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The Portrayal of Men and Women in Digital Communication: Content Analysis of Gender Roles and Gender Display in Reaction GIFs

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This article explores gender roles and gender displays in animated GIFs. The 747 most popular reaction GIFs accessible via Tenor, Giphy, and Gfycat were content analyzed. An automated approach using machine learning and a human coding approach were used to code for primary characters. Findings revealed that female characters were underrepresented in comparison to their counterparts. Across the age groups, women appeared younger than men. Compared with male figures, females were more prone to be portrayed as slightly nude, wearing sexually revealing clothing, and sometimes in attire considered unsuitable for the context of the situation. In contrast, chi-square analyses indicated no significant differences between genders in terms of nonverbal behaviors ("displays") such as expression of emotions, smiling, or gazing, and use of gestures. The results of sentiment analysis in reaction GIFs' titles showed no different sentiment scores for GIFs depicting either male or female main characters.

Keywords: gender representation, gender display, reaction GIF, nonverbal behavior, instant messaging

Over the past decade, trends have shown an increase in the use of messaging apps as more users go online to stay connected with family, friends, and colleagues. In fact, the latest messaging app usage statistics show that the top-five messaging apps have more than 5.5 billion users worldwide.[1] As technology-mediated communication becomes popular, novel multimodal practices (photos, videos, or sound) have emerged to express thoughts and feelings without touch or direct eye contact. The use of graphical interchange formats (GIFs) is one such multimodal practice (Tolins & Samermit, 2016), one in which users

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[1] WhatsApp has 2.0 billion users worldwide, Facebook Messenger has 1.3, WeChat has 1.1, QQ Mobile has 0.7, and Telegram has 0.4 (Clement, 2020).

are not leveraging self-represented or renderings of themselves (i.e., Facebook's avatars) to communicate, but rather using an entirely other person (Klein, 2020). Nowadays, GIFs are an essential part of the vernacular visual lexicon that people—mainly digital natives—use to communicate, express themselves, and shape their relationships. Furthermore, proof of the relevance of visual media in today's interpersonal communication is the recent acquisitions by Google and Facebook of two main online libraries of GIFs, Tenor and Giphy, respectively.

However, some questions have arisen about the way men and women are portrayed in these short moving images. Are women and men portrayed differently in those stand-ins? Do these gender portrayals perpetuate stereotypes spread in traditional media such as TV programs, movies, or advertisements? If so, are these stereotypical gender portrayals based on age, ethnicity, or nonverbal behavior? Research on gender representations in the media has generally focused on traditional mass media. This research attempts to contribute to this field by exploring gender roles and gender displays in popular reaction GIFs accessible via Tenor, Giphy, and Gfycat using different coding categories for the central characters.

Numerous studies from different fields highlight the importance of considering gender as a cultural construct that contemplates the difference between sex (biological) and gender (cultural) in order to introduce it as a category in research (de Beauvoir, 1949/1981; Oakley, 2015; Valcárcel, 1997). Gender is a phenomenon that is learned and taught, descriptive, and prescriptive, and different from human nature and the particular personality. A system that attributes each gender a series of values whose characteristics are complementarity and inequity are symmetrical and antithetical (Beaudoux, 2014; Burgess & Borgida, 1999). Nevertheless, this dual construction proves more vital because it implies unequal control over symbolic and material resources between men and women.

The content of these stereotypes is multifaceted, and there are numerous proposals for dividing and measuring them. Williams and Best (1990) propose the first division between role and feature stereotypes, separating those that refer to activities appropriate to each sex (role) and those that refer to psychological, physical, or behavioral characteristics (feature). Hence, women must play roles linked to care, education, and upbringing, and must represent values of beauty, perfection, fragility, and generosity (Castillo-Mayén & Montes-Berges, 2014; Morales & López, 1993; Williams & Best, 1990).

This social stereotype is spread and reproduced by socializing institutions such as schools or families, and, in more recent times, by the media. The representation of gender in mass media has been extensively studied, even legislated, given their ability to perpetuate and spread stereotypes, thanks to their essentially socializing role (Ceulemans & Fauconnier, 1979; McArthur & Resko, 1975; Sanz, 2001).

However, the importance of stereotypes is not only reproductive, but productive. The new visual lexicon, born in a sexist society, assumes this stereotype and combines it with image and sound, turning the stereotype into a symbol (del Campo, 2006). Thus, the new visual lexicon interprets reality, but it is not the reality itself. It can be analyzed through different gender representations (del Campo, 2006) such as the use of phrases or words to clamp stereotypes (verbal coding); the use of different typography for masculinity or femininity (scriptural coding); the differentiated use of color ranges for each genre (chromatic coding); the ability to retouch, stylize, or mold bodies (photographic coding); the use of bodies, even parceled to direct messages or used as canvases (morphological coding); and the physical aspect, the proper gesture of nonverbal language, or the designation of different objects and roles (sociocultural coding).

Research on gender representations in media has led to the consensus that gender role portrayals remain stereotypical. Quantitative content analyses of gender roles in media have included two special issues of *Sex Roles* (Rudy, Popova, & Linz, 2010, 2011), made clear that women are underrepresented in media and that they are typically scantily dressed and relegated to stereotypical roles (Collins, 2011).

The meta-analysis of the research on gender roles in TV and radio advertising by Eisend (2010) reveals that stereotyping is prevalent in advertising mainly related to gender's occupational status. More recently, the extensive review of 51 content-analytic studies of TV advertisements from different countries, conducted by Furnham and Lay (2019), indicates a high prevalence of gender stereotypes around the world that are "surprisingly stable over time" (p. 120). Studies about gender representation in the film industry have reached similar conclusions. Cath Sleeman (2017) research on British filmography shows that women are often cast in gender-stereotypical unnamed roles such as prostitutes, housekeepers, nurses, secretaries, and receptionists. The leading characters study from the Geena Davis Institute on Gender and Media (2019) reveals that sexualization and age continue to be significant variables that need progress.

There is equally substantial research covering different aspects of gender representation in organizations and practices of production in the news media industry. There remain persistent gaps in the portrayal and representation of women in not only traditional, or digital, news media forms. According to the Global Media Monitoring Project (2015), women are far less likely than men to be seen as subjects, experts, or reporters. The same pattern of results has been found in content-analytic studies in other media such as video games (Downs & Smith, 2010), music videos (Wallis, 2011), music lyrics (Flynn, Craig, Anderson, & Holody, 2016), and social media (Döring, Reif, & Poeschl, 2016).

