Asian Women
September 2024, Vol. 40, No. 3, pp. 27-51, https://doi.org/10.14431/aw.2024.9.40.3.27

Men are Angry, and Women are Happy: A Transfer-Learning Approach for Analyzing Gender Stereotypes in Social Media Challenge Postings*

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Abstract

This research examines the gender stereotypes portrayed in South Korea's "Thanks To" Challenge social media campaign, which aimed to express gratitude to healthcare workers during the COVID-19 crisis. Utilizing cutting-edge transfer-learning techniques for image processing, this study found that gender stereotypes persist in terms of age and the emotions extracted from the social media posts of those who participated in the challenge. The results indicate that among the 4,943 postings randomly selected from those who participated in the challenge, men were three times more likely to appear than women, whereas their extracted ages did not differ. Additionally, for those classified as posting male images, negative emotion scores (sadness and anger) were higher than was the case for female images, whereas female images exhibited higher levels of happiness. Moreover, we found that the emotionality score for happiness was extremely high through the quantifying process using transfer learning, thus reaffirming emotional stereotypes for women in the social media realm.

Key words

Gender stereotypes, emotion, emotionality, social media challenge, transfer learning, machine learning

* This research was supported by Sookmyung Women's University Research Grants (1-2203-2023).

Introduction

Since the first case was discovered, the COVID-19 pandemic (as declared by the World Health Organization on March 12, 2020) has significantly impacted the global economy, politics, and public health systems. As of January 7, 2024, 774,075,242 COVID-19 cases had been reported (34,571,873 cases in South Korea); of these, 7,012,896 cases resulted in confirmed deaths (35,934 in South Korea) (World Health Organization, 2024). As we transition from the pandemic period, the public has become more accustomed to the new patterns of our lives. Many scholars of communication and psychology have attempted to understand the "new normal" era and public behavior. Scholars (e.g., Campbell, Inman, Kirmani, & Price, 2020; Kirk & Rifkin, 2020; Ross, Meloy, & Carlson, 2020) have explored the psychological state of the public, particularly the influence of threats and uncertainty on social behavior. We argue that social networks connected through the online environment can help reduce public uncertainty and the fear of COVID-19 (Nitschke et al., 2021).

The current study is inspired by the "Thanks To" Challenge campaign, considered a successful government public relations campaign aimed at achieving two major goals: 1) encouraging frontline healthcare workers, and, more importantly, 2) helping the public feel connected to enhance resilience during the uncertain situation of the COVID-19 public health crisis (Nitschke et al., 2021). This study sought to evaluate gender portrayals and stereotypes in the social media environment in the context of the "Thanks To" Challenge, which commenced on April 16, 2020, and was initiated by the Ministry of Health and Welfare and the Korea Disease Control and Prevention Agency through its official Instagram account (@thanks_challenge). This challenge involved posting a selfie while showing the word "respect" in sign language to demonstrate appreciation of and gratitude to healthcare workers. Simultaneously, the public could participate in this campaign by posting pictures with hashtags such as #덕분에캠페인 (#thankstocampaign), #덕분에챌린지(#thankstochallenge), #의료진덕분에 (#thankstohealthcareworkers), and #thankstochallenge. Beginning with the President of South Korea, Moon Jae-in, numerous public figures and celebrities, including figure skater Kim Yuna and actress Song Hye-kyo, participated in this campaign, capturing public attention (Yonhap News Agency, 2020).

Despite the success of the "Thanks To" Challenge, analysis of this campaign raises some questions, both conceptual and methodological in nature. Conceptually, as Kim (2020) posited, do gender portrayals and stereotypes still exist in new types of social media activities, such as challenges (Burgess, Miller, & Moore, 2018) or public referrals (Kwon, 2019)? Methodologically, how can we more efficiently extract image features from raw data such as social media posts for content analysis?

In this study, we analyze how men and women are depicted differently in the posts made by those who participated in the "Thanks To" Challenge, using the theoretical lenses of gender stereotype and gender portrayal (Eisend, 2010; Peñaloza, Prothero, McDonagh, & Pounders, 2023; Pounders & Mabry-Flynn, 2019; Pratto & Bargh, 1991; Santoniccolo, Trombetta, Paradiso, & Rollè, 2023), employing cutting-edge image-recognition algorithms based on transfer learning (Son & Park, 2023; Weiss, Khoshgoftaar, & Wang, 2016).

We collected and analyzed 4,943 Instagram posts from the public using hashtags for the "Thanks To" Challenge. We found that 1) the number of postings with male images was approximately three times more than that with female images; 2) the extracted ages from the postings did not differ; and 3) in terms of the emotions expressed by men and women, gender stereotypes were reflected. Specifically, for men, negative emotion scores (i.e., anger and sadness) were higher than they were for women. In contrast, the positive emotion score of happiness was higher for women than for men, supporting the idea that gender stereotypes in social media are partially reaffirmed.

Literature Review

Challenges and the "Thanks To" Challenge in South Korea

Academically, "challenges" can be defined as "an activity to urge members of an online community to construct their own version of something around an ever-evolving, collectively produced format" (Burgess et al., 2018, p. 1036). This "challenge" can also be defined as a "public referral," which is a "viral campaign strategy that takes advantage of the existence of networked culture in social media" (Kwon, 2019, p. 87). By encompassing these two definitions of challenge and public referral, the core component of the challenge—virality (Burgess et al., 2018; Kwon, 2019)—should be considered when analyzing this phenomenon. The rule of the "Thanks To" Challenge was to tag three people to take part in the campaign together, and through this encouragement, the participation rate significantly increased, by more than 36,000 participants within seven weeks of launching the campaign (Lee, 2020). Figure 1 shows examples of "Thanks To" Challenge posts from both the official account and from users.

Gender Stereotypes and Media

As a theoretical foundation, we adopted the concept of gender stereotypes (Åkestam, Rosengren, Dahlén, Liljedal, & Berg, 2021; Deaux & Lewis, 1984; Ellemers, 2018; Grau & Zotos, 2018; Hall & Carter, 1999), which is defined as the belief that specific characteristics, attributes, and behaviors differ by gender (Eisend, 2010; Vinacke, 1957). This gender stereotype is a type of stereotype that refers to the general expectations about members of a certain social group (Ellemers, 2018).

