

# CLOSING THE STEM GENDER GAP



**A STUDY OF GENDER & STEM REPRESENTATIONS IN UK FAMILY TELEVISION**



**UK Government**

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

**USC Viterbi**  
School of Engineering

# INTRODUCTION

In the UK, men outnumber women three-to-one in science, technology, engineering, and mathematics (STEM) professions (78% compared with 22%).<sup>1</sup> This enormous gender gap persists, despite decades of government and private programs aimed at increasing the number of girls and women in STEM.

The British Consulate General in New York partnered with the Geena Davis Institute for Gender in Media to conduct the first systematic assessment of the role media plays in this persistent STEM gender gap. In this report, we examine representations of STEM characters in the top UK children's film, television, and streaming content. Media are influential in shaping the values and career paths of young viewers. Understanding what messages girls, boys, and gender non-conforming kids are getting about STEM in their favorite TV shows is key to understanding whether this powerful medium is encouraging or discouraging girls from pursuing STEM.

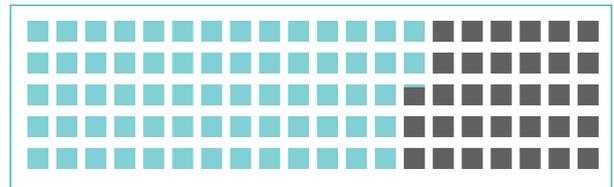
## GENDER

*Female STEM characters are underrepresented.*

**MALE STEM CHARACTERS OUTNUMBER FEMALE STEM CHARACTERS 2-TO-1**



**67.1% OF STEM LEADS ARE MALE**



*Media reinforces gender stereotypes about girls & women in STEM.*

**YOUNG MALE STEM CHARACTERS ARE MORE LIKELY TO BE ENCOURAGED IN STEM PURSUITS**



**MALE STEM CHARACTERS ARE MORE LIKELY TO BE LEADERS IN STEM**



**FEMALE STEM CHARACTERS ARE MORE LIKELY TO BE IN REVEALING CLOTHING**

(1.8% compared to 0.0%)



*Media flips gender STEM stereotypes.*

**MALE CHARACTERS ARE MORE LIKELY TO BE IN LIFE SCIENCES**

(29.6% compared with 13.4%)



**FEMALE CHARACTERS ARE MORE LIKELY TO BE IN COMPUTING OR ENGINEERING**

(11.5% compared with 2.8%)

(12.0% compared with 2.5%)



**MALE & FEMALE STEM CHARACTERS ARE EQUALLY LIKELY TO BE COMPETENT EXPERTS**

(12.8% compared to 10.5%)

(32.2% compared to 25.0%)

(17.2% compared to 17.3%)

**HIGHLY INTELLIGENT**

(34.4% compared to 34.3%)



STEM portrayed in ways that appeal to girls & women.

**85.7%**  
OF STEM  
CHARACTERS  
ARE SHOWN  
**WORKING IN  
COLLABORATION**



**80.3%**  
OF STEM  
CHARACTERS ARE  
SHOWN  
**USING STEM TO  
HELP OTHERS**



**ONLY 7.8%**  
OF EPISODES  
HAVE ONE  
OR MORE  
**STEM  
TROPES**



## DIVERSITY

STEM characters of color are well represented compared to the UK Population.

**PEOPLE OF COLOR MAKE UP**



**12.9%**  
OF  
THE UK  
POPULATION

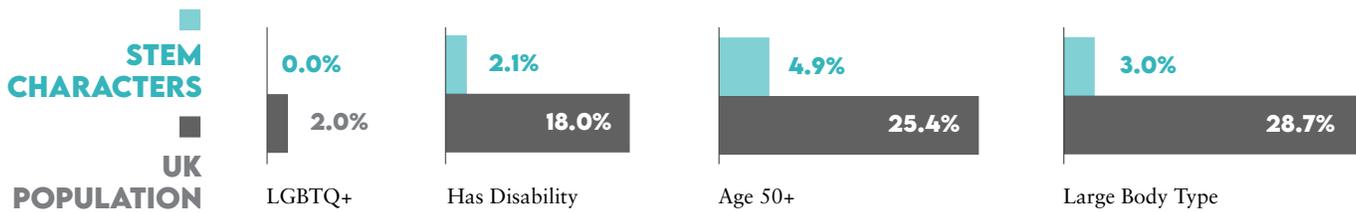
**28.6%**  
OF  
STEM  
CHARACTERS



**1-IN-3**  
FEMALE STEM  
CHARACTERS  
ARE  
**WOMEN  
OF COLOR**



Some identity groups vastly underrepresented in STEM.



## UK VERSUS US

UK has more prominent female STEM characters.



UK depicts STEM in ways that appeal to women & girls.

FEMALE STEM CHARACTERS IN THE UK ARE **MORE LIKELY** THAN IN THE US TO BE SHOWN **WORKING COLLABORATIVELY** (87.3% compared to 69.8%) AND **HELPING OTHERS** (83.2% compared to 64.0%)



FEMALE STEM CHARACTERS IN THE UK ARE **LESS LIKELY** THAN IN THE US TO **SACRIFICE THEIR PERSONAL LIFE** (5.5% compared to 42.9%)



# EXECUTIVE SUMMARY

## GENDER

- Male STEM characters outnumber female STEM characters nearly two-to-one (60.7% compared with 39.3%).
- The gender gap is even larger with leading STEM characters, 67.1% of whom are men.
- Young male STEM characters are more likely to be encouraged to engage in STEM pursuits than young STEM female characters (25.8% compared with 21.9%).
- Male characters are significantly more likely to be shown as STEM leaders than female characters (32.2% compared with 25.0%).
- Male and female STEM characters are equally likely to be shown as competent in STEM, experts in STEM, empowered, and highly intelligent.
- Male STEM characters are more likely to be shown working in life science occupations (29.6% compared with 13.4%), while female characters are more likely to be shown in computer (11.5% compared with 2.8%) or engineering (12.0% compared with 2.5%) occupations. This is a reversal of gender gaps in these fields in the real world where women have higher numbers in life sciences and far lower numbers in computer and engineering occupations.
- The vast majority of STEM characters (85.7%) are shown working in collaboration with others, which makes STEM more appealing to everyone. More female characters are shown working collaboratively than male characters (87.3% compared with 83.7%).
- Eight-in-ten (80.3%) STEM characters are shown as using STEM to help others rather than for self-interest, which is particularly appealing to girls and women. More female characters are shown helping others with STEM (83.2% compared with 77.4%).
- Female STEM characters are more likely to be depicted as physically attractive as male characters (31.5% compared with 15.2%) and more are shown in revealing clothing (1.8% compared with 0.0%).

