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See It, Be It:

What Families Are Watching On TV

Geena Davis Institute on Gender in Media
If she can see it, she can be it.™

USC Viterbi School of Engineering

Google

Nielsen

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Purpose

The goal of this report is to reveal the status of inclusion and representation in scripted television in the U.S., and how it has evolved over the past 12 years. Entertainment media, like scripted television, profoundly shapes the minds of young people as well as social narratives. It influences how we perceive the world, how we see ourselves holding place in society, what we should value, what we should respect, what careers we may pursue, who gets to be the hero, and more.

Analyzing and measuring inclusion and representation in entertainment media contributes to eliminating unconscious bias that can reinforce negative behavior, prejudice, colorism, body shame, low self-esteem, and other harmful stereotypes. We hope this report inspires the creation of more equitable media content.

We partnered with Google Research to undertake this longitudinal representation study of the most popular scripted TV shows over the past 12 years. This study is pioneering in four meaningful ways:

1. With Google Research's machine learning innovations, we inferred human-centric signals at scale, including perceived gender expression, perceived age, perceived skin tone, and detecting visual speech.
2. We extrapolated many intersectional patterns across the various human-centric signals.
3. Leveraging technology, we were able to process a large volume of data: 440 hours of video viewing time in about 24 hours, as well as a total of about 12 million face tracks, which would have taken a significantly longer time and expense with human raters.
4. With the speed of automation, we spanned the study over a large breadth of time, giving us historical trends across 12 years.

Executive Summary

We begin with a presentation of the main findings from our analysis of the most popular scripted TV shows from 2010 through 2021:

The share of female characters on screen is up, though male characters still occupy about 16 percentage points more screen time: Male characters' share of screen time in popular programming outpaces female characters' share of screen time by a large margin, but screen time for female characters is increasing. Over the past 12 years, there has been an estimated 7.1 percentage-point increase in female characters' share of screen time, suggesting the casts for popular scripted programs are changing and achieving greater gender parity.

FIGURE 1 • **Share of screen time for female characters over time in the most popular scripted TV shows**

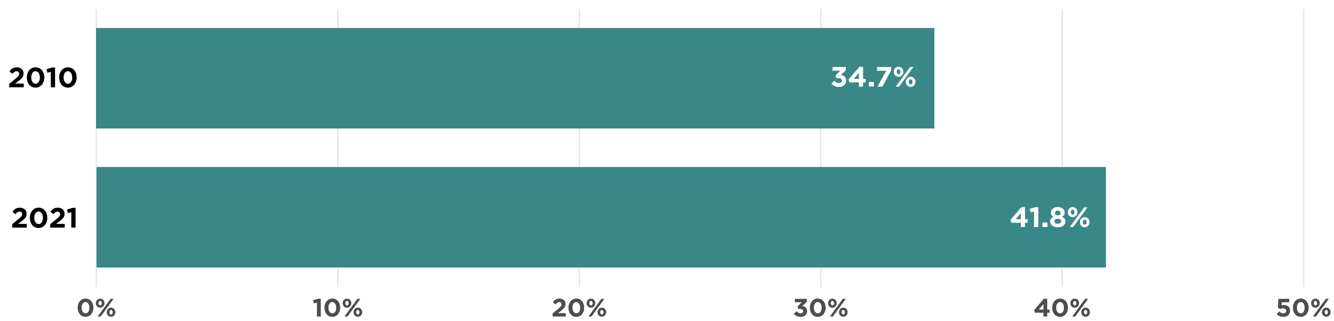


CHART NOTES: SHARE OF SCREEN TIME IS THE GROUP'S TOTAL SHARE OUT OF 100%. REMAINING SCREEN TIME BELONGS TO MALE CHARACTERS.

Screen time is increasing for male and female characters with medium and dark skin tones, but the majority of screen time is occupied by male and female characters with a light skin tone: The share of screen time for characters with medium and dark skin tones is steadily increasing over the 12 years analyzed. This increase is especially large for female characters with medium and dark skin tones. In 2021, their share of screen time is up to 5.4% and 6.9%, from 2.0% and 0.3% respectively.

FIGURE 2 • **Share of screen time for male and female characters with dark and medium skin tones in the most popular scripted TV shows**

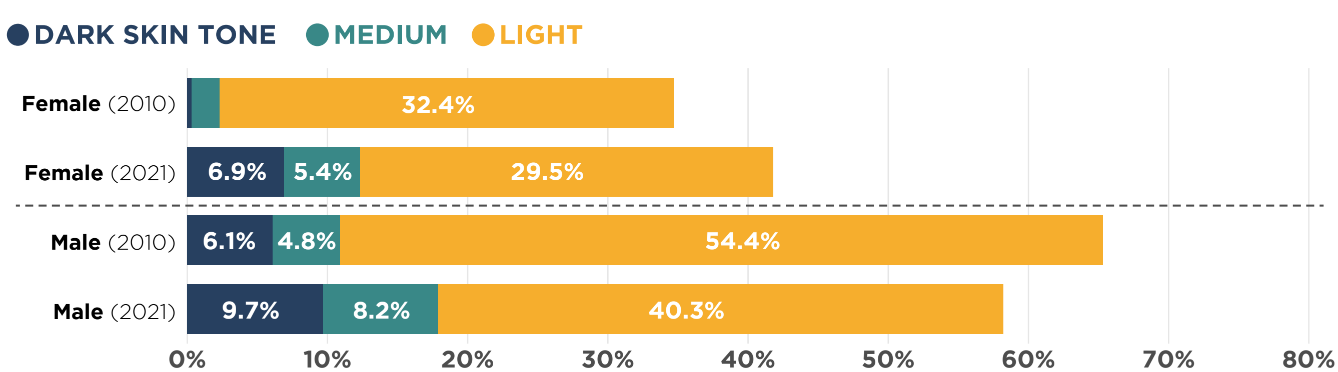


CHART NOTES: SHARE OF SCREEN TIME IS THE GROUP'S SHARE OUT OF 100%.

Visual speaking time has increased for female characters with dark skin tone about 1.2% per year, the highest rate of all race and gender groups. However, their overall speaking time when they are on screen is still the lowest.

Older men but younger women dominate on screen, however the gap is less over time: In more recent programming, the most common group on screen for women are characters over 18, under 33 (31.2% of screen time), but for men the most common group on screen are characters over 33, under 60 (28.5% screen time). The share of screen time for female characters over 33, under 60 is just 8.0%, an age gap of 20 points.