This gender stereotype in the media, including news, advertising, and marketing content, is one of the most important research areas (Peñaloza et al., 2023; Santoniccolo et al., 2023). For example, a recent meta-analysis revealed that approximately 3% of articles published from 1993 to 2021 were related to gender issues (Peñaloza et al., 2023). Previous studies have shed light on three main topics: 1) sex/gender differences and traits, 2) gender stereotypes, and 3) gendered bodies (Butkowski, Dixon, Weeks, & Smith, 2020; Campbell, Sands, McFerran, & Mavrommatis, 2023; Döring, Reif, & Poeschl, 2016; Kennard, Willis, Robinson, & Knobloch-Westerwick, 2016; Peñaloza et al., 2023; Pounders & Mabry-Flynn, 2019; Prieler, 2020).

Historically, researchers have documented gender stereotypes by investigating which stereotypes are used to describe women and men and the antecedents and consequences of gender stereotypes in individuals' decision-making processes (Grau & Zotos, 2018). By focusing on the basic definition of gender stereotypes and portrayals, the initial stage of this research stream elaborated on the reasons that gender stereotypes occur. Similar to other stereotypes, gender stereotypes arise through heuristics to facilitate information processing and reduce cognitive burden (Pratto & Bargh, 1991). Additionally, social comparison has been identified

Figure 1. Examples of "Thanks To" Challenge Posts.

as an important factor influencing the effects of gender stereotypes. Social comparison may influence women's self-perceptions and self-esteem, especially among adolescents (Martin & Kennedy, 1993).

From the perspective of media scholars, several content analyses have investigated components of gender stereotypes: physical characteristics, occupational status/role, and traits (Grau & Zotos, 2018). Females are portrayed as attractive in terms of body size and height (e.g., Grabe, Ward, & Hyde, 2008; Pounders & Mabry-Flynn, 2019) for the idealization (Richins, 1991) of thin and beautiful standards in the media (Knoll, Eisend, & Steinhagen, 2011; Lynch, Tompkins, van Driel, & Fritz, 2016; Webb, Vinoski, Warren-Findlow, Burrell, & Putz, 2017). For example, Webb et al. (2017) found that models on the Yoga Journal's cover page embodied the thin-and-lean fitness aesthetic.

In terms of roles and traits, women are often presented as decorative (Pounders, 2018), family-oriented/unprofessional (Knoll et al., 2011; Uray & Burnaz, 2003), and unimportant (Lynch et al., 2016). For instance, Knoll et al. (2011) found that women are portrayed at home in dependent roles and as users of domestic products. Lynch et al. (2016) also found that female characters in video games are often characterized by secondary and sexualized roles.

Based on these preliminary theoretical foundations, recent research—both into gender and in general—has extended the effects of gender stereotypes on various stakeholder reactions (Åkestam et al., 2021), finding that the effects of these stereotypes are predominately negative (e.g., Åkestam, 2018; Åkestam et al., 2021; Antioco, Smeesters, & Le Boedec, 2012; Chu, Lee, & Kim, 2018; Martin & Gentry, 1997). For example, Antioco et al. (2012) documented how stereotyped physical portrayals of women led to lower levels of self-esteem in France, and Åkestam (2018) found that stereotyped female roles reduced favorable attitudes toward advertisements and brands in Sweden. Stereotyped gender portrayals also influence individuals' psychological status, such as anxiety (Halliwell & Dittmar, 2004) and life satisfaction (Li, Liu, & Song, 2022).

Based on these research streams, we focused on how social media is utilized to portray women. It is well documented that the stereotypical portrayal of women is continuing in the new media environments, such as on social media (e.g., Butkowski et al., 2020; Döring et al., 2016; Jarman, McLean, Slater, Marques, & Paxton, 2024; Mahon & Hevey, 2021). Similar to Kim's (2020) proposition of a new research direction for gender and digital media, scholars have documented gender roles and stereotypes in the social media environment. For instance, gender display is prevalent in female Instagram selfies, and selfies with exaggerated gender displays receive more engagement, such as the number of likes (Butkowski et al., 2020). More importantly, Döring et al. (2016) found that male and female Instagram users' selfies reflect traditional gender stereotypes and are even more stereotypical than traditional media content, such as magazines.

Therefore, this study focused on two important characteristics of gender portrayals: age and emotions. Despite the abundant documentation of gender portrayals and stereotypes, few empirical studies have investigated the depiction of age and emotions in media content. For instance, Prieler (2020) revealed that older women and men rarely appear in the media and, when represented, are frequently described negatively. Additionally, by comparing men and women, Knoll et al. (2011) found that female characters were more likely to be depicted as younger on German television shows than was the case for male characters. However, what about social media such as Instagram? Therefore, we postulated the first and second research questions as follows:

RQ1: To what extent does the number of postings participating in the "Thanks to" Challenge vary in terms of gender?

RQ2: To what extent do ages extracted from postings participating in the "Thanks to" Challenge vary in terms of gender?

Gender and Emotion Stereotypes

Although knowledge of gender, gender portrayal, and gender stereotypes has accumulated considerably over the past several decades, the portrayal of emotions in media content is not fully understood (Collins, 2011; Jungblut & Haim, 2023; Li, Zhou, Zhuang, & Zhang, 2023; Martin, 2017; Shields, 2013). Previous literature mainly focused on the gender stereotype as a gender role, such as the dependent housewife (Knoll et al., 2011). However, there is a new dimension of stereotypes in terms of emotion and emotionality based on gender (Collins, 2011; Givon et al., 2023; Löffler & Greitemeyer, 2023; Martin, 2017; Rodgers, Kenix, & Thorson, 2007; Rose et al., 2012; Shields, 2013; van Breen & Barreto, 2023).

Rooted in Goffman's (1976) pioneering work, which analyzed facial expressions along with pose and body language and found that emotion could demonstrate gender stereotyping in newspapers, several studies revealed gender differences in emotion in media content, but the results were mixed. For instance, Wanta and Leggett (1989) analyzed the emotionality of tennis players in newswire photographs and found that men and women were equally emotional. However, in news photos, women were generally portrayed as happy (Rodgers et al., 2007), while men were depicted a wider range of emotions, such as happy, sad, angry, and fearful, in children's TV programs (Martin, 2017). More recently, Jungblut and Haim (2023) found a significant difference in the depictions of male and female politicians during the 2019 European elections across 28 countries, with women often described as happy. However, recent studies from psychology have found that the belief that women are more emotional than men is not true in many contexts (Givon et al., 2023; Löffler & Greitemeyer, 2023; Paganini, Summers, ten Brinke, & Lloyd 2023; van Breen & Barreto, 2023). For example, Givon et al. (2023) revealed that women produced negative emotions more efficiently than men, and there was no gender difference in the bias for reporting negative emotions across nine experiments. Similarly, Löffler and Greitemeyer (2023) found that the specific emotion of empathy is influenced by contextual factors. However, despite these recent research trends, we still observe emotional stereotypes based on gender.