Nevertheless, the nature of the expression of stereotypes is neither immutable nor always conscious. Stereotypes are readjusted, and new expressions of the contradiction and conflict between egalitarian values and residual negative feelings toward women still persist today (Cameron, 2001; Tougas, Brown, Beaton, & Joly, 1995). This transformation toward more subtle, less evident, and explicit forms of sexism interacts with the increasing use of messaging apps and the use of GIFs as new forms of creative expression and feelings.

In producing and coordinating talk in social media, speakers use GIFs to reproduce depictions of others' embodied actions as stand-ins for their nonverbal behavior. They are used to reproduce nonlinguistic actions that, in face-to-face conversation, do not require demonstration such as embodied displays as sighs, smiles, winks, facepalms, or high fives (Tolins & Samermit, 2016).

One of the most common uses of GIFS is the representation of affection. They can augment and shape affective manifestations. The action captured in the GIF makes it useful to communicate a variety of raw feelings, emotions, and affective states (Miltner & Highfield, 2017). The GIF is synonymous with the "reaction GIF": a brief animated clip, usually on a mesmerizing autoplay loop, posted to convey a specific emotion (Haider, 2017) or idea. Understood as gestures, they can communicate more nuance and concision than their verbal translations (Eppink, 2014).

Reaction GIFs proliferate, along with the rest of the media, depictions of gender. These silent movies, composed of brief excerpts of classic cinema or famous culture sequences, can be thought of as gender displays that distinguish the way men and women participate in communicative interaction. As with nonverbal behavior, they are chosen by users to express themselves. Furthermore, such (selected) depictions of masculinity and femininity are socially acquired, patterned, used, and understood concerning others (Wallis, 2011). Therefore, reaction GIFs can convey gender stereotypes through an image, nonverbal, symbolic, and sentimental language.

The popularity and extensive use of GIFs have attracted the attention of communication researchers. There are studies on the use of GIFs in areas such as academics and politics or those referring to new modes of communication (Marmo, 2016; Miltner & Highfield, 2017; Prosperi, 2019); studies focused on GIFs as instruments to teach computers how to recognize, learn, and identify human feelings (Christian, 2015); and some research projects on GIFs from feminist studies (Kuo, 2019; White, 2018). Most of these studies consider GIFs as a tool, not as their object of study.

The research goal guiding this study is the development of an analysis model to describe the gender roles and displays of male and female main characters in the most popular reaction GIF published by the repositories Tenor, Giphy, and Gfycat. To meet this goal, we focused on verbal, morphological, and sociocultural gender representations, addressing four main research questions:

RQ1: What is the relationship between gender and the portrayal of male and female characters in reaction GIFs regarding gender and ethnicity?

RQ2: Compared with male characters, are female characters depicted in a more sexualized or objectifying manner?

RQ3: What are the main nonverbal display differences between women and men among reaction GIFs?

RQ4: What is the difference in sentiment polarity (or sentiment orientation) between titles of reaction GIFs with male or female main characters?

Method

This study examined gender role and gender display of men's and women's main characters in a sample of GIFs published on Giphy, Tenor, and Gfycat. These repositories are used for searching, discovering, sharing, and popularizing animated GIFs and as sources for media embedded in messenger apps such as Telegram or WhatsApp.

Giphy provides different solutions for sharing GIFs across the Web, along with content created by GIF artists and brands. Similarly, Tenor is an online GIF search engine and database owned by Google. Gfycat is a user-generated higher-quality GIF-hosting company that uses video-based technology.

We selected the repositories based on the following criteria. First, we wanted to have access to the most relevant and highly shared GIFs. For that reason, we included repositories with a high number of users, those with a set of tools to deliver GIFs for other applications, and those with multiple ways to access their databases. Second, we wanted to analyze a diverse sample of animated GIFs. In this regard, we selected platforms with extensive and wide-ranging GIF databases and exclusive content.

In April 2020, Giphy had more than 700 million users, with more than 10 billion pieces of content shared every day and a 33% increase in usage since March (Giphy, 2020). Tenor had more than 300 million users, and it was powering 12 billion GIF searches daily (Tenor, 2020). Also, GIPHY: Animated GIFs Search Engine and Android application GIF Keyboard by Tenor achieved more than 10 million installs (Androidrank, 2020). Gfycat, meanwhile, had 300 million daily active users (techcrunch, 2020). Moreover, each provides developers with tools to use them across apps and websites.

Data Sample Generation

To obtain the study sample, we used an application programming interface (API) data extraction pipeline to retrieve 747 reaction GIF entities. Each entity was composed of the GIF image itself and the relevant metadata embedded in each of the entities. The API pipeline, as depicted in Figure 1, connects to each of the API endpoints for each repository (Tenor API: https://tenor.com/gifapi/documentation; Giphy API: https://developers.giphy.com/; Gfycat API: https://developers.gfycat.com/) and retrieves the desired GIFs.

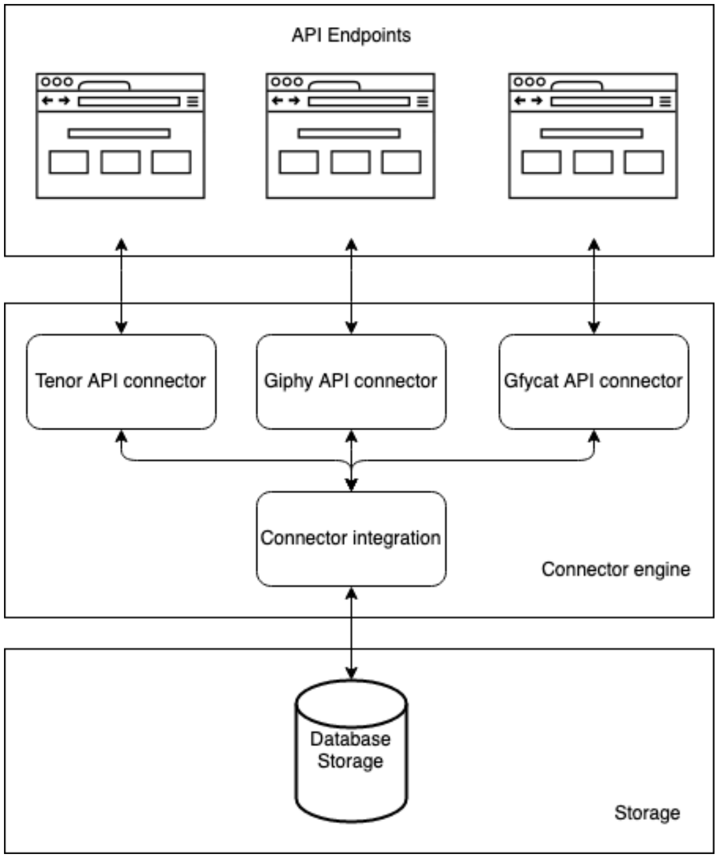

Figure 1. Data retrieval pipeline.