FIGURE 3 • **Share of screen time for male and female characters in different age groups in the most popular scripted TV shows in 2021**

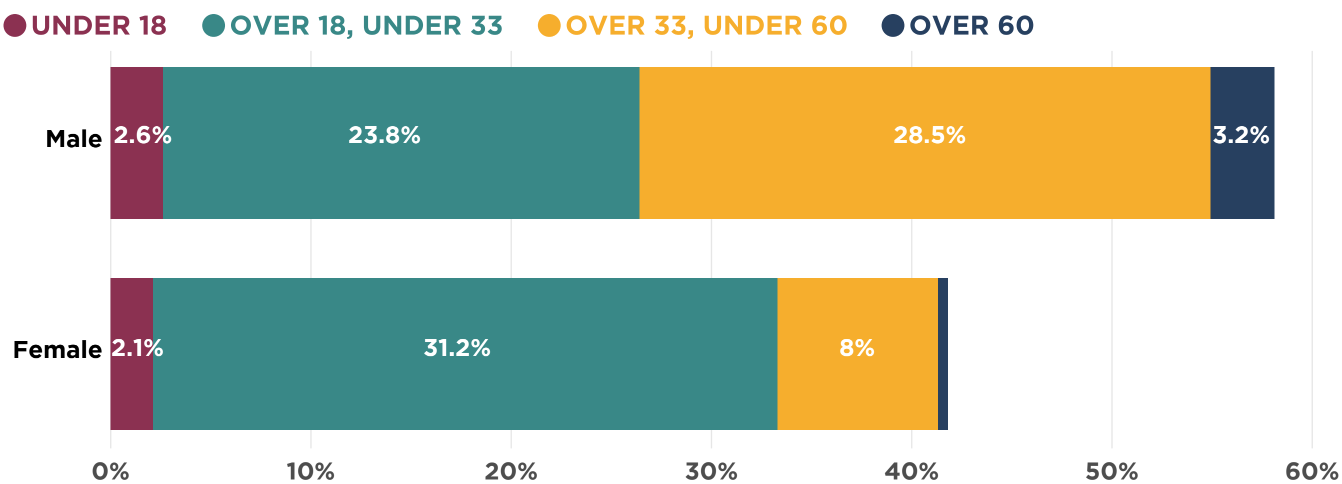


CHART NOTES: REPORTED SHARE OF SCREEN TIME IS THE GROUP'S SHARE OUT OF 100%.

Older female characters remain rarely seen: The share of screen time for female characters over 18, under 33 and over 33, under 60 is up slightly over the past 12 years (3 points and 2 points, respectively). There is no change in the share of screen time for female characters ages over 60 or under 18.

FIGURE 4 • **Share of screen time for female characters in difference age groups in the 10 most popular scripted TV shows**

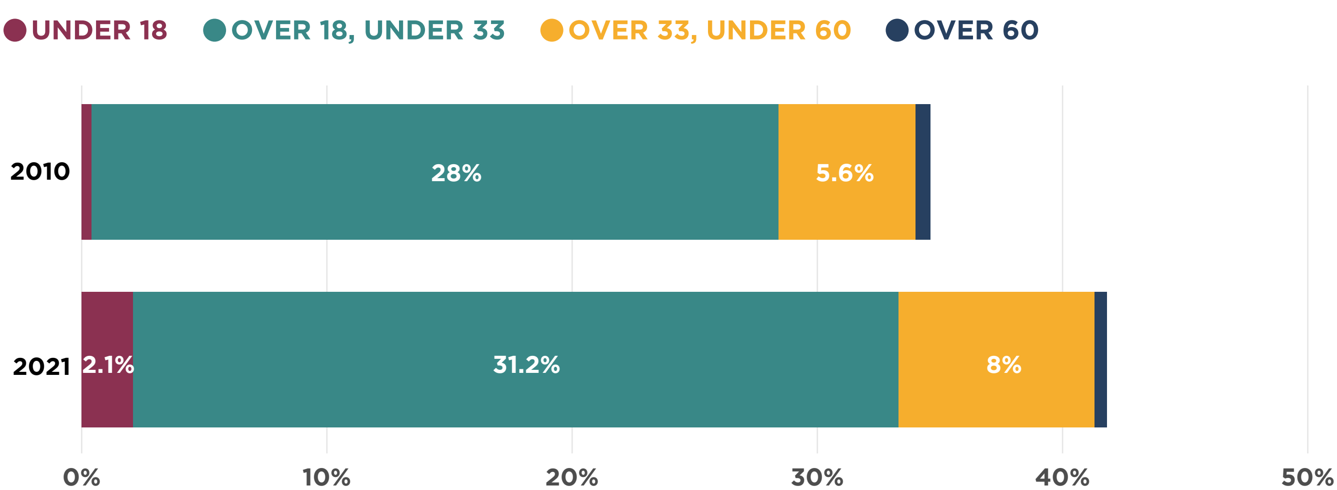


CHART NOTES: SHARE OF SCREEN TIME IS THE GROUP'S SHARE OUT OF 100%. REMAINING SCREEN TIME BELONGS TO MALE CHARACTERS IN THESE AGE COHORTS.

Data and Methodology

The data for this analysis is the most popular scripted broadcast television shows in the U.S. from 2010 through 2021, according to Nielsen metrics. For each year, we look at the 10 most popular shows. The sample includes four episodes from each show (the second and penultimate episodes as well as two additional episodes selected randomly). To analyze how the inclusion of perceived gender expression, perceived age, and perceived skin tone in popular television has evolved over the past 12 years, we report statistical estimates of "screen time" from a linear mixed model. Linear mixed models are appropriate for examining longitudinal data like this, where some shows are in the dataset over many years because of their longstanding popularity. This model accounts for data dependencies in the observations. The data presented in this report include analysis of the raw data, and insights based on the statistical analysis of the raw data. In this report, "screen time" refers to the percentage of all faces that are localized in a video, for a given attribute (e.g. perceived gender expression, perceived age). We also report "visual speaking time," which estimates how often a group is speaking when they are on screen. Essentially, when groups are seen, are they also hear

The Institute, in collaboration with Nielsen, curated the TV episode dataset described above. As the next step, the Institute, in partnership with Google Research, applied the *Represent Pipeline* (RP) on the datasets to derive raw analytics of the people present in the episodes. RP was designed to run at scale to process large volumes of data and uses machine learning models to infer signals perceived from face images: age, gender expression, skin tone, and whether people on screen are speaking. RP provides aggregates of these signals and their intersections over face tracks across the videos. By modeling perceived attributes, the RP shines a light on how a character might be perceived by the contemporary audience. The current study does not attempt to measure the attributes of the actors cast in corresponding roles (e.g., an older actor playing the role of a younger character). We recognize that gender is complex and multifaceted, using algorithmic estimates in RP of perceived gender expression is one way to identify depictions of female and male characters. For more information about RP, please see the Appendix.

Using the output measures from RP, GDI and the Signal Analysis and Interpretation Laboratory at the University of Southern California's Viterbi School of Engineering collaborated on conducting statistical analyses for examining the video-level measures in the study sample, summarized findings, drew societal insights, and offered recommendations, which are all presented in this report.