Since gender role stereotypes are amplified when the study context changes from traditional to social media (Butkowski et al., 2020; Döring et al., 2016; Li et al., 2023), it is necessary to investigate how emotional stereotyping differs in the social media context, such as in challenges. In addition, media content, such as pictures of sports players, may translate emotional reactions visually, including happiness as victory and sadness as defeat. (Rodgers et al., 2007; Wanta & Leggett, 1989), and this connection could lead to stereotypes in gender roles (Collins, 2011; Shields, 2013).

Therefore, we postulated the following research question:

RQ3: To what extent do emotions extracted from the postings participating in the "Thanks to" Challenge vary in terms of gender?

Method

In this section, we describe a data collection/analysis method that adopts a transfer-learning approach for image analysis (Krizhevsky, Sutskever, & Hinton, 2017; Son & Park, 2023; Weiss et al., 2016). Figure 2 shows an overview of the methodology and statistical analysis procedure.

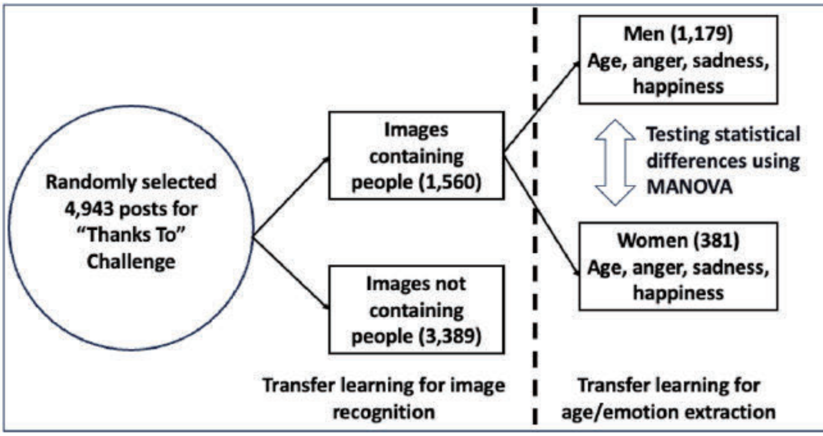


Figure 2. Overview of Methodology.

Transfer Learning of Image Analysis

As a methodological approach, we adopted cutting-edge machine learning techniques for image recognition using transfer learning (Son & Park, 2023; Weiss et al., 2016). Several machine learning approaches have been proposed to analyze large image datasets since Krizhevsky et al. (2017) proposed a new deep-learning framework using ImageNet, which uses a large convolutional neural Networks (CNNs)-based model for image classification.

However, researchers have struggled with two main difficulties: 1) a lack of labeled data and 2) image ambiguity. Machine learning techniques rely on the assumption that the training and testing datasets should have identical input features and the same distribution (Weiss et al., 2016), which indicates that we need a large amount of data in a specific domain. For instance, if researchers wanted to investigate the image classification of a cat/dog, we would need a large amount of data labeled "dog" or "cat." For instance, the COCO dataset (Common Object in Context, Lin et al., 2014) for object detection contains 328,000 images with more than 200,000 annotated with object labels; it includes 80 object categories and 250,000 people with labeled key points.

However, this labeling process is very expensive; the typical cost for the image labeling of 1,000 images is approximately \$24,000 (iMerit, 2022). Therefore, to obtain a satisfactory number of labeled images—in this case, 328,000 images—would cost around \$7 million.

The ambiguity of an image, which refers to multiple explanations of a particular image, is another problem (Rajeswar, Rodriguez, Singhal, Vazquez, & Courville, 2022). For example, an image of a dog can be labeled as a dog, a German Shepherd, or Pluto from the Disney movie. Therefore, this ambiguity can influence model accuracy, and several different approaches have been proposed. One is the semi-supervised learning method (Zhu, 2005; Zhu et al., 2011), utilizing unlabeled data and presuming that the labeled and unlabeled data are from the same domain and follow the same distribution. However, this semi-supervised learning method has some limitations: in particular, it cannot handle data from different domains (e.g., is Pluto from the Disney movie a dog compared to the picture of a real German Shepherd?).

Therefore, a transfer-learning method is proposed to solve this problem. Figure 3 provides an intuitive explanation of this method. We utilized a pre-trained large dataset collected and labeled by major technology companies, such as Facebook or Google. They have already created the model for image classification and objective detection as a "teacher," then independent researchers (i.e., "students") can utilize this pre-trained model to classify or detect the objects in the image. For example, if a sports player can perform well at football, the knowledge regarding football can facilitate the player's learning curve for rugby, since learners can generalize based on their experience (Zhuang et al., 2020).

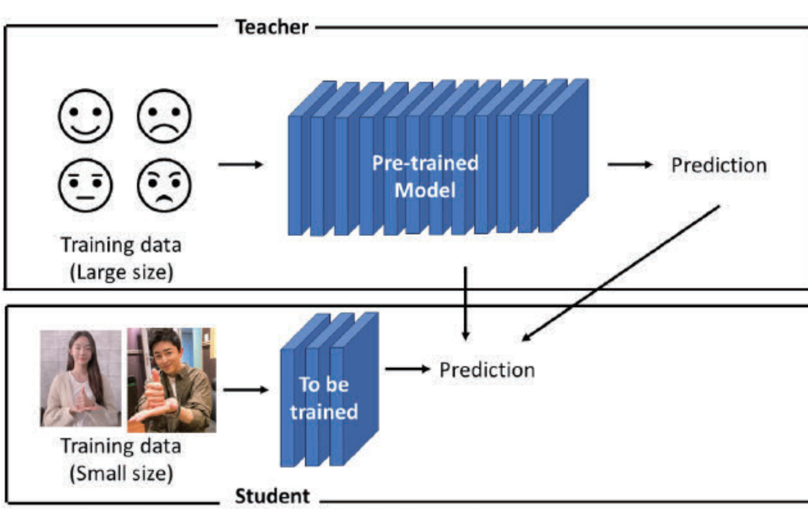


Figure 3. Intuitive Explanation of Transfer-Learning Approach.

