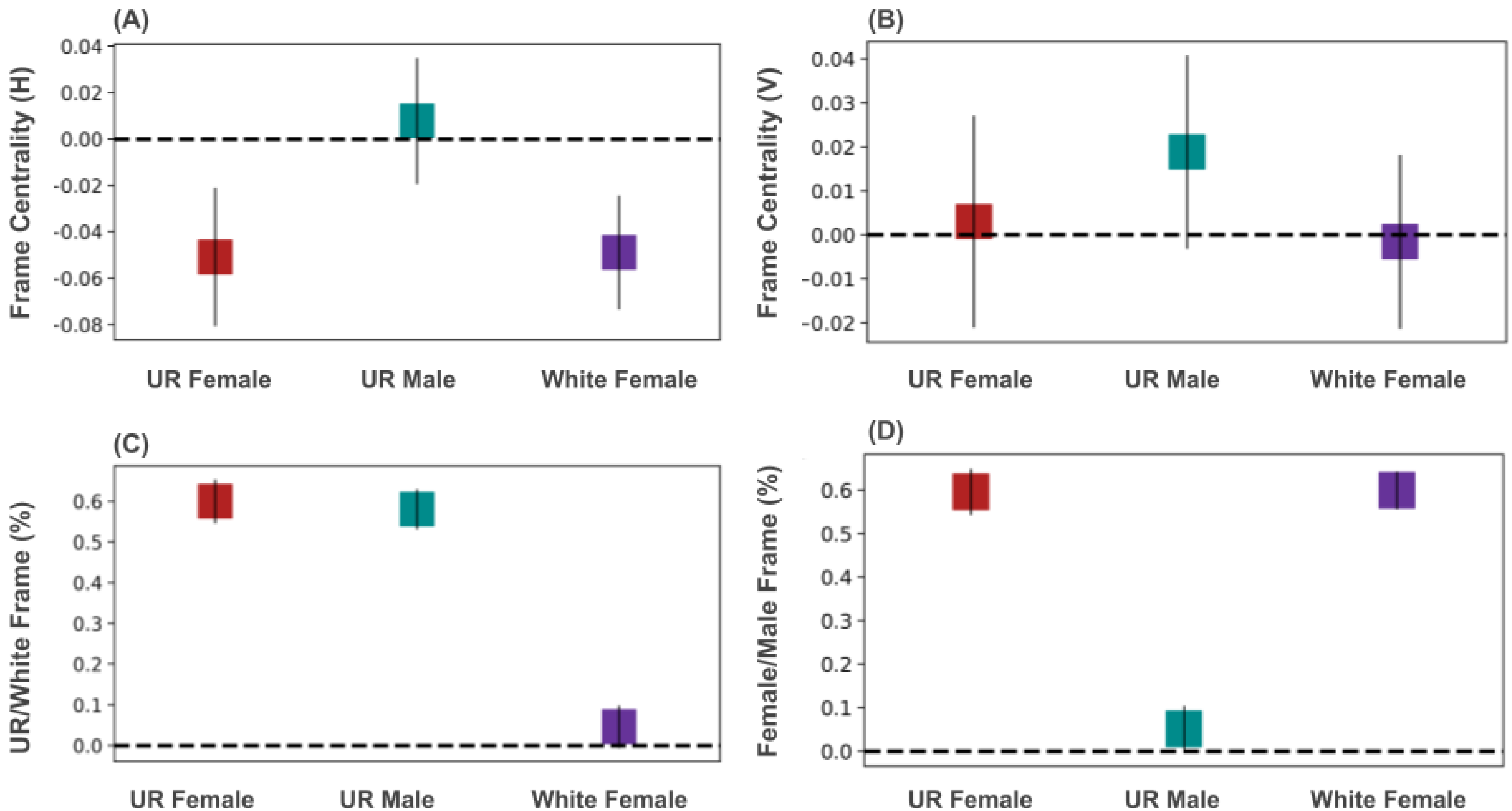
Figure 11. *Standardized beta estimates for the unique effect of specific demographics upon the visual portrayal measures (A) screen time, (B) scale, (C) singular shots, (D) groups.*



With regards to our frame centrality measures, i.e., to what extent does the face of a character deviate from the center of the screen frame, we found no significant effects of unique demographic groups upon the vertical frame centrality measure. However, and consistent with our findings of increased visual attention for UR females, we indeed observe significantly *reduced* horizontal frame centrality for UR females ($\beta = -.051$, $p = .00$) as well as White females ($\beta = -.049$, $p = .00$) as compared to White males. Additionally, while our pairwise comparisons suggest no significant difference along this visual portrayal measure between UR males (95% CI [-.014, .030]) and White males, we indeed find evidence suggesting significant differences between UR males and UR females (95% CI [-.075, -.026]) as well as White females (95% CI [-.069, -.029]).

