Cracking the Code:
The Prevalence and Nature of Computer Science Depictions in Media

Executive Summary

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PREFACE

GOOGLE CS IN MEDIA TEAM

Computer Science (CS) in Media was born out of Google's research that perceptions of CS account for 27% of a girl's desire to go into the field. This is second only to adult encouragement to explore CS, which is *also* influenced by perceptions of what the career is and who does it. To inform the public about CS and inspire a new, inclusive vision of CS, our team set out to influence and create new content in a highly fragmented media landscape. We were inspired by the "*CSI effect*." Five years after the premiere of the original CSI television series, forensic science majors in the U.S. increased by 50%, with an over index of women. This has been ascribed to the presence of female lead characters. More recently, the Geena Davis Institute found a 50% increase in U.S. girls pursuing archery since the release of *The Hunger Games* and *Brave* in 2012. Seventy percent of girls in their survey attributed their interest in the sport to one of the two female protagonists.

We began the process with several phone calls to individuals who were champions of diversity and inclusion around Hollywood. With the backing of Megan Smith, those initial calls led to presentations on the lack of representation in CS to Disney Channel, Freeform (then ABC Family) and other networks. Those calls also led us to HBO and our early work with *Silicon Valley*. These original interventions are the focus of this research study.

The Google CS in Media team has worked directly with several shows. For our work with *Miles from Tomorrowland*, *The Fosters*, *Silicon Valley*, *The Powerpuff Girls* and *Ready, Jet, Go*, we either brought the show's writing and producing staffs to Google or brought Google to them. This work included tailored campus visit meetings with a diverse group of our engineers to "speed dating"-style events where our engineers shared their experiences and expertise in 7 minute chunks. For other shows, we provide phone or email feedback—a "lighter touch" where our engineers are on-call to answer specific questions or converse on specific topics.

In the case of certain series, we provided on-going advisement. *The Fosters*, *Miles from Tomorrowland*, *Halt and Catch Fire*, *Ready, Jet, Go*, *The Powerpuff Girls* and *Odd Squad* are examples of this. In addition to our continuing interactions, we engaged in extensive PR and marketing support including social media outreach, events and press. For programs we advised briefly, such as *Silicon Valley*, TV series *Stitchers*, and two Disney Channel films, we offered little to no additional PR or marketing support.

The 10 shows assessed in this study represent only our first year of work in television. Since we began this work, we've also invested in film development, including a project about the inventor of programming language, Ada Lovelace, and 3 scripts in partnership with *The Black List*. We've held several partnerships and events with major motion pictures including Fox's *Hidden Figures*, and WB's *Storks*, which has led to further studio partnership interest. Also, we've advised on several episodic shows or TV movies since this evaluation began. These have both in-depth and light touch projects, including FOX's *Empire*, Netflix's *Project MC2*, Netflix's *Coin Heist*, Cartoon Network's *The Amazing World of Gumball*, and Amazon's *Gortimer Gibbons Life on Normal Street*. On the digital side, we've launched an original YouTube series, *GodComplX*, starring YouTube influencer Shameless Maya and helped fund 58 web episodes across 13 different creators for the YouTube Women's Initiative. We also premiered a full length feature documentary, *Code Girl*, on YouTube. The film has reached almost 1M people and 100K teen girls watched the film in its entirety.

Combining all the content the CS in Media Team has touched, we have reached over 100M viewers, plus 1.6B+ impressions through marketing and social channels. The evaluation presented here only covers our first year. Additionally, many of the recommendations listed here have already begun to be implemented organically. We are excited to continue on our path as there is so much work left to be done.

KEY FINDINGS SUMMARY

The purpose of the present investigation is to evaluate the impact of the Google CS in Media intervention. The study employs both quantitative and qualitative methods to assess media content as well as including in depth interviews with content creators who participated in the intervention. Five samples of television and film were examined. These included: content influenced by Google, a matched sample of content, series popular with adults 18-49 (prime time), series popular with viewers age 2-12 (total day), and popular films from 2015. Additionally, a pre and post assessment of the frequency and nature of computer science in three Google influenced programs: *Silicon Valley*, *Halt and Catch Fire*, and *The Fosters* was conducted.

Depictions of computer science are still rare in both popular programming and series influenced by Google.

- In the Google influenced and non-Google influenced samples, a total of 3.4% (*n*=65) of characters were depicted talking about or engaging in computer science. The sample of Google influenced content (5.9%, *n*=61 of 1,039) had a higher percentage of characters engaging in computer science than a matched sample of programming (.5%, *n*=4 of 883).
- Of 2,138 speaking characters evaluated, a total of 46 (2.2%) engaged in computer science across three samples of popular media (20 series popular with viewers age 18 to 49, 20 series popular with viewers age 2 to 12, and 20 top-grossing films from 2015).

Demographically, ***the profile of computer science characters is still skewed in favor of White males***. Viewers would need to watch a great deal of entertainment content before seeing a female using CS—especially if looking for depictions of underrepresented females.

- In the Google influenced content, 24.6% (*n*=15) of CS characters were female, and 75.4% (*n*=46) were male. This is a ratio of 3.1 males to every 1 female CS character.
- Slightly more than two-thirds (67.2%, *n*=39) of CS characters in the Google influenced content were White, 17.2% (*n*=10) were Asian, and 15.5% (*n*=9) were from underrepresented racial/ethnic groups.
- The sample of non-Google influenced content contained no females or characters from underrepresented racial/ethnic groups engaging in CS.
- Prime time series (38.1%, *n*=8) featured a greater percentage of females in CS than did popular films (15%, *n*=3. Although series popular with 2- to 12-year-olds had the greatest percentage of female CS characters (40%, *n*=2), this small sample size should be interpreted cautiously. Despite this, in each sample, male CS characters still outnumbered female CS characters (prime time=61.9%, *n*=13; total day=60%, *n*=3; film=85%, *n*=17).
- Popular prime time series (28.6%, *n*=6) and films (23.5%, *n*=4) showcase a percentage of underrepresented characters in CS higher than what is seen in the Google influenced content. Once again, series popular with 2- to 12-year-olds have the highest share of underrepresented CS characters (50%, *n*=2), but the smallest sample size.

Portrayals of computer science in film and television continue to reflect a view of the field that is rooted in stereotypes. This includes showcasing few CS characters who are referenced as attractive, shown in romantic or parental relationships, or who state prosocial goals for CS use. In the Google influenced sample, 62.3% of CS characters (*n*=38 of 61) were shown in stereotypical attire versus 75% (*n*=3) of the CS characters in the match sample. Nearly half of CS characters were shown in stereotypical attire in the combined samples of popular content (45.7%, *n*=21).

Tech-focused and non-tech focused series can be targeted for CS interventions. In Google-influenced content, CS characters primarily appear in tech-focused series. Among the Google influenced content, 51 CS characters were in tech driven narratives and 10 CS characters were not.

In the sample of non-Google influenced content, all of the CS characters were featured in non-tech stories. In the samples of popular media, CS characters were more likely to appear in shows and movies that did *not* feature a technology-oriented theme (80.4%, *n*=37) than those that did (19.6%, *n*=9).

EXECUTIVE SUMMARY

The purpose of the present investigation is to evaluate the impact of the Google CS in Media intervention. The study employs both quantitative and qualitative methods to assess media content and includes in depth interviews with content creators who participated in the intervention. Consequently, this analysis focuses not only on *stories* but also the perceived impact Google is having on *storytellers* in entertainment. Five samples of television and film were examined. These included: (1) content influenced by Google; (2) a matched sample of content; (3) series popular with adults 18-49 (prime time); (4) series popular with viewers age 2-12 (total day); and (5) popular films from 2015. Additionally, a pre and post assessment of the frequency and nature of computer science in three Google influenced programs: *Silicon Valley*, *Halt and Catch Fire*, and *The Fosters* was conducted.

The primary unit of analysis was the independent speaking or named character.[1] Each character was assessed for whether they engaged in or talked about computer science. This included the study, creation, design, adaptation, and/or implementation of an algorithm or algorithmic procedure (computing) to store, transform, transfer, and/or generate information. All characters —whether CS or not— were assessed quantitatively for demographics, domestic roles, and appearance indicators. For CS characters, a series of qualitative measures captured stereotypical and counter-stereotypical aspects of computing based on theory and previous research.

Below, the report is comprised of four major sections. The initial sections examine the effectiveness of the Google intervention in two ways. The first section takes a close look at a sample of content that was influenced by Google as well as a roughly equivalent "matched" set of shows and movies. The second section features a pre and post assessment of the frequency and nature of computer science in three Google influenced programs: *Silicon Valley*, *Halt and Catch Fire*, and *The Fosters*. The third section examines the portrayals of computer science in the broader ecology of popular film and television content. The final section focuses on the perceptions of content creators. This element of the report examines the qualitative trends that emerged from in depth interviews with content creators that have worked with Google's CS in Media Team. The report closes with an overview of the lessons learned and recommendations for future research, advocacy, and action. For more detailed information on the analyses presented here, see the full report.

COMPUTER SCIENCE IN GOOGLE AND NON GOOGLE INFLUENCED CONTENT

Our first research question asked, *"How does computer science in Google influenced shows compare to computer science in a matched sample of non-Google influenced content?"* We constructed two samples to address this query. The first consisted of 2 made-for-TV movies and 8 television series that participated in Google's intervention (see Table 1). The movies and TV programs were assessed in their entirety. Across Google influenced programming, 1,039 speaking characters appearing in 152 episodes and 2 TV movies were evaluated.

Next, a "matched set" of content was created to compare computer science in Google influenced stories to similar TV programs and movies. A match was carefully constructed by the authors, in partnership with Nielsen. The process accounted for the gender of the lead character(s) of the content, genre, episode segmentation, and key words from online databases describing the shows.[2] The set of matched content is outlined in Table 1 and includes 883 speaking characters appearing in 127 episodes and 2 TV movies.

To answer the first research question, we assessed every speaking character in every episode across the entire series for the season evaluated. Every character was only counted once, despite how many times they appeared across a TV series. This was done so that TV shows and movies could be compared in a similar way. However, qualitative measures were applied at the character level per episode and aggregated for analysis. Below, we report on quantitative and qualitative trends.