Findings

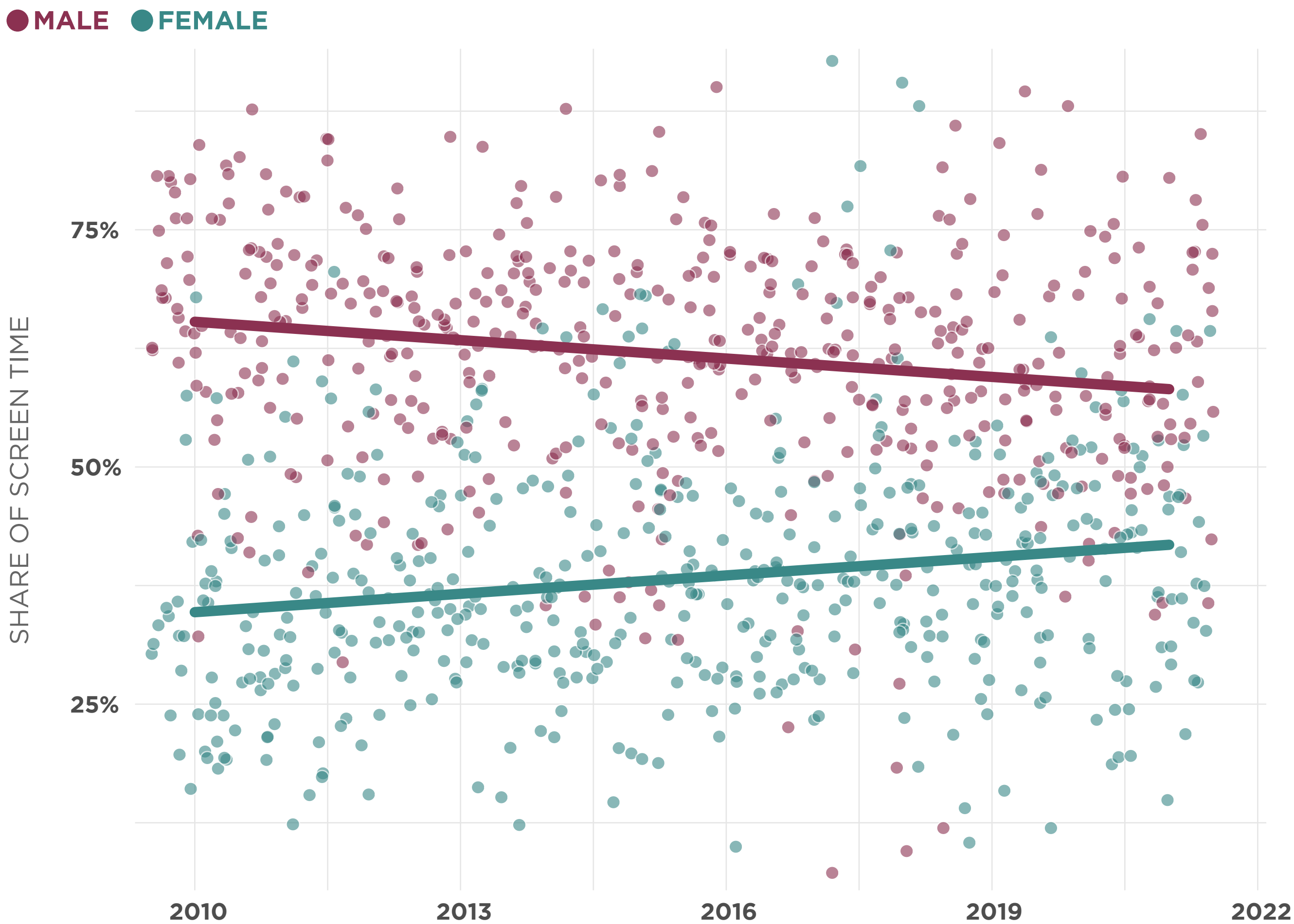
HOW HAS THE SHARE OF FEMALE CHARACTERS' SCREEN TIME CHANGED OVER THE PAST 12 YEARS?

In our analysis of the 10 most popular scripted shows from 2010 through 2021, we find that male characters' share of screen time outpaces female characters' share of screen time by a large margin. However, screen time for female characters is increasing. Over the past 12 years, there has been an estimated 7-percentage-point increase in female characters' share of screen time, suggesting the casts for these popular programs are moving toward greater gender parity. The gap in screen time between male characters was an estimated 31 points in 2010, but in 2021, that gap has dropped to 16 points.

Visual speaking time has increased for male and female characters to a similar degree over the time period analyzed — about 0.5% per year. Additionally, on average over all years, when female characters are on screen, their speaking time is similar to male characters' speaking time (24.4% compared to 24.9%).

FIGURE 5 • **The share of male and female characters on screen in the most popular scripted TV shows, 2010–2021**

Male characters are still the majority of characters on screen, but that is changing



But among which female characters is screen time increasing? If we consider characters' perceived age cohort (under 18, over 18, under 33, over 33, under 60, over 60), the biggest increase in screen time is among female characters whose perceived age is over 18, under 33. Over the past 12 years, there's been an estimated 3-point increase in this group on screen. We also observe a 2-point increase in screen time of female characters whose perceived age is over 33, under 60. This is a positive development, given the historical exclusion of older female characters in the film and television industry.[1] However, among female characters whose perceived age is over 60, the analysis shows no significant change in either direction. The same is true for male characters in this age cohort.

The share of screen time for male characters estimated to be between ages 33 and 59 has declined by an estimated 9 points over this time period. However, compared with female characters in this age group, the gap is still wide — 20 points. Of all age groups analyzed, the screen-time gender gap is largest for this age cohort. There has been a small increase (2 points) in screen time among male characters whose perceived age is under 18 across the 12-year time period.

Visual speaking time has increased for all age cohorts for male and female characters over the time frame analyzed, but that change is only significant for male characters over 60 (about 0.5% per year). There is a gender gap in visual speaking time for this age cohort – male characters over 60 are speaking about 25% of the time they are on screen compared to just about 17% for female characters over 60, on average over the 12 years analyzed, a 7 point gap. For female characters over 60, they are therefore rarely seen or heard.