- Only 7.8% of episodes have at least one STEM trope. The most common tropes are the STEM Smurfette, where one female STEM character is depicted in a group of male STEM characters (5.1% of episodes) and the Overly Confident Male STEM character (5.1% of episodes).

## DIVERSITY

- People of color are well-represented as STEM characters in family television compared to the UK population (28.6% compared with 12.9%).
- STEM female characters of color are even better represented (33.5%) compared to the UK population, which sends a clear message that STEM is for everyone.
- Compared to the UK population, STEM characters are vastly underrepresented when it comes to LGBTQ+ individuals, people with disabilities, adults ages 50+, and people with large body types.

## UK & US

- The percentage of female STEM characters is roughly equal in the US and UK (39.3% and 37.1%, respectively).
- The number of female STEM leads is much higher in the UK compared to the US (32.9% compared to 7.5%).
- Female STEM characters in US content are significantly more likely to be shown sacrificing their personal lives for work than STEM characters in the UK (42.9% compared with 5.5%).
- Female STEM characters in the US are twice as likely to be shown as leaders (50.0% compared with 25.0%).
- A greater percentage of female STEM characters in the UK are shown working collaboratively (87.3% compared with 64.0%) and helping others (83.2% compared with 64.0%) than female STEM characters in the US.

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# FULL REPORT

In the UK, the number of women in science, technology, engineering, and mathematics (STEM) has increased rapidly in recent decades, but women remain underrepresented in most STEM professions.<sup>2</sup> Today, only one-in-four (26%) STEM university majors are women, and only one-in-five (22%) STEM professionals are women.<sup>3</sup>

The purpose of this report is to understand the role that entertainment media in the UK contributes to encouraging and discouraging girls from pursuing STEM. More specifically, we are interested in knowing whether girls, boys, and gender non-conforming kids are seeing female characters equally represented in STEM activities and professions in their favorite films and TV shows. We also want to know whether female STEM characters are represented in ways that encourage girls to go into these professions rather than as negative stereotypes.

We begin this report with a review of previous studies on gender disparities in STEM— what we already know. Then we discuss the methodology of our study, followed by a presentation of the findings. We end this report with recommended interventions for parents and content creators who play key roles in whether girls go into STEM.

## PREVIOUS STUDIES

Previous research on the gender gap in STEM has identified a “leaky pipeline” where girls and women leave STEM at key “joints” in the pipeline— during childhood, in school, and in STEM professions.<sup>4</sup> In this section, we examine previous studies on the pipeline, as well as the role that media play in discouraging girls from pursuing STEM.

### THE LEAKY PIPELINE

#### *Childhood Bias*

From a very young age, girls and boys are given different messages about STEM. They start life with similar levels of interest in STEM-related activities, but parents provide sons more encouragement to engage in STEM activities than daughters.<sup>5</sup> Parents of boys are far more likely to discuss STEM careers with their sons than parents of daughters (70% compared with 50%).<sup>6</sup> This disparity in STEM encouragement means boys have more opportunities to discover an interest in STEM. Even though girls in the UK outperform boys in maths throughout primary school,<sup>7</sup> a significant gender gap emerges in early adolescence due to years of boys receiving more early encouragement and opportunities for STEM.<sup>8</sup>

#### *Educational Bias*

By the time they reach secondary school, boys have a significantly higher interest in STEM than girls.<sup>9</sup> High school girls and boys have similar

STEM scores in courses and standardized tests, but the overall proportion of girls in STEM drops off at “A” level.<sup>10</sup> At the university level, men pursue STEM degrees at much higher rates than women.<sup>11</sup> Currently, only 26% of STEM university graduates are women.<sup>12</sup> The biggest gender gaps are found in computer science (81% compared with 19%), engineering and technology (81% compared with 19%), with smaller (but still significant) gaps in maths (63% compared with 37%) and the physical sciences (61% compared with 39%).

#### *Professional Bias*

Fewer women pursue careers in STEM than men. According to the Office for National Statistics Labour Force Survey, only 22% of STEM professionals are women.<sup>13</sup> This is a 1% drop from the previous year, which means that women’s STEM advancements in recent years appear to have stalled. Women are especially missing in engineering (12%) and Information Technology (16%) but are better represented in science (43%).<sup>14</sup> When it comes to leadership,

men in STEM are far more likely to advance to leadership positions than women, even in fields with roughly equal numbers of men and women.<sup>15</sup> Only one-in-ten STEM managers are women (10.2%). About one-in-ten (9.0%) STEM business owners are women.<sup>16</sup>

## MEDIA MATTERS

Research from the past decade definitively concludes that gender differences in ability do not account for the gender gap in STEM.<sup>17</sup>

So what does account for the attrition of girls and women at each joint in the leaky pipeline? We know that parents and educators are more likely to encourage male students to pursue STEM, and that women in STEM face gendered obstacles to success in the field. We also know that stereotypes—transmitted from parents, educators, and media—play a role in the STEM gender gap.

More broadly, media profoundly affects an individual's attitudes, behaviors, and beliefs. Albert Bandura's work finds that individuals model their behavior based on the behavior of others, including fictional media characters.<sup>18</sup> Even when viewers are not conscious of the effects, fictional characters engage in behaviors that subtly encourage and discourage activities, professions, and life paths.

Girls are discouraged from pursuing STEM through media stereotypes that define science as primarily a pursuit for men.<sup>19</sup> Media often reinforce the stereotype of the lone, nerdy scientist in a lab coat, mostly portrayed as an awkward white man<sup>20</sup> or a "mad scientist."<sup>21</sup> The white, male scientist is pervasive. In the classic 1983 "Draw a Scientist" study, children drew only 28 "scientists" as women out of 5,000! The vast majority of boys and girls continue to draw male scientists in this study today.<sup>22</sup>

Previous studies have documented the effect of STEM stereotypes. High school girls who associate "men" with "maths" are less likely to be interested in STEM,<sup>23</sup> and women who pair "men" with "maths" have more negative perceptions of STEM.<sup>24</sup> Kids perceive of men as being better at science than women,<sup>25</sup> and young women internalize stereotypes and see themselves as less competent in maths than

men.<sup>26</sup> In short, girls and women internalize the stereotype of STEM as being for men, and this, coupled with experiences of gender bias from parents, educators, and others, discourages many from pursuing a STEM career.<sup>27</sup>

Different forms of media reinforce the stereotype that STEM is mostly for men. For example, a recent study of the two top-circulated science publications in the UK, *Science* and *Nature*, finds that only 15% of authors and 27% of featured scientists are women.<sup>28</sup>

When it comes to entertainment media, the Geena Davis Institute on Gender in Media conducted the first large-scale study of gender and stereotypes about STEM in entertainment media in 2018. This study focused solely on US media. We found that:

- Male STEM characters outnumbered female STEM characters two-to-one (62.9% compared with 37.1%). This has not improved in the past decade.
- Fewer women STEM characters were portrayed as physical scientists (6.4% compared to 11.8%), engineers (2.4% compared to 13.7%), or in computer occupations (8.6% compared to 11.5%) than men STEM characters.
- Entertainment media sends the message to girls and young women that they will have to sacrifice their personal and family life if they go into a STEM profession. Nearly 43% of STEM characters were shown as sacrificing their personal life to work in STEM.