In summary, we can utilize a preexisting facial expression recognition model with a large amount of pre-labeled data by fine-tuning the hyperparameters to maximize the accuracy of the classification problem (Son & Park, 2023). Notably, a benchmark study found that the accuracy rate of the DeepFace algorithm for facial expression detection was 97.25%, which is almost equivalent to human-level accuracy (97.53%) (Kaur et al., 2022). In addition, high accuracy rates have been consistently generated across different study contexts (Li & Deng, 2020).

Data Collection and Image Feature Extraction

We randomly collected 4,943 posts that related to the "Thanks To" Challenge campaign from April 15, 2020, to April 22, 2022, using three hashtags: #덕분에챌린지, #덕분에캠페인, #의료진 덕분에.

After building the dataset, we adopted a transfer-learning procedure for image feature generation. Utilizing a pretrained image dataset from cvlib (Ponnusamy, 2020) and DeepFace (Serengil & Ozpinar, 2020, 2021), we automatically extracted 1) whether an image contained a human being, 2) that person's gender, 3) that person's age, and 4) their facial expressions.

Specifically, the cvlib dataset utilized Microsoft COCO-prelabeled data with 91 object types. Therefore, by utilizing the COCO-prelabeled dataset, we were able to identify the images containing people and the gender of those people. We utilized the Python DeepFace package to analyze the facial expressions of those in the images, estimate their ages, and identify the emotions being expressed. This algorithm utilizes 2.6 million face images of 2,622 people as prelabeled training data, called the VGG Face Dataset (Parkhi, Vedaldi, & Zisserman, 2015). The DeepFace algorithm analyzed the images and predicted gender (male vs. female), age (numeric), and emotion scores (ranging from 0 to 100) for the dominant emotions (characterized as anger, disgust, fear, happiness, sadness, surprise, and neutral).

For example, by analyzing Kim Yuna's post about participating in the "Thanks To" Challenge, we obtained the following results: female, 31 years old, dominant emotion of happiness, with the following numerical scores for each emotion (anger: .0003, disgust: 9.82, fear: 5.01, happiness: 66.23, sadness: .0004, surprise: 3.89, and neutral: 33.76). Therefore, we utilized these features for the statistical analysis (see Figure 4 for the analysis example).

Figure 4. Transfer-Learning Analysis Example.

Results

Descriptive Statistics

We extracted and analyzed the images posted for the "Thanks To" Challenge to answer the research questions. Among the 4,943 posts initially collected, 2,639 contained images of people, and of these the image processing algorithm could identify the gender in 1,561.

For Research Question 1, we counted the number of men and women in the posts containing images of human beings. A total of 1,179 images were classified as male (75.6%) and 381 female (24.4%). Therefore, male images were dominantly represented in the "Thanks To" Challenge participants.

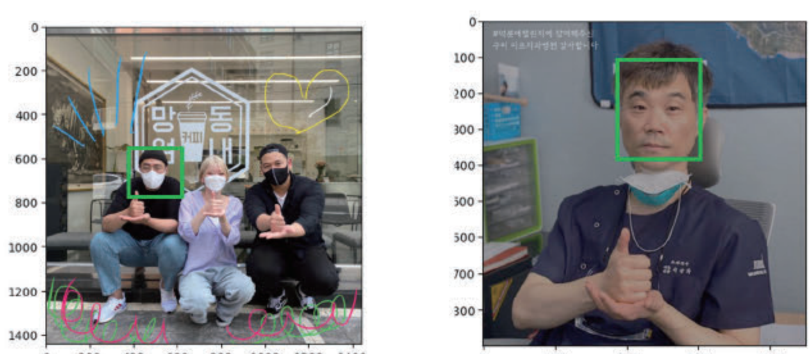
Table 1 displays the descriptive statistics for emotions expressed and age data based on the transfer-learning image recognition analysis, differentiated by the identified gender in the images. Figure 5 shows examples of images classified as predominantly sad and fearful.

Table 1
Descriptive Statistics.

	Male				Female			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Age	30.41	4.55	16	54	30.20	3.74	16	42
Anger	8.55	19.65	0	100	4.94	14.18	0	100
Disgust	3.33	5.27	0	93.43	3.75	8.19	0	84.73
Fear	14.70	26.59	0	100	14.43	25.66	0	100
Sadness	21.51	32.36	0	100	15.37	27.15	0	99.92
Happiness	19.77	33.77	0	100	30.89	39.90	0	100
Surprise	4.63	15.04	0	99.99	3.90	14.21	0	99.82
Neutral	32.38	37.38	0	100	31.79	36.52	0	100
Observations	1,179				381			

For questions 2 and 3, we performed a one-way multivariate analysis of variance (MANOVA) to reveal the differences between men and women in the predicted emotions and ages on the images. We observed significant differences in emotions (anger, disgust, fear, sadness, happiness, surprise, and neutral) and age based on gender (Wilk's lambda = .97, $F(8, 1551) = 5.31$, partial eta squared = .03, $p < .001$).

First, we identified no relationship between gender (male = 0, female = 1) and



Note: Anger: 0.23; Disgust: 2.07; Fear:1.24; Happiness: 5.13; Sadness: 98.28; Surprise: 5.12; Neutral: 0.25.

Note: Anger: 0.001; Disgust: 1.35; Fear: 85.28; Happiness: .01; Sadness: 14.70; Surprise: .002; Neutral: 0.00004.

Figure 5. Examples of Images Classified with Dominantly Sad and Fearful Facial Expressions.

age (F(1, 1560) = .66, p = .42, partial eta square = .007). Evaluating the mean age of men and women, there was no significant gender effect (F(1, 1560) = .66, p = .42, partial eta square < .001; M_{male} = 30.41, SD_{male} = 4.55 vs M_{female} = 30.20, SD_{female} = 3.74) (RQ2).

Regarding research question 3, gender (male = coded as 0, female = coded as 1) had a significant effect on anger (F(1, 1560) = 10.97, p < .001, partial eta square = .01), happiness (F(1, 1560) = 28.48, p < .001, partial eta square = .02), and sadness (F(1, 1560) = 11.15, p < .001, partial eta square = .01). However, gender had no significant effect on disgust (F(1, 1560) = 1.40, p = .24, partial eta square = .001), fear (F(1, 1560) = .03, p = .86, partial eta square < .001), surprise (F(1, 1560) = .68, p = .41, partial eta square < .001), and neutral (F(1, 1560) = .11, p = .74, partial eta square < .001).