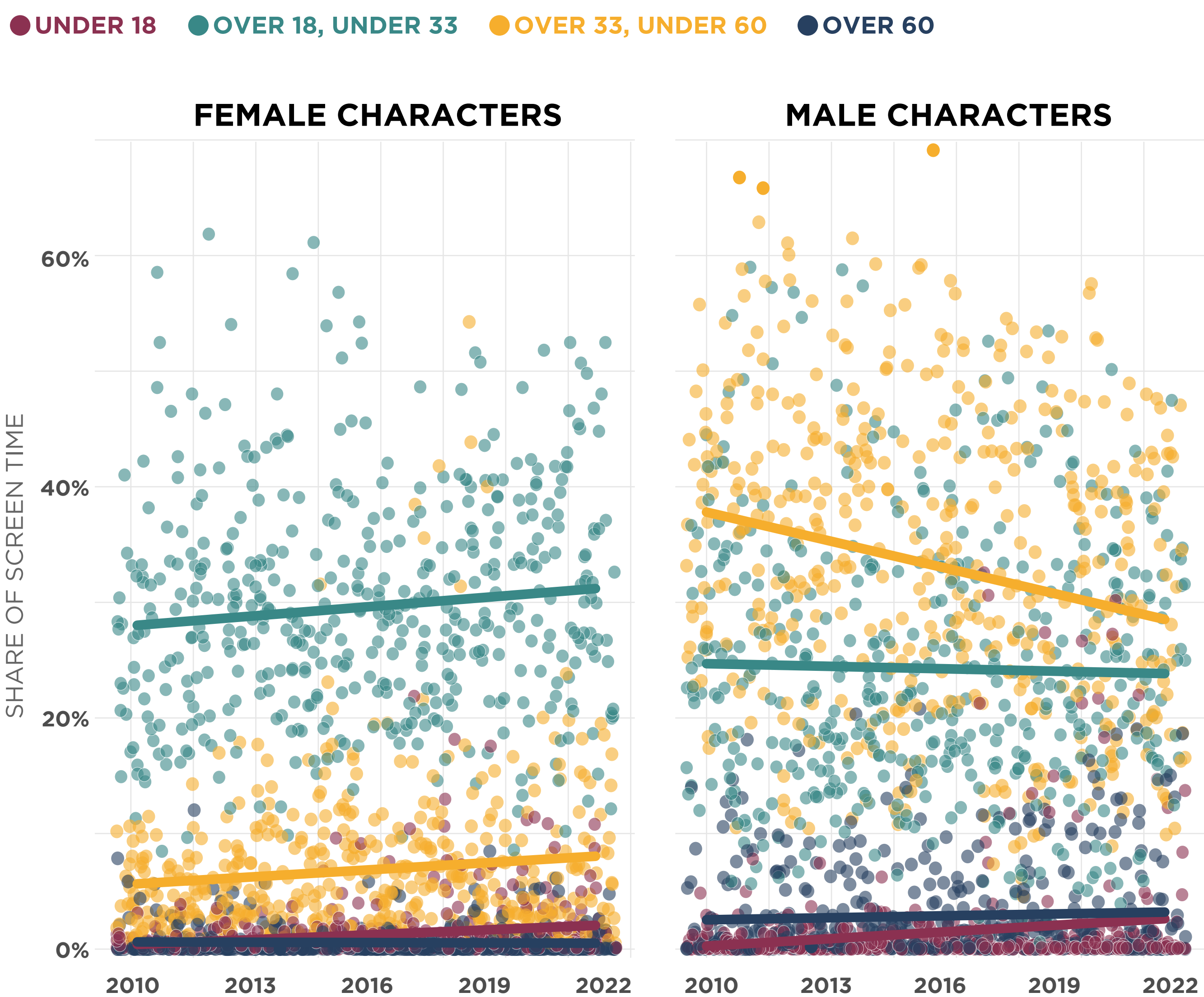
Visual speaking time is similar for male and female characters under 18 (about 11%). For characters over 33, under 60 there is a small gender gap — male characters speak 27% of the time they are on screen compared to 25% of female characters. There is also a gender gap in visual speaking time for characters over 18, under 33. Here, female characters are speaking about 24% of the time they are on screen compared to about 20% for male characters in this age group, on average across all years analyzed, a 4 point difference.

Among female characters, the share of screen time for those with a dark skin tone has increased an estimated 7 points over the past 12 years, and the share of screen time for those with a medium skin tone has increased an estimated 3 points. The share of screen time for women with a light skin tone has declined an estimated 3 points across the same timeframe.

Screen time of male characters with a light skin tone has declined (14 points). However, relative to other groups (defined by their gender and skin tone), male characters with a light skin tone still occupy the largest share of screen time of any other single group. The screen time of male characters with dark and medium skin tones also increased over this time period (4 points and 3 points, respectively).

FIGURE 6 • **The share of older and younger female characters on screen in the most popular scripted TV shows, 2010–2021**

The share of female characters estimated to be over 18, under 33 is seeing increased screen time, as is the share estimated to be over 33, under 60



Visual speaking time has increased for male and female characters with light, medium and dark skin tone over time, but most sharply for female characters with a dark skin tone (1.2% per year). Visual speaking time increased for female characters with medium skin tone about 0.9% per year. For male characters with dark and medium skin tone, their visual speaking time increased about 0.6% per year.

The group that is most likely to be speaking when they are on screen is male and female characters with a medium skin tone — they are speaking 29% and 27% of the time they are on screen, respectively, with a 2 point gender gap. Male and female characters with a light skin tone speak 24%. Male characters with a dark skin tone speak 20% of the time they are on screen, compared to 16% for female characters with a dark skin tone, a 4 point gender gap.

Among female characters, the share of screen time is increasing among those whose perceived age is between 18 and 32 with dark and medium skin tones (5 points and 2 points, respectively), and declining among this age group for characters with a light skin tone (4 points). The share of screen time is increasing among female characters whose perceived age is under 18 with light skin tone (just 1 point).

Among male characters, the share of screen time is declining for those with a light skin tone whose perceived age is between 18 and 32 as well as those between 33 and 59 (7 and 10 points, respectively). But the share of male characters whose perceived age is between 18 and 32 with dark skin and medium tones is increasing (4 points and 2 points, respectively).

FIGURE 7 • **The share of male and female characters with light, medium and dark skin tone, on screen in the most popular scripted TV shows, 2010–2021**

The share of screen time for male and female characters with medium and dark skin tones is increasing