We found that media can also play a positive role in encouraging girls and women to pursue STEM professions:

- Women were just as likely to be portrayed as leaders in a STEM profession as men, which normalizes women's leadership.
- Nearly four-in-five girls and young women in junior high, high school, and college (82.7%) said it was important to see women STEM characters in film and television.
- Most girls and women who plan to pursue STEM said that popular STEM characters in entertainment media inspired them to pursue a STEM major or career.

This study builds upon the US study by extending the analysis to family entertainment content in the UK.

# METHODOLOGY

We begin this section with an overview of how we generated our unique sample. We then describe the two methods we used for analysis: automated machine coding and expert human content analysis.

## THE SAMPLE

We analyzed STEM characters in the most-watched streaming television/cable and original content family programs in the UK from October 2019 to October 2020. While our initial study design included a separate analysis television/cable and film, we made the decision to only analyze streaming content (which includes some films) given the popularity of streaming content during the pandemic and the closure of most movie theaters. Our sample therefore includes the most-watched content from the past year, a good measure of media that kids saw the most.

To locate STEM characters, we first generated a list of the 100 most-streamed shows. We then excluded shows that did not feature leading or supporting STEM characters. Leading and supporting characters are those featured prominently in more than one scene and integral to the plot. We started with an overall list of 2,803 episodes containing STEM characters. From there, we generated a representative, random sample with a +3% confidence interval at the 95% level. Our final TV/cable sample included 996 STEM characters from 254 episodes. We report gender gaps in STEM representations that are significant at the .05 level throughout this report.

## AUTOMATED CONTENT ANALYSIS

For the automated analysis in this report, we used the Geena Davis Inclusion Quotient (GD-IQ), a revolutionary automatic audio-visual tool—the first of its kind developed specifically to analyze media content—that took a team of engineers and social scientists two years to develop. Automated analysis of media content gets around some of the limitations of human coding. Beyond the significant advantage of being able to efficiently analyze more episodes in less time with minimal human labor, this tool can also calculate content with a level of accuracy not possible with human review. For this report, we measured on-screen time by partitioning the episode into shots and detecting the gender of the person in each shot. We then calculated total screen time by gender. We measured speaking time by partitioning the episode into shots and applying an automatic speech detection program that classifies speaker gender. For more information about this automated processing tool, see Appendix A.

## EXPERT HUMAN CONTENT ANALYSIS

A trained team of eleven researchers analyzed these characters in the top-rated television, cable, and streaming shows. Prior to initiating the work, the research team engaged in a total of 36 hours of training that included codebook development and tests to measure inter-rater reliability. Initial inter-rater reliability tests were performed on characters in a popular STEM show to ensure that agreement was reached on each of the variables being measured. Inter-rater reliability was achieved in terms of both absolute agreement (.88) and the interclass correlation coefficient (.76).



# FINDINGS

We begin this section with a STEM character profile to get a better sense of what child viewers are seeing when they watch shows featuring their favorite STEM characters. The second part of this section is a deep dive into gender and STEM representations, and the last section compares media representations in the US and the UK.

## STEM CHARACTER PROFILE

STEM characters in this study are defined as those in a STEM profession (e.g., a chemistry professor), a student in a STEM class (e.g., a junior high biology class), or a character engaged in sustained STEM activities (e.g., building a rocket).

As shown in Table 1, there are more supporting STEM characters in streaming content than leading characters. Also, it is more common for characters to be engaged in STEM activities than to be in a formal STEM profession or a STEM student. Many characters in family streaming content are child characters who are not yet in a profession.

In terms of diversity in STEM character representations, family television content under-represents women, people with disabilities, characters ages 50+, and characters with large body types as compared with the broader UK population. We unpack these representations further below.

### *Race/Ethnicity & Skin Tone*

People of color constitute 12.9% of the UK population, so the fact that 28.6% of STEM characters are characters of color sends a positive message to kids that STEM is for everyone. Black STEM characters are the best represented (11.6%) followed by South Asian (7.4%), Latinx (6.9%), and Asian (2.7%) STEM characters.

We also measured character skin tone using a five-point scale ranging from light tones, medium-light tones to medium tones, medium-dark tones, and dark tones. Two-thirds of the STEM characters kids see in their favorite shows are light (39.6%) and medium-light (34.1%) tones. Few STEM characters (15.9%) have medium-dark or dark skin tones.

**TABLE 1**  
TYPES OF STEM CHARACTERS

STEM Character Type	% of Characters
Lead Character in a STEM Profession/Student	13.4%
Lead Character engaged in a STEM activity	21.3%
Supporting Character in a STEM Profession/Student	27.9%
Supporting Character engaged in a STEM activity	37.4%

**TABLE 2**  
STEM CHARACTER PROFILE

Identity Group	% of Characters	% of UK Population
Girls/Women	39.3%	50.6%
People of Color	28.6%	12.9%
LGBTQ+	0.0%	2.0%
People with Disabilities	2.1%	18.0%
People Ages 50+	4.9%	25.4%
People with Large Body Types	3.0%	28.7%

**TABLE 3**  
STEM CHARACTER RACE/ETHNICITY

Race/Ethnicity	% of Characters
White	71.4%
Black	11.6%
South Asian	7.4%
Latinx	6.9%
Asian	2.7%

**TABLE 4**  
STEM CHARACTERS BY SKIN TONE

Skin Tone	% of Characters
Light Tones 🖐️	39.6%
Medium-Light Tones 🖐️	34.1%
Medium Tones 🖐️	10.4%
Medium-Dark Tones 🖐️	7.8%
Dark Tones 🖐️	8.1%

### STEM Characters with Disabilities

Only 2.1% of STEM characters have a physical, communication, or cognitive disability compared to 18.0% of the broader UK population. It is worth noting that all the STEM characters depicted with disabilities were shown with a physical disability (e.g., using a wheelchair). This means that STEM characters with communication disabilities (e.g., deafness) or cognitive disabilities (e.g., a character on the Autism Spectrum) are mostly missing in the most popular kid’s TV shows in the UK.