To compose the study sample, we extracted the 279 most-used reaction GIFs from each GIF repository. More specifically, the GIFs classified as "reaction" GIFs were the ones of concern because those GIFs represent the ones by which users express a reaction or emotion in the context of a text-based conversation.

The flow for data extraction was as follows: Each API connector generates a request to retrieve 249 GIFs labeled as reaction GIFs for each of the repositories. The connector integration processes all of the responses, making sure that all the requested data are complete. Finally, the database stores both the GIF itself and its metadata for later analysis.

Data Sample Preparation

The data sample stored in the database was not suitable for direct analysis. Among other things, format and completeness of the items extracted from each of the repositories needed to be verified, validated, and prepared for analysis by the coders and the machine learning models. A second pipeline prepared the data for analysis. The data preparation pipeline iterated each of the items downloaded from the previous pipeline and checked that all variables had a value and were in the correct format and all GIF images could be viewed.

Once the validation process finished, the final stage of this pipeline generated a visual representation of the data items so that they could be easily accessed and analyzed. To do so, we chose an online visual tool to facilitate human coders in their tasks.

Procedure

The present study involved two levels of analysis: individual character level and GIF level. At the individual character level, we performed an automated approach using machine learning and a human coding approach to code for primary characters. Primary characters were defined as the person on whom the focus of the animated GIF is placed and receives the most screen time. The present study focused on the gender representation of the main character of reaction GIFs. Only those with male or female characters (real people or cartoons) were identified and coded.

Furthermore, GIFs with more than one main character or those with no evident main character were excluded. Two research team members measured the visual gender of the characters. In total, 747 GIFs were selected to be included in the study, resulting in 249 for each repository.

Based on previous content analyses of the portrayal of men and women in the media, we coded the following characteristics of each central character: demographic (i.e., gender, ethnicity, age) and physical appearance (i.e., body weight, hair color, hair length). Furthermore, specific attributes related to gender representation such as variables related to depictions of overt sexuality (i.e., sexually revealing clothing and nudity) and objectification (i.e., breast size, appropriateness of attire for the task at hand; Downs & Smith, 2010); and variables related to stereotyping in regards to the setting (workplace/home; i.e., role and location; Valls-Fernández & Martínez-Vicente, 2007). These are standardized measures in research about gender role content areas as (under)representation, sexualization, roles, or body image (Collins, 2011). Finally, concerning stereotypical portrayals of men and women in reaction GIFs, we coded variables for gesturing and nonverbal expressions of sexuality (i.e., type of gesture, primary emotion, facial expressions, self-touching, gaze, use of hands). All of them were in line with Goffman's (1979) categories and Smith's (1996) revision of the principles of gender display as relative size, feminine touch, or ritualization of subordination.

At the GIF level, we performed an automated approach using machine learning, specifically, sentiment analysis of the GIFs' titles that were available on their publishing site. These titles described the content depicted in the GIF using few words and providing some context. Sentiment analysis detected the tonality of titles and computationally identified and categorized these texts into four sentiments: positive, negative, neutral, or mixed when texts carried both positive and negative statements at the same time. Because of the extensive amount of available research and demonstrated performance of natural language processing to generate sentiment scores for texts, there was no need to ask coders to annotate the tonality of the titles.

Human Coding Approach

The coding team consisted of three coders, two women and one man, in their early 20s. Coders were undergraduate students of audiovisual communication from a major university in Spain. A training session on using the codebook was held online. Afterward, coders had one week to independently code 90 GIFs that were not included in the study sample. An online workspace in Slack was set up to solve the coders' doubts. Intercoder reliability was determined by using the average pairwise percent agreement (Neuendorf, 2002), which was calculated using Recal3 (2020). During training, questions about determining hair color, hair length, and body weight were explained. To assess emotions, we decided to use results from the project GIFGIF built at the MIT Media Lab (Rich & Hu, 2020). In the preliminary design, variables dealing with the role, location, and gaze staring were discarded because of the lack of context and the difficulties identified by coders to measure them accurately. Lastly, the codebook was refined.

All coders coded 83 GIFs from each repository (249 in total). They made their decisions independent of one another. After the coding process was carried out, a new analysis was performed on 54 randomly selected GIFs from each repository (162 in total) to perform the reliability test. As in the training phase, the average pairwise percent agreement was used to compute reliability. The coefficient for each retained variable was primary character style (97.98%), ethnicity (89.29%), age (85.05%), body weight (70.51%), hair color (78.99%), hair length (77.17%), sexually revealing clothing (92.32%), nudity (92.12%), breast size (71.26%), appropriateness of attire (92.73%), objectification (99.19%), type of gesture (76.77%), main emotion (35.96%), facial expression smiling (84.24%), facial expression open mouth (84.65%), facial expression pouting (97.58%), self-touching face (93.54%), self-touching hair (99.19%), self-touching body (95.96%), gaze big eyes (90.71%), and gesture hands (88.89%). Finally, variables dealing with body weight, hair color, hair length, breast size, type of gesture, and main emotion were discarded because of a lack of intercoder agreement (<80%).

Automated Coding Approach

The automated coding approach used machine learning to measure gender, age range, emotion, facial expression smiling, and the title sentiment analysis. The rest of the variables were disregarded because the applied model could not provide measures with enough accuracy to have them included in the results of this study.

Machine learning (ML) is currently one of the most outstanding subfields of computer science. It is a branch of the artificial intelligence world, and its fundamental aspiration is to develop techniques that allow computers to learn (González Pérez, 2018). Actually, ML is about creating applications capable of generalizing behaviors from information provided in the form of examples. It is, therefore, a process of knowledge induction. In many cases, the field of action of ML overlaps that of computational statistics given that the two disciplines are based on data analysis. However, ML also focuses on the study of the computational complexity of problems.

To accomplish this type of coding approach, we designed a machine learning pipeline to produce the defined outputs. Figure 2 shows how the pipeline was built. In this case, from each GIF entity, two types of analyses were performed.