Specifically, for those who were classified as male, we observed a lower level of anger (M_{male} = 8.55, SD_{male} = 19.65 vs M_{female} = 4.94, SD_{female} = 14.18), lower level of sadness (M_{male} = 21.51, SD_{male} = 32.36, vs. M_{female} = 15.37, SD_{femal}e = 27.15), and higher level of happiness (M_{male} = 19.77, S_{Dmale} = 33.77, vs. M_{female} = 30.89, SD_{female} = 39.90) (RQ3). Figure 6 presents the results of the statistical analysis regarding the research questions.

Figure 6. Results of MANOVA.

Discussion and Conclusions

Summary of Findings and Theoretical Implications

This study provides an in-depth understanding of gender stereotypes and portrayals in the newly emerged social media phenomenon called "challenge" or "public referral." First, despite the initial stage of the "Thanks To" Challenge having been initiated by female public figures and celebrities, including Kim Yuna, the majority of those who participated in the challenge, based on the random sample selected for our dataset, were men by a factor of 3:1 (1,179 vs. 381) (RQ1). This trend is also confirmed when checking the top posts for #덕분에챌린지(#thankstochallenge) as of February 5, 2024. Among the 28 posts on the Top Results page, 12 were men and 6 were women. Considering that the Instagram user statistics in South Korea consistently indicate that female users outnumber male users across all age segmentations over 18 (e.g., age 18-24: 4.3 million female users vs. 3.1 female users; age 25-34: 4.6 million female users vs. 3.7 male users; age 35-44: 2.9 million female users vs. 2.2 male users), our finding is noteworthy (Jobst, 2023). Since we randomly collected approximately 5,000 data points by following the random extraction method, it is unlikely that this was due to a problem with an unbalanced sample. Instead, we argue that there is still a gender difference in portrayals on social media, especially in terms of self-portrayal motivations (Haferkamp, Eimler, Papadakis, & Kruck, 2012; Smith & Sanderson, 2015). Previous research has confirmed that men and women differ in their self-portrayal in social media profiles (Haferkamp et al., 2012) and social media posts (Smith & Sanderson, 2015). Smith and Sanderson (2015) found that self-presentation is one of the most important motivations for using social media, and a meta-analysis of 355 studies confirmed that men tend to be more narcissistic (Grijalva et al., 2015), which is highly related to self-presentation behavior (Yu & Kim, 2020). Therefore, it is possible that men were motivated by the desire for self-presentation to participate more frequently in the "Thanks To" Challenge.

Regarding research question 3, we also find a gender stereotype in the emotions expressed in social media posts participating in the "Thanks To" Challenge. Specifically, images of men contained more negative emotions, such as anger and sadness, whereas images of women were associated with positive emotions (i.e., happiness). This finding also needs to be considered as a concept of emotionality (Rodgers et al., 2007; Shields, 2013). Our finding indicates that among female images in the "Thanks To" Challenge, not only are positive emotions predominant, but their emotionality is also more intense than that of male images. For instance, our machine learning algorithm quantified the level of negative emotions, which was more prominent among male participants, at 8.55 (anger) and 21.51 (sadness), whereas the level of positive emotion was 30.89 (happiness) for the most prominent emotion among female participants.

Considering that stereotyped gender portrayals of emotion can lead to distorted gender roles (Shields, 2013), our research extends the theoretical understanding of gender stereotypes regarding emotion. For example, masculine emotions are described as a passionate drive to achieve, create, and dominate, whereas feminine emotions are illustrated as a comparatively ineffective emotionality (Shields, 2013).

As our findings reconfirm the existence of gender stereotypes not only for the types of emotions (female for happiness, male for anger and sadness) but also for the intensity of emotion, the current work is the first to investigate the two dimensions of stereotyped emotions by gender (Figure 7).

Figure 7. Plotting of Analysis Result Regarding Emotion Extracted from Male vs Female Posts.

Methodological and Practical Implications

Methodologically, we add to our understanding of gender stereotypes using a fully automated process in a quantitative manner. Content analysis is traditionally considered a time- and labor-intensive research process (Renz, Carrington, & Badger, 2018) requiring enormous amounts of time and effort from researchers. In addition, despite the usefulness and value of content analysis in research efforts, a significant associated concern is the researchers' subjectivity (Krippendorff, 2018). We therefore propose a framework to overcome both major drawbacks of content analysis methodology by integrating a machine learning technique.

In addition to our contributions to theory and methodology, the findings of the current study are valuable for social media campaign practitioners and policymakers. Although the "Thanks to" Challenge was extremely popular and successful, our study reconfirmed that gender stereotypes persist in the social media environment. Recognizing the effects of stereotyped gender roles on the public's mental health, such as lowering self-esteem (Good & Sanchez, 2010), campaign makers and policymakers must consider the issue of gender stereotypes and implement appropriate measures to reduce them.

Limitations and Future Research Directions

Despite the robustness of our findings, this study has some limitations and offers several opportunities for future research. This study was mainly descriptive, showing the persistence of gender stereotypes in social media campaigns. Therefore, future studies should revisit the causal relationship between stereotyped media and various dependent variables, such as public engagement in social media campaigns and actual public behavior (Park, 2024).

Researchers have primarily focused on social media engagement to investigate the effects of social media content on consumer engagement (e.g., Ahn, Son, & Chung, 2021; Son, Ahn, Chung, & Drumwright, 2023; Son & Park, 2023). Because we successfully extracted features related to gender stereotypes, such as emotions and age, future research could extend our study's findings by linking the causal relationship between the usage of stereotyped images and social media users' engagement. For instance, the negative effects of stereotypical social media posts have recently received considerable attention (e.g., Dempsey, Looney, McNamara, Michalek, & Hennessy, 2022). Therefore, the effects of emotionally stereotyped social media posts, such as those portraying women as happy participants in social media challenges, need to be examined through controlled experiments to isolate confounding factors in terms of attitudes toward campaigns or issues. In addition, because we can quantify the number of stereotypical posts daily, econometric models can reveal the effects of these posts on actual public behaviors, including vaccination rates (Park, 2024).

Given the advanced techniques of transfer learning for large-scale data analysis, future studies should expand this research context to utilize different types of social media data, including video and text, and their interactions with the image features that we extracted in the current study. Such an intensive and detailed analysis would provide a more in-depth understanding of gender stereotypes in social media content and their effects in various dimensions.

Conclusions

This study has shown that gender stereotypes and portrayals persist in public challenges, which are an emerging form of public participation in social media campaigns. We demonstrated this through an analysis of social big data, utilizing cutting-edge transfer-learning techniques. This study highlights that women continue to be underrepresented in social media environments and are often portrayed as more emotional than men, particularly in terms of emphasizing positive emotions (i.e., happiness).