In order to evaluate racial homogeneity biases prevalent on-screen across Snap Partnered content, we calculated the frequency of UR characters as a percentage of both UR and White characters present, within a single frame, when a unique character appeared on screen. We observed strong evidence for the effects of unique demographic groups upon our UR/White Frame percentage measure, i.e., the percentage of UR characters that appear within a single frame. Specifically, we found that UR female characters ($\beta = .600$, $p = .00$) as well as UR male characters ($\beta = .581$, $p = .00$) are significantly more likely to appear within narratives, as compared to White males, with *other* UR characters (but far less likely with other White characters). White females ($\beta = .046$, $p = .034$) demonstrate a significantly higher UR/White Frame percentage association as compared to White males. However, as demonstrated in Figure 12 (C), these effects remain almost negligible when compared to those associated with UR females and UR males. Similarly, in order to evaluate gender homogeneity biases prevalent on-screen across Snap Partnered content, we calculated the frequency of female characters as a percentage of both female and male characters present, within a single frame, when a unique character appeared on screen. We found striking similarities between our racial and gender homogeneity measures and observed strong evidence for the effects of unique demographic groups upon our Female/Male Frame percentage measure, i.e., the percentage of female characters that appear within a single frame. Specifically, we found that UR female characters ($\beta = .596$, $p = .00$) as well as White female characters ($\beta = .599$, $p = .00$) are significantly more likely to appear within narratives, as compared to White males, with *other* female characters (but not other male characters). We observe that UR males ($\beta = .051$, $p = .021$) demonstrate a significantly higher Female/Male Frame percentage association as compared to White males. However, again as demonstrated in Figure Figure 12 (D), these effects remain almost negligible when compared to those associated with UR females and White females.

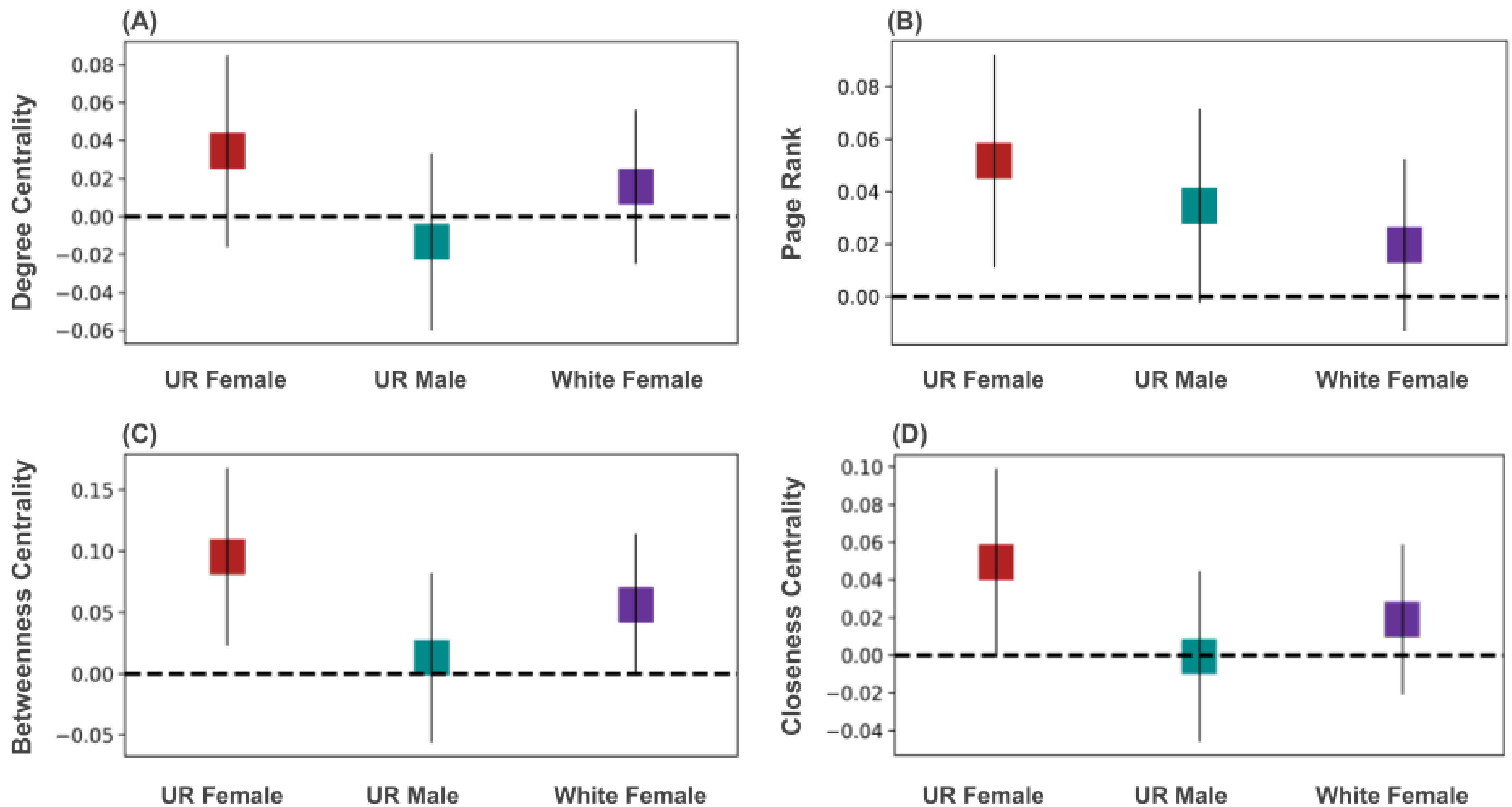
Figure 12. *Standardized beta estimates for the unique effect of specific demographics upon the visual portrayal measures (A) horizontal frame centrality, (B) vertical frame centrality, (C) UR/White Frame percentage, (D) Female/Male Frame percentage.*