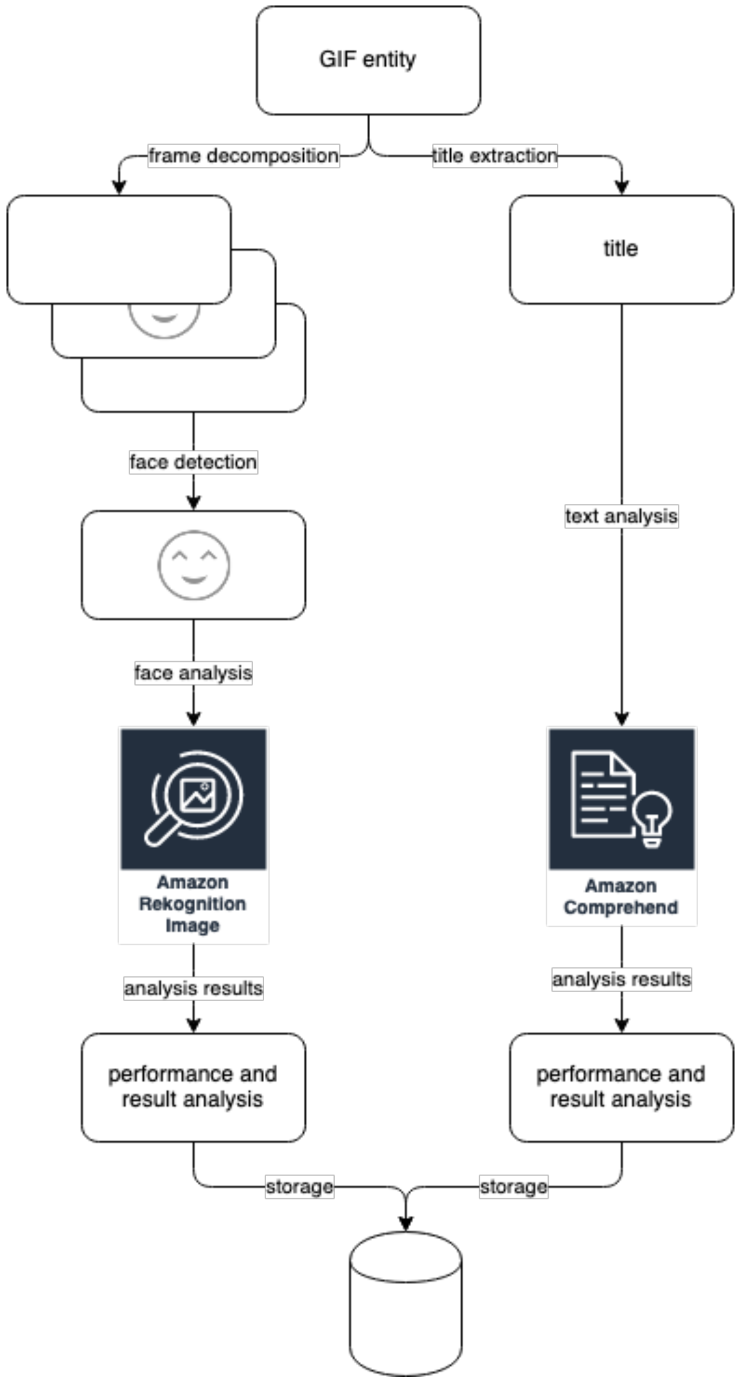

Figure 2. Automated coding pipeline.

The first analysis extracted every GIF file and decomposed it in frames. For each frame, face detection and the extraction machine learning model were applied to extract only those frames with at least a recognizable face; the others are disregarded as they lacked interest in this analysis. Once all face-containing frames were extracted, they were passed to a face analysis engine that used state-of-the-art machine learning models. Using convolutional neural networks (Balaban, 2015), it extracted face landmarks (e.g., mouth, eyes, and nose positions) to derive the results for the image-related variables as well as a confidence measures for gender, emotion, and facial expression smiling. This confidence measure was calculated using state-of-the-art approaches, such as the modified indifference zone method, to estimate the confidence interval of the number of features (Yan, 2008).

To measure the confidence of the automated approach, we calculated a mean of all confidence measures from each of the analyzed images. As shown in Table 1, the overall confidence of the available measures surpassed the 80% score. The second analysis used a different type of machine learning model based on natural language processing to calculate the sentiment of each of the provided GIF titles. Once both analyses were done, their results were stored in the shared database for future reference and study.

Table 1. Confidence Measures: Automated Coding.

Variable	Confidence (%)
Gender	88.82
Emotion	92.09
Facial expression smiling	87.52

Results

A set of analyses was conducted to answer the general research question: What are the gender roles and displays of male and female main characters in the most popular reaction GIFs published by Tenor, Giphy, and Gfycat? To assess differences in the portrayal of male and female main characters, we created a shared dashboard in Tableau[2] to explore, visualize, and analyze the data. In addition, chi-square analyses were performed on the frequency of the appearance of males and females within each variable. In some cases, variables were collapsed as a low number of instances were coded. The sample size for some analyses varied, as items coded "cannot tell" or "not applicable" were excluded. Finally, those variables with levels of reliability less than 80% were removed from the analysis.

Demographic

In the 747 reaction GIFs coded, 62.7% (n = 468) were male, compared with 37.3% (n = 279) females. This means that male characters were overrepresented, which clearly is a distortion of reality, $\chi^2(1, N = 747) = 44.12, p < .001$. We compared the proportion of males and females in this study with the

[2] Tableau is a business intelligence and analytics software. The dashboard is available to anyone (https://tabsoft.co/3co8wmk).

number of men and women in the world, where of 1,000 people, 505 are men and 495 are women (World Bank Group, 2020). This led us to think that it is easier for male characters to appear in reaction GIFs.

Most characters in the sample were real people, 93.84% (n = 701), followed by cartoons, 6.16% (n = 46). Concerning the ethnic background of the main characters,[3] across all 721 GIFs, nearly three-quarters of all characters were White. We observed a White ethnicity in approximately 76.8% (n = 554); Blacks or African Americans accounted for 14.6% of the main characters (n = 105); Asian people were approximately 3.5% (n = 25) of the people; and Hispanic, American Indian, and native Hawaiian combined equaled approximately 5.0% (n = 37). Our analysis shows that if we concentrate on gender differences within the ethnic groups, the relation between these variables was significant, $\chi^2(3, N = 721) = 9.05$, $p = .029$. White male and White female characters were more likely than other ethnicities to appear as leading characters.