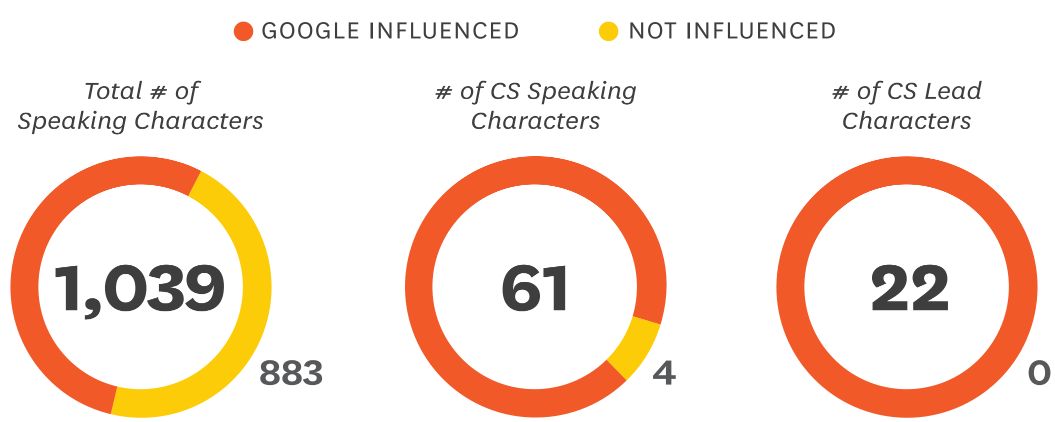
TABLE 1
LIST OF GOOGLE AND NON GOOGLE INFLUENCED SHOWS

GOOGLE INFLUENCED	# OF EPISODES	NOT INFLUENCED	# OF EPISODES
BAD HAIR DAY (DISNEY)	N/A	JINXED	N/A
HOW TO BUILD A BETTER BOY (DISNEY)	N/A	ZAPPED	N/A
SILICON VALLEY (HBO)*	10	IT'S ALWAYS SUNNY...	10
STITCHERS (FREEFORM)	11	IZOMBIE	19
HALT AND CATCH FIRE (AMC)*	10	THE AMERICANS	13
THE FOSTERS (FREEFORM)*	21	PARENTHOOD	13
MILES FROM T-LAND (DISNEY JR.)	30	PAW PATROL	26
ODD SQUAD (PBS)	40	TEAM UMIZOOMI	19
POWERPUFF GIRLS (CARTOON NETWORK)	11	STAR VS. THE FORCES OF EVIL	7
READY JET GO! (PBS)	19	PJ MASKS	20
TOTAL	**152**	**TOTAL**	**127**

Note: * indicates that season 1 of the series was also evaluated for CS. Within the # of episodes column, n/a is used for TV movies.

PREVALENCE. A total of 3.4% (*n*=65) of characters were depicted talking about or engaging in computer science. Sixty-one of those characters (93.8%, *n*=61) appeared in the Google influenced sample and four (6.2%, *n*=4) appeared in the matched sample. Of all speaking characters, 5.9% were depicted with CS in the Google sample and <1% percent (.5%) in the matched sample (see Table 2). Turning to main characters,[3] just over a fifth of the leads (20.6%, *n*=22) were depicted using or talking about CS and *all* were in the Google influenced sample (42.3% of all leads in this content).

TABLE 2
CS CHARACTERS BY SAMPLE TYPE & ROLE



Note: CS Characters were those that talked about or engaged in computer science behavior.

Given that the findings are aggregated at the film or series level, we were curious to see how many times CS characters were depicted *across* an entire season of TV content. Sample wide, 52.3% (*n*=34) of CS characters were shown in engaging in the activity in only one episode. Just under a third (32.4%, *n*=21) were portrayed doing/talking about CS in two to four episodes, 10.8% (*n*=7) in five to seven episodes, and 4.6% (*n*=3) in eight to ten episodes. Overall, CS characters appear infrequently and primarily in only one episode of a series.

The rate of CS per episode by sample type is shown in Table 3. CS characters appeared in 1-10 episodes in the Google influenced sample and 1-2 episodes in the matched sample. It must be noted that the most frequent portrayal of CS involved a female series regular in one of the Google influenced shows (i.e., *Halt and Catch Fire*). This character appeared in all 10 episodes of the series.

TABLE 3
CS CHARACTERS BY EPISODE RATE & SAMPLE TYPE

SAMPLE	1 EPISODE	2-4 EPISODES	5-7 EPISODES	8-10 EPISODES	TOTAL
GOOGLE INFLUENCED	50.8% (*n*=31)	32.8% (*n*=20)	11.5% (*n*=7)	4.9% (*n*=3)	93.8% (*n*=61)
NOT GOOGLE INFLUENCED	75% (*n*=3)	25% (*n*=1)	0	0	6.1% (*n*=4)
TOTAL # OF CS CHARACTERS	**34**	**21**	**7**	**3**	**65**

Note: Cells illuminate the number of episodes in which a CS character was shown talking about or engaging in CS behavior.

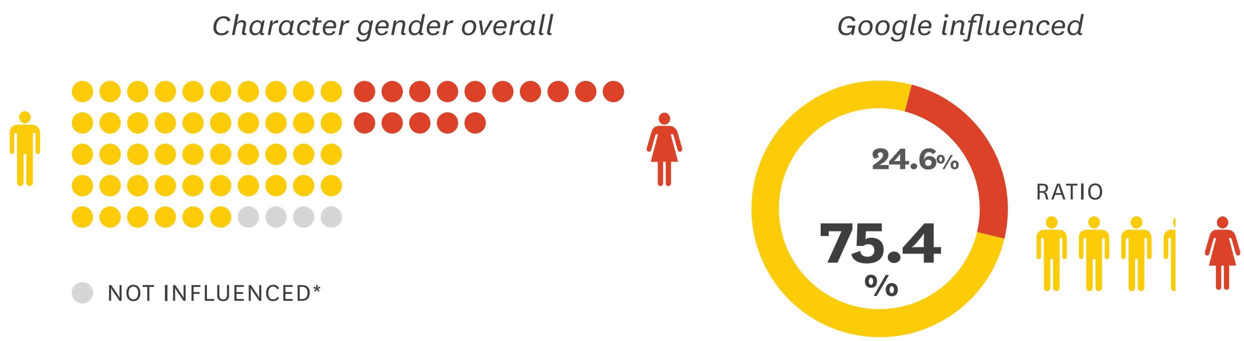
The nature of the show in which CS occurred was assessed. This was determined by looking for key terms (e.g., terrorism program, video games, technology wiz) or elements related to technology in IMDbPro summaries.[4] CS was most likely to occur in technology-focused shows, which is not surprising. Over three-quarters of the CS characters (78.5%, *n*=51) appeared in storylines described by phrases or attributes of technology. Only 21.5% of CS characters (*n*=14) were depicted in non-technology shows and movies.

Among the Google influenced content, 51 CS characters were in tech driven narratives and 10 CS characters were not. For the matched sample, all of the CS characters were featured in non-tech stories. Given the heavy technology focus in the Google influenced content, the goal was to examine whether such portrayals conform to or disrupt stereotypes about computer science.

CS CHARACTER DEMOGRAPHICS. Of the 65 CS characters, 76.9% (*n*=50) were male and 23.1% (*n*=15) were female. This translates into a gender ratio of 3.3 CS males to every one CS female on screen. No female characters, leading or otherwise, were shown engaging in CS in the non influenced content. See Table 4. In the Google influenced sample, almost one-quarter of CS characters were female. Among leads, however, the percentage of females jumps to 40.9% (*n*=9 of 22).

TABLE 4

GENDER OF CS CHARACTERS BY SAMPLE TYPE



*All CS characters in the not influenced sample were male

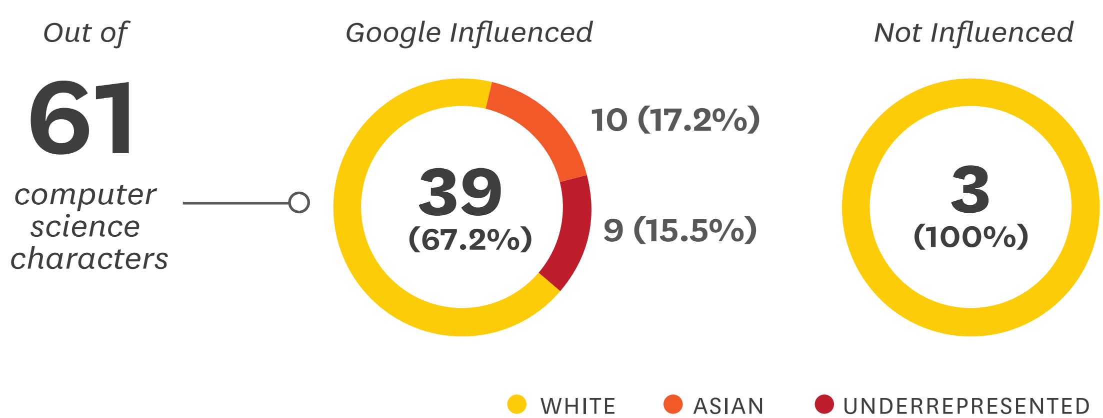
Looking at the distribution of race/ethnicity, CS characters were 68.9% White (*n*=42), 4.9% Black (*n*=3), 4.9% Hispanic/Latino (*n*=3), 16.4% Asian (*n*=10), 1.6% Native Hawaiian/Pacific Islander (*n*=1), and 3.3% mixed race/other (*n*=2). We collapsed these categories into three groups reflecting the stereotypical (i.e., White, Asian) and non stereotypical (i.e., Underrepresented) perceptions of CSers. As shown in Table 5, 15.5% of all CS characters in Google influenced content were not White or Asian.

Examining the intersection of gender and race, the distribution for male characters was 70.2% White (*n*=33), 4.3% Hispanic/Latino (*n*=2), 2.1% Black (*n*=1), 19.1% Asian (*n*=9), 2.1% Native Hawaiian/Pacific Islander (*n*=1), and 2.1% mixed race/other (*n*=1). The breakdown for females was as follows: 64.3% White (*n*=9), 7.1% Hispanic/Latino (*n*=1), 14.3% Black (*n*=2), 7.1% Asian (*n*=1) and 7.1% mixed race/other (*n*=1).

Two additional patterns are worth noting. First, the matched sample featured four CS characters. Three were white and one character's race/ethnicity was not ascertainable. Second, all of the underrepresented females were in the Google sample. Three of these girls and women (1 Black, 1 Hispanic/Latino, 1 mixed race) were main characters (Gabby, *How to Build a Better Boy*; Mariana, *The Fosters*; Loretta, *Miles from Tomorrowland*).

TABLE 5

RACE/ETHNICITY OF CS CHARACTERS BY SAMPLE TYPE



Note: Four CS characters were coded "can't tell" for race/ethnicity (i.e., Pip Whipley and Mirandos, *Miles from Tomorrowland*; Squiddy the Squid, *Team Umizoomi*; Silico, *The Powerpuff Girls*) bringing the overall number to 61 characters rather than 65.