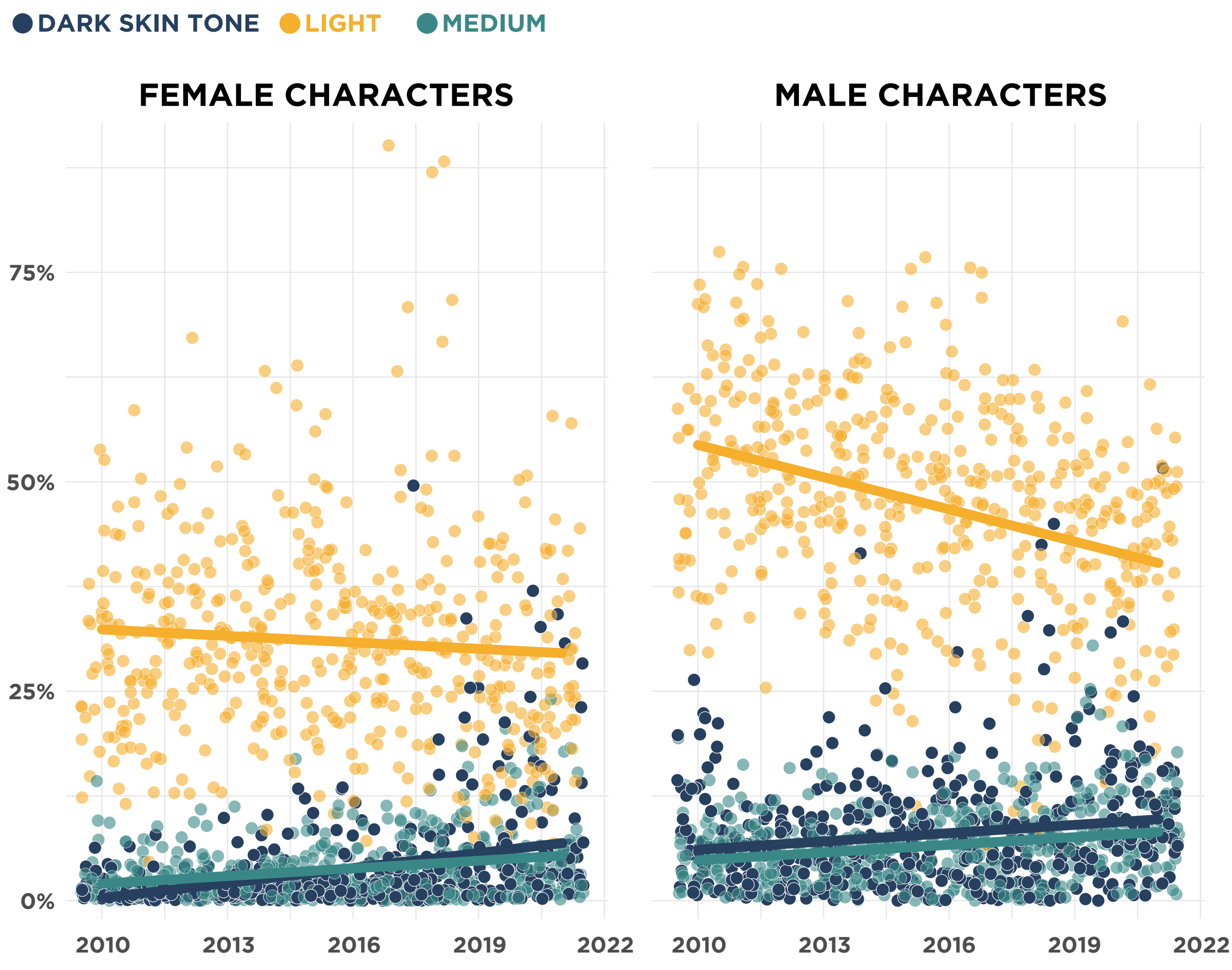
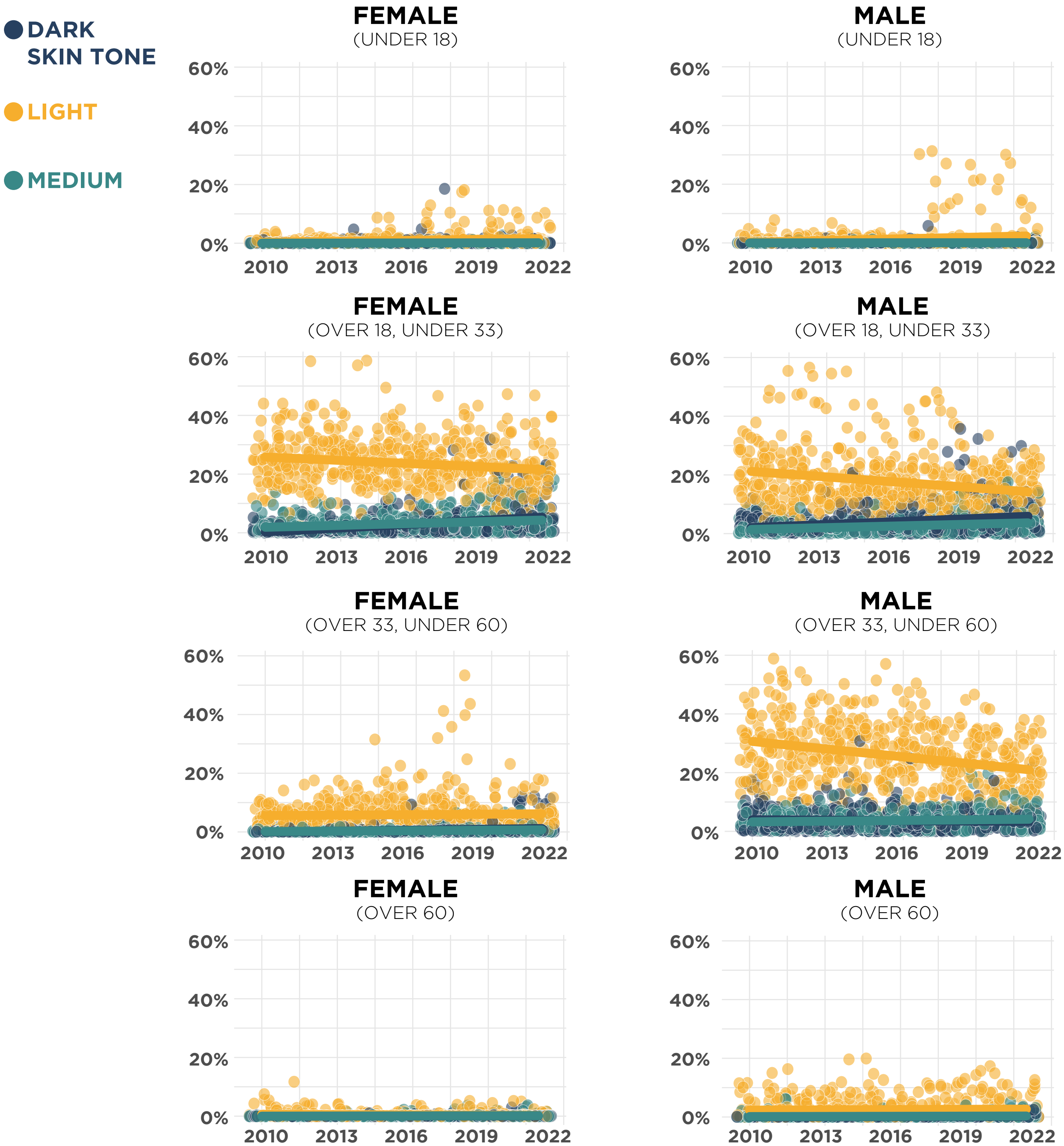


FIGURE 8 • **The share of older and younger male and female characters with light, medium and dark skin tone in the most popular scripted shows, 2010–2021**

The share screen time of younger men and women with dark and medium skin tones is increasing



