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她的偏見不是他的偏見：比較女性與男性雜誌的性別偏見

Her bias is not his bias: A comparison of embedded gender bias between gender-targeted magazines

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摘要

因為能夠反應社會上的價值觀，再加上其性別化的訊息，還有新聞性的本質，流行雜誌時常是性別研究的研究對象。先前的研究表明，詞嵌入模型能夠揭示媒體中性別之間的微妙偏見。本研究以針對特定性別的時尚雜誌為研究對象，不僅呈現出不同文本中各自的性別差異，更透過比較雜誌之間的偏見，對性別研究做出貢獻。

蒐集女性雜誌和男性雜誌超過 10 年的雜誌文章後，本研究先以主題模型查看時尚雜誌中的主題分佈，還有時間變化與性別差異。並分別構建了詞嵌入模型，接著比較了它們在性別偏見方面的差異。除了用於檢查性別偏見的詞彙表，如職業和形容詞，還考慮了出現在女權主義辯論中的其他話題，如身體部位、浪漫愛情、性愛、快樂等。

研究結果發現，個別雜誌中出現了性別偏見，這並不是令人意外之事。然而，進一步發現，在針對性別的雜誌之間，表現出的性別偏見有著不同方向，例如外表有關的形容詞，以及身體部位，在女性和男性之間，表現出明顯差異。

關鍵字

性別偏見, 時尚雜誌, 詞嵌入, 自然語言處理

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Abstract

As a subject of a gender study, popular magazines are distinctively scrutinized due to their journalistic essences reflecting the social value and often sexualized messages. Previous research shows that word embedding models can reveal subtle bias between gender in media. This research contributes to gender studies by not only presenting gender differences within texts but also comparing differences of bias between gender-targeted magazines. With 10-year-long magazine articles from a woman's magazine and a man's magazine, I construct word embeddings models respectively and compare their divergence of gender bias. In addition to word lists used to inspect gender bias, such as vocations and adjectives, other topics appearing in the feminism debate have been considered, such as body parts, romantic love, sexiness, and so on. I found gender bias appears in the individual magazines, which is not a surprise. However, it is also found that gender biases between magazines are different. Appearance-related adjectives and body parts show remarkably different directions between males and females.

Keywords

Gender bias, Fashion Magazine, Word Embeddings, Natural Language Processing

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Introduction

Gender bias in texts can be evident and deliberate or subtle and unintentional. For instance, feminists are represented as irregular political radicals in newspapers, framed as a kind of minority (Jaworska & Krishnamurthy, 2012). On the contrary, using specific terms may not possess direct malice, but prejudice can still be found when examining word associations by calculating co-occurrences of vocabularies (Rudinger et al., 2017). Advanced computational approaches such as word embeddings are used to gauge gender bias (Bolukbasi et al., 2016). Moreover, techniques are developed to mitigate bias (T. Wang et al., 2020). However, many works take the source of texts as a whole and thus overlook that there may be biased thoughts held or conveyed differently between genders as well. In this work, I present gender bias within texts from two gender-targeted magazines and compare biases between them, aiming to show differentiated biases between gender.

It is not astonishing that data gathered from magazines show a particular tendency toward women, which are often materialized and objectified in advertisements designed for a male audience (Monk-Turner et al., 2008). A paper written in the 1990s studied a male-directed magazine, disclosing that the editors of this magazine formed the feminine in a misogynic way (Velding, 2017), and the stereotype and prejudice were found. Previous research using qualitative methods has told stories about many subjects in magazines, ranging from weights (Roberts & Muta, 2017), sexualities (Wada et al., 2015), to age (Hurd Clarke et al., 2014). The consumption of these materials may make readers internalize these societal ideals and act according to them (Morry & Staska, 2001). Thus, it is necessary to dig deeper into how these magazines

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shape the supreme gendered image of the audience and their objects' gaze, especially in the era of changing views of beauty (Han & Rudd, 2015).

Fashion and lifestyle magazines depict a specific kind of masculinity and femininity (Shiau, 2013; Velding, 2017). They sketch the perfect model of their audience's gender, guiding them to learn and follow. It is worth mentioning that researchers have shown that gender discrimination against women and men both happen, though the effect on men is under contention (Manzi, 2019). Also, gender discrimination held by each gender varies (Hamberg et al., 2004). It is essential to add the gender of audience dimension when dissecting gender bias, considering the fact that gender-specific magazines also share reflections about people of the opposite sex.

This study aims to compare two gender-specific magazines, *GQ* and *Vogue*, owned by the same international group. To comprehend how gender was sketched and treated differently not only within the same magazine but also between magazines, I performed several text mining techniques. First, all articles published by *GQ* and *Vogue* websites in Taiwan between 2019 and the middle of 2021 have been assembled. Second, I preprocessed the texts and executed word segmentation. Third, to understand the content media delivered for each gender, I built topic models for two magazines based on the segmentation outcomes. I also computed two magazines' term frequency and word co-occurrence and compared the results. Fourth, after filtering advertisement content with regular expression, I examined the categories of products the brands want to advertise. Fifth, the segmentation results were used to create word embeddings models, one for GQ and one for Vogue. Aiming to gain knowledge of gender bias, I retrieved several dimensions of word lists and inspected the distance between them and genders within each magazine. Moreover, the abovementioned gender biases were

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compared between magazines. It helped grasp how the audience of each magazine perceives the opposite sex. With hybrid methods from various fields, the article tries to thoroughly understand the overall gender differences and embedded bias within fashion magazines.

Literature Review

According to Oxford Learner's Dictionary ("Bias," n.d.), bias refers to "a strong feeling in favour of or against one group of people, or one side in an argument, often not based on fair judgment." There are assorted kinds of biases, such as racial bias (Obermeyer et al., 2019; Snowball & Weatherburn, 2007; Zeisel, 1981), gender bias (Fay & Williams, 1993), social class bias (Freedle, 2008; Liu et al., 2007), sexual orientation bias (Badgett et al., 2009; Morrison & Morrison, 2011), and so on. Among all biases, gender bias is seen across societies and times. There is gender bias related to roles in family and work, leadership (Braun et al., 2017), research, and ironically, research that reveals gender bias itself may not be seen (Cislak et al., 2018).

Biases can result from stereotypes and prejudices. For instance, Heilman (2012) first explained descriptive and prescriptive gender stereotypes, then pointed out that these stereotypes caused workplace bias and affected women's careers. Likewise, Chua and Freeman (2021) argue that people will possess thoughts, which constantly are stereotypes, about others' personalities based on their facial aspects. Thus, people then keep biases toward others.

Additionally, biases will drive discrimination when people behave according to them. Take Puhl and Brownel's work for instance (2001), they pay attention to bias toward

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obese people, which then turns into systematic discrimination related to employment, education, and health care. Anthony (2004) takes care of gender bias in nursing education, leading to discrimination against male students and further affecting the recruitment and retention of male professionals.

As researchers argue, media furnishes stereotypical content associated with people, then influences its audiences through communications (Bissell & Parrott, 2013). For instance, there is a prevalence that media outlets would use stigma frames to characterize people with mental illness and present stereotypes (Gwarjanski & Parrott, 2018), which can be explained by news framing concepts (Vreese, 2005). The bias within media can be encountered in all kinds of mediums, from broadcasting networks (Greer et al., 2009) to print magazines (Eagleman, 2011). The portrait of a specific group of people from media outlets is imprecise, or even the representation itself is not equal (Billings & Angelini, 2007; Rada, 1996).