Li et al. (2023), by analyzing posts from Weibo, a leading social media platform in China, found that women in China expressed high levels of anxiety and anger during the Changsheng fake vaccine crisis and higher levels of anxiety during COVID-19 than their male counterparts. One possible interpretation of this finding is that women might be forced to express happiness during public campaigns, even if they feel anxious about COVID-19. This suggests a systematic bias due to gender roles and stereotypical attitudes that expect women to express positive emotions.

These findings suggest that public campaign designers and policymakers should address this imbalance in gender representation and stereotypes and make efforts to promote diversity, equity, and inclusion. According to news reports (e.g., Yonhap News Agency, 2020), most of the female participants highlighted in the early stages of the campaign were classified as celebrities or athletes, including Kim Yuna, Kim Yeon-young, Han Ye-Seul, and Lee Young-ae. In contrast, the male participants had diverse backgrounds, including politicians, entrepreneurs, and government officials. Therefore, policymakers and public campaign designers should be aware of the importance of diversity when initiating this type of challenge campaign and should include a variety of participants in terms of gender, social background, and demographics.

References

Ahn, J., Son, H., & Chung, A. D. (2021). Understanding public engagement on Twitter using topic modeling: The 2019 Ridgecrest earthquake case. *International Journal of Information Management Data Insights*, *1*(2), 100033. doi: https://doi.org/https://doi.org/10.1016/j.jjimei.2021.100033

Åkestam, N. (2018). Caring for her: The influence of presumed influence on female consumers' attitudes towards advertising featuring gender-stereotyped portrayals. *International Journal of Advertising*, *37*(6), 871–892.

Åkestam, N., Rosengren, S., Dahlén, M., Liljedal, K. T., & Berg, H. (2021). Gender stereotypes in advertising have negative cross-gender effects. *European Journal of Marketing*, *55*(13), 63–93.

Antioco, M., Smeesters, D., & Le Boedec, A. (2012). Take your pick: Kate Moss or the girl next door?: The effectiveness of cosmetics advertising. *Journal of Advertising Research*, *52*(1), 15–30.

Burgess, A., Miller, V., & Moore, S. (2018). Prestige, performance and social pressure in viral challenge memes: Neknomination, the Ice-Bucket Challenge and SmearForSmear as imitative encounters. *Sociology*, *52*(5), 1035–1051.

Butkowski, C. P., Dixon, T. L., Weeks, K. R., & Smith, M. A. (2020). Quantifying the feminine self (ie): Gender display and social media feedback in young women's Instagram selfies. *New Media & Society*, *22*(5), 817–837.

Campbell, C., Sands, S., McFerran, B., & Mavrommatis, A. (2023). Diversity representation in advertising. *Journal of the Academy of Marketing Science*. doi: https://doi.org/10.1007/s11747-023-00994-8

Campbell, M. C., Inman, J. J., Kirmani, A., & Price, L. L. (2020). In times of trouble: A framework for understanding consumers' responses to threats. *Journal of Consumer Research*, *47*(3), 311–326.

Chu, K., Lee, D.-H., & Kim, J. Y. (2018). The effect of non-stereotypical gender role advertising on consumer evaluation. In K. Chu, D.-H. Lee, & J. Y. Kim (Eds.), *Social and environmental issues in advertising* (pp. 116–144). London: Routledge.

Collins, R. L. (2011). Content analysis of gender roles in media: Where are we now and where should wego? *Sex Roles*, *64*, 290–298.

Deaux, K., & Lewis, L. L. (1984). Structure of gender stereotypes: Interrelationships among components and gender label. *Journal of Personality and Social Psychology*, *46*(5), 991–1004. doi: https://doi.org/10.1037/0022-3514.46.5.99 1

Dempsey, B., Looney, K., McNamara, R., Michalek, S., & Hennessy, E. (2022). An experimental investigation of adolescent and young adult responses to stigmatizing and supportive social media posts in response to a depressed peer. *Computers in Human Behavior, 131*, 107229. doi: https://doi.org/https://doi.org/10.1016/j.chb.2022.107229

Döring, N., Reif, A., & Poeschl, S. (2016). How gender-stereotypical are selfies? A content analysis and comparison with magazine adverts. *Computers in Human Behavior, 55*, 955–962. doi: https://doi.org/https://doi.org/10.1016/j.chb.2015.10.001

Eisend, M. (2010). A meta-analysis of gender roles in advertising. *Journal of the Academy of Marketing Science, 38*, 418–440.

Ellemers, N. (2018). Gender stereotypes. *Annual Review of Psychology*, *69*(1), 275–298. doi: https://doi.org/10.1146/annurev-psych-122216-011719

Givon, E., Berkovich, R., Oz-Cohen, E., Rubinstein, K., Singer-Landau, E., Udelsman-Danieli, G., & Meiran, N. (2023). Are women truly "more emotional" than men? Sex differences in an indirect model-based measure of emotional feelings. *Current Psychology*, *42*(36), 32469–32482.

Goffman, E. (1976). *Gender advertisements.* Cambridge, MA: Harvard University Press.

Good, J. J., & Sanchez, D. T. (2010). Doing gender for different reasons: Why gender conformity positively and negatively predicts self-esteem. *Psychology of Women Quarterly*, *34*(2), 203–214.

Grabe, S., Ward, L. M., & Hyde, J. S. (2008). The role of the media in body image concerns among women: A meta-analysis of experimental and correlational studies. *Psychological Bulletin*, *134*(3), 460.

Grau, S. L., & Zotos, Y. C. (2018). Gender stereotypes in advertising: A review of current research. In Y. C. Zotos, S. L. Grau, & C. R. Taylor (Eds.), *Current research on gender issues in advertising*, (pp. 3–12). London: Routledge.

Grijalva, E., Newman, D. A., Tay, L., Donnellan, M. B., Harms, P. D., Robins, R. W., & Yan, T. (2015). Gender differences in narcissism: A meta-analytic review. *Psychological Bulletin*, *141*(2), 261–310. doi: https://doi.org/10.1037/a0038231

Haferkamp, N., Eimler, S. C., Papadakis, A.-M., & Kruck, J. V. (2012). Men are from Mars, women are from Venus? Examining gender differences in self-presentation on social networking sites. *Cyberpsychology, Behavior, and Social Networking*, *15*(2), 91–98.