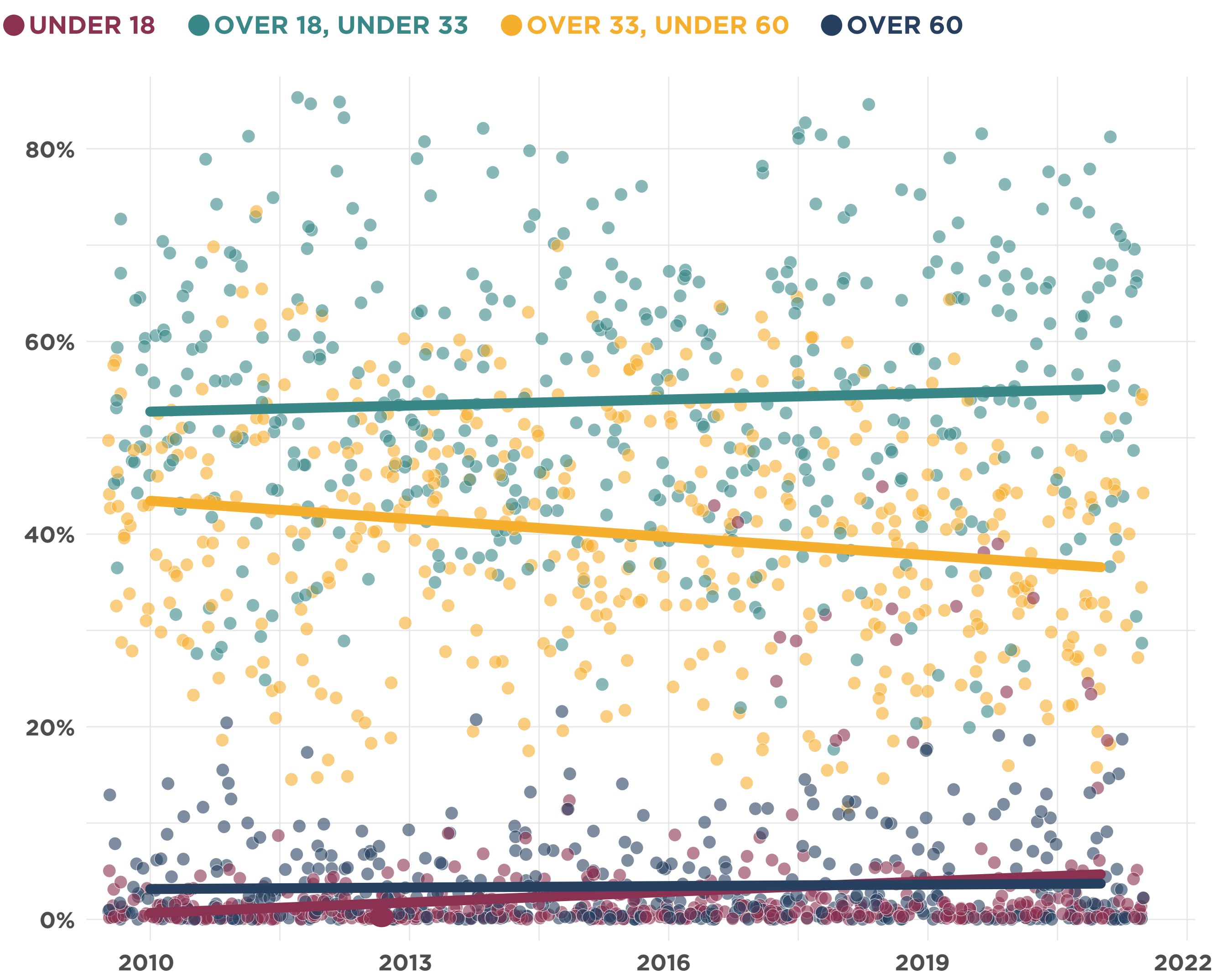
DO DIFFERENT AGE COHORTS APPEAR ON SCREEN MORE OFTEN THAN OTHERS?

From 2010 through 2021, the majority of screen time on the 10 most popular scripted shows has been occupied by characters whose perceived age is between 18 and 32, followed by those between 33 and 59. Characters whose perceived age is under 18 and over 60 were on screen the least amount of time of the age cohorts.

Although characters over 18, under 33 and over 33, under 60 are on screen more than other age cohorts, there has been some change over the past 12 years, including a 12-percentage-point decline in the share of screen time for characters over 33, under 60. But the share for characters over 18, under 33 and 60 or older has been steady over the years analyzed. There has been a slight increase in the share of screen time for characters under 18 (4 points).

FIGURE 9 • **The share of younger and older characters on screen in the most popular scripted TV shows, 2010–2021**

There has been an increase screen time for characters under 18, and a decline in characters over 33, under 60