There are explicit and implicit measures of bias. Respondents will consciously complete self-report surveys featuring cognitive, affective, and behavioral questions for the explicit measures. Researchers use these surveys to assess respondents' stereotypes, prejudice, and discrimination toward different target groups of people (Hewstone et al., 2002). On the contrary, implicit measures are used to evaluate unintentional or unaware bias. Examples include nonverbal indicators, implicit association tests, indirect self-report, and reaction-time tests (Fiske & North, 2015).

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Gender Bias in Magazines

From television shows or movies to customer reviews, social platforms, and even scholarly work, manifold origins of corpus exhibit varying degrees of gender bias (Coyne et al., 2014; Mishra et al., 2019; Rios et al., 2020). Exposure to content with bias may influence beliefs, behaviors, and body esteem (Coyne et al., 2016; Pennell & Behm-Morawitz, 2015).

It is not unanticipated that content under popular culture context is revealed with bias likewise, especially gendered ones. The messages in fashion or lifestyle magazines, which communicate a particular ideal lifestyle, can replicate gender stereotypes predominant in society (Kozlowski et al., 2020). Fashion journalism can be categorized as a genre of lifestyle journalism, which is a “distinct journalistic field that primarily addresses its audiences as consumers, providing them with factual information and advice, often in entertaining ways, about goods and services they can use in their daily lives” (Hanusch, 2012, pp. 3–4). The range of content under fashion topics can be broad, including lifestyle, culture, and consumption (Kristensen & From, 2012).

Fashion magazines can be seen as both “cultural products and commodities” because they provide "recipes, patterns, narratives, and models" for the reader. They are “products of the print industry and crucial sites for the advertising and sale of commodities” (Brian, 2004, p. 260).

In terms of cultural products, for instance, magazines gradually ask girls to be thin (Sypeck et al., 2004), but the perfection constructed is too demanding to reach, directly affecting people’s choice of food (Krahé & Krause, 2010). As for commodities, fashion magazines feature specific models with products in advertisements, showing homogenized beauty standards and high levels of objectification (Tan et al., 2013).

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Many fashion/lifestyle magazines are gender-targeted or gender-oriented. Both manual content analysis (Kasmiran & Ena, 2019) and more computational approaches are used to analyze them. For example, Kozlowski et al. (2022) explore longitudinal data with topic modeling and word frequencies and demonstrate that the prejudice of objectifying women by sexualization in a male magazine has been reduced.

Since content in gender-targeted magazines is designed to direct single-gender audiences, it would be crucial to understand how they produce role models for their audiences and the opposite gender. In other words, asking how men's magazines shape and promote an ideal man is salient. How do women's magazines describe men? Furthermore, what is the discrepancy between depictions of men and women in men's and women's fashion magazines?

To solve the questions above, researchers review the representations of women and men in magazines. It is frequently the case that the shape of bodies and appearance have been underscored by female magazines (Malkin et al., 1999). For instance, it has been discovered that describing how a celebrity snaps back to a lithe figure after pregnancy is not practical for ordinary readers without resources (Gow et al., 2012). Moreover, researchers found that media consumption of thinness depiction content related to disordered eating and body dissatisfaction for women audiences and thinness endorsement for men audiences, which could be explained by the social learning theory that argues audiences would recognize content in these magazines as some kind of cultural ideal (Harrison & Cantor, 1997).

The worries about bodies are shared by men's magazines as well. A systematic reexamination of men's magazines shows that one of the common themes in them is "men's concerns about health and body image, and the production of those anxieties in

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the magazines themselves" (Waling et al., 2018, p. 9), and audiences of them would then pursue these male ideals. Consumption raises concerns for men's bodies though this ideal body may be unattainable for most men. Media exposure to these male magazines is also associated with thinness standards for women's bodies (Hatoum & Belle, 2004). It is worth noting that men's magazines often treat women as sexual objects, which is only like a kind of "men's interest" (Edwards, 2003). There is a hierarchical system of women's bodies, which "are the currency used to represent sex" (Attwood, 2005) in men's magazines.

In addition to bodies, female magazines have been deemed "a site for the production of feminine self" (Malik, 2005). Thus, consumption practices cannot be divided between fashion and beauty. Indeed, by examining cover photos, advertisements, images, and texts, it is found that fashion magazines - male and female both - promote a better life in different aspects (Hurd Clarke et al., 2014; Minowa et al., 2019; Shiau, 2013). Though consumption is a feminine arena traditionally, men have been attracted to buying things, which is described as "the mascularization of consumption" (Galilee, 2002). In the chapter talking about men's consumption, Rinallo (2007) argues that "Fashionable media representations of masculinities lure straight men into appearing beautiful according to inspirational models codified by advertising and to indulge in consumption practices." Men are aware of fashion and are affected by mass media and personal media (Shephard et al., 2016).

The way to construct masculinity and femininity has also been reviewed (Tan et al., 2013; Velding, 2017). It is found that despite each men's magazine presenting different genres of masculinity, such as "metrosexuality," the hegemonic masculinity is still

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depicted, implying a power hierarchy among men, with wealthy heterosexual men at the top (Ricciardelli et al., 2010).

There are intriguing discoveries when comparing women's and men's magazines. For instance, Conley & Ramsey (2011) investigated women's portrayal across mixed genres of magazines and found that women's fashion magazines and men's magazines portrayed women similarly. Nevertheless, the authors highlight that the similarity may have distinct contexts. That is to say, women's images in the former can be connected to problems such as disordered eating, but women's images in the latter have associations with "unrealistic standards for women's bodies" (p.475). In another study, researchers display that women can enjoy sexual desire similarly though this kind of realization may not be realistic and can be gained only through consumption (Machin & Thornborrow, 2006). Still, there are temporal changes in female magazines. For instance, Paff & Lakner (1997) uncovered that feminism and abortion are emerging topics in female magazines.

It is worth noting that when it comes to female magazines, post-feminism or popular feminism can be a valuable lens to understand the link between consumption and showing attitudes or even liberating females (Kang, 2019). Promotion of shopping can be a viable business model and true beliefs for these media concurrently (Yang, 2020), which is a win-win to act on what people believe and survive for both media and consumers.

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Word Embeddings and Bias

There are many approaches developed to identify and gauge gender bias with various units of analysis. For instance, Ross (2007) manually inspected the sex of sources that emerged in news articles and displayed an imbalanced result. Gaucher et al. (2011) collected job advertisements and examined whether they included masculine and feminine words. Similarly, Dacon & Liu (2021) gives a comprehensive breakdown of gender bias in media articles with relatively straightforward yet effective procedures such as computing female/male occurrence percentages and associations with typical topics such as career words. Fast et al. (2016) analyze actions along with behaviors on a sentence level and apply statistical tests to check differences in associations between genders. Breitfeller et al. (2019) combine human-annotated data and a classifier using support vector machines to detect microaggression together, regarding its nuanced nature. Other researchers use more computational methods such as deep learning to detect condescension (Z. Wang & Potts, 2019).

Among all techniques, word embeddings can serve as a tool to recognize underlying bias in texts. Word embeddings are "vector representations" derived from words that can capture syntactic and semantic similarities between these words (Mikolov, Chen, et al., 2013; Mikolov, Sutskever, et al., 2013; Turian et al., 2010). They can quantify the slight distance between "a city and the country it belongs to, e.g. France is to Paris as Germany is to Berlin" (Mikolov, Chen, et al., 2013, p. 5). Thus, word embeddings can be applied to numerous tasks such as document classifications (Khabiri et al., 2019), content recommendations (Musto et al., 2016), and language translations (Xing et al., 2015).