### STEM Character & Age

Kids receive both positive and negative messages when it comes to age and STEM depictions. As shown in Table 5, most STEM characters (63.1%) are children ages 12 and younger. This is positive because children can see themselves and other children engage in STEM activities. On the other hand, streaming content reinforces ageism with few STEM characters who are 50+. This fits a larger media pattern where older adults are mostly erased in media content.

### STEM Characters with Large Body Types

Only 3.0% of STEM characters have large body types compared to nearly three-in-ten (28.7%) people in the UK. This is consistent with previous research on sizeism that finds that people with large body types are mostly erased in the more popular films and TV shows.

### Types of STEM Work

When it comes to the types of STEM work represented in family TV content, most STEM characters are depicted as working in life sciences (41.8%). About one-in-ten are shown in computer occupations (11.6%) and engineering (11.9%).

Considering how STEM work is depicted, the vast majority (85.7%) are shown working in collaboration with others, which is an accurate portrayal of STEM. Previous research shows this makes STEM work more appealing to everyone.<sup>29</sup>

When it comes to portrayals of motivations for pursuing STEM, 80.3% of characters are shown as working in STEM to help others. Far fewer characters are shown as going into STEM for self-interested reasons (15.7%). Previous research finds that helping others in STEM is more appealing to girls and women than self-interested motivations.<sup>30</sup>

**TABLE 5**  
STEM CHARACTER AGE

Age Group	% of Characters
Child (1-12)	<b>63.1%</b>
Teen (13-19)	<b>6.1%</b>
20s (20-29)	<b>10.9%</b>
30s (30-39)	<b>10.0%</b>
40s (40-49)	<b>5.0%</b>
50s (50-59)	<b>3.8%</b>
60s and Older	<b>1.1%</b>

**TABLE 6**  
STEM JOB TYPES

Job Type	% of Characters
Maths/Science Occupations	<b>3.1%</b>
Architects, Surveyors, & Cartographers	<b>7.8%</b>
STEM Professors	<b>1.0%</b>
Physical Scientists	<b>8.5%</b>
Life Scientists	<b>41.8%</b>
Life/Physical Science Technicians	<b>2.7%</b>
STEM-Related Sales	<b>1.7%</b>
Drafters, Engineering Technicians & Mapping Technicians	<b>9.9%</b>
Engineers	<b>11.9%</b>
Computer Occupations	<b>11.6%</b>

**TABLE 7**  
STEM WORK ALONE & COLLABORATION

Depiction of Work	% of Characters
Mostly Working Alone	<b>11.3%</b>
Mostly Working Collaboratively	<b>85.7%</b>
Equally Alone & Collaboratively	<b>3.0%</b>

**TABLE 8**  
STEM MOTIVATION

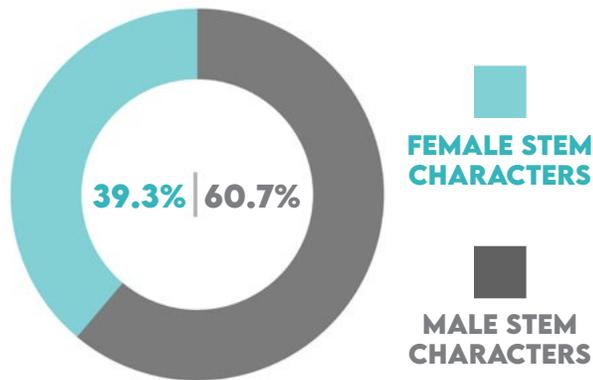
Depiction of Motivation	% of Characters
Mostly Self-Interested	<b>15.7%</b>
Mostly Helping Others	<b>80.3%</b>
Equally Self-Interested & Helping Others	<b>4.0%</b>

# GENDER & STEM REPRESENTATIONS

## Character Prominence

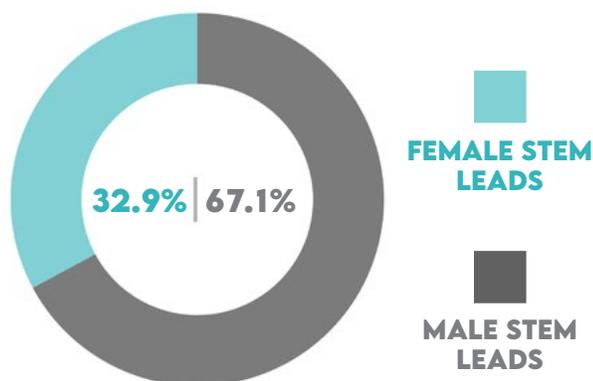
Figure 1 shows that family TV content has a massive gender gap when it comes to STEM. Male STEM characters outnumber female STEM characters nearly two-to-one (60.7% compared with 39.3%).

**FIGURE 1**  
OVERALL STEM CHARACTERS BY GENDER



The gender gap in STEM characters is even larger with leading characters. A vast majority of STEM characters kids see in their favorite shows are men (67.1%). This means that kids get the message that STEM is mostly for boys and men, reinforced by the fact that the most prominent STEM characters are men.

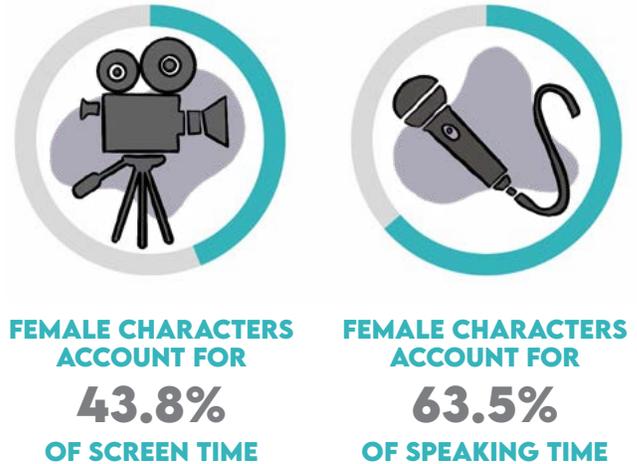
**FIGURE 2**  
LEADING STEM CHARACTERS BY GENDER



We also measured character prominence by the amount of screen time and speaking time characters receive, using our automated GD-IQ technology.<sup>31</sup> Figure 3 shows that female characters receive less screen time in content featuring STEM than male characters, but

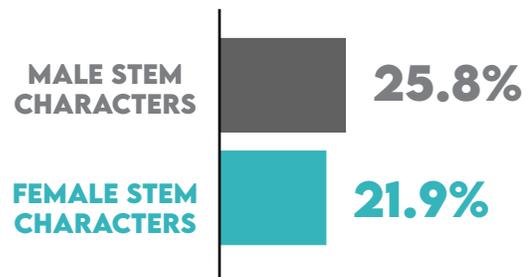
they speak nearly two-thirds of the time. In other words, while female characters in STEM content are not featured on screen as often as male characters, they are carrying more of the dialogue in each episode.