Finally, only one CS character was LGBT identified across the sample of Google influenced shows and movies. *Halt and Catch Fire* featured a bisexual White male (Joe MacMillan) as a series regular.

By and large, the boys' club is alive and well with CS characters in the Google and non Google influenced content evaluated. However, two encouraging patterns emerged that are important to note. In the Google sample, 41% of all CS leads were female and 28.6% of all CS female speaking characters were underrepresented (i.e., not White, not Asian). These trends suggest that content creators are capable of leaning in when it comes to inclusion but they still have a ways to go to be *all in* and fully woke.

STEREOTYPICAL PORTRAYALS. Besides demographics, other attributes of media characters can contribute to liking, interest, and even identification. Given the small sample size of CS characters, subsequent analyses focus on all speaking characters and only note compelling differences by gender and occasionally race/ethnicity. As revealed in the previous section of the report, the majority of CS characters only appear in one episode (52.3%). Results are presented here as the overall presence of a specific attribute per CS character. These findings should be interpreted as the percentage of CS characters that demonstrate the particular quality *at any point* in the series' season or the film. Additionally, for those characters possessing the trait in question, the rate of occurrence is reported in the full report. The rate reveals the total number of times the presence of a particular attribute occurs out of the total number of episodes a character is featured with CS.[5]

TABLE 6
CS CHARACTERS APPEARANCE & INTELLECT

MEASURE	MALES	FEMALES	TOTAL
% DEPICTED IN STEREOTYPICAL CS ATTIRE	72% (*n*=36)	33.3% (*n*=5)	63.1% (*n*=41)
% REFERENCED AS ATTRACTIVE	6% (*n*=3)	13.3% (*n*=2)	7.7% (*n*=5)
% REFERENCED AS INTELLIGENT	16% (*n*=8)	66.7% (*n*=10)	27.7% (*n*=18)
TOTAL # OF CS CHARACTERS	**50**	**15**	**65**

Note: The columns do not add to 100%. Each cell features the proportion of men and/or women with a particular attribute. Subtracting the cell from 100% will yield the percentage of CS characters without the trait within gender. The last row contains the total number of CS characters.

Clothing. In terms of appearance, we assessed the presentation and style of each CS character's clothing and hair. Guided by research and theorizing, characters' appearance while doing or talking about CS was coded qualitatively as "stereotypical" (i.e., unkempt or non traditional hair style, glasses, t-shirt/hoody, or specific media/tech reference on clothing) or not stereotypical (i.e., stylized or traditional hair style, no glasses, button down shirt, or business suit).[6]

In the Google influenced sample, 62.3% of CS characters (*n*=38 of 61) were shown in stereotypical attire versus 75% (*n*=3) of the CS characters in the match sample. See Table 6. Males were more likely to be portrayed in stereotypical attire than females across the Google influenced (71.7% male vs. 33.3% female) sample. Research demonstrates that a stereotypical presentational style of male *or* female role models can *decrease* females' interest in CS.[7] Thus, if she sees it, she *won't* want to be it.

Physical attractiveness. The physical attractiveness of every CS character was also evaluated. Any reference to a CS character's physical beauty was coded. At least one study shows that attractive characters are associated with increased wishful identification for boys (w/male characters) and girls (w/male or female characters).[8] Other research documents the pull of attractive characters for women only.[9] Very little attractiveness emerged across the samples evaluated. Only 7.7% (*n*=5) of CS characters were referenced as physically beautiful and all of these occurred in Google influenced content. Six percent of male CS characters (*n*=3 of 50) and 13.3% of female CS characters (*n*=2 of 15) were referenced as attractive.

Intelligence. Similar to attractiveness, references to CS characters' intelligence were assessed. Studies show that character intelligence is one factor that heightens identification among viewers, particularly males.[10] Over one-quarter of CS characters (27.7%, *n*=18 of 65) were called intelligent. All intelligence comments were observed in the Google influenced sample. Female CS characters in the Google sample (66.7%, *n*=10 of 15) were more likely than males (17.4%, *n*=8 of 46) to be referenced as intelligent. Looking at the row percentages, 55.5% of all comments were directed at females and 44.4% were directed at men. In the Google sample, 33.3% (*n*=3) of underrepresented characters, 30.8% of White characters (*n*=12), and 20% (*n*=2) of Asian characters were referenced as intelligent.

CS Character Skill and Goals. The skill level of CS characters was evaluated, as were the stated goals for use of CS. Few characters across the samples exhibited highly skilled use of CS (Google influenced=16.9%, *n*=11). These characters included 5 males and 6 females, all in the Google influenced sample. Examples include but are not limited to being commissioned by the military to build and program a multi-billion dollar weaponized robot, building an anti-virus software that was the basis for $10 million in financing, and developing a code to search for life in space under the premise of intergalactic diplomacy.

The motives underlying computer science activity were also assessed. Research indicates that STEM fields and computing are viewed as more consistent with agentic than communal goals, including helping others or society.[11] Given this, it was important to understand whether the characters who used CS in media illuminated the societal benefits to computing. In addition to the prosocial actions that demonstrated highly skilled computer science work, the self-stated goals of characters engaged in computer science were assessed. Here, statements were required to reference that CS could benefit others, whether at an individual or societal level.

Similarly, there was little mention of using CS to accomplish prosocial goals. In the Google influenced and match sample 10.8% (*n*=7; all in the Google sample) of CS characters expressed a prosocial reason for CS use. Five of the characters who stated that CS could benefit others were female, and two were male. Some of the goals that characters shared included using CS to save lives, increase the efficiency of travel, and encourage connectivity. Of the characters who discussed the goals of science, six were coded as highly skilled, and five of those characters utilized CS for a prosocial motive.

CS Characters' Relationships. Stereotypical perceptions of computer scientists include a belief that individuals in this arena have poor social skills, or that computer science is isolating.[12] This stereotype was explored with multiple measures.

First, we assessed the degree to which computer science was depicted as a solo effort on screen. Every time a character was shown engaging in CS behavior only (*n*=37), we assessed whether s/he/it was alone or in the presence of other characters. All depictions of CS talk were removed prior to this analysis.[13] Focusing on the CS context, a full 36 (97.3%) of the 37 characters that engaged in computer science related behavior were at some point in the presence of others. Every male (100%, *n*=25 with CS behavior) was shown engaging in CS actions with companions or colleagues and 91.7% (*n*=11 of 12 with CS behavior) of females.

Only one of the four CS characters in the matched sample was depicted engaging in CS behavior, so these trends are largely the function of the Google sample. As such, the Google influenced content challenges the CS stereotype. It is clear for this study, (almost) no one codes alone.

Second, the relationships of CS characters were scrutinized by looking at whether they had friends, romantic partners, and/or offspring. A full 64.6% (*n*=42) of the CS characters were depicted with friends or meaningful social ties. Forty (65.6%) of the 61 CS characters in the Google sample were depicted with friends, with CS females (93.3%, *n*=14) more likely to be shown with social contacts than CS males (56.5%, *n*=26). In terms of race/ethnicity, 88.9% of underrepresented characters (*n*=8), 64.1% of White characters (*n*=25) and 50% of Asian CS characters (*n*=5) were shown with friendships. Two of the four CS characters (both white males) in the matched set were depicted with friends (50%).

Among the CS characters that were depicted with friends, 85.7% (*n*=36) of the time those companions were affiliated with computer science. All of these characters were accounted for by the Google sample. Roughly 35.7% (*n*=15) of the time CS characters have friends that are *not* computer science affiliated. Nearly a third (32.5%) of the Google CS characters had non tech friends as did both of the CS characters with friends in the matched sample.

Few CS characters in these samples are shown with meaningful familial or romantic relationships. Of those CS characters with enough cues to measure parental status (*n*=26), only 5 (3 males, 2 females) were depicted as caregivers and they were only featured in the Google content. Almost twice as many CS characters (*n*=9) were depicted in a romantic relationship, with 5 males and 4 females portrayed in this light. Again, all nine CS characters appeared in the Google influenced sample.

Reinforcements for CS. Theory suggests and research confirms that reinforcements delivered to media characters can influence the learning and/or imitation of behavior.[14] As a result, the presence of positive and negative reinforcements related to computer science were assessed. Positive reinforcements referred to verbal or nonverbal remarks, comments, and/or behaviors that provide affirmation or praise related to CS talk and/or behavior.

Almost half (47.7%, *n*=31) of CS characters were positively reinforced. Examples of positive reinforcement for CS include, but are not limited to, "You with the computer, you were amazing. You were like Bill Gates but smarter and with no glasses," "This is amazing. If you nurture your talent, you could be a software engineer or work for NASA," and that one character's coding gave another "chills."

The samples differed dramatically. Only one male character (25% of CSers) in one episode experienced positive reinforcement in the matched sample. 49.2% of the CS characters in Google influenced content experienced positive reinforcement, with CS females (80%, *n*=12) more likely to experience praise and affirmation than CS males (39.1%, *n*=18). Centering on race/ethnicity in the Google shows, 46.1% of White CSers (*n*=18), 50% of Asian CSers (*n*=5), and 44.4% of underrepresented CSers (*n*=4) were commended or received accolades while participating in CS.

TABLE 7
CS CHARACTERS' POSITIVE & NEGATIVE REINFORCEMENT

MEASURE	MALES	FEMALES	TOTAL
% CS WITH POSITIVE REINFORCEMENT	38% (*n*=19)	80% (*n*=12)	47.7% (*n*=31)
% CS WITH NEGATIVE REINFORCEMENT	34% (*n*=17)	46.7% (*n*=7)	36.9% (*n*=24)
% STEREOTYPICAL NAMES	2% (*n*=1)	20% (*n*=3)	6.1% (*n*=4)
TOTAL # OF CS CHARACTERS	**50**	**15**	**65**

Negative reinforcements focused on verbal and nonverbal remarks, comments, or behaviors that condemn or disapprove of CS behavior or discussion. Negative reinforcement of computer science related talk and/or behaviors was directed at 36.9% of the CS characters (see Table 7), with a higher percentage of females (46.7%) experiencing it than males (34%). Examples of negative reinforcement include asking "How would it make you feel if one of us hacked into your stuff, huh?" In other contexts, computer code is referred to as a "bug factory" or "garbage" and apps are termed "horrendous."

The Google influenced and matched samples differed on negative reinforcements. For the matched shows and movies, two of the four male CS characters received condemnation or disapproval.

Among the CS characters in the Google sample, 36.1% (*n*=22) were criticized for their computer science related activities. Males (32.6%, *n*=15) were less likely to be disparaged for their CS related actions than females (46.7%, *n*=7). For race/ethnicity in the influenced sample, 38.5% (*n*=15) of White CS characters were negatively reinforced, 40% of Asian CS characters (*n*=4) and 22.2% of underrepresented CS characters (*n*=2).