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Though word embeddings enable people to solve complex tasks, it is found that word embeddings exhibit human-like stereotypes such as the accusation of sexist translation (Bolukbasi et al., 2016). The findings have aroused the concern of bias replication within machine learning models, or more broadly, artificial intelligence technologies which take human language as inputs (Caliskan et al., 2017).

Since word embeddings often serve as application foundations, the bias will go downstream and affect usage. Also, researchers are devoted to understanding bias's operation and origins (Brunet et al., 2019). In this case, there is a need to fix the problem, so there are algorithms developed that purpose to "de-bias" the embeddings but preserve the meanings simultaneously (T. Wang et al., 2020).

The bias within word embeddings can be a known problem or a helpful tool. Researchers can build word embeddings based on their target corpus and measure bias within them. In this way, word embeddings serve as a helpful instrument for revealing bias. Despite the above-stated methods aiming to uncover bias other than word embeddings, there are inherent difficulties, as the example provided by Bolukbasi et al. (2016). The argument is that the result of counting word co-occurrences to expose gender stereotypes may not be accurate since there are more "male nurses" than "female nurses" in texts. The hidden logic is that "common assumptions are often left unsaid," a reporting bias that leads us to refer to "female nurses" as "nurses simply." To bypass the reporting bias, Bolukbasi et al. (2016) propose using word embeddings instead.

Researchers gradually use word embeddings as a technique to catch bias in various categories, including race and religion, such as the piece of work done by Manzini et al. (2019). The method has been adopted in different countries (Scott et al., 2019),

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compared within multiple languages (Zhao et al., 2020; Zhou et al., 2019), and across eras (Wevers, 2019) and various social groups (Fraser et al., 2021). The measurement has been validated by cross-examining results of global survey data (Garg et al., 2018) and local questionnaires (Zhu & Liu, 2020). Based on previous research, scientists can detect whether there is a masculine-centric viewpoint dominating the corpus (Petreski & Hashim, 2022).

Previous research often uses occupation-related words and adjectives (for example, see Jiao & Luo, 2021) to test whether there is bias or not and how strong it is. There are also methods created to discover new biased word categories such as the school subject, personality, and preference of something in life (Chaloner & Maldonado, 2019).

Though there are multiple well-performing methods papers detecting bias in media, Blodgett et al. (2020) provided concrete and relevant recommendations for future researchers. They argue that there is a need to seek insights from literature other than NLP fields since the bias comes from the "relationship between language and social hierarchies." Also, they push researchers to "provide explicit statements of why the system behaviors that are described as 'bias' are harmful, in what ways, and to whom."

For example, Xu et al. (2019) clearly show their concern about "the emotional dependency of females on males," as depicted in movie synopsis, scripts, and books. They accentuate that stereotype is reinforced through people, actions, ideas, and narratives. Similarly, Mendelsohn et al. (2020) focus on the dehumanization of LGBTQ people, which affects them and causes intergroup bias. They also adopt word embedding methods and train models based on texts from the mass media.

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Since popular magazines provide lifestyle recipes for their audiences and foster a specific kind of “better life,” there is a need to pay attention to what they are talking about. Middle-class audiences as commodities are advertised with products, so the research examines consumption within magazines. Also, readers are provided with cultural and lifestyle content, so words related to often-seen topics such as job and career, romantic love, and sex have been collected. Similar to prior work, vocation and adjective word lists are also retrieved.

The study also takes care of bodies and sexualities mainly. As Kopina put it (2007), “ Gendered bodies and sexualities are ’dressed’ not only in actual clothes but in fashion and style” (p. 366). Thus, I focus on how body-related words such as breast, legs, hands, faces, eyes, and body control words are depicted and associated with gender in two magazines. The research questions and the choice of words enable the comparison between not only gendered and gender-indifference target audiences, e.g., online media segmenting readers by age, but also male and female-targeted texts in a systematic way.

Research Questions

It seems that texts in magazines will hold gender bias. However, as we know that perceptions toward gender inequality differ by gender (García-González et al., 2019), can we observe that the bias measured in gender-targeted magazines shows a similar pattern? In other words, would the pattern replicate social stereotypes, or may it be discrepant? This study intends to enrich the knowledge of whether there is a difference or no difference in bias between male and female fashion/lifestyle magazines and, if

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any, what it looks like. Thus, the priority of this study is on the following research questions:

RQ1: What are the themes of articles magazines provide to their unique audience?

It is explicit that fashion magazines would talk about fashion, styles, brands, and cosmetics. However, whether the appeal to self-improvement or living a better life for audiences is strong enough to surpass gender differences remains unknown. Also, magazines may ask readers to be better, but the ways to achieve this goal differ. As discussed above, advertisements often contain gender stereotypes, and fashion magazines especially, since each gender has been said to have its way of reaching the goal. Thus, I expect that these two magazines talk about similar things no matter the gender it targets. However, there may be differences in terms of the emphasis of each magazine.

RQ2: What are the biases within magazines?

Previous research found that the media have multiple kinds of bias. Fashion magazines are not an exception. They ask men and women to live a certain way, catering to a specific lifestyle. However, they are gender-targeted, and this feature may affect the editors of magazines. Take career development as an instance, people may have gender discrimination when women choose careers over their children. Nevertheless, editors may encourage their readers to strive for their own life. Thus, it will be interesting to observe gender bias within magazines, considering the fact that magazines want to both "enlighten" and relieve their audiences.

RQ3: What are the biases between magazines?

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Would gender-targeted magazines bias toward their audience or merely replicate social stereotypes? For instance, what is the way that male magazines create a hierarchy between men and women if any? What are the dimensions they focus on? In the previous question, I considered the audience-catering nature of media. In this research question, I want to not only understand which types of gender bias appear in male and female magazines, respectively but also the difference in bias between male and female magazines.

Data and Methods

Data Collection

I collected all the online articles from a women's magazine, Vogue, and a men's magazine, GQ, as sample data, with 32k pieces for the former and 46k for the latter. Vogue ranks 10th with an average of 1.78m visits, and GQ ranks 12th with 1.13m visits under fashion & apparel category websites in Taiwan, according to Similar Web, a web traffic tracker company, from 2008 to mid-2021.

In addition to the closeness of ranking, these two magazines are owned by the same international group with similar topics and sections, so there is a natural advantage when comparing articles. Among magazines in the Taiwan market, there are leading female fashion magazines great at attracting viewers, which include Elle, Marie Claire, and Bella. However, the male magazine, Esquire, which is under the same group as Elle and Marie Claire, could not make itself up to the top 100 in the list, making it problematic to compare. As for Bella, it is a local female magazine with no male counterparts.

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Content Analysis with Topic Modeling

To answer the first research question, I chose to take advantage of automatic content analysis considering the size of the articles. I constructed one topic model with articles in two magazines as a whole with the *stm* library in R (Roberts et al., 2019), which can help identify topics automatically according to co-appearing words in articles. There is a parameter *k* that has to be decided beforehand, which equals the number of topics. Thus, I tested different values of k and manually checked the results. After the examination, I took $k = 30$ since the results contain broad topics which do not overlap with each other too much. Using the *oolong* library in R (Chan & Sältzer, 2020), I then validated the topic model with word intrusion tests. The result reached 96.67% precision, indicating that topics identified with the topic modeling method are clear enough that people can identify words that do not belong to specific topics. By looking into words with the highest probability of each topic, I manually added the labels of each topic (see Figure 1). In addition to checking the result of topics, I examined the temporal change of topics by calculating topics proportion each year. Also, I check the gender differences between magazines by comparing the prevalence of topics.

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Figure 1. 30 topics and corresponding words with the highest prevalence within topics.

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The x-axis shows topic proportions of each topic. The y-axis shows topics named by the author based on keywords. The sum of them equals 100%. Original texts are in Chinese, as the figure below.