**FIGURE 3**  
SCREEN & SPEAKING TIME BY GENDER



For characters who are children, teens, or young adults, we measured whether they were shown receiving encouragement from parents, teachers, coaches, mentors, or others to pursue STEM. Male characters are more likely to be shown receiving encouragement for STEM, which reinforces the idea that STEM is for boys.

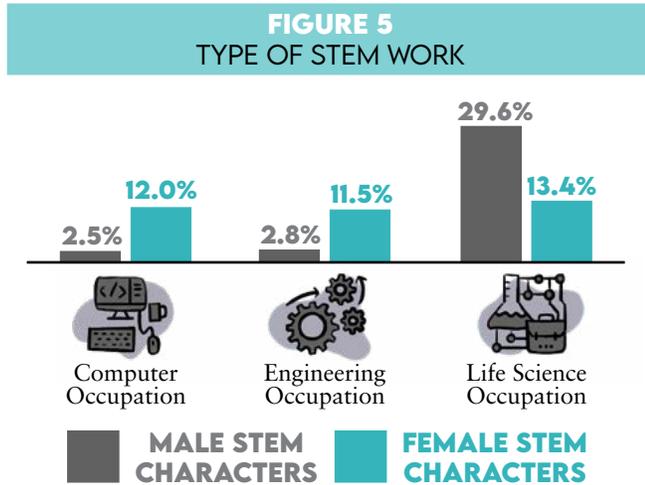
**FIGURE 4**  
ENCOURAGED IN STEM BY GENDER



## Types of STEM Work

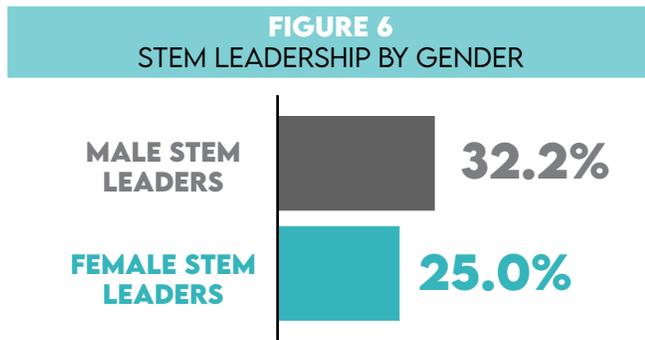
As shown in Figure 5, male STEM characters are more likely to be shown working in life science occupations (29.6% compared with 13.4%) while female characters are more likely to be shown in computer or engineering occupations. Gender gaps are never positive, but their reversals here are positive considering that in the real world, women are better represented in the

ranks of life sciences and less so in computer occupations and engineering.

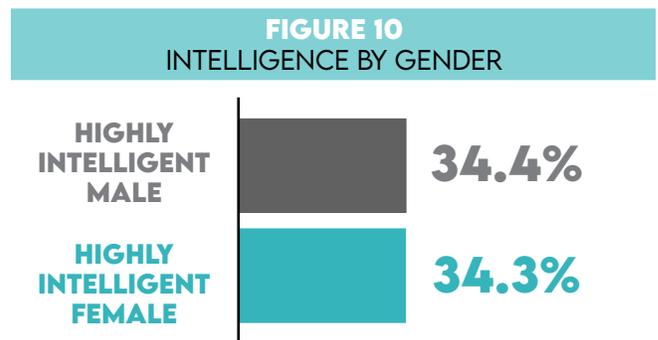
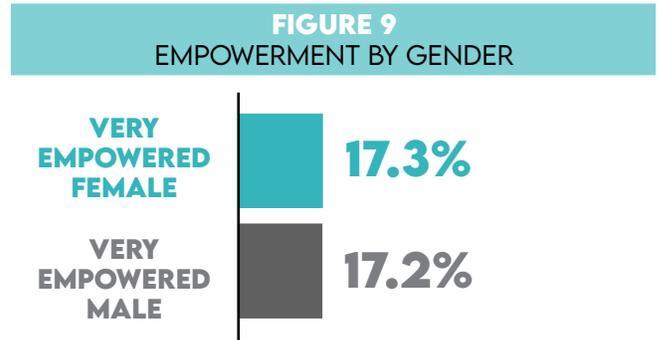
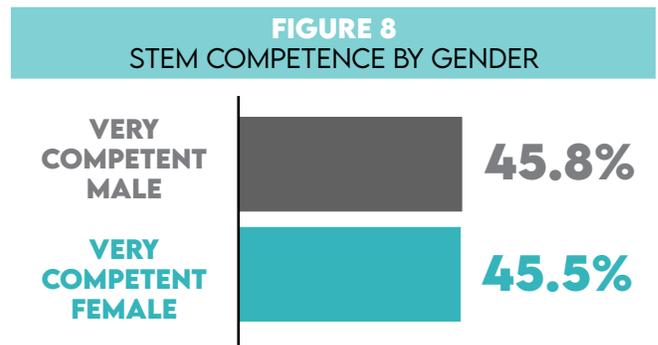
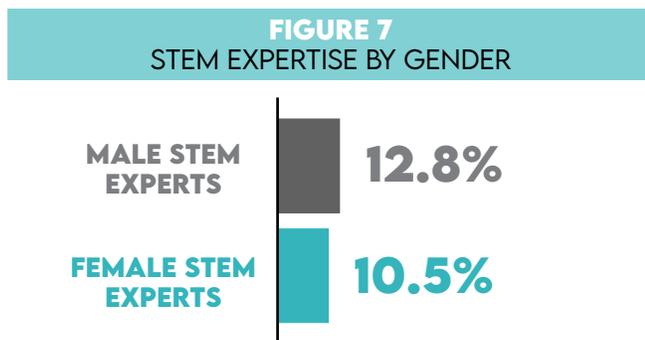


**STEM Leadership & Expertise**

Male characters are significantly more likely to be shown as STEM leaders than female characters. One-in-three (32.2%) male STEM characters are shown as leaders compared to one-in-four (25.0%) female STEM leaders.