Another form of potential negative reinforcement is name-calling. Stereotypical terms or references to people who like computers or computer science include, but are not limited to, geek and nerd. Few instances of stereotypical CS names emerged. Only 4 of the 65 CS characters were coded with stereotyped language, with all instances appearing in the Google shows. Of the four characters, three were female and only one was male. Examples of the types of names used were "dorks," "geek," "Miss Hackey Pants," "lab rat," and "tech nerd."

In summary, there are places for praise and progress in the Google influenced content. Content created following Google's intervention had more characters using CS, and those characters were more likely to be shown in contexts with others and with friends. Female characters were praised for intelligence rather than attractiveness, and were more often rewarded for their CS activities than males. However, both samples of content still primarily depict White, male characters engaging in CS, who are often stereotypically attired. The nature of these depictions also reflects CS stereotypes, namely that friendships are primarily with other CS individuals and a lack of children or romantic relationships. Few characters appear to be highly skilled at computer science or explicitly mention the benefits CS could have for others. Thus, while there may be *more* portrayals of CS in Google influenced content, they are also *more* stereotypical in nature.

COMPUTER SCIENCE IN GOOGLE INFLUENCED CONTENT OVER TIME

The second research question asked, *"How does computer science in Google influenced shows compare to computer science in an earlier season before intervention?"* To address this question, three series were assessed: *Silicon Valley*, *The Fosters*, and *Halt and Catch Fire*. These series had aired at least one season of content prior to Google's intervention, and the first season of each was chosen as the baseline for comparison.

As noted above, every speaking character in each episode was assessed and counted once across the entire series. In the first season of each of these programs, there were 360 total speaking characters. In the season following Google's intervention, 348 speaking characters appeared on screen. Qualitative measures reported below were evaluated at the program level for each character but reported across the entire series. Due to the small sample size for some measures, only variables that met a certain threshold (i.e., 10 or more observations) are reported.

Below, we report on selected CS prevalence indicators, including the percentage of all speaking characters in CS and series regular characters with CS. Then, demographic trends are reported, followed by stereotypical attributes.

CS PREVALENCE. There were 72 characters who engaged in or discussed computer science across the two seasons of content evaluated. Of these 72 individuals, 44.4% (*n*=32) were in the initial season of content and 55.6% (*n*=40) appeared following Google's influence. This represents a gain of ***eight*** characters over time. The percentage of CS characters in the sample of content "post" Google's influence (11.5%) is on par with the larger sample it is drawn from, described above. The prevalence of series regulars did not differ by pre and post sample, with 11 series regulars (50%) in each set of programming engaging in computer science.

CS CHARACTER DEMOGRAPHICS. Of the male CS characters, 46% (*n*=29) appeared in the first season of content, while 54% (*n*=34) appeared following Google's influence. Five additional male characters were seen using CS after Google's involvement. Among females, one-third (*n*=3) were seen in shows prior to Google's involvement and two-thirds (*n*=6) appeared "post" influence. This represents an overall gain of 3 female characters in CS. See Table 10. Similarly, among series regulars, males decreased while females increased post-Google's intervention. Due to the gain and loss only accounting for one character respectively, this pattern should be interpreted cautiously.

TABLE 10
FREQUENCY OF CS CHARACTERS PRE AND POST GOOGLE INFLUENCE

MEASURE	MALES			FEMALES		
	PRE	POST	+/-	PRE	POST	+/-
% OF ALL CS SPEAKING CHARACTERS	46% (*n*=29)	54% (*n*=34)	+5	33.3% (*n*=3)	66.7% (*n*=6)	+3
% OF ALL CS SERIES REGULAR CHARACTERS	52.9% (*n*=9)	47.1% (*n*=8)	-1	40% (*n*=2)	60% (*n*=3)	+1
% OF WHITE CS CHARACTERS	47.5% (*n*=19)	52.5% (*n*=21)	+2	42.9% (*n*=3)	57.1% (*n*=4)	+1
% OF ASIAN CS CHARACTERS	50% (*n*=8)	50% (*n*=8)	0	0	100% (*n*=1)	+1
% OF UR CS CHARACTERS	28.6% (*n*=2)	71.4% (*n*=5)	+3	0	100% (*n*=1)	+1
% OF LGBT CS CHARACTERS	50% (*n*=1)	50% (*n*=1)	0	0	0	0

The proportion of White males and females increased from before to after Google's influence. Among Asian characters, one additional female character appeared following the Google intervention. The percentage of male underrepresented characters increased between seasons. And, one underrepresented female was added following Google's work. See Table 10.

There has been no change in LGBT characters over time. The same bisexual White male character appeared in *Halt and Catch Fire* both before and after Google's influence.

Overall, there have been modest gains over time for CS characters. Eight additional characters participated in CS following Google's influence. Importantly, there were more female and underrepresented characters following Google's influence. This suggests that some of the Google CS in Media Team's goals for the program were met with the addition of these characters.

STEREOTYPICAL PORTRAYALS. Once again, the appearance of CS characters was scrutinized for the presence of stereotypical apparel. Evaluating the gender of characters from pre to post, more females in the season airing after Google's influence were depicted in stereotypical attire (pre=33.3% vs. post=66.7%). For males, there was a slight increase (pre=46% vs. post=54%) over time. As shown in Table 11, four additional male characters and two additional female characters were dressed stereotypically after Google's involvement.

References to characters' intellect were evaluated. The prevalence of intelligence comments increased over time for both

TABLE 11
NATURE OF CS CHARACTERS PRE AND POST GOOGLE INFLUENCE

MEASURE	MALES			FEMALES		
	PRE	POST	+/-	PRE	POST	+/-
% OF CS CHARACTERS WITH STEREOTYPICAL ATTIRE	46% (*n*=23)	54% (*n*=27)	+4	33.3% (*n*=2)	66.7% (*n*=4)	+3
% OF INTELLIGENT CS CHARACTERS	14.3% (*n*=1)	85.7% (*n*=6)	+5	33.3% (*n*=2)	66.7% (*n*=4)	+2
% OF CS CHARACTERS WITH FRIENDS	36.4% (*n*=12)	63.6% (*n*=21)	+9	25% (*n*=2)	75% (*n*=6)	+4
% OF CS CHARACTERS W/POS REINFORCEMENT	54.5% (*n*=12)	45% (*n*=10)	-2	28.6% (*n*=2)	71.4% (*n*=5)	+3
% OF CS CHARACTERS W/NEG REINFORCEMENT	52.2% (*n*=12)	47.8% (*n*=11)	-1	40% (*n*=2)	60% (*n*=3)	+1

males and females. Of the intelligence comments made toward males, 14.3% (*n*=1) occurred prior to Google's influence, while 85.7% (*n*=6) took place following the intervention. This same pattern occurred among female characters, with 33.3% (*n*=2) of female characters referenced as intelligent in the baseline sample and 66.7% (*n*=4) following Google's work. See Table 11.

We assessed the nature of characters' friendships. As shown in Table 11, male characters and female characters with friendships increased over time. The majority of characters were shown only with friends who shared an interest in CS (83%, *n*=34). This increased over time. Of the characters depicted only with friends who were involved with computer science, 29.4% (*n*=10) appeared in episodes prior to Google's involvement. 70.6% (*n*=24) of the individuals with CS-involved friends were shown following the Google intervention. There were fewer characters "post" Google's intervention (42.9%) than prior to their influence (57.1%) who were shown with friends outside of computer science.

Of males who had friends only in CS, there was an increase over time (34.5% vs. 65.5%). Five CS females had friends only in CS following the intervention, versus none in the baseline sample. For characters with friends not only in CS, the percentage of males remained stable (50% vs. 50%), while the percentage of females decreased (66.7% vs. 33%). However, this reflects a change in only one female character and should be interpreted cautiously.

Positive reinforcements for CS behavior were also assessed. More male characters (54.5%, *n*=12) received accolades prior to Google's influence, compared to male characters in the "post" influence sample (45.5%, *n*=10). On the other hand, of the females receiving approbation, 71.4% of those comments (*n*=5) occurred after Google's involvement, and 28.6% (*n*=2) prior to Google's work.

Finally, negative reinforcement for CS activity was evaluated. Slightly fewer male characters (47.8%, *n*=11) were disparaged following Google's influence, compared to male characters in the "pre" influence sample (52.2%, *n*=12). For females, the opposite pattern occurred. Of females receiving negative feedback, 60% (*n*=3) appeared following Google's influence and 40% (*n*=2) were depicted in the initial season of the show.

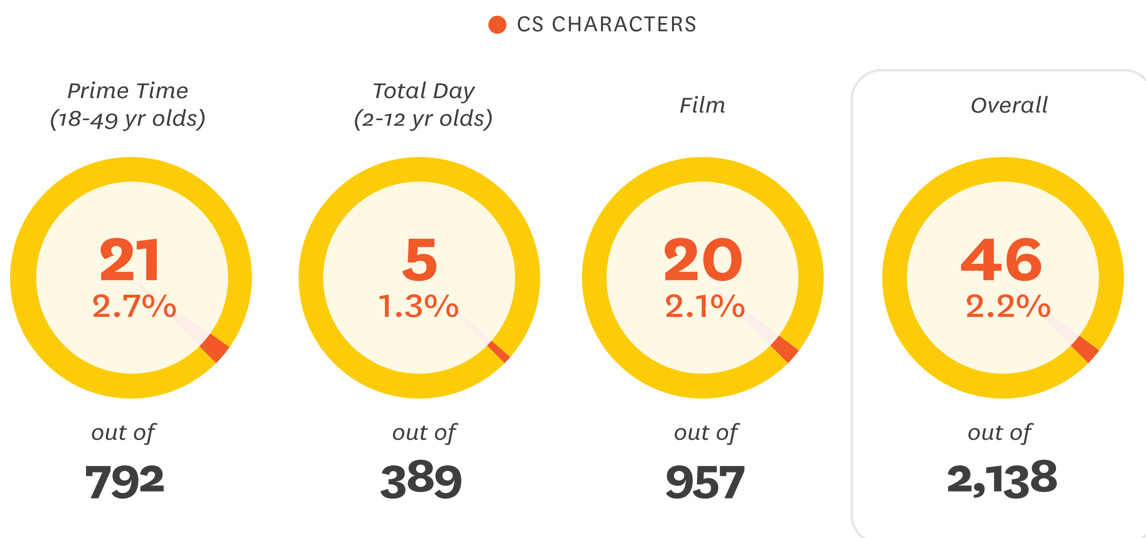
In sum, there is still a stereotypical emphasis on computer science characters in these series. Most characters are attired in ways that align with stereotypes of computer scientists, and CS characters are enmeshed in relationships primarily with other CS-focused individuals. There are increases in the number of characters referred to as intelligent, however. Female characters are also more likely to receive praise for their CS work following Google's influence. This may be an important step toward demonstrating to viewers the value of CS activities.