To compare the effects of age and gender, coders recorded the age of each main character by placing them in one of the following categories: infants and young children (5 years and younger), "tweens" and teens (ages 6–20 years), adults (ages 21–50 years), and older adults (ages 51 years and older). Table 2 shows the age groups by gender.

Table 2. Percentages and Frequencies of Characters by Age Group: Human Coding.

	Age (years)				
Primary character	5 and younger	6–20	21–50	51 and older	Total
Female					
within Female (%)	16.06	20.44	58.39	5.11	100.00
within Age (%)	6.00	7.64	21.83	1.91	37.38
Frequency (n)	44	56	160	14	274
Male					
within Male character (%)	6.32	11.11	73.86	8.71	100.00
within Age (%)	3.96	6.96	46.25	5.46	62.62
Frequency (n)	29	51	339	40	459
Total					
within Primary character (%)	9.96	14.60	68.08	7.37	100.00
Frequency (n)	73	107	499	54	733

[3] Categories with small numbers (Hispanic, Latino, or Spanish origin; Asian; American Indian or Alaska Native; Middle Eastern or North African; Native Hawaiian or Other Pacific Islander and some other race, ethnicity) were combined.

A one-way chi-square test yielded a significant effect for age across male and female characters combined, $\chi^2(3, N = 733) = 229.07$, $p < .001$. A significantly higher proportion of people between the ages of 21 and 50 (68.08%) was featured in sample GIFs than those reported by the United Nations (2020). A similar pattern held when examining male, $\chi^2(3, N = 459) = 181.31$, $p < .001$, and female characters separately, $\chi^2(3, N = 274) = 81.87$, $p < .001$. A significant chi-square test was observed for this variable by gender, $\chi^2(3, N = 733) = 35.62$, $p < .001$. There were significantly fewer older (>50 years old) and younger (<20 years old) in these portrayals than male and female characters between 21 and 50 years old.

The age distribution generated from the automated analysis of GIFs offered greater accuracy in relation to the data related to the age group adults. However, there were fewer characters that could be identified as male ($n = 402$) or female ($n = 266$), 668 in total. As shown in Table 3, across all 668 age-coded GIFs, most characters were coded to be between 20 and 49 years old. In addition, there were fewer portrayals of characters over 50 for women as compared with men. Indeed, 4.34% ($n = 29$) of the male main characters were estimated as over 50 years old, whereas only 0.45% ($n = 3$) of female characters were estimated to be over that age. Female characters in their 20s (18.56%, $n = 124$) and male characters in their 30s (23.80%, $n = 159$) were more likely to appear in reaction GIFs, $\chi^2(4, N = 668) = 92.75$, $p < .001$.

Table 3. Percentages and Frequencies of Main Characters Between 21 and 50 Years: Automated Coding.

	Age range (years)					
Primary character	<20	20s	30s	40s	>50	Total
Female						
within Female (%)	21.80	46.62	24.06	6.39	1.13	100.00
within Age range (%)	8.68	18.56	9.58	2.54	0.45	39.82
Frequency (*n*)	58	124	64	17	3	266
Male						
within Male (%)	7.96	24.38	39.55	20.90	7.21	100.00
within Age range (%)	4.79	14.67	23.80	12.57	4.34	60.18
Frequency (*n*)	32	98	159	84	29	402
Total						
within Primary character (%)	13.47	33.23	33.38	15.12	4.79	100.00
Frequency (*n*)	90	222	223	101	32	668

Depictions of Overt Sexuality

The second research question asked whether female characters are depicted in a more sexualized or objectifying manner than male characters. We observed how gender is related to the sexualized portrayal of primary characters. Each overt sexuality variable (nudity, sexually revealing clothing, appropriateness of attire, and objectification) was assessed by gender (see Table 4).

Table 4. Percentages and Frequencies of Sexuality Variables: Human Coding.

	Nudity (n = 739)		Sexually revealing clothes (n = 738)		Appropriateness of attire (n = 721)		Objectification (n = 747)	
Primary character	None	Some	No	Yes	Appropriate	Inappropriate	No	Yes
Female								
within Female (%)	31.97	77.22	84.19	15.81	96.60	3.40	97.13	2.87
within Sexuality Variables (%)	28.55	8.25	31.03	5.83	35.51	1.25	36.28	1.07
Frequency (n)	211	61	229	43	256	9	271	8
Male								
within Male (%)	96.15	3.85	99.14	0.86	98.90	1.10	99.57	0.43
within Sexuality Variables (%)	60.76	2.44	62.60	0.54	62.55	0.69	62.38	0.27
Frequency (n)	449	18	462	4	451	5	466	2
Total								
within Primary character (%)	89.31	10.69	93.63	6.37	98.06	1.94	98.66	1.34
Frequency (n)	660	79	691	47	707	14	737	10

The nudity variable was collapsed into two levels to reflect no nudity (none, 660 of 739) versus some nudity (partial, 79 of 739; full, 3 of 739). As expected, there were hardly any nude reaction GIFs. When looking across genders, there was a significant difference in the way bodies were exposed, $\chi^2(1, N = 739) = 62.10$, $p < .001$. Female characters were depicted nude (partial or full) in a higher proportion (8.25%) than were male characters (2.44%).

Regarding the way characters were dressed, a significant chi-square analysis indicated that there was a difference in terms of sexually revealing clothing, $\chi^2(1, N = 738) = 64.38$, $p < .001$. Female characters were more likely to be portrayed wearing provocative clothes compared with male characters (5.83% vs. 0.54%).

Next, the suitability of the garments worn by the primary character in the activity depicted in the GIF was examined. Most main characters, both male and female, were dressed suitably. However, the number of main characters inappropriately dressed was relatively low: 1.25% (n = 9) females and 0.69% (n = 5) males. A chi-square test revealed a significant difference in suitability by gender, $\chi^2(1, N = 721) = 4.66$, $p = .031$. Female characters were more likely than male characters to be shown in unsuitable attire for the task at hand.

Regarding the objectification of the main characters, the percentage of GIFs showing only body parts rather than a complete human was virtually nonexistent. Across the entire sample of characters, only 1.07% (n = 8) female and 0.27% (n = 2) male characters of 747 were observed. Because these numbers were too low, chi-square analysis could not be performed to test the association between gender and objectification.