Structural Representations

In line with the *visual portrayal* analyses reported above, and as demonstrated in Figure 13, we again found a consistent pattern emergent with regards to the *structural representation* of UR female characters in Snap Partnered content. While we observe no significant differences between individual demographic groups for predicting degree centrality, i.e., the total number of characters with whom an individual character is directly connected with, UR females are, as compared to White males, represented with significantly greater Page Rank ($\beta = .052$, $p = .002$) , i.e., the influence of a specific character within a narrative that extends beyond their direct connections into the wider character network. In a similar fashion, we observed that the unique effect of UR females, as compared to White males, on betweenness centrality ($\beta = .096$, $p = .002$), i.e., the positioning of a specific character that connects otherwise disconnected and separate parts of a character network, and closeness centrality ($\beta = .049$, $p = .017$), i.e., the positioning of a specific character within a network that allows it to quickly influence other characters as well. In summary, these structural representations of UR females indicate that, within the narratives that they do appear, they remain central to the building of the narrative and presumably for narrative sensemaking from the perspective of audiences. We do emphasize here, however, that our pairwise comparisons between UR females, UR males, and White females, do not show significant differences along these structural metrics. Thus, the relationships outlined above should only be considered within a comparative framework between UR females and White males.

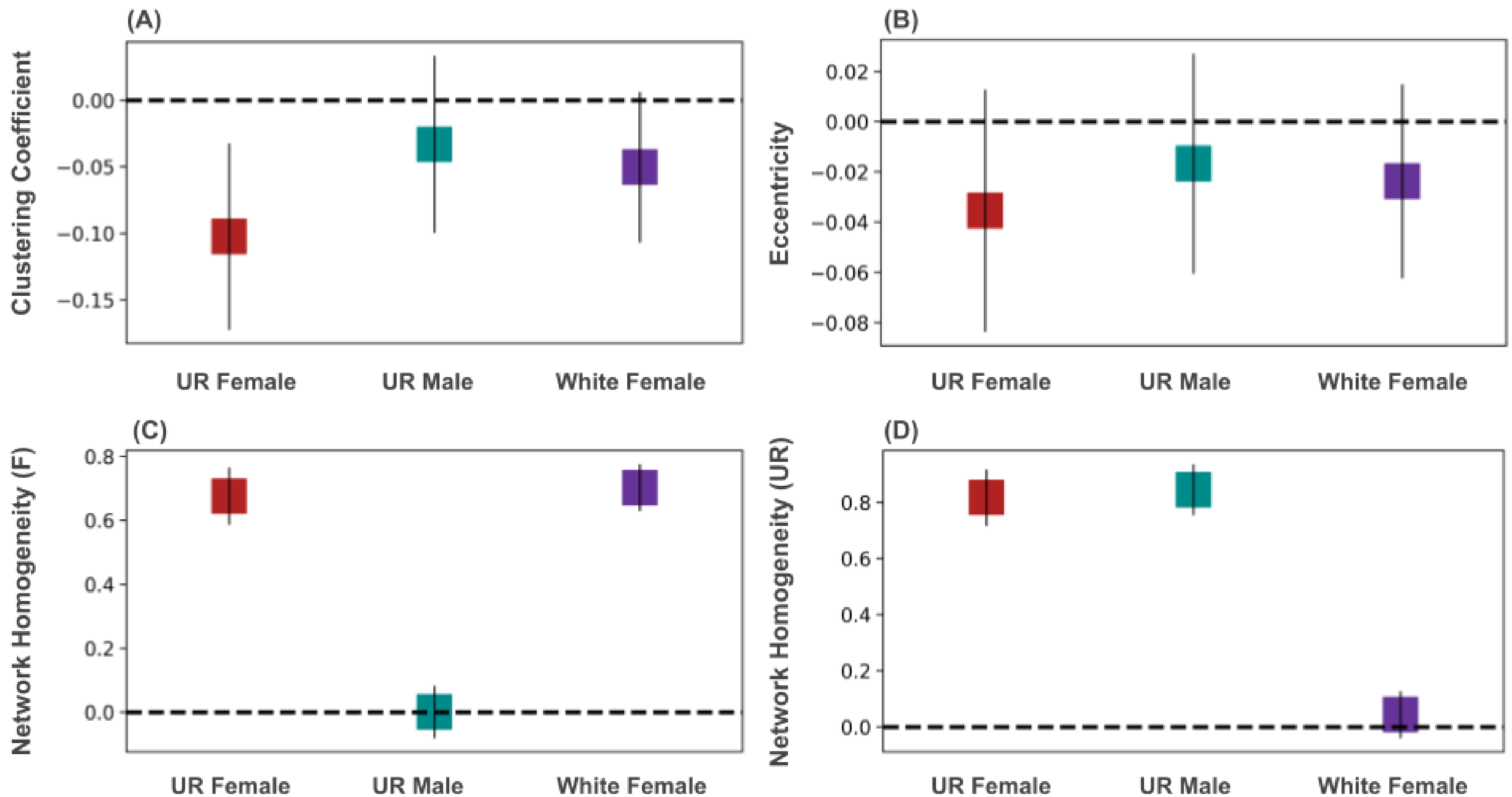
Figure 13. *Standardized beta estimates for the unique effect of specific demographics upon the structural representation measures (A) degree centrality, (B) page rank, (C) betweenness centrality, (D) closeness centrality.*



With regards to our clustering coefficient measure, i.e., the degree to which characters *within the neighborhood* of a specific character in a network structure are connected, or “cluster”, amongst each other. In line with our previous findings on UR females receiving increased visual attention via screen time, scale, and singular shot metrics, we notice that they are also significantly less likely, as compared to White males, to be associated with a high clustering coefficient ($\beta = -.102$, $p = .00$) suggesting that UR females are more likely to be structural represented within sparse character networks that gravitates narrative attention more towards them. Likewise, we observe that UR females demonstrate no significant differences, as compared to other demographic groups, in terms of structural eccentricity, i.e, the extent to which a character is marginalized *within* the narrative.