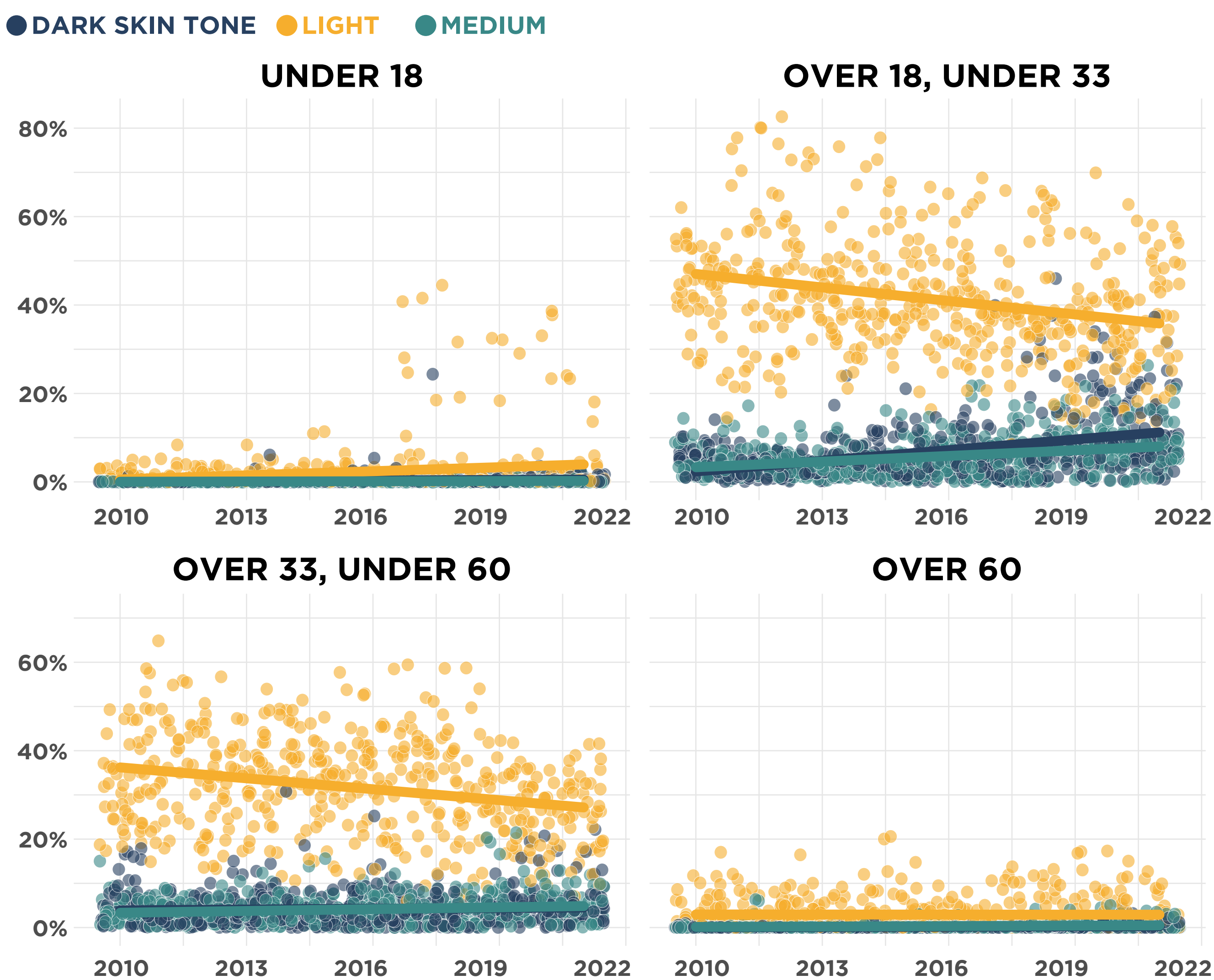


Visual speaking time has increased for characters 60 and older about 0.4% per year, but not for other age cohorts. However, as discussed above, this is largely unique to male characters 60 and older. Female characters 60 and older did not see an increase in their visual speaking time.

Although the share of screen time overall for characters over 18, under 33 is largely unchanged, among those in this age cohort with dark and medium skin tones screen time is increasing (9 points and 5 points, respectively). Overall, visual speaking time is greatest for characters over 60 and characters over 33, under 60 — when they are on screen they speak about 27% of the time. Characters under 18 speak about 12% of the time they are on screen, and characters over 18, under 33 speak about 23% of the time they are on screen.

FIGURE 10 • **The share of young and older character with light, medium and dark skin tone on screen in the most popular scripted shows, 2010–2021**

Although the share of screen time overall for characters over 18, under 33 has not changed significantly, it is up among this age cohort for characters with dark and medium skin tones



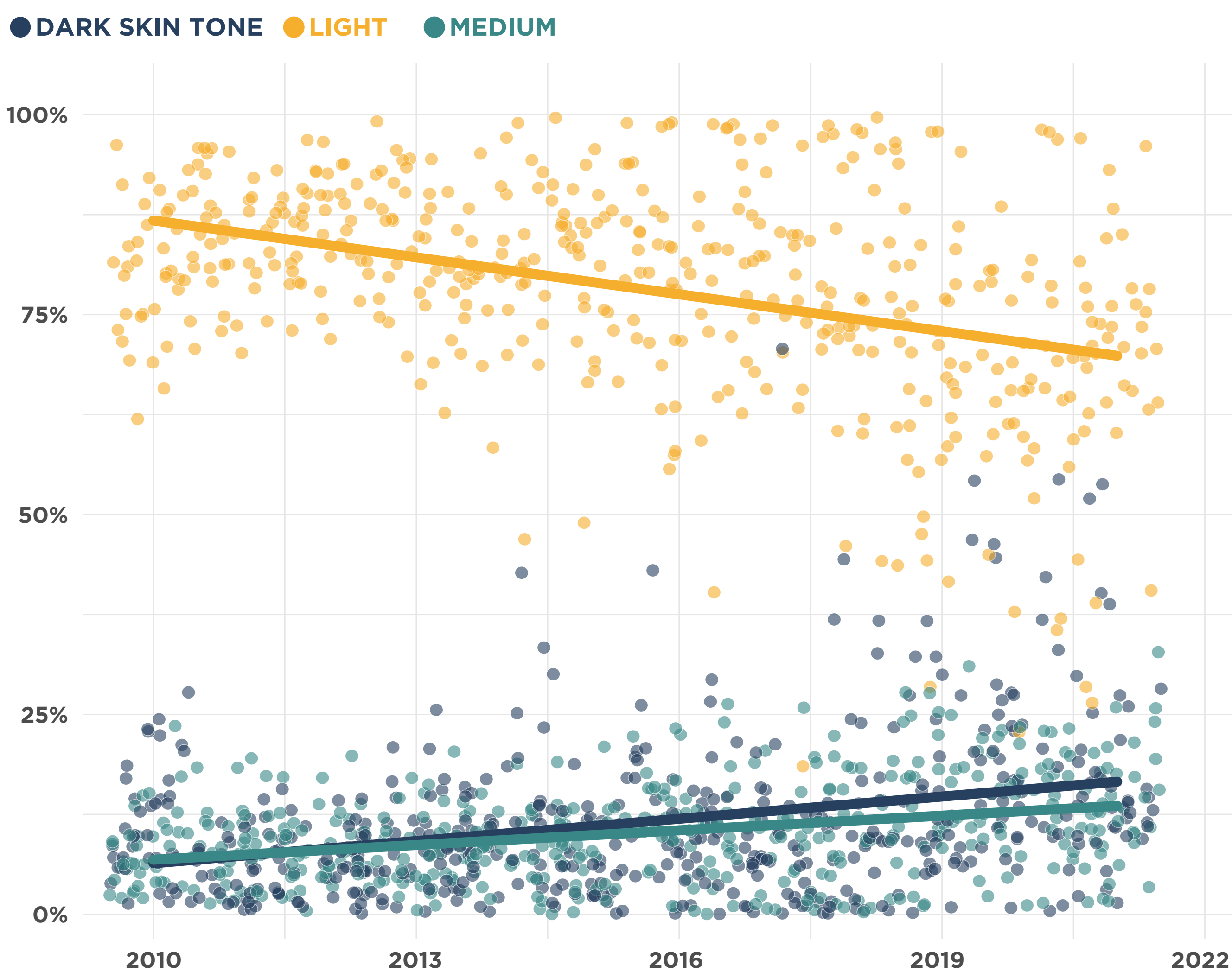
HOW HAS SKIN TONE DIVERSITY ON SCREEN EVOLVED OVER THE PAST 12 YEARS?

From 2010 to 2021, characters with light skin tone made up the vast majority of characters on screen. However, the share of screen time is increasing for characters with medium and dark skin tones. Over the past 12 years, there has been a 8-percentage-point increase in the share of screen time for characters with a medium skin tone, and a 9-point increase for characters with a dark skin tone. As reported above, the increase in screen time among characters with medium and dark skin tones is observed for male and female characters — but is primarily among characters whose estimated age is between 18 and 33. That said, the skin-tone gap is still wide. In 2010, the estimated gap in the share of screen time between characters with light and dark skin tone was 81%. In 2021, that gap is 55%, a narrowing of 26 points.

Visual speaking time has increased for characters with a dark skin tone about 0.8% per year. However, characters with a dark skin tone are least likely to be speaking when they are on screen — 20% of the time, compared to 29% of the time for characters with a medium skin tone, and 24% for characters with a light skin tone.