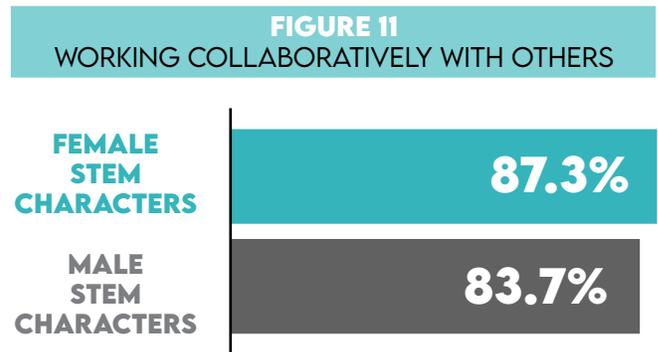


No gender differences are found with STEM expertise, STEM competence, or level of empowerment or intelligence by gender. This means that while more male STEM characters are leaders, men and women in STEM are equally likely to be shown as experts in STEM, competent in STEM, empowered in their STEM role, and highly intelligent.



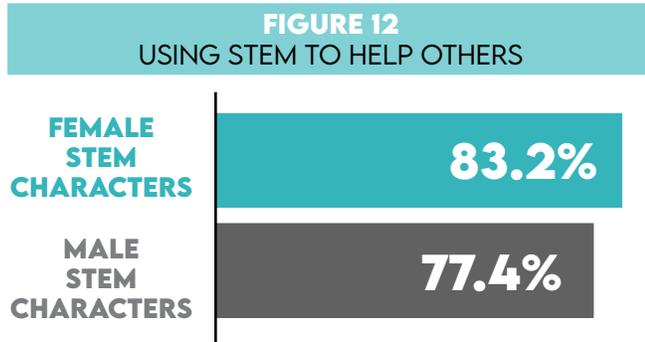
**STEM Work Arrangements**

Some gender differences are found in STEM work styles and motivations. While most characters are shown work collaboratively in STEM rather than working alone, female characters are significantly more likely to work collaboratively (87.3% compared with 83.7%).

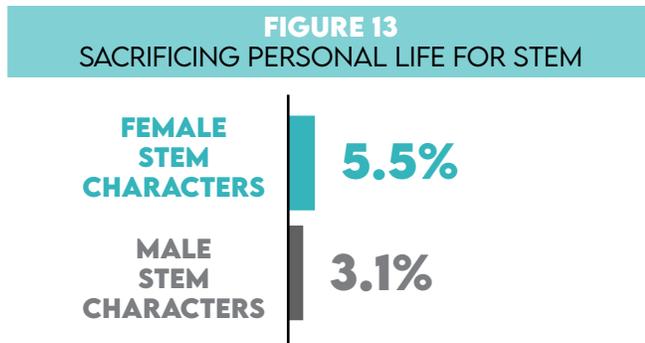


Female STEM characters are also more likely to be depicted as using STEM to help others

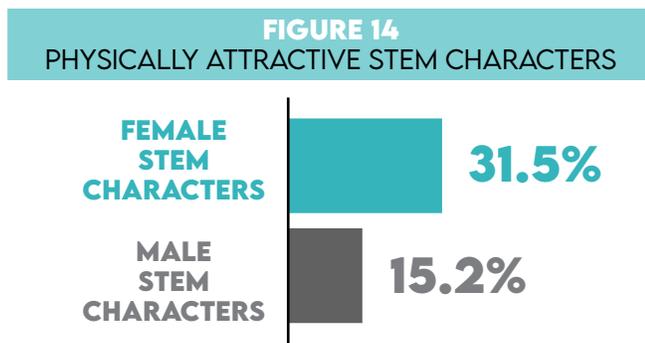
instead of for self-interest (83.2% compared with 77.4%).



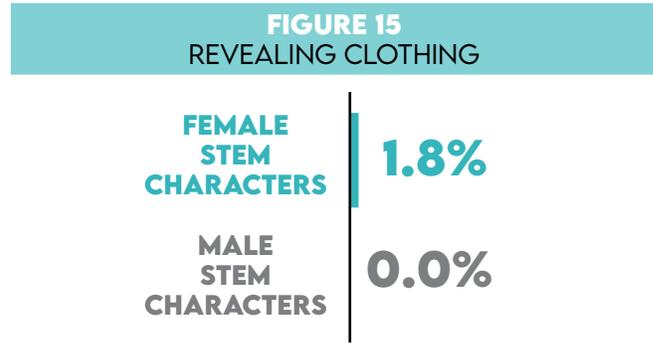
Few STEM characters are shown sacrificing their personal lives for their career, and male and female characters are about equally likely to do so.



**STEM Character Appearance & Sexualization**  
 Female STEM characters are twice as likely to be depicted as physically attractive as male characters (31.5% compared to 15.2%). In fact, one-in-three female STEM characters are shown as “better than average looking” or “stunning.” Additionally, male STEM characters are nearly twice as likely to be shown as “worse than average looking” (9.6% compared with 5.5%).



No male characters are shown in revealing clothing, while 1.8% of female STEM characters are shown in revealing clothing.



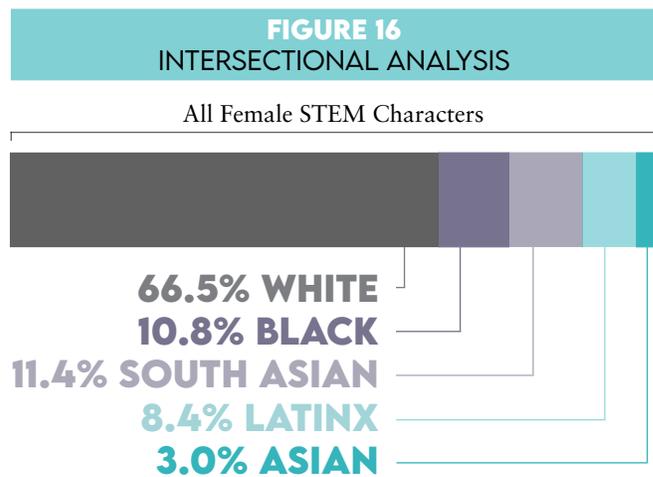
**Tropes & Stereotypes**

We examined whether characters are reduced to STEM stereotypes in family streaming content. We measured a series of tropes (characters who embody stereotypes) and stereotypes (moments where a character is stereotyped). We find that only 7.8% of episodes have at least one STEM trope and 7.1% have at least one STEM stereotype. This means that most STEM characters in family TV content are presented with nuance and complexity.

The most common tropes are the STEM Smurfette where one female STEM character is depicted in a group of male STEM characters (5.1% of episodes) and the Overly Confident Male STEM character (5.1% of episodes).