Finally, concerning our female and UR network homogeneity measures, we observed striking similarities between our findings from our analyses on the prevalence of gender and racial homogeneity patterns illuminated within our visual analyses. Specifically, we noticed that female characters, both UR ($\beta = .676$, $p = .00$) and White ($\beta = .703$, $p = .00$) are significantly more likely to be associated with greater female network homogeneity. In other words, female characters, regardless of their race/ethnicity, are more likely to appear within narratives that generally feature female dominant narratives. In a similar manner, we noticed that UR characters, both male ($\beta = .845$, $p = .00$) and female ($\beta = .818$, $p = .00$) are significantly more likely to be associated with greater UR network homogeneity. In other words, UR characters, regardless of their gender, are more likely to appear within narratives that generally feature UR dominant narratives.

Figure 14. *Standardized beta estimates for the unique effect of specific demographics upon the structural representation measures (A) clustering coefficient, (B) eccentricity, (C) female network homogeneity, (D) UR network homogeneity.*



Innovations Extending Beyond Contractual Agreements

Some of the innovations that MNL & AII generated were inspired by the need to circumvent limitations faced when integrating datasets as provided by the Snap team. Other innovations were inspired by our own motivations to push the envelope on extending research in computational inclusion and performing an exhaustive analysis of Snap Partnered content. We were interested in answering not just questions of *prevalence*, as was intended with the original proposal, but wanted to also conduct advanced statistical analyses for evaluating the *visual portrayals* and *structural representations* of computationally identified characters. Below we provide details of six unique innovations that were generated during this project. Specifically, these innovations pertain to 1) developing Snap data acquisition pipelines, 2) implementing genre classification procedures for Snap Partnered channel genres, 3) constructing speech-to-text pipelines for automated Snap story captioning files, 4) evaluating the *visual portrayals* and *structural representations* of computationally identified characters, 5) introducing a multiracial category to extant racial/ethnic classification solutions, and 6) performing automated character alignment and reliability analysis for character evaluations by human coders.

First, our work was initially restricted to single asset Snap content (fully stitched Snap stories) as provided via Looker datafiles. However, a random sample of Snap Partnered content consisted of both default assets as well as single asset content. Unlike single assets, default assets were not provided in a stitched format and required post-hoc stitching of individual snaps. The MNL team experimented with aligning these individual snaps into coherent "stories" based on the provided unique Snap IDs (within Looker datafiles) but soon discovered, despite sincere and best efforts, that there was no inherent logical structure that could assist in maintaining temporal coherence within the constructed videos. Therefore, the MNL team decided, after determining their sample of interest, to construct a selenium-based pipeline that watched, scraped, and aligned complete stories directly from Snap servers and in an automated fashion. This procedure was efficient as well as helpful in maintaining the temporal coherence required for our analyses. This pipeline has been particularly useful for retrieving the desired Snap content without compromising on quality. The MNL team would be happy to provide guidance, if helpful, on how to incorporate unique Snap identifiers for default assets within current Looker datafiles to avoid similar obstacles for subsequent inclusion analyses in the future.

Second, datasets linking Partnered channels with specific genre categories were shared by the Snap team on January 24th, 2022. As per email correspondence, MNL and AII were informed that methodological and taxonomical changes in relation to content tagging procedures were underway at Snap. This meant that the data files shared with AII and MNL were not finalized versions and were subject to further refinement and improvement over the course of the next year. One important consequence of these organizational shifts has been that not every Partnered channel that was associated with the randomly extracted selection of Snap stories was tagged with a genre classification. In addition to this, there were discrepancies in naming conventions across the content tagging datasets and the publisher formal names as identified within Looker datafiles. These limitations rendered 155 Partnered channels unable to be integrated within our master files for a genre-specific analysis. In order to circumvent this problem, MNL and AII resolved naming convention discrepancies via approximate string matching pipelines as well as manual quality assurance procedures. Furthermore, MNL & AII resolved the issue of absent content tags via another collaboration and conducted a thematic analysis of Partnered publisher channels for the appropriate association of a genre category with specific channels. The determination of a genre category was made contingent on the fact that it also belonged to the taxonomical structure provided within the previously shared Snap content tagging datasets.

Third, for the computational assessment of LGBTQ identity, MNL and AII collaboratively decided to conduct this evaluation at the program level instead of at the character level. Taking inspiration from the idea that characters might engage in self-disclosure behavior, have their sexual identity be referred to by other characters in the narrative, or simply engage in discussions surrounding LGBTQ identity related discussions as the narrative unfolded, MNL decided to leverage state-of-the-art automated speech recognition pipelines to convert auditory information from the audiovisual narrative into textual data. This pipeline was developed especially for this computational assessment task. As per contract, the Snap team was supposed to deliver captioning text for the video content MNL and AII were instructed to evaluate. Unfortunately, approximately two-thirds of the Snap stories as provided via Looker datafiles were not accompanied with captioning text and therefore jeopardized the chances of fair analyses for this demographic. Therefore, for the sake of ensuring representative computational analyses MNL implemented automated speech recognition pipelines across the entire sample. Subsequently, for measuring the prevalence of LGBTQ identity across these Snap Partnered content units, MNL performed a straightforward keyword detection procedure, as it would have performed on Snap provided textual files, where the frequency of LGBTQ identity keywords were assumed to correlate with the visual presence of LGBTQ characters as well.