Hall, J. A., & Carter, J. D. (1999). Gender-stereotype accuracy as an individual difference. *Journal of Personality and Social Psychology*, *77*(2), 350–359. doi: https://doi.org/10.1037/0022-3514.77.2.350

Halliwell, E., & Dittmar, H. (2004). Does size matter? The impact of model's body size on women's body-focused anxiety and advertising effectiveness. *Journal of Social and Clinical Psychology*, *23*(1), 104–122.

iMerit. (2022). *Data labeling for machine learning.* Retrieved January 24, 2024, from https://imerit.net/blog/data-labeling-for-machine-learning-all-una/

Jarman, H. K., McLean, S. A., Slater, A., Marques, M. D., & Paxton, S. J. (2024). Direct and indirect relationships between social media use and body satisfaction: A prospective study among adolescent boys and girls. *New Media & Society*, *26*(1), 292–312. doi: https://doi.org/10.1177/14614448211058468

Jobst, N. (2023). *Instagram user number South Korea 2023, by age and gender.* Statista. Retrieved February 5, 2024, from https://www.statista.com/statistics/988771/south-korea-number-instagram-users-by-age-gender/

Jungblut, M., & Haim, M. (2023). Visual gender stereotyping in campaign communication: Evidence on female and male candidate imagery in 28 countries. *Communication Research*, *50*(5), 561–583. doi: https://doi.org/10.1177/00936502211023333

Kaur, J., Saxena, J., Shah, J., & Yadav, S. P. (2022). Facial Emotion Recognition. In 2022 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES) (pp. 528-533): IEEE.

Kennard, A. R., Willis, L. E., Robinson, M. J., & Knobloch-Westerwick, S. (2016). The allure of Aphrodite: How gender-congruent media portrayals impact adult women's possible future selves. *Human Communication Research*, *42*(2), 221–245. doi: https://doi.org/10.1111/hcre.12072

Kim, S.-A. (2020). [Editor's Note] Gender and digital media. *Asian Women*, *36*(4), 143–146.

Kirk, C. P., & Rifkin, L. S. (2020). I'll trade you diamonds for toilet paper: Consumer reacting, coping and adapting behaviors in the COVID-19 pandemic. *Journal of Business Research*, *117*, 124–131.

Knoll, S., Eisend, M., & Steinhagen, J. (2011). Gender roles in advertising: Measuring and comparing gender stereotyping on public and private TV channels in Germany. *International Journal of Advertising*, *30*(5), 867–888.

Krippendorff, K. (2018). *Content analysis: An introduction to its methodology*. Los Angeles, CA: Sage.

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, *60*(6), 84–90.

Kwon, K. H. (2019). Public referral, viral campaign, and celebrity participation: A social network analysis of the Ice Bucket Challenge on YouTube. *Journal of Interactive Advertising*, *19*(2), 87–99.

Lee, S. (2020). *More than 36,000 participatns in 7 weeks: Thanks to Challenge.* KTV. Retrieved February 4, 2024 from https://m.ktv.go.kr/program/again/view?content_id=601690

Li, J., Liu, Y., & Song, J. (2022). The relationship between gender self-stereotyping and life satisfaction: The mediation role of relational self-esteem and personal self-esteem. *Frontiers in Psychology*, *12*, 769459.

Li, L., Zhou, J., Zhuang, J., & Zhang, Q. (2023). Gender-specific emotional characteristics of crisis communication on social media: Case studies of two public health crises. *Information Processing & Management*, *60*(3), 103299. doi: https://doi.org/10.1016/j.ipm.2023.103299

Li, S., & Deng, W. (2020). Deep facial expression recognition: A survey. IEEE transactions on affective computing, 13(3), 1195-1215.

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., & Zitnick, C. L. (2014). Microsoft coco: Common objects in context. In D. Fleet, T. Pajdla, B. Schiele, & T. Tuytelaars (Eds.), *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part* V (pp. 740–755). Cham: Springer.

Löffler, C. S., & Greitemeyer, T. (2023). Are women the more empathetic gender? The effects of gender role expectations. *Current Psychology*, *42*(1), 220–231.

Lynch, T., Tompkins, J. E., van Driel, I. I., & Fritz, N. (2016). Sexy, strong, and secondary: A content analysis of female characters in video games across 31 years. *Journal of Communication*, *66*(4), 564–584. doi: https://doi.org/10.1111/jcom.12237

Mahon, C., & Hevey, D. (2021). Processing body image on social media: Gender differences in adolescent boys' and girls' agency and active coping. *Frontiers in Psychology*, *12*, 626763.

Martin, M. C., & Gentry, J. W. (1997). Stuck in the model trap: The effects of beautiful models in ads on female pre-adolescents and adolescents. *Journal of Advertising*, *26*(2), 19–33.

Martin, M. C., & Kennedy, P. F. (1993). Advertising and social comparison: Consequences for female preadolescents and adolescents. *Psychology & Marketing*, *10*(6), 513–530.

Martin, R. (2017). Gender and emotion stereotypes in children's television. *Journal of Broadcasting & Electronic Media*, *61*(3), 499–517. doi: https://doi.org/10.1080/08838151.2017.1344667

Nitschke, J. P., Forbes, P. A., Ali, N., Cutler, J., Apps, M. A., Lockwood, P. L., & Lamm, C. (2021). Resilience during uncertainty? Greater social connectedness during COVID-19 lockdown is associated with reduced distress and fatigue. *British Journal of Health Psychology*, *26*(2), 553–569.

Paganini, G. A., Summers, K. M., ten Brinke, L., & Lloyd, E. P. (2023). Women exaggerate, men downplay: Gendered endorsement of emotional dramatization stereotypes contributes to gender bias in pain expectations. *Journal of Experimental Social Psychology*, *109*, 104520. doi: https://doi.org/10.1016/j.jesp.2023.104520

Park, Y. E. (2024). BERTopic analysis of the impact of media coverage of COVID-19 vaccinations on vaccination rates: Combination of machine learning and modeling techniques. *Korean Journal of Advertising, 35*(3), 59–90.

Parkhi, O., Vedaldi, A., & Zisserman, A. (2015). Deep face recognition. *BMVC 2015-Proceedings of the British Machine Vision Conference 2015*. Durham: British Machine Vision Association.