Exploring Gender Bias with Word Embeddings

After data preprocessing and word segmentation, I construct word embeddings of two magazines respectively, with *wordVectors* developed by Benjamin Schmidt (Schmidt, 2015/2022). The author implemented the original *word2vec* developed by Mikolov et al. (2013) in R. I trained two 300-dimension-models with the skip-grams method.

Afterward, referring to the word lists of "gender neutral words" developed by Bolukbasi et al. (2016), Dev & Phillips (2019), and Garg et al. (2018), I constructed three similar traditional Chinese versions of gender word lists with slight differences. The gender word lists consist of gender words such as "she," "her," "woman," "daughter," and "mother" for females. I then computed "gender vectors" via averaging gender words' space in vector models.

With gender vectors, I am able to calculate the distance between them and words in several thematic target word lists. For instance, I can measure the distance between "she vectors" and "nurse" or "he vectors" and "cute" in *GQ* and *Vogue*. Whether positive or negative, the difference in distances and direction of bias are regarded as the indicator of bias within texts.

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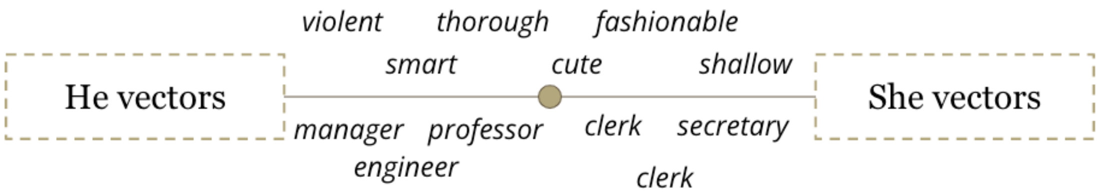

Figure 2. Measuring gender bias with distance between words and gender vectors.

The location of each word indicates its distance to "he/she vectors". For instance, "manager" is closer to "he vectors" than to "she vectors". Thus, it is biased toward "he vectors".

Since gender vectors are used to measure bias in word embeddings, it would be necessary to pick an appropriate gender word list to use. As Zhang et al. (2020) pointed out, to include or exclude a word in base pairs such as gender vectors or race vectors would affect the result of bias a lot. To evaluate the performance of three gender word lists, I extracted the most female-skewed and male-skewed adjectives from the AGSS (Adjectives List with Gendered Skewness and Sentiment) dataset developed by Zhu & Liu (2020), which contains human-coded gender skewness of Chinese adjectives. Then, I checked the direction of bias revealed in embeddings. With the results, I am able to compare human-labeled skewness and bias in embeddings. Three tested word lists and the description for the selection process can be found in appendix 1.

As for target word lists, scholars have used multiple ones to measure gender bias in various categories. Garg et al. (2018) measure gender and ethnic bias with adjectives and occupation lists. Wevers (2019) measures gender bias with job titles, psychological and cognitive states, and emotions. Lewis & Lupyan (2020) evaluate gender bias across countries with careers, families, and occupation word lists. Lucy et al. (2020) take home, workplace, and politics as their targets.

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Similar to their work, I collected three kinds of thematic word lists. First, I borrowed the AGSS dataset. Second, similar to the work of Jiao (2021), I translated the professions list used by Dev & Phillips (2019), which are developed by Bolukbasi et al. (2016). The slight change is that some professions do not have corresponding words in Chinese or do not match the local context in Taiwan, such as rabbi (拉比) and chaplain (隨軍牧師). Third, based on the topic modeling results, I self-constructed dictionaries related to several themes such as exercise, love, and sex. Complete word lists can be found in appendix 2.

With these thematic lists and gender vectors, I am able to explore gender bias in word embeddings. To answer the second question, I use a hybrid method including inductive and deductive approaches. First, inductively, I compare the closest words to "she vectors" and "he vectors" between magazines. These words serve as concrete cases to compare concepts related to gender words in gender-targeted articles. Thus, I am able to understand how magazines link certain concepts, people, and objects to genders.

After that, I took a relatively deductive approach. To investigate whether fashion magazines replicate social bias, I checked the correlation result between human-labeled gender skewness and bias detected in embeddings. For instance, "coquettish"(嬌媚) is scored 1.20, which is closer to female. I computed its distance to gender vectors in *GQ* and *Vogue* models. Then I computed the correlation. Previous scholars also validated word embedding models with calculating correlation between model results and survey response (Kozlowski et al., 2019). This step helps solidify the hypothesis that automated-found bias echoes the human-found bias if the correlation coefficient gets closer to 1.

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Subsequently, I adopted two commonly used methods explicitly designed for word embeddings models, WEAT (Word-Embedding Association Tests) and Embedding Coherence Test (ECT), to scrutinize gender bias in models.

Several studies discuss gender bias in word embeddings other than English, such as German and Italian (Lauscher & Glavaš, 2019). The piece of work done by Jiao (2021) aiming at Chinese word embeddings provides practical insights into the dictionary-picking and translation process.

WEAT is inspired by the Implicit Association Test (IAT). IAT is a test developed to measure implicit bias by presenting two concepts and attributes. For instance, researchers would take flower names and insect names as concepts, and take pleasant/unpleasant words as attributes, then ask subjects to complete a test by putting a concept along with an attribute together as a bundle on two sides. Then, subjects will be asked to label a word on the right-hand or left-hand side according to its attribute or concept. As Figure 3 shows, the left-hand side can be a bundle of flowers or unpleasant, and the right-hand side will be insects or pleasant.

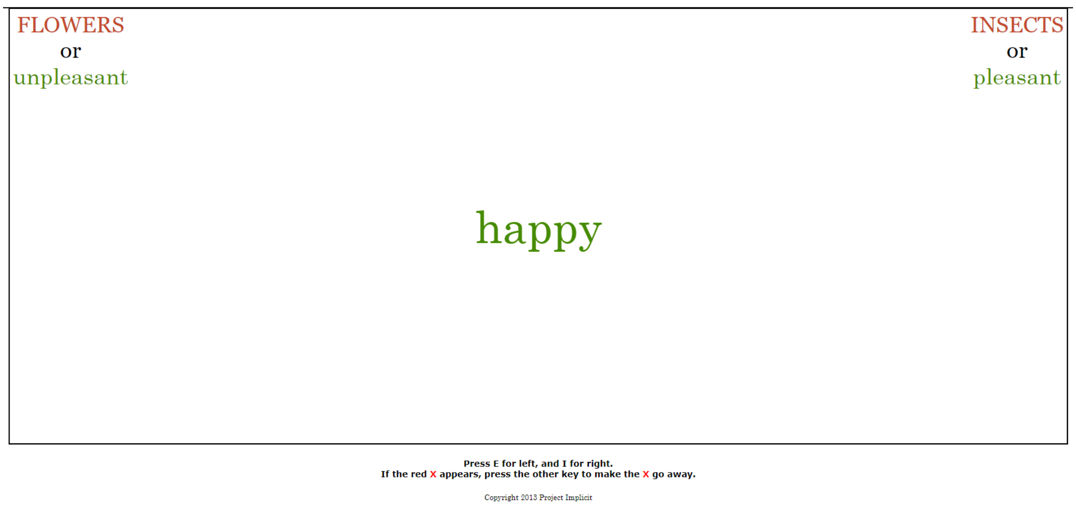

Figure 3. Measuring implicit bias with IAT.

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Both sides contain a bundle of an attribute and a concept. The subject needs to label the word appearing in the middle “left” or “right”, and the response time will be recorded. Screenshot from “Project Implicit”.