Fourth, our analyses on the visual portrayals and structural representations of characters featured in Snap Partnered content revealed a more nuanced understanding of the inclusion patterns emergent within the Snap Partnered ecosystem. On the one hand, our hybrid and computational analyses answered questions of *prevalence* and revealed that female and UR characters are indeed not being proportionally represented across a large and diverse sample of Snap Partnered content. On the other hand, however, our statistical modeling and in-depth analyses that answer questions of *visual portrayals* and *structural representations* reveal an additional insight which might prove to be a critical perspective for evaluating inclusion in narratives. While prevalence measures are indeed important for straightforward frequentist analyses, they remain limited in providing insights pertaining to the permeation of systematic biases *within* the fabric of the narrative creation process. In this study, we do not espouse that the statistical modeling of computational measures, as outlined in the third section of this report, is a replacement for qualitative inclusion research in general but we do believe that it provides a complementary perspective for the diagnostic evaluation of demographic-specific narrative features that might be unconsciously salient within the creative processes of Snap Partnered content publishers. Our successful identification of visual and structural biases in narratives, at-scale, lends itself promisingly for robust inclusion monitoring procedures to be implemented for future studies. We believe that these analyses should invite a more in-depth, qualitative analysis of associated content for the holistic understanding of what makes (or not) individual Snap stories, and not just the Snap Partnered ecosystem in general, more inclusive.

Fifth, within the computational evaluation procedure, MNL applied biological sex and race/ethnicity classification models generated from previous research efforts so as to identify gender/racial/ethnic categories as defined by AII. MNL performed multiple computational experiments and gained insight that models trained on images from previous datasets were unable to generalize to those extracted and presented to AII coders within the hybrid evaluation procedure. In particular, popular datasets leveraged for the delivery of automated solutions towards racial/ethnic classification have systematically ignored the multiracial category. MNL leveraged insights generated from the hybrid approach in order to construct computational indicators for the reliable identification of multiracial characters.

Finally, MNL devised a sophisticated technique for matching character lines of data and calculating reliability coefficients via the data collection platform. This has traditionally been a complicated process carried out by trained research assistants or staff at AII and requires significant time investment to complete. By automating this process, the MNL team improved efficiency and made it possible to reliably evaluate and process data for a significantly larger quantity of videos than AII would typically be able to assess. Human coder unitization of characters, i.e., characters not detected via automated pipelines, is subject to substantial data entry variations. Different coders identify different characters at different time-stamps with different descriptions. The character alignment pipeline developed by MNL takes this 4 x 4 matrix of possibilities and unitizes characters with approximately 95% accuracy. This character alignment procedure was successfully validated and implemented during AII's coding procedures for Snap Originals as well as Partnered Content.

Recommendations for Future DEI Research at Snap

MNL and AII have successfully designed a standardized and full workflow for 1) Snap data acquisition, 2) video content processing, 3) small-scale DEI quality assurance procedures, and 4) large-scale computational pipeline implementations. In this same spirit of generating novel and innovative solutions for pushing the envelope on classical and computational inclusion research, we would like to invite future research opportunities that take advantage of the extensively validated and purposefully designed infrastructure that MNL and AII have worked towards this past year in collaboration with Snap. In particular, we would be very excited to deliver on an API provisioning for evaluating DEI metrics within Snap Partnered content on an almost real-time basis. Given the strong parallels we have identified in this study between our human-assessed hybrid procedures and automated computational pipelines, especially for answering questions of *prevalence* at-scale, we believe that relatively fast and comparatively large-scale DEI evaluations of video content is a technically feasible solution via the implementation of the procedures we describe in this study. Similarly, we look forward to providing access to our datasets and results in interactive formats for public consumption. We strongly believe in the values of open science and collaborative research and, to this end, we would be very excited to engage in future partnerships that advance the interactive dissemination of findings via a dedicated Measuring and Tracking Inclusion platform tailored for Snap (MTI-Snap) and thereby ensure maximum accessibility of research findings for various stakeholders.

Conclusion

The purpose of this study was to investigate inclusion in Snap's 2021 Partnered content. Gender, race/ethnicity, and LGBTQ identification were evaluated for *speaking or named* characters within our hybrid procedures as well as *visually detected* characters and content within our computational procedures.

This paper recognizes the areas in which Snap is making progress in diversity and inclusion measures. This report also reveals current inclusion gaps and areas of improvement for future Partnered content. From the results of this comprehensive analysis, Snap can evaluate its content to determine how it aligns with external population data, and thus its user base. Using the techniques outlined and with the empirical, theoretical, and methodological strength of the research teams, the groups examined the inclusion profile of social media content that reaches millions of users each day. The development of integrated computational and human assessment tools for inclusion, diversity, and equity metrics constitutes important research conducted in the public interest.

Endnotes

1. Phone Swap India, The Best Snaps Show, and The Me and You Show were extracted from the sample per direction from Snap. The Best Snaps Show and The Me and You Show were removed due to the limited control Snap has over the content. Phone Swap India was removed because the show is not U.S. content.

2. Snap provided a list of U.S. Snap Original series with release dates in 2021. The sample was determined by country, year, and level of control Snap has over the cast and direction of the show.