Gesturing and Nonverbal Expressions of Sexuality

The third research question asked whether there are gender differences in nonverbal behaviors ("displays") such as the expression of emotions, smiling or gazing, and use of gestures.

Regarding emotions, the affective function of reaction GIFs to demonstrate basic feelings or affective states was assessed via a twofold approach. First, human coders coded reaction GIFs for 17 different emotions, and, as expected, there was no reliable result. The ambiguity inherent in nonverbal behaviors, the lack of fixed meanings for each gesture, or the absence of emotion provided obstacles to reaching firm conclusions. Second, using an automated analysis based on machine learning of GIF content, coders coded eight different emotions. However, the improvement in precision came at the cost of a higher rate of items coded as "cannot tell" (n = 76 of 747). Table 5 shows the findings for each gender and emotion. The analysis yielded no significant difference in the distribution of emotions by gender, $\chi^2(7, N = 668) = 8.42$, $p = .297$. We observed that both male and female characters expressed calm, surprise, and happiness.

Table 5. Percentages and Frequencies of Detected Emotions: Automated Coding.

	Emotion								
Primary character	Angry	Calm	Confused	Disgusted	Fear	Happy	Sad	Surprised	Total
Female									
within Female (%)	7.51	23.32	2.77	2.37	6.32	24.11	10.28	23.32	100.00
within Emotion (%)	2.84	8.83	1.05	0.90	2.40	9.13	3.89	8.83	37.87
Frequency (*n*)	19	59	7	6	16	61	26	59	253
Male									
within Male (%)	8.43	32.05	2.41	1.69	5.30	18.31	8.19	23.61	100.00
within Emotion (%)	5.24	19.91	1.50	1.05	3.29	11.38	5.09	14.67	62.13
Frequency (*n*)	35	133	10	7	22	76	34	98	415
Total									
within Primary character (%)	8.08	28.74	2.54	1.95	5.69	20.51	8.98	23.50	100.00
Frequency (*n*)	54	192	17	13	38	137	60	157	668

Nonverbal gender displays included in this study, such as self-touch (face, hair, or body), smiling, opening the mouth (jaw dropping), pouting, or opening eyes (big eyes), hardly appeared across the sample. Table 6 and Table 7 show the percentage and frequency that each gender display occurred in the reaction GIFs. As shown in the tables, the percentage for all displays was found to be low, less than 15%, in both male and female main characters. In contrast, of 743 reaction GIFs, 49.32% (n = 365) depicted men and women using their hands while gesturing and 28.13% (n = 209) depicted them smiling.

Table 6. Percentages and Frequencies of Self-Touching Variables and Use of Hands: Human Coding.

	Self-touch variables							
	Face (n = 746)		Hair (n = 745)		Body (n = 742)		Use of hands (n = 740)	
Primary character	No	Yes	No	Yes	No	Yes	No	Yes
Female								
within Female (%)	90.68	9.32	98.56	1.44	97.83	2.17	46.72	53.28
within Self-touch variables (%)	28.55	8,25	31.03	5.83	35.51	1.25	17.30	19.73
Frequency (n)	253	26	274	4	270	6	128	146
Male								
within Male (%)	92.93	7.07	99.36	0.64	96.57	3.43	53.00	47.00
within Self-touch variables (%)	60.76	2.44	62.60	0.54	62.55	0.69	33.38	29.59
Frequency (n)	434	33	464	3	450	16	247	219
Total								
within Primary character (%)	92.09	7.91	99.06	0.94	97.04	2.96	50.68	49.32
Frequency (n)	687	59	738	7	720	22	375	365
χ^2	1.22, p = .270		—[a]		0.96, p = .328		2.73, p = .098	

[a] Frequencies were not large enough to conduct chi-square analysis.

As shown in Tables 6 and 7, fewer females used their hands (19.73%, n = 146) compared with male characters (29.59%, n = 219). Similarly, there were more men portrayed smiling (16.15%, n = 120) than women (11.18%, n = 89). Regarding smiling, automated coding showed similar results. Male characters were portrayed smiling in 11.58% (n = 77) of 665 coded GIFs, and women were in 8.87% (n = 59).

Table 7. Percentages and Frequencies of Face Expression and Gaze Variables: Human Coding.

	Face variables							
	Smiling (n = 743)		Open mouth (jaw dropping) (n = 743)		Pouting (n = 744)		Gaze (big eyes) (n = 738)	
Primary character	No	Yes	No	Yes	No	Yes	No	Yes
Female								
within Female (%)	67.99	32.01	84.89	15.11	97.48	2.52	89.09	10.91
within Face variables (%)	25.44	11.98	31.76	5.65	36.42	0.94	33.20	4.07
Frequency (n)	189	89	236	42	271	7	245	30
Male								
within Male (%)	74.19	25.81	87.53	12.47	96.57	3.43	88.77	11.23
within Face variables (%)	46.43	16.15	54.78	7.81	60.48	2.15	55.69	7.05
Frequency (n)	345	120	407	58	450	16	411	52
Total								
within Primary character (%)	71.87	28.13	86.54	13.46	96.91	3.09	88.89	11.11
Frequency (n)	534	209	643	100	721	23	656	82
χ^2	3.32, p = .069		1.04, p = .309		0.49, p = .485		0.02, p = .893	

Contrary to the stereotypical view of women, the chi-square analysis revealed that there were no significant differences between genders in any of these variables by both human and automated coding.3

Sentiment

The fourth research question asked whether there is gender bias in sentiment polarity (or sentiment orientation) of the GIFs' titles. The interpretation and classification of sentiment or polarity (positive, negative, neutral, and mixed) within titles revealed the attitude expressed from the repositories. Mixed and neutral were collapsed as only one mixed instance was coded. Therefore, the neutral could be interpreted as no sentimental expression or a mixture of positive and negative sentiment.

Results showed that there was a substantially higher percentage of neutral instances, 65.86% (n = 490), than positive, 17.88% (n = 133) or negative, 16.26% (n = 121). The analysis yielded no significant difference in the distribution of sentiment by gender, $\chi^2(2, N = 744) = 1.30, p = .523$. GIFs had no different distributions of sentiment scores for GIFs depicting either male or female main characters.

Discussion

This human and automated content analysis of popular reaction GIFs revealed two main findings. First, there was little evidence of depictions of overt sexuality and nonverbal expressions of sexuality, and only two of 12 dichotomous variables were more than 15% of positive answers. Second, the present study results show that gender stereotypes are partially conveyed in popular reaction GIFs.