Responses time of the subjects is interpreted as implicit attitudes since implicit attitudes would affect the word associations in subjects’ minds (Greenwald et al., 1998). In this case, flower names are generally seen as more pleasant than insect names. Thus, subjects are expected to take more time when flowers and unpleasant words are linked together than when flowers and pleasant words are linked together.

WEAT is quite similar to IAT. The main difference is that WEAT does not test response time of human subjects. Instead, researchers can calculate distances between concept words and attribute words with word embeddings. Caliskan et al. (2017) developed WEAT, and they successfully replicated famous IAT results. They took flowers/insects as target words and pleasant/unpleasant as attribute words, instruments/weapons as target words and pleasant/unpleasant as attribute words, math/arts as target words and male/female terms as attribute words, and male/female names as target words and career/family as attribute words. In these cases, flowers are closer to pleasant and insects are closer to unpleasant words. Other cases have similar association results. For the practical part, I use the *sweater* package (Chan, 2022) and perform WEAT on word embedding models. Since focusing on the gender aspects of each magazine, I chose gender vectors as attribute words. As for target words, I picked math/arts translated by Jiao (2021), career/family terms used by Lewis & Lupyan (2020), and male/female adjectives derived from AGSS.

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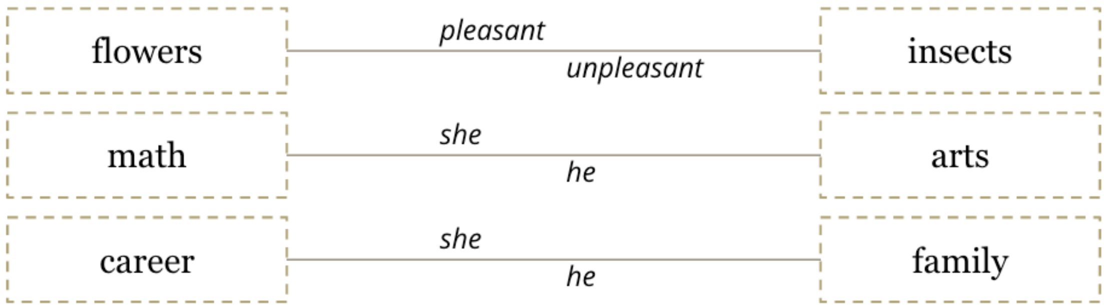

Figure 4. Examining bias in word embeddings with WEAT.

The test checks associations/distances between 2 sets of attribute words and 2 sets of target words.

ECT is another way to assess bias within word embedding models (Dev & Phillips, 2019). Similar to WEAT, ECT needs an attribute word and two target words. For instance, the attribute word can be a list of occupations, and the target words can be gender terms. The first procedure is calculating the distance between each word in attribute word lists and two target words separately. Then, with the similarity vector of “she vectors” and “he vectors”, the second procedure is to compute the Spearman coefficient between the rank order of the two similarity vectors.

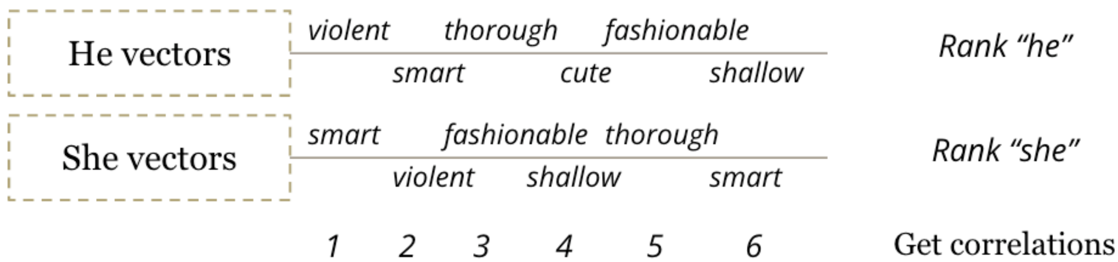

Figure 5. Examining bias in word embeddings with ECT.

The test checks correlations between 2 sets of attribute words and 1 set of target words.

The result of the Spearman coefficient can show whether there is bias within word embeddings models. As the coefficient gets closer to 1, it indicates that the distance between genders is quite the same, so the ranking is similar. Thus, it represents less

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bias within the model than the coefficient getting closer to 0. For the practical part, I borrowed functions created by the *sweater* package and self-calculated the ECT results. Similar to WEAT, I chose gender vectors as attribute words in ECT. As for target words, I picked the AGSS dataset and professions lists then executed the test.

Comparing Gender Bias between Word Embeddings Models

To further compare gender bias between magazines, distances between gender vectors and occupation word lists and adjectives describing appearance word lists are calculated. Since the word vectors comparison between different vector models needs further transformation with linear mapping (Hamilton et al., 2018; Mikolov et al., 2013; Spinde et al., 2021; Tan et al., 2015) or adopting the neighbor-based approach (Azarbonyad et al., 2017), the specific value bias may encounter stability problems (Dridi et al., 2018; Pierrejean & Tanguy, 2019; Wendlandt et al., 2018). Thus, I take the signum(+/-) a.k.a. direction, as indicators of occupation bias toward each gender instead.

I took McNemar's Chi-squared test to check directions between nominal matched pairs in *Vogue* and *GQ* models. First, I extracted the direction of each word in both models. Second, I combine results on a paired basis. Third, I check paired samples such as "directors" or "beautiful" share the same directions or not. With paired McNemar's Chi-squared test, I am able to know whether the same word has a similar direction of bias between models. I also took the AGSS dataset and translated professions lists to evaluate bias between magazines.

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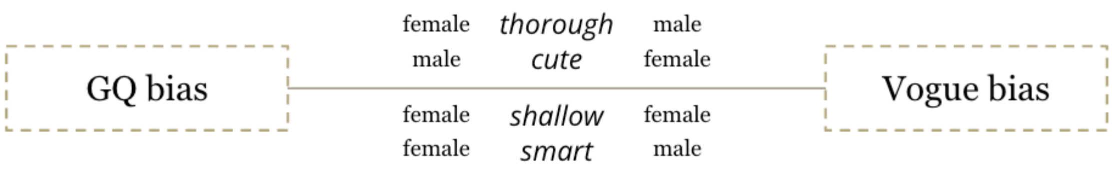

Figure 6. Examining bias between word embeddings with paired McNemar's Chi-square test.

The test executes paired t-tests of directions of each word.

Accompanying McNemar's Chi-squared test, I borrowed the concept of the ECT test and modified it. Initially, ECT tests measured the distance between a thematic word list and two target words based on a single model. For instance, I can calculate the distance of gender-skewed adjectives between gender vectors. Thus, "he vectors" and "she vectors" are two target words. Then I will rank the order according to its respective distance and get the rank correlation coefficient.

In the cross-corpus-ECT test, I want to compare the rank of words between two different models. To modify it, I still calculate the distance of the attribute list and target words. However, I got the results of two models instead of one. In the correlation part, the attribute words remain the same. Regardless, instead of setting target words as "he vectors" and "she vectors", I compare the same gender vectors across models. To put it in a function, originally, it would be ECT*(Attribute = adjectives, Target A = he vectors, Target B = she vectors)*. As Figure 3 indicates, the modified version would be ECT*(Attribute = adjectives, Target A = he vectors from GQ, Target B = he vectors from Vogue)*. The spirit is still the same. Cross-corpus-ECT test also compared the rank of attribute word lists. The only difference is that it now evaluates the difference between models instead of genders. Similar to paired McNemar's Chi-square test, I used the AGSS dataset and translated professions lists in cross-corpus-ECT.