COMPUTER SCIENCE IN POPULAR MEDIA CONTENT

Our third research question asked, *"What is the frequency and nature of computer science portrayals in popular entertainment?"* To answer this query, we conducted an analysis of three different samples of popular media content. The first and second samples were the 20 top prime-time shows among 18- to 49-year olds and the 20 most popular programs among 2- to 12-year olds as rated by Nielsen from June 1st, 2015 to May 31st, 2016.[15] For these samples, the first two episodes of the corresponding season from each series were assessed. The third sample included the 20 highest earning films within the U.S. for 2015.[16] See Appendix A for the three media samples. In total, 60 TV shows or films and 2,138 characters were evaluated for CS.

PREVALENCE. Of 2,138 speaking characters evaluated, a total of 46 (2.2%) engaged in computer science across the three samples (see Table 12). While the percentages differ little by sample, prime-time programs (*n*=21) and films (*n*=20) featured four times as many computer science characters as shows popular with 2- to 12-year olds. In addition to sample type, CS characters differed by leads. Films featured the most leading characters (12.1%, *n*=4 of 33) engaged in CS, while among TV series regulars, 6.2% (*n*=12 of 195) of leads in prime time and 3.3% (*n*=4 of 122) of leads in highly rated shows among 2- to 12-year olds were depicted engaging in computer science. See Table 12.

TABLE 12
FREQUENCY OF CS CHARACTERS BY SAMPLE TYPE

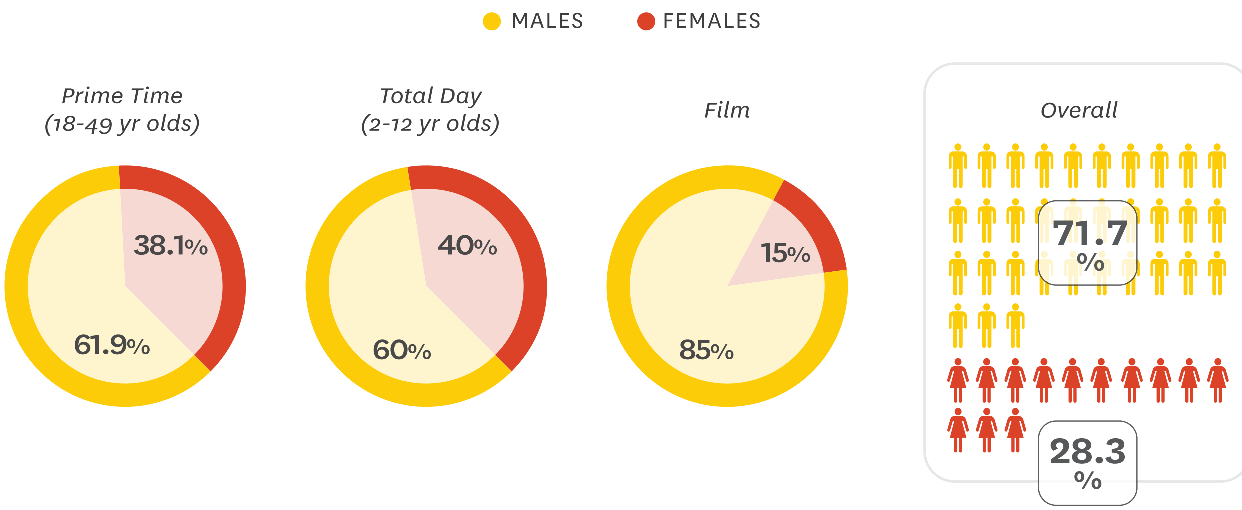


Again, we assessed whether each TV series or movie featured a technology focus or not. CS characters were more likely to appear in shows and movies that did *not* feature a technology-oriented theme (80.4%, *n*=37) than those that did (19.6%, *n*=9). This finding reveals that the majority of CS portrayals can be embedded in content that does not have an overarching focus on computer science or technology, which can increase the footprint of Google's impact beyond shows like *Silicon Valley* or *Halt and Catch Fire*.

CS CHARACTER DEMOGRAPHICS. Of the 46 CS characters, 71.7% were male (*n*=33) and 28.3% were female (*n*=13). Gender varied across the three samples, as shown in Table 13. Prime time and shows popular with 2- to 12-year olds were more likely to depict female characters engaged with CS than were films. Given that programs attractive to children only featured 5 CS characters, the results for this sample should be interpreted with caution. Of the 20 leading CS characters, 12 (60%) were male and 8 (40%) were female. Seven of these leading ladies doing CS were in prime-time shows and only 1 was in children's series. No leading female characters were shown engaged in CS across the 20 most popular movies of 2015 or 957 coded speaking characters.

TABLE 13

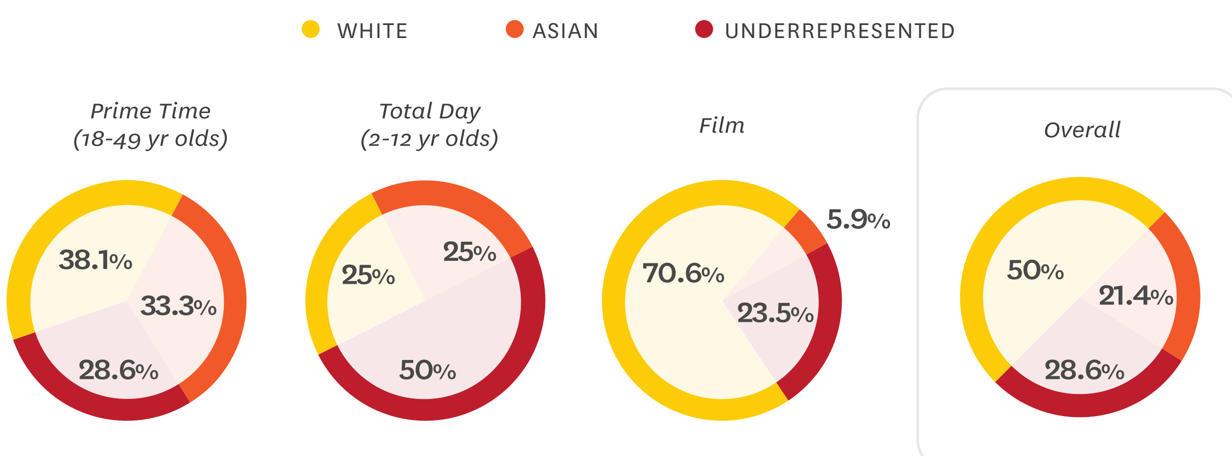
GENDER OF CS CHARACTERS BY SAMPLE TYPE



Focusing on race/ethnicity, 50% of all CS speaking characters were White, 21.4% Asian, 11.9% mixed race or other, 7.1% Hispanic, 7.1% Black, and 2.4% Middle Eastern. We collapsed the race/ethnicity variable into three levels: White, Asian, or Under represented (i.e., Black, Hispanic, Middle Eastern, mixed race/other). The distribution of these three levels by sample type is shown in Table 14. Roughly a quarter of all CS characters in film and prime-time programs were from underrepresented racial/ethnic groups. Fully half of the CS characters in children's shows were minorities, but the small sample size precludes any definitive conclusion about this pattern.

TABLE 14

RACE/ETHNICITY OF CS CHARACTERS BY SAMPLE TYPE



Note: Four CS characters were coded "can't tell" for race/ethnicity (i.e., Simon, *Alvin and the Chipmunks*; Plankton, *Spongebob Squarepants*; Ultron, Vision, *Avengers: Age of Ultron*) bringing the overall number to 42 characters rather than 46.

Turning to underrepresented characters, the results are similar to gender. Popular prime time series (28.6%, *n*=6) and films (23.5%, *n*=4) showcase a percentage of underrepresented characters in CS higher than what is seen in the Google influenced content. Once again, series popular with 2- to 12-year-olds have the highest share of underrepresented CS characters (50%, *n*=2), but the smallest sample size.

It is important to examine the intersectionality of gender and race/ethnicity when it pertains to media portrayals. The distribution of race/ethnicity for CS males was 41.4% White (*n*=12), 6.9% Hispanic (*n*=2), 6.9% Black (*n*=2), 27.6% Asian (*n*=8), 3.4% Middle Eastern (*n*=1), and 13.8% mixed race (*n*=4). Among the 13 CS female characters in the sample, 69.2% were White (*n*=9), 7.7% Hispanic (*n*=1), 7.7% Black (*n*=1), 7.7% Asian (*n*=1), and 7.7% mixed race (*n*=1). This latter pattern reveals that after watching more than 85 hours of popular TV shows and movies, viewers would have only seen a single instance of computer science involving a Latina, Black and mixed race female character. That same viewer would not be exposed to one Middle Eastern girl or woman talking about or doing computer science.

Only two computer science characters were depicted from the LGBT community. Both were young adult, gay Asian men that appeared in the prime-time sample. One character was on the *The X-Files* (i.e., Dr. Sanjay) and the other was on *How to Get Away with Murder* (i.e., Oliver Hampton). Neither character was a series regular.

STEREOTYPICAL PORTRAYALS. As with the Google influenced and match samples, stereotypical aspects of CS were assessed for characters in the popular media samples (i.e., appearance, intellect, skill, relationships, reinforcements). Below, trends are reported across all three content platforms due to small sample sizes.

Clothing. Twenty-one CS characters or 45.7% were presented with a stereotypical appearance, with 48.5% (*n*=16) of males and 38.5% (*n*=5) of females shown in this light. Underrepresented characters (41.7%, *n*=5) were more likely to be shown with a stereotypical appearance than Asian characters (33.3%, *n*=3). White characters (57.1%, *n*=12) were the most likely group to be shown stereotypically.

Physical Attractiveness. Just under a sixth (13%, *n*=6) of the CS characters were referenced as attractive by other characters across 60 prime-time programs, TV shows popular with 2- to 12-year olds, and top-grossing films. Three males and three females were depicted as attractive, which calculates to 9.1% (3 of 33) of CS males and 23.1% (3 of 13) of CS females. Interestingly, 25% (*n*=3 of 12) of underrepresented CS characters were coded as physically attractive, 11.1% (*n*=1 of 9) of Asians, and 9.5% (*n*=2 of 21) of Caucasians.