FIGURE 11 • **The share of characters with light, medium and dark skin tone on screen in the most popular scripted TV shows, 2010–2021**

There has been an increase in screen time for character with medium and dark skin tones




Sally Anscombe/Stone via Getty Images

Recommendations

The findings from this analysis of the most popular scripted television shows suggest that there has been steady progress toward gender parity over the past 12 years, but that gaps still remain. And as the intersectional analysis shows, gender gaps are largest for characters whose estimated age is between 33 and 59, an age cohort in which female characters trail male characters considerably. The findings from this analysis also reveal that skin-tone diversity is increasing, but in 2021, the screen-time gap is still wide between characters with the lightest and darkest skin tones. To continue to push the needle forward on inclusion and representation, we make the following recommendations:

1. **Change things up.** One of the most direct ways to broaden inclusion in popular entertainment media is to grow the casts of long-running shows to include more people of color with diverse skin tones. Popular scripted TV shows are often shows that have been on the air for many years. Add to these casts with more diverse and authentic characters and storylines, including minor roles and background characters.

2. **Diversify behind the scenes.** More diversity behind the scenes leads to more diversity in front of the camera. Studios can hire more diverse writers and directors, but they can also get at the root of the problem by supporting or creating programs that address deeper pipeline issues.

3. **Eliminate the age gap.** As our report found, older men but younger women dominate the screen. For decades, entertainment media has paired younger women with older men for flirty or romantic storylines. By keeping the age gap in mind when casting roles for such storylines, the large disparity between older men and women on screen can be reduced.

4. **Challenge expectations about who can play what.** This report finds female characters over 60 are rarely seen. Consider older women, especially women of color with diverse skin tones, to play characters in male-dominated occupations, such as criminal justice, even in background roles, to bridge this gap.

Appendix

REPRESENT PIPELINE (RP) METHODOLOGY

The Represent Pipeline (RP) was developed by Google Research. It provides AI-enabled technology toward measuring and understanding the presence and portrayals of people in media content at scale. RP uses machine learning models to infer human-centric signals perceived from faces: perceived age, perceived gender expression, perceived skin tone, and whether people on screen are speaking.

The first step of the pipeline runs a model that localizes the appearance of faces in a video at the rate of 10 frames per second. This approach comes with some limitations despite continued development and training. In particular, the accuracy of the system decreases for situations of low light or poor image quality. Since most of the content we analyzed is produced in high quality, we believe this limitation has minimal effect on our findings.

Once the faces in frame have been localized, the model uses the output features from the bounding box and facial landmarks to compute a cropped region of the image around each face. We then run these “face thumbnail” images through several classification models to produce the attributes that we wish to measure. Note that this approach means that any face that is not detected in the first stage of the pipeline cannot be classified and therefore will not contribute to our overall statistics.

Share of screen time for a group (e.g. over 60 characters with light skin tone) in a given video is based on the fraction of detected faces associated with different possible attribute combinations. For example, to estimate the share of screen time of middle-aged female characters in a video, we divide the number of feminine faces estimated to be between the ages of 33 and 60 by the total number of detected faces in the video. Normalizing by the total number of faces in a video allows for a comparison of these summary estimates across the videos in the study sample.

Details of the specific classifiers and summary groups used in this study follow.

PERCEIVED GENDER EXPRESSION

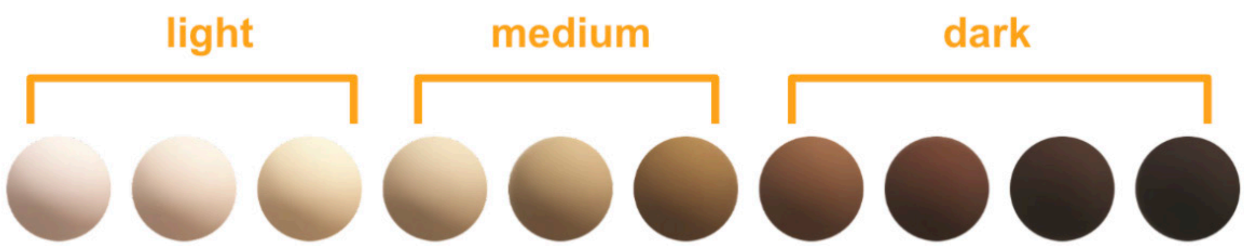
We recognize that gender is not a simple binary attribute and that one’s gender identity may not match one’s gender expression. For the purposes of this study, we use a model that classifies perceived gender expression as either predominantly feminine or predominantly masculine based on face thumbnails. Because we are interested in how characters depicted on screen are perceived by the audience, we use the algorithmic estimates of perceived gender expression to identify female and male characters. We do not analyze representation of people whose gender expression falls outside of this binary representation, and we do not attempt to infer the gender identity of the actors cast in the roles. We note that norms around gender expression vary across cultures and that no single aspect of a person’s appearance suffices to determine their gender expression. A limitation of this study is that the model does not consider aspects of a person’s appearance outside of the cropped face thumbnail.

PERCEIVED AGE

The age attribute is computed by a multiclass classifier that produces an estimated probability distribution over the age range zero through 100 years, in intervals of 0.5 years. We estimate the age of a face as the mean of this probability distribution for the purposes of statistical analysis. For the purposes of this study, age is grouped into four groups: under 18, over 18, under 33, over 33, under 60 and over 60.

SKIN TONE

The RP uses a multiclass classifier model to measure skin tone from the face using a 10-point scale referred to as the Monk Skin Tone (MST) Scale. Developed by Harvard professor Dr. Ellis Monk, the MST Scale provides a broader spectrum of skin tones than alternatives based on the Fitzpatrick Scale. For the purposes of this study the 10-point scale has been further grouped into three coarser categories that we refer to as "light," "medium," and "dark" skin tones. We never attempt to use skin tone to guess or infer an individual's race or ethnicity.



Monk Skin Tone (MST) Scale

VISUAL SPEECH DETECTION

Visual speech detection classifier looks at up to seven consecutive frames, depending on how many frames are available in a sequence of localized faces, and provides a score giving the probability that the face is speaking. We threshold this score and smooth the resulting binary decision over consecutive frames to get an attribute of whether a face shown on screen is speaking or not. Since this classifier is only based on the visual track, it can misclassify cases where someone is moving their mouth but not speaking.

ENDNOTE

1. Geena Davis Institute on Gender in Media. 2021. *Women Over 50: The Right To Be Seen On Screen*. Available at https://seejane.org/wp-content/uploads/GDIGM-Next50-WomenOver50-Study.pdf

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About the Geena Davis Institute on Gender in Media

Founded in 2004 by Academy Award Winning Actor Geena Davis, the Institute is the only research-based organization working collaboratively within the entertainment industry to create gender balance, foster inclusion and reduce negative stereotyping in family entertainment media.

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