3. Hosts and talent were classified by names identified as "Starring" from https://snaporiginals.snapchat.com/. Names identified as "Starring" for scripted series were the "real-life" actor/actress names. In the analysis, character names were identified instead of actor/actress names. Character and actor/actress names for each scripted series were collected via IMDb.com to match character names with their respective actors/actresses. Characters who appeared more than once in a given series were counted once as a series level measure. The highest level and most true judgment were selected when differences in variables occurred.

4. Consistent with most Annenberg Inclusion Initiative studies, there were two units of analysis. The first was program level. The second was the individual speaking or named character. A speaking or named character is defined as a live being that utters one or more words discernibly and overtly or is referred to by name. Speaking or named characters were included in the analysis as a single line of data. Identical individuals are defined as two or more characters that speak independently but their individual identities can not be distinguished. Identical individuals did not occur during the analysis. A new line of data was created for characters that experienced a demographic change (e.g., type, age, sex, race/ethnicity). For example, a character may be shown as a child at the beginning of the program, but that same character may be presented as an adult at the end of the program.

   Research assistants were taught to analyze content via a series of online training sessions. The training sessions were centered around a codebook used for roughly 15 years with measures that are based on other content analytic work that predates our studies, as well as the U.S. Census. Research assistants used both the character's appearance as well as other cues within the plot/story (e.g., name, location, cultural artifacts, others' statements, self-identification) to render a judgment on race/ethnicity. Then, research assistants were issued a series of three "practice" diagnostics to ensure that the content can be reliability evaluated. It is ensured that one individual is not responsible for making a judgment across any piece of content by having multiple evaluators. Reliability was calculated per episode for each series.

   After calculating reliability, a subgroup of research assistants reviewed coding decisions and made an executive decision based on evidence. A team of 10 research assistants performed a manual quality check on the completed sample. We provided a list of rules for evaluating the decisions of three coders and selecting a final answer. We trained the research assistants in these processes. First, they unitized the lines of data and flagged misalignments. Second, they analyzed variables in which there were disagreements and reliability fell below 80% to make an executive decision. Race and ethnicity variables were separated for a more comprehensive analysis. After the team resolved disagreements, the data was checked to confirm the race and ethnicity of characters by last names.

5. The program type of each series was determined by information from https://snaporiginals.snapchat.com/. The three categories for storytelling medium of 2021 U.S. Snap Original series were identified as scripted, unscripted, and docuseries. Scripted series is defined as content produced with a script. Unscripted series is content produced without a script

(i.e., talk shows, game shows, etc.). Lastly, docuseries follows a person or group and their involvement in real events and situations over a period of time.

Phone Swap, Hype School, VS The World, Teen Code, and *Art of The Drop* were provided by Snap in the U.S. 2021 Snap Original sample, but not provided on https://snaporiginals.snapchat.com/. AII and MNL categorized each of the five series into the appropriate storytelling medium by analyzing the episodes of the series.

6. Gender balance is a percentage calculated by dividing the number of female characters by the number of all characters per series. Series at or above the threshold of 45.7% are gender balanced. We determine the threshold of 45.7% because it is the lower 10% threshold around the population metric.

7. Jeffrey M. Jones (2022). *LGBT Identification in U.S. Ticks Up to 7.1%*. Gallup. Retrieved on October 18, 2022 from https://news.gallup.com/poll/389792/lgbt-identification-ticks-up.aspx.

8. Speaking or named characters were determined to have a disability when a condition led to a limitation related to 'major life activities' or 'major bodily function' for longer than six months. A disability could manifest in the following domains: Communicative, Cognitive, and/or Physical. The presence of a disability and the presence of the physical domain were evaluated for Snap.

9. We would like to highlight at this point that video content from the *Daily Mail* Partnered channel was excluded from the analyses reported in this section. During the hybrid evaluation procedure, AII and MNL realized that performing human-based character unitization for *Daily Mail* videos was not feasible as the sheer number of *speaking or named characters* identified by coders was much higher than the average Partnered content unit (109 vs. 5). Therefore, in order to 1) ensure consistency within the content exclusion rationales adopted and 2) mitigate the risk of introducing channel-induced biases, across the two evaluation procedures, MNL and AII conducted hybrid and computational analyses on a random sample of Snap Partnered video content *excluding* the *Daily Mail* Partnered channel. Nonetheless, an independent and purely computational analysis of *Daily Mail* content is provided for comparison purposes in the Appendix section.

10. MTI implements facial detection and clustering techniques to perform this unitization task for improving procedural efficiencies that involve coder decisions while watching video content.

    The unitization of individual characters via machine vision technologies is an important innovation that MTI provides for bolstering content-analytic procedural efficiencies. However, the definition of what factors constitute a "character" in inclusion research is a variable across different research teams and a methodological difference between how AII and MNL approach the problem of character unitization in general.

    AII unitizes a character conditional on whether or not it is a speaking or named character. This type of a character is defined as a live being that utters one or more words discernibly and overtly or is referred to by name. However, an important caveat to note here is that if an individual on-screen is provided sufficient visual attention, but does not speak or is specifically named, it is unlikely that it would be captured as a unique character via such deterministic content-analytic codebooks. On the other hand, MNL unitizes a character conditional on whether or not it is a visually detected character. This type of a character is defined as a human face that visually appears within the narrative. Within the computational unitization procedure, facial image clustering is applied to the full-length Snap Partnered content unit. This procedure primarily involves detecting faces in an identity-agnostic fashion, generating a 128-dimensional facial embedding for each detected face, and grouping these facial embeddings within unique clusters.