TABLE 15
CS CHARACTERS APPEARANCE & INTELLECT

MEASURE	MALES	FEMALES	TOTAL
% DEPICTED IN STEREOTYPICAL CS ATTIRE	48.5% (*n*=16)	38.5% (*n*=5)	45.7% (*n*=21)
% REFERENCED AS ATTRACTIVE	9.1% (*n*=3)	23.1% (*n*=3)	13% (*n*=6)
% REFERENCED AS INTELLIGENT	15.1% (*n*=5)	7.7% (*n*=1)	13% (*n*=6)
TOTAL # OF CS CHARACTERS	**33**	**13**	**46**

Note: The columns do not add to 100%. Each cell features the proportion of men or women with a particular attribute. Subtracting a cell from 100% will yield the percentage of CS characters without the trait within gender. The last row contains the total number of CS characters.

Intelligence. Turning to intelligence, a total of 13% (*n*=6) of the 46 CS characters coded were referenced as smart. Five of these comments were directed at CS males and only one was directed at a CS female. This latter finding is a bit of a double-edged sword, however. On one hand, intellectual praise should not vary with gender. On the other, some researchers have conjectured that the stereotype of computer scientists as "intelligent" may deter women from the field.[17] Of the intelligent CS characters, three were Caucasian, two Asian, and one underrepresented.

CS Character Skill and Goals. Eight CS characters were shown with high skill that could have major societal impact, seven of which were men (87.5%) and only one was a woman (12.5%). White characters were most often depicted with high skill used for prosocial reasons (71.4%, *n*=5). One Asian (14.3%) and one underrepresented character (14.3%) were also depicted with expertise that benefited others.

These eight characters' capabilities ranged from building artificial intelligence to end civilization, creating a surveillance system/technology prized by the military, creating a computer model to predict earthquakes, or talented hacking abilities to access an advanced security system, an aerospace company, or using such skills to shut down a secret intelligence system in the UK.

Only 8.7% (*n*=4) of characters referenced that computer science could be used to help others. This ranged from using computer science to protect their family to protecting the world and instilling "peace in our time." Two of the four characters who noted the potential benefits of computer science were also coded as highly skilled. Of those expressing a goal, more males (75%, *n*=3) than females (25%, *n*=1) stated that computer science could be utilized to benefit others.

CS Characters' Relationships. A full 94.1% of CS characters engaged in CS activity with others present at some point while they were on screen. Of those CS characters, 91.3% (*n*=21) of males and 100% of females (*n*=11) were shown in the company of other characters. Looking to race/ethnicity, 94.7% of White characters (*n*=18), 100% of Asian characters (*n*=2), and 90.9% (*n*=10) of underrepresented characters had others nearby while engaging in CS. Clearly, the context of CS activity in popular media is anything but isolated.

Over half (54.3%, *n*=25) of CS characters were shown with friends or social relationships. Roughly half of the CS males (54.5%, *n*=18) and half of the CS females (53.9%, *n*=7) were depicted with friends. Nearly two-thirds (64%, *n*=16) of CS characters had friends that were both interested and not interested in CS. Only 3 CS characters were depicted with social relationships solely about or revolving around computer science.

Moving from social to romantic relationships, only 24 of the CS characters had enough information present to evaluate their "significant other" status. 12.5% (*n*=3) were depicted with a relational partner and all three of these CS characters were men. Similarly, only 3 CS characters out of 25 possible were shown as parents. Two-thirds (2 of 3) of these caregivers were men. Thus, the stereotypical portrayal of a computer scientist is either about the relational life of a man or lacking sufficient cues to detect their interpersonal connectivity to others.

Reinforcements for CS. A full 32.6% (*n*=15) of all CS characters were positively reinforced for their skill or action. In terms of gender, 30.3% (*n*=10) of all male characters engaging in CS were positively reinforced and 38.5% (*n*=5) of all female characters. One-third (33.3%, *n*=4) of underrepresented characters were praised for their CS activity, compared to 11.1% (*n*=1) of Asian characters and 38.1% (*n*=8) of White characters. Positive reinforcements ranged from one character telling another "wonderful, good job, you're doing great" to glowing YouTube product reviews for a game created by two seventh graders.

In contrast, less than a fifth of CS characters received negative reinforcements, with a higher percentage of CS males (24.2%, *n*=8) than CS females 7.7% (*n*=1). Under a quarter (23.8%, *n*=5) of White characters received negative reinforcements, as did 8.3% (*n*=1) of underrepresented characters. No Asian characters were the object of condemnation or disapproval for CS. Negative reinforcements included calling a character's activities a "cyber failure," saying "when you two programmed him to save the human race, you amazingly failed," and one character was even imprisoned for felonious computer science behaviors.

TABLE 16
CS CHARACTERS' POSITIVE & NEGATIVE REINFORCEMENT

MEASURE	MALES	FEMALES	TOTAL
% CS W/POSITIVE REINFORCEMENT	30.3% (*n*=10)	38.5% (*n*=5)	32.6% (*n*=15)
% CS W/NEGATIVE REINFORCEMENT	24.2% (*n*=8)	7.7% (*n*=1)	19.6% (*n*=9)
% CALLED STEREOTYPICAL NAMES	12.1% (*n*=4)	23.1% (*n*=3)	15.2% (*n*=7)
TOTAL # OF CS CHARACTERS	**33**	**13**	**46**

Note: The columns do not add to 100%. Each cell features the proportion of men and/or women with a particular attribute. Subtracting the cell from 100% will yield the percentage of CS characters without the trait within gender. The last row contains the total number of CS characters.

Use of stereotypical names was also evaluated. Only 15.2% (*n*=7) of CS characters were verbally disparaged by such terms from other characters. Less than an eighth of CS males and under a quarter of CS females were the recipients of negative nicknames. In terms of race/ethnicity, 19.1% of White characters (*n*=4) were labeled with a negative name, as were 16.7% (*n*=2) of underrepresented characters and 11.1% (*n*=1) of Asian characters.

Taken together, the landscape of popular media showcases computer science rarely, but stereotypically. It is important to note that the computer science in this content primarily occurred in TV series and movies that were not focused on technology. This indicates that integrating computer science into plotlines does not require a storyline to focus on the topic, nor does it require the viewing audience to be CS-savvy.

In terms of demographics, females were underrepresented in CS compared to males, particularly in film. Underrepresented characters also fall below the percentage of individuals from underrepresented racial/ethnic groups in the population.[18] The intersection of gender and race/ethnicity is also problematic. Very few Latinas, African American females, and no Middle Eastern girls or women engage in CS across the sample.

The nature of CS portrayals is mixed as well. CS characters embody stereotypes about computer science, particularly when it comes to their appearance and lack of romantic or familial connections. Only one female is shown as a highly skilled computer scientist, although several expert portrayals demonstrate that computer science can be used to benefit others. A handful of characters even echoed this sentiment. Characters also receive more accolades than criticism on the whole for their computer science activities. Thus, for a young viewer watching these CS portrayals, there may be little to facilitate identification with characters involved with computer science but much to emulate.

CONTENT CREATORS' PERCEPTIONS OF THE GOOGLE CS IN MEDIA INTERVENTION

The findings presented above demonstrate the prevalence and stereotypical nature of computer science portrayals in television and film. Yet, these portrayals do not originate in a vacuum. They are the product of the imaginations of content creators and creative executives who help bring them to life. The Google CS in Media Team's work has been to intersect the decision-making process that ultimately leads to the on screen representation of computer science. Through engagements with show creators and corporate representatives, the Google Team has attempted to integrate computer science portrayals into TV movies and ongoing series that deviate from stereotypes and showcase diversity.

The purpose of this section is to provide a window into the Google Team's activities and to assess their success. To that end, this section will address four major questions from the perspective of content creators, detailed below. Nine in-depth interviews were conducted with individuals affiliated with the content influenced by the Google CS in Media Team.[19] Of these nine individuals, 66.7% (*n*=6) were male and 33.3% (*n*=3) were female. Participants had an average age of 39.9 years, and had an average of 12.7 years of experience in entertainment. Responses were transcribed, and answers to each question assessed for meaningful patterns. Responses could fit into multiple categories; thus, totals do not always add to 100%. Given the small sample size for this investigation, trends reported are suggestive and are not intended to represent all individuals who participated in the Google intervention.

PURPOSE OF ENGAGEMENT. Participants were asked to describe the purpose of the engagement with the Google CS in Media Team. Responses were fairly evenly split between individuals who were recommended to Google (33.3%), those who were approached by Google (33.3%) and those who sought out Google's help (22.2%). The reasons that individuals worked with the Google team included the knowledge, expertise, or reputation of Google (55.5%), and because they were working on a storyline or episode that dealt with technology or CS (44.4%). Individuals in the latter category stated that the Google Team's assistance was employed to improve a particular storyline or episode. These creators were working on plotlines with a tech-focus or they intended to integrate computer science into a narrative. Google's help was seen as a means to obtain correct information or provide authenticity to the project. Two-thirds of individuals stated that their ideals or desires were to showcase women and girls in STEM. This alignment of objectives is likely a key reason for Google's success in integrating portrayals of females in CS into the media landscape.

PROGRAM OUTCOMES. A second set of questions addressed the notable outcomes of the interaction with the Google CS in Media Team. All participants indicated that Google influenced their content, from subtle insights to embedding specific CS elements. Other outcomes included clarifying or affirming values related to showcasing diversity in STEM portrayals (66.7%). Some individuals stated that they had a pre-existing desire to showcase diversity. Others noted that the need to increase portrayals of women and girls in STEM had not been a primary concern before the intervention. A few individuals (44.4%) stated that external engagement was a beneficial by-product of the intervention. Finally, 22.2% of participants shared that Google's work had an influence on internal conversations or processes related to creating more multidimensional content.

Over half of participants (55.5%) stated that Google *outperformed* their expectations. Answers revealed that the scope of Google's intervention was broader than anticipated. Individuals were pleased by the resources that they were provided, the enthusiasm shown by the team, and the outreach Google offered. One-third (*n*=3) shared that Google's impact was about what they expected. These individuals had either high expectations when beginning the project, or appreciated the level of support they received. Finally, one participant indicated that Google's influence was less than anticipated, seemingly because of a difference in expectations at the start of the intervention.