**Intersectional Representations**

STEM characters of color are well-represented in family TV shows (28.6% of characters compared with 12.9% of the UK population). Women of color are even better represented at 33.5%. In other words, one-in-three female STEM characters are girls and women of color, which sends a clear message that STEM is for everyone.



# REPRESENTATION TESTS

Beyond STEM representations, we measured the overall presence of traditionally under-represented groups in family TV content using basic tests for each identity:

## *The See Jane Test (Gender)*

1. At least one prominent character (leading, co-leading, supporting character) who is a woman who;
2. Is not depicted with gender stereotypes or tropes.

## *The Sidney Poitier Test (Race/Ethnicity)*

1. At least one prominent character (leading, co-leading, supporting character) who is a character of color who;
2. Is not depicted with race/ethnicity stereotypes or tropes.

## *The Vito-Russo Test (LGBTQ+)*

1. The film must contain a character that is identifiably lesbian, gay, bisexual, transgender, and/or queer.
2. That character must not be solely or predominantly defined by their sexual orientation or gender identity (i.e. they are comprised of the same sort of unique character traits commonly used to differentiate straight/non-transgender characters from one another).
3. The LGBTQ character must be tied into the plot in such a way that their removal would have a significant effect, meaning they are

not there to simply provide colorful commentary, paint urban authenticity, or (perhaps most commonly) set up a punchline. The character must matter.

## *The Marlee Matlin Test (Disability)*

1. At least one prominent character (leading, co-leading, supporting character) with a physical, cognitive, or communication disability who;
2. Is not depicted with disability stereotypes or tropes.

## *The Betty White Test (Age)*

1. At least one prominent character (leading, co-leading, supporting character) who is 50+ who;
2. Is not depicted with age stereotypes or tropes.

## *The Cooper Test (Body Size)*

1. At least one prominent character (leading, co-leading, supporting character) with a large body type who;
2. Is not depicted with size stereotypes or tropes.

As shown in Table 9, few episodes of the top family streaming content in the UK pass these representation tests. Nearly half (44.9%) of episodes pass the Sidney Poitier Test for race/ethnicity, but far fewer episodes pass the other tests, despite the low bar that the episode include at least one character of that identity who is not depicted as a stereotype or trope.

**TABLE 9**  
REPRESENTATION TESTS

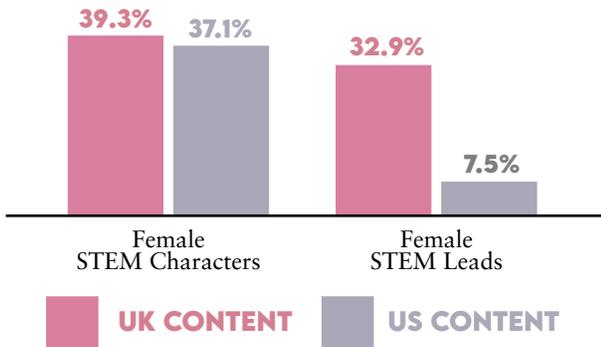
Test Name	Identity Group	% of Passing Episodes
See Jane Test	Gender	96.1%
Sidney Poitier Test	Race	44.9%
Marlee Matlin Test	Disability	13.8%
Betty White Test	Age (50+)	10.2%
Cooper Test	Body Size	3.5%
Vito Russo Test	LGBTQ+	0.8%

# US VERSUS UK STEM REPRESENTATIONS

In this section, we compare STEM representations in the US and the UK.<sup>32</sup>

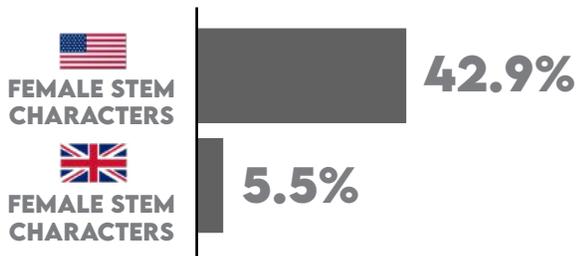
- The percentage of female STEM characters is roughly equal, but the number of female STEM leads is much higher in the UK compared to the US.

**FIGURE 17**  
PROMINENCE BY GENDER, US VERSUS UK



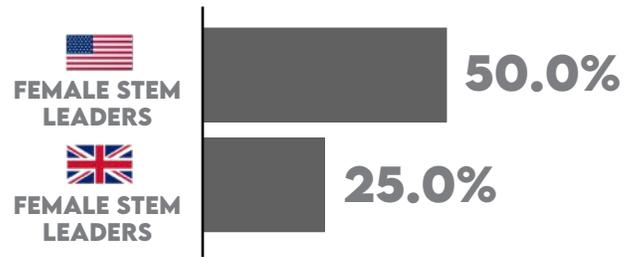
- Female STEM characters in US content are far more likely to be depicted sacrificing their personal lives for work than in the UK (42.9% compared with 5.5%).

**FIGURE 18**  
SACRIFICING PERSONAL LIFE, US VERSUS UK



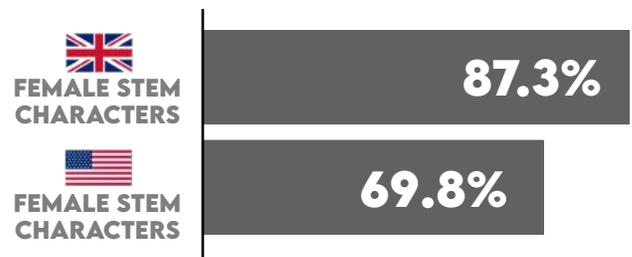
- Female STEM characters in the US are twice as likely to be shown as leaders (50.0% compared with 25.0%).

**FIGURE 19**  
STEM LEADERSHIP, US VERSUS UK



- A greater percentage of female STEM characters in the UK are shown working collaboratively and helping others with STEM than female characters in the US.

**FIGURE 20**  
WORKING COLLABORATIVELY, US VERSUS UK



**FIGURE 21**  
USING STEM TO HELP, US VERSUS UK



# INTERVENTIONS

Based on previous research coupled with our findings, we propose the following interventions to increase the participation of girls and women in STEM majors and careers in the UK:

## ACTION STEPS FOR PARENTS

- Encourage girls to pursue STEM activities and studies. Don't wait for them to tell you that they have an interest; cultivate it!
- Engage in childhood STEM activities with your daughter(s), such as playing with blocks, Legos, and other construction toys, playing board games, and coding video games.
- Make a point to watch content that features girls and women in STEM, especially shows with girls and women of color.
- Provide STEM role models for your daughter(s), whether they are real life STEM professionals or STEM characters in popular films or television.
- Openly challenge gendered stereotypes about STEM being a male pursuit with your daughter(s) any time you see them come up (in conversations, media, etc.).