    The successful identification of visually detected characters by MNL's character recognition pipelines, however, is also subject to external influences such as visual obfuscation patterns (e.g., human face is not visible due to another individual and/or object on-screen), character presence limited to a trivial period of time (e.g., only 1 ~ 3 seconds of appearance), and auditory presence in favor of visuals (e.g., narrators that guide the unfolding of a storyline). In other words, if an individual on-screen is not provided sufficient visual attention it is also unlikely that it would be captured as a unique character via MNL's character recognition pipelines.

To circumvent methodological differences in unitization procedures, MTI further provides inclusion coders the technological affordance of 1) additional character identification and 2) character evaluation along the gender/race/ethnicity/LGBTQ dimensions in a fashion quite similar as to how they would evaluate the aforementioned visually detected characters. Additionally, MTI applies multiple biological sex and race/ethnicity/sexuality classification models generated from previous research efforts so as to identify gender/racial/ethnic/sexual categories across content and characters. Within the hybrid approach, once a speaking character was identified, they were evaluated across a series of human-assessed measures, including gender, race/ethnicity, and LGBTQ identification. Likewise, within the computational procedure, once a visually detected character was identified, they were evaluated across a series of computer-assessed measures, including gender, race/ethnicity as well as story-level LGBTQ identity prevalence. Beyond the provision of descriptive frequency measures, results from the hybrid evaluation procedure also served as a means to validate MNL's computational methods via the contrasting of demographic prevalence patterns across Snap Partnered content.

Within the computational evaluation procedure, MNL applied biological sex and race/ethnicity classification models generated from previous research efforts so as to identify gender/racial/ethnic categories as defined by AII. MNL performed multiple computational experiments and gained insight that models trained on images from previous datasets were unable to generalize to those extracted and presented to AII coders within the Hybrid evaluation procedure. In particular, popular datasets leveraged for the delivery of automated solutions towards racial/ethnic classification have systematically ignored the multiracial category. MNL leveraged insights generated from the hybrid evaluation procedure in order to construct computational indicators for the identification of multiracial characters. Additionally, it's important to note here that there were an extremely low number of Native Hawaiian/Pacific Islander characters as well as nonbinary characters identified within the hybrid evaluation procedure (see below). Datasets from previous research that could aid efforts in the computational identification of these demographic groups were also limited and, thus, MNL was regrettably unable to include them in its computational evaluation procedures.

For the computational assessment of LGBTQ identity, MNL and AII collaboratively decided to conduct this evaluation at the program level instead of at the character level. This is an important consideration to make provided the sensitivity of identity-related predictions using computational approaches. Traditional content-analytic studies have indeed studied the representation of lesbian, gay, bisexual, transgender, and queer characters in mass media formats. These representations have also been compared with that of other racial/ethnic and gender minority groups. Although these comparisons are useful, they rarely acknowledge one striking difference between the groups. LGBTQ identity members cannot be recognized definitively as a member of a sexual minority group by human-based perception or algorithmic evaluation simply via the detection of physical features such as skin color or facial structures. In traditional content-analytic studies, these determinations are made through the observation of the exhibition of sexual desires, such as romantic relationships, as well as verbal comments that might reveal characters' sexuality. Taking inspiration from the idea that characters might engage in self-disclosure behavior, have their sexual identity be referred to by other characters in the narrative, or simply engage in discussions surrounding LGBTQ identity related discussions as the narrative unfolded, MNL decided to leverage state-of-the-art automated speech recognition pipelines to convert auditory information from the audiovisual narrative into textual data. This pipeline was developed especially for this computational assessment task. As per contract, the Snap team was supposed to deliver captioning text for the video content MNL/AII were instructed to evaluate. Unfortunately, approximately two-thirds of the Snap stories as provided via Looker datafiles were not accompanied with captioning text. Therefore, for the sake of ensuring representative computational analyses MNL implemented its automated speech recognition pipelines across the entire sample. Subsequently, for measuring the prevalence of LGBTQ identity across these Snap Partnered content units, MNL performed a straightforward keyword detection procedure where the frequency of LGBTQ identity keywords were assumed to correlate with the visual presence of LGBTQ characters as well. Validations for this “first-of-its-kind” analytical approach for the identification of LGBTQ related content were conducted against human-annotated samples taken from the Hybrid evaluation procedure. Provided the relatively low prevalence of LGBTQ characters as identified in the Hybrid approach, MNL & AII decided to gauge the frequency of lesbian, gay, bisexual, transgender, and queer identity related content as a whole and not decompose the frequencies as stratified by the individual identity demographic itself.

11. Once overall prevalence patterns were determined within the Snap Partnered video content ecosystem, it was important for AII and MNL to also understand what content types could potentially be driving them. Indeed, genre categories reflect the aggregate level communication patterns that individual content units share with others and therefore reflect socially agreed upon or socially inferred conventions that have developed over time. Keeping this rationale in mind, MNL and AII expected variations in DEI patterns to emerge when analyses were subjected to contingencies on the taxonomical structures that individual channels belonged to. For instance, answering questions that target the overrepresentation of female-identified characters in beauty related content and underrepresentation of female-identified characters in science related video content offers an indication of the utility such analyses provide for exploring more nuanced prevalence biases in Snap Partnered Content. In addition, the stratification of demographic prevalence patterns by channel genre also provide an additional validation opportunity for the computational evaluation procedure as MNL and AII would predict comparable aggregate-level prevalence trends across genre categories.