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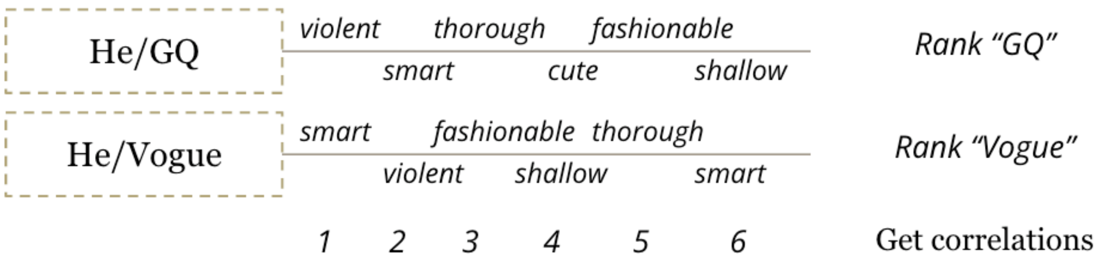

Figure 7. Examining bias between word embeddings with cross-corpus ECT.

Instead of comparing the same target words across 2 sets of attribute words, the test compares the same attribute words across 2 word embeddings.

The tests above are more deductive in nature. They can help identify the various directions and strengths of gender bias. When understanding concrete things that happened, I again rely on inductive methods. I check the words in thematic lists one by one and average their distance to gender vectors. The aim is to observe different linkages between gender-targeted magazines. Additionally, I dug into some of the words in target word lists by checking their co-occurrence words based on Dice coefficient and log-likelihood values. When it comes to co-occurrence, Dice coefficient is one of the most commonly used measures with higher performance than others (Kolesnikova & Kolesnikova, 2016). To provide more context, I also incorporate co-occurrence terms based on log-likelihood measures.

Checking Quality of Word Embeddings Models

To ensure the word embeddings are reliable, i.e. there are no natural problems in the corpus, I take two tests to assess their quality.

Before evaluating the quality of these models, in addition to *GQ* and *Vogue* models, I additionally perform all of the tests below on a pre-trained word embeddings model

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developed by the Chinese Knowledge and Information Processing Lab (CKIP, 2017), which is built on Central News Agency Corpus and Sinica Corpus. With the CKIP model, I can execute the below-mentioned methods and use it as the baseline.

Getting back to tests, first, to ensure that word embeddings models capture the **word similarity**, I conduct the word similarity tests with several datasets. These datasets consist of word pairs and corresponding similarity scores. Human coders label the similarity score between words A and B in the word pair. The label is taken as the golden standard. With these datasets, I can check the correlation coefficient between similarity constructed by my word embedding models and the golden standard. The datasets include COS960 (Huang et al., 2019), Wordsim-240 (WANG et al., 2011), Wordism-296 (Jin & Wu, 2012), PKU-500 (Wu & Li, 2016), Chinese MEN-3k (Bruni et al., 2014), Chinese MTurk-287 (Radinsky et al., 2011), Chinese WordSim-353 (Agirre et al., 2009), Chinese SimLex-999 (Hill et al., 2015), and the Chinese version word lists above are translated and verified by Chen & Ma (2018).

Huang et al. (2019) took three metrics to evaluate the results of word similarity tests, including Spearman correlation coefficient, Pearson correlation coefficient, and third, the product of square root of Spearman correlation coefficient and Pearson correlation coefficient. I follow their practice, calculating three kinds of metrics. Table 1 shows that three models perform relatively poorly on PKU-500 and SimLex-999. In other datasets, GQ and Vogue models present a relatively acceptable correlation compared with the CKIP baseline. It indicates that GQ and Vogue word embeddings models capture the word similarity relationships. I include several research using these datasets in evaluating embeddings with word similarity tests (Chen & Ma, 2018; Chen et al., 2022; Chen et al., 2015; Huang et al., 2018).

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similarity dataset	model	Spearman	Pearson	Product of S^(-2) and P^(-2)
COS960	Chen (2022)	0.56 to 0.61		
COS960	GQ	0.47	0.40	0.43
COS960	Vogue	0.52	0.43	0.48
COS960	CKIP	0.52	0.46	0.49
Wordsim-240	Chen (2015)	0.56		
Wordsim-240	GQ	0.55	0.52	0.53
Wordsim-240	Vogue	0.48	0.48	0.48
Wordsim-240	CKIP	0.58	0.56	0.57
Wordsim-296	Chen (2015)	0.52 to 0.59		
Wordsim-296	GQ	0.60	0.60	0.60
Wordsim-296	Vogue	0.56	0.59	0.57
Wordsim-296	CKIP	0.59	0.61	0.60
PKU-500	Huang et al. (2018)	0.26 to 0.56	0.28 to 0.51	
PKU-500	GQ	0.29	0.27	0.28
PKU-500	Vogue	0.34	0.33	0.34
PKU-500	CKIP	0.45	0.46	0.45
MEN-3k	Chen & Ma (2018)	0.65		
MEN-3k	GQ	0.67	0.63	0.65
MEN-3k	Vogue	0.69	0.65	0.67
MEN-3k	CKIP	0.70	0.68	0.69
MTurk-287	Chen & Ma (2018)	0.60		
MTurk-287	GQ	0.56	0.58	0.57
MTurk-287	Vogue	0.58	0.58	0.58
MTurk-287	CKIP	0.61	0.63	0.62
WordSim-353	Chen & Ma (2018)	0.62		
WordSim-353	GQ	0.63	0.57	0.60
WordSim-353	Vogue	0.60	0.57	0.58
WordSim-353	CKIP	0.66	0.62	0.64

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SimLex-999	Chen & Ma (2018)	0.40		
SimLex-999	GQ	0.34	0.30	0.32
SimLex-999	Vogue	0.36	0.32	0.34
SimLex-999	CKIP	0.35	0.33	0.34

Table 1. Results of similarity test.

Spearman and Pearson are the abbreviations of Spearman correlation and Pearson correlation. Models with brackets such as Chen (2022) are results from previous researchers adopting the same datasets. Baseline models do not compute all three metrics.

Second, to ensure that the word embeddings model captures the **word associations**, I conduct the word analogy tests with the Chinese version of the Google analogy test dataset (Mikolov et al., 2013). The translation, along with validation, is also completed by Chen & Ma (2018). The dataset contains semantic and syntactic relationships. For instance, there are semantic word pairs such as “Athens/Greek - Berlin/Germany.” Likewise, there are syntactic word pairs such as “boy/girl - brother/sister.” With the dataset, I first computed the nearest neighbor words with “Greek - Germany + Berlin” and then inspected whether the outcome was “Athens” or not. Only perfectly matching indicates that the model grabs the relationship. After scanning all the word pairs, I can have the overall accuracy of analogy tests.

The evaluation of the word analogy test is based on the accuracy of its matching results. *GQ* reaches 47%, and Vogue reaches 58%. The baseline model reaches 57%. Though *GQ* performs not as accurately as *Vogue*, it is still acceptable when reviewing the accuracy of other Chinese word embeddings analogy tasks such as models of Chen & Ma (2018) reach around 34% to 55%.

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source	n of analogy questions	accuracy
GQ	671	47%
Vogue	803	58%
CKIP	3,879	57%

Table 2. Results of analogy test.

The numbers of analogy questions are different because not all models contain all the words in analogy questions.

Results

RQ1: Themes of Content

Topics appearing in these two magazines can be categorized into more prominent themes. There are five kinds of themes: hobbies such as Popular Music, better-looking such as Skin Care, life such as Love & Sex, fashion such as Fashion Show, and products & ads such as Comprehensive Advertorial.