Peñaloza, L., Prothero, A., McDonagh, P., & Pounders, K. (2023). The past and future of gender research in marketing: Paradigms, stances, and value-based commitments. *Journal of Marketing, 87*(6), 847–868. doi: https://doi.org/10.1177/00222429231154532

Ponnusamy, A. (2018). cvlib - high level Computer Vision library for Python. Retrieved January 24, 2024, from https://github.com/arunponnusamy/cvlib

Pounders, K. (2018). Are portrayals of female beauty in advertising finally changing? *Journal of Advertising Research, 58*(2), 133–137.

Pounders, K., & Mabry-Flynn, A. (2019). Consumer response toward plus-size models featured in the mainstream media. *Journal of Consumer Affairs, 53*(4), 1355–1379. doi: https://doi.org/10.1111/joca.12251

Pratto, F., & Bargh, J. A. (1991). Stereotyping based on apparently individuating information: Trait and global components of sex stereotypes under attention overload. *Journal of Experimental Social Psychology, 27*(1), 26–47.

Prieler, M. (2020). Gender representations of older people in the media: What do we know and where do we go from here? *Asian Women, 36*(2), 73–95.

Rajeswar, S., Rodriguez, P., Singhal, S., Vazquez, D., & Courville, A. (2022). Multi-label iterated learning for image classification with label ambiguity. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2022, 11372–11382. doi: https://doi.org/10.1109/CVPR52688.2022.01114

Renz, S. M., Carrington, J. M., & Badger, T. A. (2018). Two strategies for qualitative content analysis: An intramethod approach to triangulation. *Qualitative Health Research, 28*(5), 824–831.

Richins, M. L. (1991). Social comparison and the idealized images of advertising. *Journal of Consumer Research, 18*(1), 71–83.

Rodgers, S., Kenix, L. J., & Thorson, E. (2007). Stereotypical portrayals of emotionality in news photos. *Mass Communication and Society, 10*(1), 119–138. doi: https://doi.org/10.1080/15205430709337007

Rose, J., Mackey-Kallis, S., Shyles, L., Barry, K., Biagini, D., Hart, C., & Jack, L. (2012). Face it: The impact of gender on social media images. *Communication Quarterly, 60*(5), 588–607.

Ross, G. R., Meloy, M. G., & Carlson, K. A. (2020). Preference refinement after a budget contraction. *Journal of Consumer Research, 47*(3), 412–430.

Santoniccolo, F., Trombetta, T., Paradiso, M. N., & Rollè, L. (2023). Gender and media representations: A review of the literature on gender stereotypes, objectification and sexualization. *International Journal of Environmental Research and Public Health*, *20*(10), 5770.

Serengil, S. I., & Ozpinar, A. (2020, 15-17 Oct. 2020). LightFace: A hybrid deep face recognition framework. In *Proceedings of the 2020 Innovations in Intelligent Systems and Applications Conference (ASYU)* (pp. 1–5). IEEE. doi: https://doi.org/10.1109/ASYU50717.2020.9259802

Serengil, S. I., & Ozpinar, A. (2021). Hyperextended lightface: A facial attribute analysis framework. In *Proceedings of the 2021 International Conference on Engineering and Emerging Technologies (ICEET)* (pp. 1–4). IEEE. doi: https://doi.org/10.1109/ICEET53442.2021.9659697

Shields, S. A. (2013). Gender and emotion: What we think we know, what we need to know, and why it matters. *Psychology of Women Quarterly*, *37*(4), 423–435. doi: https://doi.org/10.1177/0361684313502312

Smith, L. R., & Sanderson, J. (2015). I'm going to Instagram it! An analysis of athlete self-presentation on Instagram. *Journal of Broadcasting & Electronic Media*, *59*(2), 342–358.

Son, H., Ahn, J., Chung, A. D., & Drumwright, M. E. (2023). From the black box to the glass box: Using unsupervised and supervised learning processes to predict user engagement for the airline companies. *International Journal of Information Management Data Insights*, *3*(2), 100181.

Son, H., & Park, Y. E. (2023). Predicting user engagement with textual, visual, and social media features for online travel agencies' Instagram post: Evidence from machine learning. *Current Issues in Tourism*, 1-15. doi: https://doi.org/10.1080/13683500.2023.2278087

Uray, N., & Burnaz, S. (2003). An analysis of the portrayal of gender roles in Turkish television advertisements. *Sex Roles*, *48*, 77–87.

van Breen, J. A., & Barreto, M. (2023). Mind the gap! Stereotype exposure discourages women from expressing the anger they feel about gender inequality. *Emotion*, *23*(1), 124.

Vinacke, W. E. (1957). Stereotypes as social concepts. *The Journal of Social Psychology*, *46*(2), 229–243.

Wanta, W., & Leggett, D. (1989). Gender stereotypes in wire service sports photos. *Newspaper Research Journal*, *10*(3), 105–114.

Webb, J. B., Vinoski, E. R., Warren-Findlow, J., Burrell, M. I., & Putz, D. Y. (2017). Downward dog becomes fit body, inc.: A content analysis of 40 years of female cover images of Yoga Journal. *Body Image*, *22*, 129–135. doi: https://doi.org/10.1016/j.bodyim.2017.07.001

Weiss, K., Khoshgoftaar, T. M., & Wang, D. (2016). A survey of transfer learning. *Journal of Big Data*, *3*(1), 1–40. doi: https://doi.org/10.1186/s40537-016-0043-6

World Health Organization. (2024). *Number of COVID-19 cases reported to WHO*. Retrieved January 21, 2024, from https://data.who.int/dashboards/covid19/cases?n=c

Yonhap News Agency. (2020). *Moon joins Thank You Challenge campaign for medical workers*. Yonhap News. Retrieved February 2, 2024, from https://en.yna.co.kr/view/AEN20200427008900315

Yu, E., & Kim, H.-C. (2020). Is she really happy? A dual-path model of narcissistic self-presentation outcomes for female Facebook users. *Computers in Human Behavior*, *108*, 106328.

Zhu, X. (2005). *Semi-supervised learning literature survey*. Madison: University of Wisconsin.

Zhu, Y., Chen, Y., Lu, Z., Pan, S., Xue, G.-R., Yu, Y., & Yang, Q. (2011). Heterogeneous transfer learning for image classification. *Proceedings of the AAAI Conference on Artificial Intelligence*, *25*(1), 1304–1309. ttps://www.aaai.org/ocs/index.php/AAAI/AAAI11/paper/view/3652

Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., & He, Q. (2020). A comprehensive survey on transfer learning. *Proceedings of the IEEE*, *109*(1), 43–76.

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Received: February 7, 2024
Revised: July 17, 2024
Accepted: August 26, 2024