12. While it is certainly possible that variations in unitization strategies across both methodologies as well as gender misclassification rates introduced via computational pipelines could contribute to such differences, we would like to emphasize here that such genre specific differences are more likely to be attributed to sample size and data representativeness limitations in the hybrid evaluative procedure. For instance, specific genres such as *General Satisfying* were associated with only 14 characters in the hybrid sample while the same genre was associated with 86 characters in the computational sample. Similarly, the genre of *DIY & Crafts* was associated with only 73 characters in the hybrid datasets while the same genre was associated with 422 characters in the computational datasets. Thus, inferences drawn from discrepancies in such frequency dependent measures should be made with caution. An optimal approach to conducting sampling was indeed discussed at great length during the initial stages of this project. However, as there were significant delays in the delivery of datasets linking Partnered channels with genre categories, a simple random sampling approach was adopted for ensuring MNL and AII were able to provide their deliverables on schedule. Future research interested in establishing these convergent gender prevalence linkages between hybrid and computational pipelines should be conducted upon a genre stratified random sample as opposed to the simple random sample that was conducted for this study.

13. As with our genre stratified gender analyses, while it is certainly possible that variations in unitization strategies across both methodologies as well as racial/ethnic misclassification rates introduced via the computational evaluative procedure could contribute to such differences, we would like to once again emphasize here that such genre specific differences are more likely to be attributed to sample size and data representativeness limitations in the hybrid evaluative procedure. For instance, specific genres such as *Technology* were associated with only 28 characters in the hybrid evaluative procedure while the same genre was associated with 363 characters in the computational evaluative procedure. Similarly, the genre of *Auto* was associated with only 53 characters in the hybrid evaluative procedure while the same genre was associated with 206 characters in the computational evaluative procedure. Thus, inferences drawn from discrepancies in our genre-stratified racial/ethnic gap metrics, as with our gender gap metrics, should be made with caution.

14. We do indeed observe a greater variation, approximately 15%, in the percentage point differentials that necessitate explanation. We would like to reemphasize here that the computational procedure performed an assessment of 372 additional and distinct Snap Partnered channels, as compared to the sample for our hybrid procedure, i.e., 1008 versus 636. It is entirely plausible that proportions derived from the *invisibility* metric remain sensitive to shifts in channel and content diversity. As the *invisibility* metric considers an absolute absence of female characters from a channel as its foundational unit of analysis, we believe that the larger and more diverse sample assessed within our computational evaluative procedure remains always susceptible to systematically providing lower estimates for the invisibility of female characters. This is simply because as we sample more videos from each channel, the probability that a female character appears within its content, regardless of their prominence or centrality to the narrative, becomes increasingly higher. Keeping this rationale in mind, and the previous alignment between hybrid and computational in relation to demographic prevalence patterns, we therefore believe that for this specific metric, our computational procedures provide *more* robust estimates than the hybrid procedure.

15. For the implementation of our computational analysis, audio envelopes from individual stories were transcribed via the implementation of MNL's automated speech recognition pipelines across the entire sample. Subsequently, for measuring the prevalence of LGBTQ identity across these unique content units, MNL performed a straightforward keyword detection procedure where the frequency of LGBTQ identity keywords, i.e., lesbian, gay, bisexual, transgender, and queer, were assumed to correlate with the visual presence of LGBTQ characters as well. Validations for the identification of LGBTQ related content were also conducted against samples taken from the hybrid evaluation procedure. Provided the relatively low prevalence of LGBT characters as identified in the Hybrid approach, MNL & AII decided to gauge the frequency of lesbian, gay, bisexual, transgender, and queer identity related content as a whole and not decompose the frequencies as stratified by the individual identity demographic itself.

Appendix

Table 14
Gender Identity of Characters across *Daily Mail* Channel

Method	Male	Female
Computational	45.5% (*n*=9350)	54.5% (*n*=11200)

Table 15
Underrepresented Status of Characters across *Daily Mail* Channel

Race/Ethnicity	Computational
White	70.8% (*n*=14556)
Underrepresented	29.2% (*n*=5994)

Table 16
Race/Ethnicity of Characters across *Daily Mail* Channel

Race/Ethnicity	Computational
White	70.8% (*n*=14556)
Black/African American	10.5% (*n*=2159)
Hispanic/Latino	2.46% (n=505)
Asian	2.8% (n=575)
Middle Eastern/North African	3.05% (n=626)
American Indian/Alaskan Native	<1% (n=140)
Multiracial/Multiethnic	9.68% (n=1989)

Table 17
Percentage of Characters by Underrepresented Status and Gender across *Daily Mail* Channel

Measure	**Computational**
White Males	31.6% (*n*=6501)
White Females	39.2% (*n*=8055)
UR Males	13.86% (n=2849)
UR Females	15.3% (n=3145)

Table 18
Genre Classifications as Defined across Snap Datasets

POP CULTURE	BEAUTY
NEWS	GENERAL SATISFYING
FASHION & STYLE	GAMING
COMEDY	AUTO
GENERAL ENTERTAINMENT	MONEY
HUMAN INTEREST	ANIMALS
SPORTS	ANIMATION
VIRAL CONTENT	FOOD
DIY & CRAFTS	HEALTH, FITNESS, & WELLNESS
SCIENCE	NON-TRADITIONAL SPORTS
PARENTING	TECHNOLOGY
TRAVEL	

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