Table 3 shows that over one-third of topics are related to hobbies since these topics are one of the reasons why readers want to read these magazines. They can follow trending films, dramas, and video games by reading magazines. The second highest is better-looking, a theme that helps readers achieve a better self by decorating their appearance. They can follow the advice in magazines, such as outfit tips and hairstyle recommendations.

themes	n of topics	% of topics	n of articles	% of articles
hobbies	11	37%	28,155	36%
better-looking	9	30%	21,300	27%
fashion	4	13%	11,652	15%
products & ads	4	13%	8,509	11%

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life	2	7%	8,669	11%

Table 3. Themes of topics.

Themes are named by the author based on topics.

The third highest theme is fashion itself, which includes new arrival outfits, fashion, fashion shows, and designer brands. However, when observing the trend across time in Figure 8, it is apparent that topics under the fashion theme have gradually decreased. The fourth highest theme is products & ads. There are many articles promoting newly-launched products and shopping events, and some of the articles are advertorials. The least high theme is life-related content. There are discussions about work-life balance, relationship advice, and weekly constellation updates. These topics are increasing in the long term.

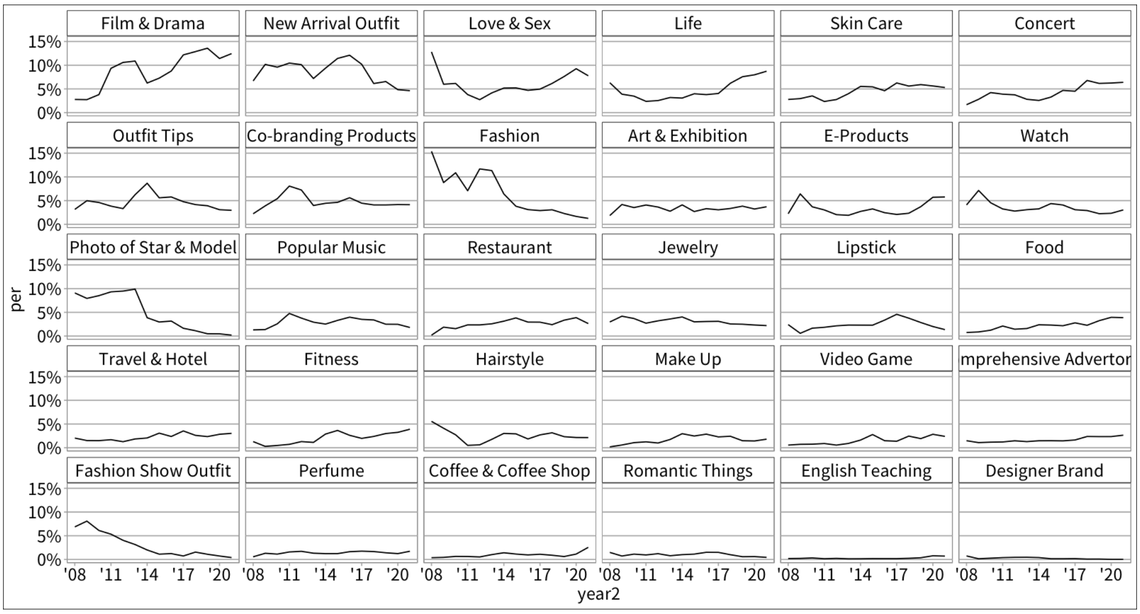

Figure 8. The share of topics across years.

The x-axis shows the published year of articles. The y-axis shows topic proportions of each topic. Topics are ordered according to the total appearance decreasingly.

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When comparing the distribution of topics across two magazines, there are huge differences between them. In the research question section, there is a discussion about whether there are gender differences when editors of magazines decide what to give to their audiences. They share tips about making hairstyles, selecting outfits, caring for the skin, and picking cosmetics. However, each magazine has its emphasis, and its decision may be a gendered one.

I present the prevalence of topics in both magazines in Figure 9. There is precise discretion in terms of some topics such as Love & Sex (point estimate: *Vogue* 6.9% and *GQ* 3.0%), Hairstyle (point estimate: Vogue 2.0% and GQ 5.4%), and Skin Care (point estimate: *Vogue* 4.7% and *GQ* 2.1%). Some of them directly match the current situation and people's image. For instance, Video Games, Photo of Star & Model, and Watch topics lean toward *GQ*, Skin Care, Lipstick, and Perfume topics lean toward Vogue.

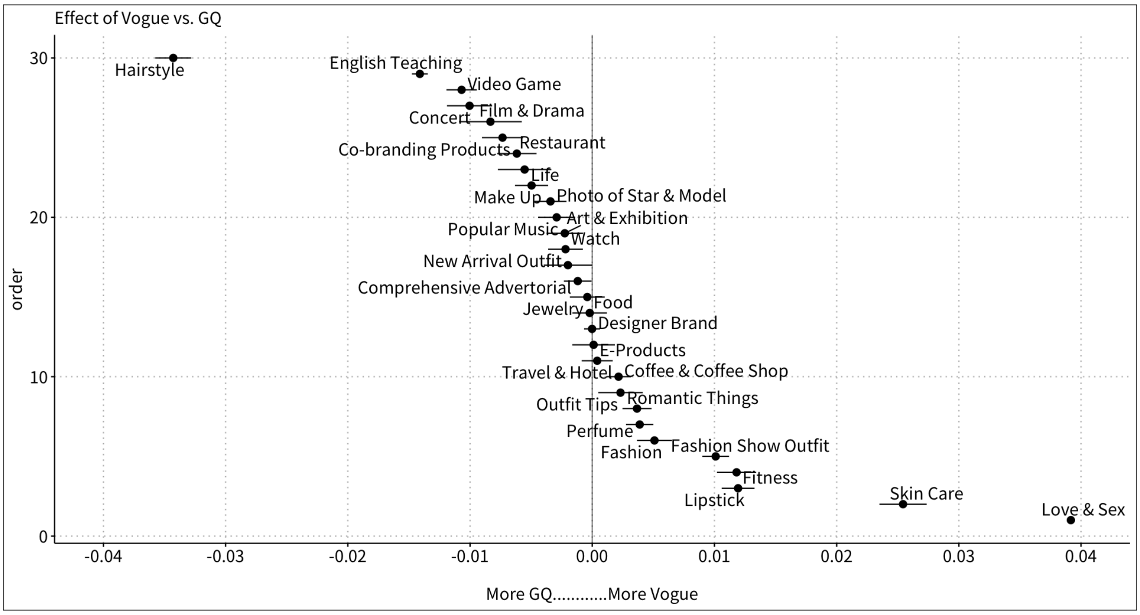

Figure 9. Difference of point estimates for 30 topics based on Bayesian regression models.

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95% credible intervals are shown. The x-axis shows estimates of topic prevalence. The y-axis shows the order of difference. Topics are ordered according to the values of difference increasingly.

RQ2: Within-Bias

After excluding words in "he vectors" and "she vectors" themselves, the results of the closest words to "he vectors" and "she vectors" for two magazines are listed below. As Table 4 shows, there are noticeable differences in closest words to gender vectors between the male and female magazines.