BROADER IMPLICATIONS FOR DIVERSITY. Third, the interview focused on whether the Google Team influenced diversity or representation more broadly. Two-thirds (*n*=6) of individuals stated that they had discussed aspects of diversity with Google representatives. This primarily focused on talking about female characters, though a few participants mentioned underrepresented racial/ethnic groups or the LGBT community. Additionally, content creators indicated that discussions aligned with an existing orientation to showcasing diverse voices in their programming. A similar pattern was found among responses to a question on unconscious bias. Over half (55.5%) of the interviewees had heard about unconscious bias from the Google team. This was generally as part of a larger presentation rather than a one-on-one discussion. Responses to questions on diversity strongly suggest that Google's media partners were convinced of the importance of representing women and people of color in storytelling *prior* to the CS intervention. Additionally, many of the individuals interviewed would like to do more to showcase women and girls on screen, especially in STEM. In this regard, Google may not have been a catalyst for change, but rather provided encouragement and resources to bolster content creators' existing commitments.

RECOMMENDATIONS. Interview participants were also asked about specific recommendations for how the intervention could be improved. Over half (55.5%) of respondents offered an idea of a new practice that the Google team should adopt. Three of those responses urged Google to consider developing its own content or funding media makers. One person suggested that Google focus on changing CS education and allowing a larger number of young people to engage in CS. The final suggestion was that Google further its support for media and creators who are working to disseminate messages around CS. This dovetails with responses to a follow-up question that asked participants which activities the Google team should continue. Interviewees stated that Google should continue its ongoing interventions. This included tracking media portrayals and expanding on their existing work.

Summing up, interviews with Google CS in Media partners reveal that in general, the Team has been successful in encouraging media makers to incorporate computer science into entertainment. This includes depictions of females in computer science. Google's success appears to be driven by two main factors.

The first is offering a unique resource as a trusted name. Creators want to ensure authenticity and accuracy; the Google team can provide those to writers and storytellers. The second factor is that Google has found allies who care about increasing representation of diverse voices in media. These individuals are aligned with Google's mission and well-positioned to support it. The result is an intervention that accomplishes Google's goals while establishing goodwill within the entertainment industry.

LESSONS LEARNED

The purpose of the present study was to provide a comprehensive overview of the Google CS in Media Team's work to improve depictions of computer science in media. To that end, five samples of film and television programming were assessed for the presence of computer science and the nature of those depictions. Additionally, interviews with content creators who have worked with Google were conducted. This concluding section will present four major lessons learned from the research and several recommendations for future research, advocacy, and action.

FOCUS ON PREVALENCE *AND* PORTRAYAL. Depictions of computer science are still rare in both popular programming and series influenced by Google. The findings from this investigation underscore the importance of Google's ongoing intervention, and highlight additional areas for improvement in the depiction of the characters using CS. Taking steps to address not just the prevalence but the nature of CS in media is crucial. As Google continues its work, it is imperative to rely on research-based evidence. While adding additional CS characters to popular media is valuable, the context and nature of those portrayals is just as—if not more—important. Google can be a leader by moving beyond the language of mere exposure to discuss the multidimensional nature of media influence.

TACKLE TECH *AND* NON-TECH FOCUSED PROGRAMS. The work of the Google CS in Media team in its first year mainly integrated CS characters into shows with a technology focus. The Google CS in Media team should certainly move forward in its work with programs that have technology as a core plot element. Yet, tech-focused content is not the only way forward. Prime-time programs, series popular with 2- to 12-year olds, and popular films were more likely to feature CS characters in non-tech focused programs. This suggests that writers and content creators *do* find ways to integrate CS into shows through guest starring roles, or even with series regulars. Google's intervention with *The Fosters* reveals that non-tech focused programs may offer prime opportunities to showcase CS in unique and counter-stereotypical ways. As the Google Team moves forward in its work with series such as *Empire*, *Girl Meets World*, *Gortimer Gibbons Life on Normal Street*, or *The Amazing Adventures of Gumball*, it appears the Team is seizing these opportunities to integrate CS into storytelling without a primary tech focus.

WORK WITH LIKE-MINDED PEOPLE *AND* THOSE WITH DIVERGENT PERSPECTIVES. Interviews with content creators who had been involved with the Google intervention illuminated the nature and reasons for the success of Google's work. All of the individuals mentioned that Google influenced storytelling—in large and small ways. The interviews also demonstrated that the content creators involved in the interventions had an existing orientation to diversity that was shared with the Google team. Finding ways to engage writers or producers who do not have a pre-existing orientation toward diversity may offer a challenge, but one that might accomplish unique ways to integrate diverse CS portrayals into content.

While the goal of this study was to illuminate the nature and prevalence of computer science in media, there are four limitations that must be noted. First, the samples of content used in this investigation are chosen to answer specific research questions and results may not generalize to the entire landscape of media content. Second, the unit of analysis employed is the character using CS rather than incidence of CS in the plot. Further, characters were analyzed at the series level, rather than per episode. This did not allow for analyses on how *often* instances of computer science occur in media, but rather the number of *individuals* who engage in CS. While the unit of analysis is appropriate for this investigation, other researchers or a follow up study may assess the rate of occurrence of CS and other stereotypical characteristics in media. Third, the stereotypical nature of environments where CS occurs was not examined. Despite research on the importance of environments for interest in CS,[20] the nature of storytelling and complexities of set decoration make any such analysis extraordinarily difficult. Other scholars may desire to examine how environments are depicted in media. Finally, other forms of media (e.g., online learning sites, children's books, video games, classroom curriculum) may also be important to assess to understand the full nature of how storytelling presents the computer science user.

Overall, this report provides a unique and comprehensive view of how storytelling presents computer science. By examining five samples of content, the study reveals how rarely and stereotypically CS is portrayed across the landscape of entertainment. Harnessing the power and success of the Google CS in Media Team's work is one way to address the gaps that still exist. As the importance of computer science continues to accelerate through industry and culture, popular media has the opportunity to keep pace. By working with experts and activists like the Google Team, that opportunity can become a reality.

FOOTNOTES

1. The unit of analysis in this investigation is the speaking character. To be included, speaking characters must be living beings who appear independently and must voice at least one discernable word on screen, or be named. Each character is assessed once per episode evaluated, save two rules. First, when characters altered aspects of their demographic characteristics (i.e., age, race/ethnicity, sex, type), an additional line of data was created. Second, a character that is shown with more than one job necessitated creating a "new line" of data. Additional lines for occupation changes were not included in any analysis except those focusing on work-related portrayals. For the impact of including demographic and occupation changes in the data analysis, see the companion report *Implicit & Explicit Biases: A Look at the Nature of Representation in Film & TV*.

For each speaking character, a series of quantitative measures were assessed. Most of the variables are detailed in the companion paper and thus redundant measures will only be briefly described here: *type* (i.e., human, animal, supernatural creature, anthropomorphized supernatural creature, anthropomorphized animal), *age* (i.e., 0-5, 6-12, 13-20, 21-39, 40-64, 65+), *sex* (i.e., male, female), *race/ethnicity* (i.e., White, Hispanic/Latino, Black/African American, Native American/Alaskan Native, Native Hawaiian/Pacific Islander, Asian, Middle Eastern, Other/Mixed Race), *apparent sexuality* (Lesbian, Gay, Bisexual, not Lesbian, Gay, Bisexual), *parental status* (no, yes), and *romantic relationship* (no, yes).

Reliability of unitizing and measures reported in both papers can be found in the companion manuscript. Below, we will overview quantitative and qualitative procedures and measures unique to this report and illuminate reliability when assessed.

Computer science was ascertained for each character (i.e., no, yes). Once computer science was identified, whether a character engaged in *talk* (i.e., no, yes) or *behavior* (i.e., no, yes) related to computer science was evaluated. Additionally, the domain in which computer science occurred was measured. This could be *education* (i.e., no, yes), *job* (i.e., no, yes), or *leisure* (i.e., no, yes). These categories were not mutually exclusive and thus characters could use computer science in more than one setting. Finally, whether a character wore *glasses* (i.e., no, yes) was evaluated.

Attributes that focused on the portrayal of characters included: *attractiveness*, measured by other characters' positive verbal or nonverbal references to the physical beauty of the character. Single or multiple references were collapsed prior to analysis to form a single indicator (i.e., no, yes). While attractiveness was assessed for every episode evaluated, for this analysis, attractiveness is reported *only* for the episodes in which a character used computer science.

Data for this investigation was captured in two waves. Initial teams of research assistants were assigned to identify characters and to assess demographics, sexualization variables, and LGBT status. Where possible, the same set of research assistants evaluated every episode in a series. If a new research assistant began to evaluate a series, the RA reviewed prior episodes before beginning data collection. A second group of research assistants was trained to assess occupation and computer science. These RAs were recruited from computer science majors and from other disciplines. This was done to ensure that individuals trained in the field of computer science were part of the process of identifying computer science portrayals in media.

All research assistants were trained to assess content in a classroom setting by one of the authors (Choueiti). Each research assistant was required to complete a series of reliability diagnostics to ensure consistent evaluation of content. Once each group had satisfactorily completed training, they evaluated content in the Media, Diversity, & Social Change Initiative lab. The first team of research assistants (i.e., unitizing, demographics, sexualization) completed their work before the second team evaluated occupation and computer science.

For the quantitative variables unique to this report, reliability was assessed per variable using the Potter and Levine-Donnerstein (1999) formula. Sample-wide reliability means, medians, and range are reported for the variables in this report: *computer science* 1.0 (X=.952, range=.57-1.0), *CS talk* 1.0 (X=.9975, range=.57-1.0), *CS behavior* 1.0 (X=.998, range=.57-1.0), *CS Job* 1.0 (X=.994, range=0-1.0), *CS Leisure* 1.0 (X=.997, range=0-1.0), *CS education* 1.0 (X=.999, range=.57-1.0), *glasses* 1.0 (X=.993, range=.57-1.0) and *attraction* 1.0 (X=.998, range=.63-1.0).

Once quantitative coding was completed, a qualitative examination of characters engaged in computer science was performed. For each CS character, two trained research assistants evaluated a suite of variables. These included *level of skill* (i.e., low, medium, high), *goals* (i.e., no, yes), *friendships* (i.e., no, yes), *type of friendship* (i.e., other individuals involved with computer science, individuals not involved with computer science, combination), *intelligence comments* (i.e., no, yes), *positive reinforcement* (i.e., no, yes), *negative reinforcement* (i.e., no, yes), and *stereotypical name* (i.e., no, yes). Disagreements in coding were resolved through discussion. Again, effort was made to ensure that the same individuals evaluated the same character consistently across multiple episodes in the sample when the situation arose.

2. The sample of Google influenced shows was determined by identifying, in partnership with the Google CS in Media Team, the programs and/or seasons that aired after Google's influence occurred. All available episodes of the influenced season were examined, with the exception of two shows that continue to air new episodes beyond the date of this report. *Ready Jet Go!* and *Powerpuff Girls* aired 19 and 11 episodes respectively before each series went on a hiatus for at least two months. Two match shows share the same circumstances: *PJ Masks* and *Star vs. The Forces of Evil*. Prior to the hiatus, every episode in each series was included. All episodes that resumed airing after the series hiatus were not included.