## ACTION STEPS FOR CONTENT CREATORS

- Continue to write/cast projects with prominent STEM characters of color.
- Continue to write female STEM characters as competent, intelligent, empowered, working collaboratively, and using STEM to help others rather than for self-interest.
- Cast/write more female characters in STEM professions and engaging in STEM activities. Cultivate girls' interest in maths and science from an early age through media role models!
- Cast/write more female STEM characters as leaders.
- Cast/write more projects that depict parents, teachers, and others encouraging girl characters in their STEM pursuits.
- Make a point to write/cast female characters across a variety of STEM occupations.
- Write/cast projects that avoid the cliché of girls and women as sex objects. Let female STEM characters be all different ages, body sizes, levels of attractiveness, etc.
- Write/cast projects that bust STEM stereotypes.
- Write/cast more projects that represent diversity in STEM characters when it comes to LGBTQ+ individuals, people with disabilities, adults ages 50+, and people with large body types. Greater diversity of STEM characters means more people will be inspired because they see themselves represented.



# APPENDIX A

The GD-IQ was funded by Google.org. Incorporating Google’s machine learning technology and the University of Southern California’s audio-visual processing technologies, this tool was co-developed by the Institute and led by Dr. Shrikanth (Shri) Narayanan and his team of researchers at the University of Southern California’s Signal Analysis and Interpretation Laboratory (SAIL), along with Dr. Caroline Heldman.

To date, most research investigations of media representations have been done manually. The GD-IQ revolutionizes this approach by using automated analysis, which is not only more precise, but makes it possible for researchers to quickly analyze massive amounts of data, which allows findings to be reported in real time. Additionally, the GD-IQ allows for more accurate analysis, and because the tool is automated, comparisons across data sets and researchers are possible, as is reproducibility. Automated analysis of media content gets around the limitations of human coding. Beyond the significant advantage of being able to efficiently analyze more films in less time, the GD-IQ can also calculate content detail with a level of accuracy that eludes human coders. This is especially true for factors such as screen and speaking time, where near exact precision is possible. Algorithms are a set of rules of calculations that are used in problem-solving. For this report, we employed two automated algorithms that measure screen time by gender and race and speaking time of characters by their gender. Here is an overview of the procedures we used for each algorithm.

## SCREEN TIME ANALYSIS

We compute the screen time of female characters by calculating the ratio of female faces to the total number of faces in the film’s visuals. The screen time is calculated using online face detection and tracking with tools provided by Google’s machine learning technology. In the interest of precision and time, we estimate screen time by computing statistics over face-tracks (boxes tracking the general outline of each face) instead of individual faces. The face-tracks returned by technology include different attributes of the face with the corresponding time of occurrence in the video. Among the attributes returned for each of the detected faces, we use two parameters are confidence of the detected face and the system’s posterior probability for gender prediction. A threshold of 0.25 was empirically chosen for determining confident face detection.

Due to multiple characters appearing on screen simultaneously, the face-tracks can be overlapping. A gender label is then assigned to each track using the average gender posterior associated with the confident faces in the track. If the average gender posterior probability of the track is greater than 0.5, the track is classified as a “female track,” otherwise, it is a “male track.” The number of frames with confident face detections in each track is summed up across all tracks to get the total number of faces. The number of female tracks is aggregated to get the total number of faces predicted as female. Finally, the screen time is computed as the ratio between the number of female face detections to the total number of face detections across the length of the movie.

Supplementary analysis shows that screen time estimated at frame-level (individual faces) instead of using face-tracks was not significantly different and was comparable. Furthermore, computing the average of gender posterior over tracks has an added benefit of “smoothing out” some of the local gender prediction errors. Face-tracking incorporates temporal contiguity information to reduce transient errors in gender prediction that may occur with analyzing individual faces independently. We performed a similar analysis for character race and screen time.

# SPEAKING TIME ANALYSIS

Using movie audio, we compute the speaking time of male and female characters to obtain an objective indicator of gender representation. The algorithm for performing this analysis involves automatic voice activity detection, audio segmentation, and gender classification.

## *Voice Activity Detection:*

Movie audio typically contains many non-speech regions, including sound effects, background music, and silence. The first step is to eliminate non-speech regions from the audio using voice activity detection (VAD) and retain only speech segments. We used a recurrent neural network based VAD algorithm implemented in the open-source toolkit OpenSMILE to isolate speech segments.

## *Segmentation:*

We then break speech segments into smaller sections to ensure each segment includes speech from only one speaker. This is performed using an algorithm based on Bayes Information Criterion (BIC), available in the KALDI toolkit. Thirteen-dimensional Mel Frequency Cepstral Coefficient (MFCC) features are used for the automatic speaker segmentation. This step essentially decomposes continuous speech segments obtained in the VAD step into smaller segments to make sure no segment contains speech from two different speakers.

## *Gender Classification:*

The speech segment is then classified into two categories based on whether it was likely spoken by a male or female character. This is accomplished with acoustic feature extraction and feature normalization.

## *Acoustic Feature Extraction:*

We use thirteen dimensional MFCC features for gender classification because they can be reliably extracted from movie audio, unlike pitch or other high-level features where extraction is made unreliable by the diverse and noisy nature of movie audio.

## *Feature Normalization:*

Feature normalization is deemed necessary to address the issue of variability of speech across different movies and speakers, and to reduce the effect of noise present in the audio channel. Cepstral Mean Normalization (CMN) is a standard technique popular in Automatic Speech Recognition (ASR) and other speech technology applications. Using this method, the cepstral coefficients are linearly transformed to have the same segmental statistics (zero mean). Classification of the speaker as either male or female is based on gender-specific Gaussian mixture models (GMMs) of the acoustic features. These models are trained on a gender-annotated subset of general speech databases used for developing speech technologies using frame-level features for each gender. The GMM we use in this system has 100 mixture components and is optimized by tuning the parameters in a held-out evaluation set. For a new input segment whose gender label is to be predicted, the likelihoods of the segment belonging to a male or female class are computed based on this pre-trained model. The class with higher likelihood is assigned to the segment as the estimated gender prediction. The total speaking time by gender is then computed by adding together the durations for each utterance classified as Male/Female. This gives us the male and female speaking time in a movie.



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31. This technology cannot be applied to animated content, so the findings here are based on 62 live-action episodes.
32. Some of the differences here may be due to differences in sample—family content in the UK versus overall content in the US, and the fact that the US sample includes film in addition to television and streaming (which was not available during the pandemic for the UK sample).

## HOW TO CITE THIS STUDY

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