The percentages found in our study of male and female characters and their age and ethnicity generally agreed with previous findings of gender role portrayal in media. The findings reveal that gender balance in reaction GIFs is slightly low; female characters compose 37.3%. This result is consistent with the significant underrepresentation of women found in studies about gender in media (Geena Davis Institute on Gender and Media, 2017, 2019; Perrone, 2018; United Nations Women, 2020).

Not only are women underrepresented, but the data also support the age difference in the representation of women and men given that there is a lower age range for women than that of the average for men. These data endorse the stereotype regarding the youth of women in media. Women are represented with a younger appearance (see Figure 3); are linked to private settings (see Figure 4); are made up and thin (see Figure 5); are adorned with earrings, rings, and luminous faces that reinforce youthful character, lacking wrinkles or marks of age (Abuín Vences, 2009; Lipovetsky & Naranjo, 1999; Peña-Marín & Frabetti, 1990).

Figure 3. GIF example: Youthful appearance.
https://gfycat.com/infantiledopeygiantschnauzer-beyonce-queen-kiss-want-interview-president

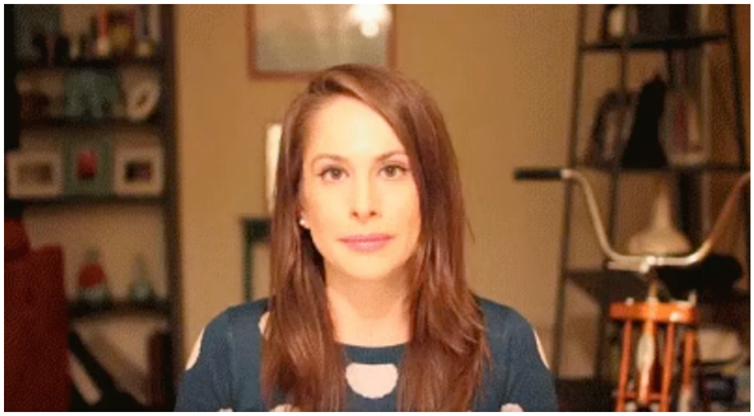

Figure 4. GIF example: Private home setting.
https://gfycat.com/largecomfortablebluebottlejellyfish-speechless-shocked

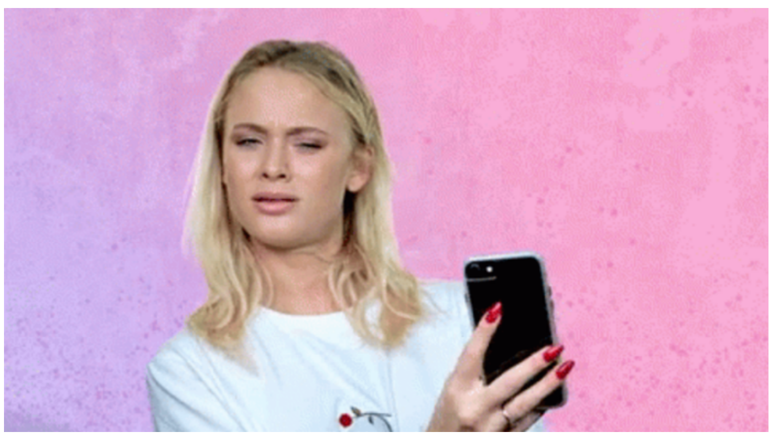

Figure 5. GIF example: Thin and made up.
https://tenor.com/view/wtf-woah-what-wow-noway-gif-11181663

Our findings show significant disparities between the numbers of White and non-White characters. Of 747 characters, White males constituted 47.85%, White females constituted 28.99%, non-White males 14.29%, and non-White females 8.88%. Therefore, whereas female characters, in general, are underrepresented, non-White females are nearly invisible. This media construction of ethnicity remains essential because of its potential impact on society. Given that reaction GIFS are usually short scenes from famous TV shows and movies, turning to the representations of ethnic minorities in mainstream media can provide some context to understand these figures. Researchers have consistently found that non-White characters are underrepresented and are often presented in negative or stereotypical ways (Dixon, Weeks, & Smith, 2019; Meltzer et al., 2017; Ross, 2019; Slaughter-Defoe, 2012).

The second question was whether GIFs meet the stereotype of sexualization and reification of women, that is, if they use the female body as something that can be chopped, exhibited, used, or mistreated (Bengoechea, 2006), and if they value women based on the exhibition of their body (Gill &

Scharff, 2013; Murnen, Smolak, Mills, & Good, 2003). The results support the existence of female stereotypes as far as femininity is presented with a higher degree of nudity and in a sexualized way of dressing. Male characters are less sexualized, and their bodies are scarcely shown. The reification, despite being present in some GIFs, was statistically irrelevant in our sample.

There were reification samples in the reaction GIFs analyzed, for example, representing parts of the woman's body (see Figure 6), as an object (see Figure 7) in which a woman's chest appears as a container where a bird is hiding, with a display of nakedness or sexualized clothing (see Figure 8). Sexualized depictions of female characters transmitted and disseminated by the reaction GIFs contribute to the perpetuation of women being nothing more than objects whose sole purpose is to fulfill the fantasies and demands of men.

Figure 6. GIF example: A woman's lips.
https://giphy.com/gifs/soa-ron-perlman-nzDez5n4biPGE

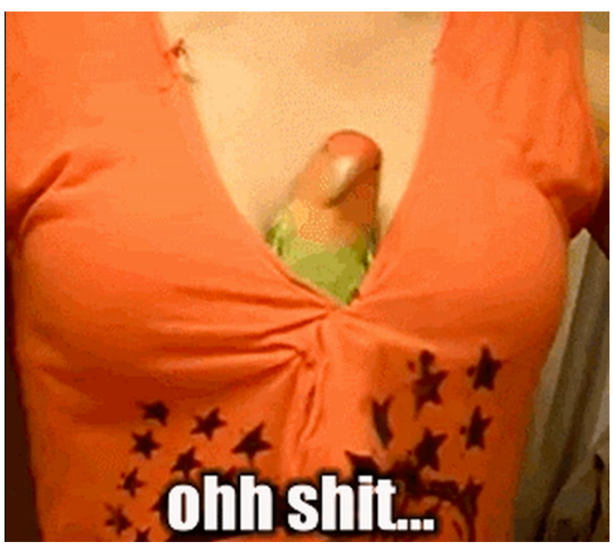

Figure 7. GIF example: Body as an object.
https://giphy.com/gifs/test-jess-abandon-thread-reaction-fuck-this-ZWR31q5ur7YBy

Figure 8. GIF example: Sexualized clothing.
https://tenor.com/view/jelena-karleusa-karleusa-jk-dance-turn-around-gif-16718293

Third, in light of the studies already carried out, there are gender differences in nonverbal behaviors ("displays") such as the expression of emotions, smiling, gazing, or hand gestures. The results obtained in the variables related to gestural stereotyping are not coincident with previous studies on gender bias in nonverbal communication (Davis & Mourglier, 1996; Hall, Carter, & Horgan, 2000; Hall & Matsumoto, 2004; Marino, 2010).