The Google CS in Media Team identified the two TV movies and one show to match the influenced sample. To compile the rest of the matched sample, information on potential comparison programs was compiled using Studio System/inBaseline, Variety Insight, IMDbPro, and other online sources. Shows were matched by examining the number of episodes in a season, the gender of the lead character(s), style of presentation (animated vs. not animated), whether the program contained episode segments, and using key search terms from online databases. Where possible, content from a different network and production company was selected.

3. Characters were classified as leads or series regulars. Information on whether a character was a series regular (i.e., no, yes) came from Variety Insight. A similar procedure was utilized in Smith, S.L., Choueiti, M., & Pieper, K. (2016). *Inclusion or Invisibility? The Comprehensive Annenberg Report on Diversity*. As described in that report, "series reg-

ulars are actors who are main cast or have an ongoing or 'regular' role on the show" (personal communication with representative at Variety Insight, 1/15/2016). A designation of "voice talent" is the equivalent to a series regular in animated content. Recurring roles and guest stars were not included as series regulars. In cases where Variety Insight did not provide information on series regulars, Studio System/inBaseline, IMDbPro, and show credits were used to make a determination. Leading characters (i.e., single lead, co lead, ensemble member) were equivalent to series regulars for film. For definitions related to ascertaining the lead character of a film, see Smith, S.L., Choueiti, M., & Pieper, K. (2016). *Inequality in 800 Popular Films*. Both reports available: http://annenberg.usc.edu/mdsci

4. IMDbPro summaries were consulted to qualitatively determine if a series or film was technology focused or not. If summaries included terms related to technology to describe the plot of the television show or film, it was considered technology focused.

5. Rate was computed by dividing the total number of times the presence of a particular attribute occurs out of the total number of episodes a character is featured with CS. For instance, if a character appears in one episode and is referenced as attractive, s/he would receive a 1.0 or 100% on rate. If another character is referenced as attractive in one episode but not in the other 9 in which they do CS, then his/her rate would be .10 or 10% of the time. The rate illuminates the frequency of juxtaposing CS with a particular stereotypical or counter-stereotypical feature. This approach is reported in the full report for applicable variables.

6. Mercier, E.M., Barron, B., & O'Connor, K.M. (2006). Images of self and others as computer users: The role of gender and experience. *Journal of Computer Assisted Learning, 22*, 335-348. Cheryan, S., Siy, J. O., Vichayapai, M., Drury, B.J., & Kim, S. (2011). Do female and male role models who embody STEM stereotypes hinder women's anticipated success in STEM? *Social Psychological and Personality Science, 2*(6), 656-664. Cheryan, S., Drury, B.J., & Vichayapai, M. (2012). Enduring influence of stereotypical computer science role models on women's academic aspirations. *Psychology of Women Quarterly, 37*(1), 72-79.

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12. Cheryan, S., Plaut, V.C., Handron, C., & Hudson, L. (2013). The stereotypical computer scientist: Gendered media representations as a barrier to inclusion for women. *Sex Roles, 69*, 58-71. Schott, G. & Selwyn, N. (2000). Examining the "male, antisocial" stereotype of high computer users. *Journal of Educational Computing Research*, 23(3), 291-303.

13. A full 58.5% (*n*=38) of characters were depicted talking about and engaging in computer science. Another 41.5% or 27 characters were shown only talking about CS in the Google influenced and match samples. In samples of popular content, 69.6% (*n*=32) of all CS characters engaged in both talk and behavior. Twelve characters (26.1%) were depicted only discussing CS and two were portrayed only doing CS (4.3%). For analysis related to performing CS in the presence of others, individuals who discussed CS were excluded.

14. Bandura, A. (2002). Social cognitive theory of mass communication. In J. Bryant & D. Zillmann (Eds.), *Media Effects: Advances in Theory and Research* (p. 121-153). Mahwah, NJ: Lawrence Erlbaum Associates. Liebert, R.M. & Sprafkin, J. (1988). *The Early Window: Effects of TV on Children and Youth* (3rd edition). NY: Pergamon Press.

15. The two samples consisted of prime-time programs popular among 18- to 49-year old viewers and programs popular among 2- to 12-year olds across the total day. Programs aired between June 1, 2015 and May 31, 2016 on broadcast and cable networks. Nielsen generated the lists using genre descriptors consistent with scripted fiction. Reruns, TV movies, and specials were excluded by the MDSC Initiative. Series were included when they met two additional parameters: 1) multiple episodes were aired; and 2) program duration was over five minutes.

Using the lists provided by Nielsen, online databases (i.e., Variety Insight, Studio System/inBaseline, IMDbPro) were consulted for the season premiere date for each series. When the season began within the stipulated time frame, the first two episodes of that season were included. In situations where the season premiered outside the time frame, the first two episodes that aired between June 1, 2015 and May 31, 2016 were sampled. The U.S. Average Audience Rating Percentage for the 20 top prime-time series ranged from 9.56 to 2.75. Ratings ranged from 3.28 to 2.76 for popular shows among 2- to 12-year olds.

16. Domestic theatrical box office revenue was identified using BoxOfficeMojo.com. Based on this information, the 20 top-performing films released in 2015 were chosen to comprise the sample. These films were evaluated for demographics, domesticity, sexualization, and apparant sexuality for the annual inequality in film report produced by the Media, Diversity, & Social Change Initiative at USC Annenberg. http://annenberg.usc.edu/sites/default/files/2017/04/10/MDSCI_Inequality_in_800_Films_FINAL.pdf

17. Cheryan, et al. (2013). Beyer, S. (1999). The accuracy of academic gender stereotypes. *Sex Roles, 40*(9-10), 787-813.

18. U.S. Census Bureau (n.d.). QuickFacts from the U.S. Census Bureau. Retrieved from: https://www.census.gov/quickfacts/table/PST045215/00

19. Interviews focused on several questions related to the Google CS in Media Team intervention. Throughout this section, responses refer to the following questions. On the topic of how content creators became involved with Google: *To begin, tell me about the origin of your partnership with Google. How did that come about? Did they approach you or did you approach them? Why? Were there specific reasons you decided to work with the team?* To address the outcomes of the intervention,

individuals were first asked: *can you describe what happened as a result of your work with the Google team?* Following this, individuals were asked a series of questions that assessed: *whether an episode or film was impacted, if working with Google altered their writing process in any way, if the writers' room process was changed, if there were others on the team who were impacted, if any new practices were adopted, if any unexpected outcomes were generated, and whether Google's influence spilled over to affect anything on the program, the network, or the content creator's other projects.* Participants were also asked how their expectations compared to the outcome of the intervention. Questions about implicit bias and diversity were also asked. A series of questions about what the Google CS in Media Team could start, stop, or continue to have greater impact were included in the interview as well.

The unit of analysis for the interviews was the entire response to each section or a set of questions. Individuals' comments could apply to more than one coding category, although the same words/phrases did not apply to multiple categories. One of the study authors coded the responses independently, and discussed these judgments with research assistants and another of the study authors.

20. Cheryan, S., Plaut, V.C., Davies, P.G., Steele, C.M. (2009). Ambient belonging: How stereotypical cues impact gender participation in computer science. *Journal of Personality and Social Psychology, 97*(6), 1045-1060.

APPENDIX A

P18-49 PRIME TIME

	SHOW TITLE	SEASON	NETWORK
1.	THE WALKING DEAD	6	AMC
2.	EMPIRE	2	FOX
3.	THE BIG BANG THEORY	9	CBS
4.	GAME OF THRONES	6	HBO
5.	FEAR THE WALKING DEAD	2	AMC
6.	THE X-FILES	10	FOX
7.	MODERN FAMILY	7	ABC
8.	GREY'S ANATOMY	12	ABC
9.	SCANDAL	5	ABC
10.	HOW TO GET AWAY WITH MURDER	2	ABC
11.	BLINDSPOT	1	NBC
12.	AMERICAN HORROR STORY	5	FX
13.	NCIS	13	CBS
14.	ACS: PEOPLE V. OJ SIMPSON	1	FX
15.	CRIMINAL MINDS	11	CBS
16.	THE GOLDBERGS	3	ABC
17.	CHICAGO FIRE	4	NBC
18.	BLACK-ISH	2	ABC
19.	THE BLACKLIST	3	NBC
20.	SCORPION	2	CBS

P2-12 TOTAL DAY

	SHOW TITLE	SEASON	NETWORK
1.	GIRL MEETS WORLD	2	DISNEY CHANNEL
2.	HENRY DANGER	2	NICKELODEON
3.	JESSIE	4	DISNEY CHANNEL
4.	NINJAGO	5	CARTOON NETWORK
5.	AUSTIN & ALLY	4	DISNEY CHANNEL
6.	SPONGEBOB SQUAREPANTS	9	NICKELODEON
7.	PAW PATROL	3	NICKELODEON
8.	TEEN TITANS GO	3	CARTOON NETWORK
9.	K.C. UNDERCOVER	3	DISNEY CHANNEL
10.	GAME SHAKERS	1	NICKELODEON
11.	LIV AND MADDIE	3	DISNEY CHANNEL
12.	BUNK'D	1	DISNEY CHANNEL
13.	EMPIRE	2	FOX
14.	DOG WITH A BLOG	3	DISNEY CHANNEL
15.	ALVINNN!!! AND THE CHIPMUNKS	1	NICKELODEON
16.	NATURE CAT	1	PBS
17.	BEST FRIENDS WHENEVER	1	DISNEY CHANNEL
18.	BLAZE AND THE MONSTER MACHINES	2	NICKELODEON
19.	THE THUNDERMANS	3	NICKELODEON
20.	THE LOUD HOUSE	1	NICKELODEON

20 TOP FILMS OF 2015

	FILM TITLE
1.	STAR WARS: THE FORCE AWAKENS
2.	JURASSIC WORLD
3.	AVENGERS: AGE OF ULTRON
4.	INSIDE OUT
5.	FURIOUS 7
6.	MINIONS
7.	THE HUNGER GAMES: MOCKINGJAY - PART 2
8.	THE MARTIAN
9.	CINDERELLA
10.	SPECTRE
11.	MISSION: IMPOSSIBLE - ROGUE NATION
12.	PITCH PERFECT 2
13.	THE REVENANT
14.	ANT-MAN
15.	HOME
16.	HOTEL TRANSYLVANIA 2
17.	FIFTY SHADES OF GREY
18.	THE SPONGEBOB MOVIE: SPONGE OUT OF WATER
19.	STRAIGHT OUTTA COMPTON
20.	SAN ANDREAS

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