Although the data indicate the absence of a differentiated allocation in the gestural expression of emotions, there are some GIFs showing stereotypes linked to femininity that reinforce gender stereotypes such as those representing women with their mouths ajar, associated with fragility and lack strength (see Figures 9 and 10) and men with rigidity and expressive force (see Figure 11), perhaps because "that is why men do not appear with their mouths open" (Lerch, 1970, p. 231).

Figure 9. GIF example: Pouting expression.
https://gfycat.com/gargantuanfaroffkatydid-speechless

Figure 10. GIF example: Woman with mouth ajar.
https://tenor.com/view/im-just-so-bored-so-bored-boredom-weary-dull-gif-14108256

Figure 11. GIF example: Man with closed mouth.
https://tenor.com/view/embarrassed-awkward-smile-uncomfortable-the-gif-14345746

We also appreciate GIFs linked to the perpetual smile of women that Nancy Henley (1977) described as the "appeasement badge" (see Figures 12, 13, and 14). Alternatively, the so-called self-touching behavior is observable in Figures 12, 13, and 14, which implies that women touch their hair, face, and body more profusely than men and relate it to a demonstration of insecurity or flirting (Moore, 2010).

Figure 12. GIF example: Self-touching behavior.
https://tenor.com/view/blushing-shy-gif-7803763

Figure 13. GIF example: Self-touching behavior.
https://gfycat.com/welllitsanedairycow-alexa-bliss-wwe-the-bump-alexa-bliss-reaction

Figure 14: GIF example: Self-touching behavior.
https://giphy.com/gifs/heart-kristen-bell-PQKlfexeEpnTq

Overall, this study was designed to describe the gender roles and displays of male and female main characters in the most popular reaction GIFs from a gender perspective. At the individual character level, the gender stereotyping described in other areas of mass media does not appear in this study concerning nonverbal language or expression of feelings associated with masculinity or femininity. Therefore, we cannot conclude that gender stereotyping, which appears unequivocally in some GIFs, is extended to reaction GIFs as cultural texts and devices.

In addition, at the GIF level, we also found no signs of stereotyping in the titles assigned by users to reaction GIFs. The polarity of the title found by the sentiment analysis model (positive, negative, or neutral) does not necessarily reflect the user's attitude toward the GIF. Many users describe the content of the reaction GIF to improve their findability. Moreover, some challenging problems seriously affect sentiment analysis accuracies such as the language within titles (too informal, with misspellings, incorrect punctuation, slang and even new words), irony, sarcasm, or negations. Consequently, sentiment analysis on titles should be complemented with similar analysis on tags and category names.

It is worth noting that our results came from a sample of popular reaction GIFs. The repositories rank them based on of how many, usually young, users consciously choose them to communicate and express themselves. The more a reaction GIF is selected, the higher position it gets. Therefore, the absence of gender-stereotypic nonverbal displays of reaction GIFs might suggest that there is an advance in the construction of new masculinities to the detriment of the traditional oppressed model because the new masculinities men use are based on egalitarian dialogue and overcome gender stereotypes. Alternatively, it might suggest that users do not choose stereotype images referring to feelings associated with gender, but, instead, maintain a sexualized vision of women.

Finally, this study has shown the inherent limitations of human coding in quantitative content analysis. Hence, some of the variables related to the physical appearance of main characters, such as hair color and length or bodyweight, were discarded because of lack of intercoder agreement. Moreover, the extreme difficulty for humans to unanimously capture the same meaning in a communication device was exposed in coding the reaction GIFs' emotional content where agreement sharply dropped. Conversely, automated coding has shown advanced precision and reliability. The data generated from the face analysis engine integrated in our automated coding pipeline open the door to extend the use of automated content analysis of nonverbal displays to more media.

We must remember that the animated GIFs that were the subject of this study were expression GIFs. They constituted nonverbal support for the expression of a feeling to a written text. We understand that we have analyzed the GIF outside its context of use, that is, as an autonomous unit outside the analysis of the written, verbal context that may or may not be stereotyped. Further investigation is needed on the use of GIFs in a conversational context; the use of GIFs by men and women; if there is a difference determined by gender in the use of these GIFS; and if they can, despite not having stereotypes in their set, be used stereotypically in conversation.

It is our opinion that it would also be useful to review the stereotypes linked to the expression of feelings that are assigned to each gender. The review would facilitate the discovery of whether old stereotypes have been replaced by new ones in light of sexism and the advances of the feminist movement in equal opportunities.

Conclusion

GIFs have become a fundamental part of digital culture. Their use and frequency in computer-mediated communications are continually developing and expanding among a diverse target of people across multiple social networks. In this context, GIFs' depictions of women and men are part of young people's day-to-day gender socialization and identity development. As isolated cultural fragments of larger texts, GIFs add nonverbal aspects to computer-mediated conversations that can be polysemic depending on who is using them and in what context.

Our study confirms that this new visual lexicon entails gender stereotyping through gender, age, ethnicity bias, and sexualized depictions of women. The lack of positive results about gender displays reflects the complexity of current beliefs about the condition of women and, therefore, the need to review the classifications and study variables of stereotyping proposed by gender studies to date. Exposure to such portrayals may have detrimental effects and should not be considered a minor problem. It could play a crucial role in the reinforcement of sexist attitudes and opinions. In the long run, they might end up in attitudes of self-objectification, underestimation, childhood hypersexualization, and legitimization of violence against women.

Therefore, we consider it necessary to expand the scope of future analysis to get a deeper understanding of how people create, share, and use GIFs: knowledge of what people have in mind when dealing with GIFs affordances such as polysemy, repetition, decontextualization, malleability, and versatility, as well as the way they understand and use reaction GIFS in their social media timelines, personal conversations, or group messages. The prevalence of stereotypes linked to sexism and the low capacity for agreement over other proposed stereotypes invite us to deepen this reflection.

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