	Vogue		GQ	
ranks	closest to "he vectors"	closest to "she vectors"	closest to "he vectors"	closest to "she vectors"
1	Eric Bana	stylish models	gentleman	supermodel
2	Sam	beautiful	war of resistance	love me?
3	frightened	WeiWei (a celebrity)	strike	beautiful
4	younger brother	Pupupepe (a celebrity)	grandest	ageless woman
5	elder brother	makeups	father and son	beauty
6	buddy	bright red	grandfather	actress
7	silent	makeups	retire	cold beauty
8	Guy Ritchie	grace	team	marry to...
9	dismissed	makeups	heavy motorcycle	free from vulgarity
10	Arthur: The Sword of the King	spring makeup	wave	hot

	Vogue		GQ	
rank	closest to "he vectors"	closest to "she vectors"	closest to "he vectors"	closest to "she vectors"
1	艾瑞克巴納	潮模	男仕	超級名模

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2	山姆	美麗	抗戰	愛我嗎
3	聞風喪膽	唐葳	吹襲	美貌
4	弟弟	涓機	遠大	美魔女
5	哥哥	美妝	父子	美麗
6	哥們	嫣紅	爺爺	女演員
7	沉默寡言	彩妝	退居	冷豔
8	蓋瑞奇	優雅	戰隊	嫁人
9	失散	彩粧	重機	脫俗
10	亞瑟：王者之劍	春季彩妝	浪潮	火辣

Table 4. Top 10 words closest to "he vectors" and "she vectors" in magazines.

For the male magazine, the words closest to "he vectors" are those males want to become (gentleman, grandest) or traits (persistent, unruly), things (team, heavy motorcycle) they possess, or actions they take (strike, retire, resist war). Compared with that, the words closest to "she vectors" are what they gaze at (supermodel, ageless woman, beauty, actress, cold beauty), or ideal traits of women they like (beautiful, free from vulgarity, and hot).

For the female magazine, the words closest to "she vectors" are also women who want to become (stylish models, WeiWei, Pupupepe) and things that help them become beautiful (makeups appearing four times in the top 10). Compared with that, the words closest to "he vectors" are people they appreciate (Eric Bana) or words that describe men (frightened, silent, dismissed).

After qualitatively examining the results of two inductive approaches, I test the correlation between gender bias in word embeddings and human-labeled scores with the AGSS dataset. Table 5 shows that gender bias in word embeddings in both magazines correlates with human-coded gender bias positively and significantly.

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model	estimate	statistic	p.value	parameter	confidence-lower	confidence-upper
GQ	0.52	9.74	0.00	255	0.43	0.60

Table 5. Summary of the result of Pearson's correlation between human-labeled gender-skewness and word embeddings models

From the correlation coefficient, it is shown that data support the hypothesis that there is gender bias in both magazines. To dig further, WEAT and ECT can help understand more.

Table 6 shows WEAT results. Since the Spearman coefficient indicates whether target words have a similar ranking between genders, it is observable that the CKIP is the model with relatively low gender bias. The model is built based on Taiwan's central news agency, which typically writes in a neutral stance without leaning into any dimensions or too many emotions. Besides, it does not have to target a specific audience. Thus, it is unsurprising that the CKIP model shows only a slight gender bias with coefficients of 0.88 and 0.92, which are close to 1. Compared with CKIP, both *GQ* and *Vogue* models show gender bias. Though some results do not correspond to long-lasting societal bias, such as math is associated with females in Vogue, the result is insignificant. Results that are significant all consistently lean toward the male, which is the same as the result of the original IAT and WEAT.

model	word lists	result	association (first set)	significance
CKIP	math vs. art	bias = 0.043205, p-value < 2.2e-16	male	yes
GQ	math vs. art	bias = 0.021247, p-value = 0.005901	male	yes
Vogue	math vs. art	bias = -0.0025012, p-value = 0.5541	female	no
CKIP	career vs. family	bias = 0.022594, p-value = 0.06901	male	no
GQ	career vs. family	bias = 0.017501, p-value = 0.1038	male	no

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Vogue	career vs. family	bias = -0.03122, p-value = 0.9408	female	no
CKIP	male vs. female adj.	bias = 0.10229, p-value < 2.2e-16	male	yes
GQ	male vs. female adj.	bias = 0.099838, p-value < 2.2e-16	male	yes
Vogue	male vs. female adj.	bias = 0.13617, p-value < 2.2e-16	male	yes

Table 6. WEAT results.

Turning to ECT, compared with CKIP, both *GQ* and *Vogue* models show gender bias, and the results are not subtle at all. *GQ* models have less gender bias than *Vogue*. Coefficients of the former equal 0.54 and 0.70, and the latter equal 0.27 and 0.48.

model	word lists	Spearman correlation coefficient	p.value	significance
CKIP	adjectives	0.88	0.00	yes
GQ	adjectives	0.54	0.00	yes
Vogue	adjectives	0.27	0.02	yes
CKIP	job	0.92	0.00	yes
GQ	job	0.70	0.00	yes
Vogue	job	0.48	0.00	yes

Table 7. ECT results.

RQ3: Between-Bias

In the beginning, I present the result of paired McNemar's Chi-square test. The goal of this statistical test is not to examine whether there is gender bias or not, but to study whether there are differences between the two models. In the within-bias part, I have confirmed that there is gender bias both in *GQ* and *Vogue*. With this knowledge in mind, as Tables 8 and 9 show, there are significant differences of bias between gendered magazines in occupation and adjective word lists. Complete results can be found in Appendix 4.

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statistic	p.value	parameter
30.01	0.00	1.00

Table 8. Summary of the result of paired McNemar's Chi-square test with adjectives as test set.

statistic	p.value	parameter
59.07	0.00	1.00

Table 9. Summary of the result of paired McNemar's Chi-square test with professions lists as test set.

The biased directions between *GQ* and *Vogue* are not the same in interpreting the result. Paired words lean in different directions. The result of cross-corpus-ECT echoes the finding. I compare "he vectors" and "she vectors" on *GQ* and *Vogue* one by one. Since there have not been any researchers who have adopted ECT across many corpus, I do not have a baseline to compare my cross-corpus-ECT results. However, as far as the notion of the correlation coefficient is concerned, for adjectives and jobs thematic word list, both "he vectos" and "she vectors" possess dissimilarity across models. The perfect alignment is 1, and my result is between only 0.3 to 0.4, as Table 10 shows.

word lists	genders compared	Spearman correlation coefficient	p.value	significance
adjectives	male	0.32	0.01	yes
adjectives	female	0.31	0.01	yes
job	male	0.40	0.00	yes
job	female	0.37	0.00	yes

Table 10. cross-corpus-ECT results.

A certain degree of cleavage occurs in the direction of gender bias when comparing two magazines' word embeddings results. The power of gazing and being gazed at are

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intersecting. Take parts of the body and sexy for example, as Table 11 shows, they are leaned toward females in men's and women's magazines. In contrast, body shape leaned toward females in men's magazines and females in women's. The complete word lists can be found in appendix 2.

topic	GQ	Vogue
parts of body	female	female
shape of body	female	male
sex	female	male
love	female	male
love - negative	female	male
workout	male	female
shopping	female	female
self	female	female
value	female	male
people	female	male
work	female	male
sexy	female	female

Table 11. Leaning of thematic word lists between magazines.

Similarly, sex, love, and "love - negative" leaned in different directions. Also, the way of being sexy is mainly gender-targeted, but not per specific gender. That is to say, the sexiness of females is connected with "nude" in male magazines and with other attitudes/traits such as "charming" in female magazines.

Other than the lean of thematic word lists between magazines, I present co-occurrence words of four single words, which are "sexy"(性感), "body shape"(身材), "relationships"(感情), and "happy"(快樂). By observing Table 12, it is known that terms in *Vogue* related to sexy is about dressing women, but terms in *GQ* is about watching women. Table 13 depicts a similar story with words related to body shape in

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GQ linked to women, but those in *Vogue* mainly relate to self-improvement.

	sexy				body shape			
	Vogue		*GQ*		*Vogue*		*GQ*	
rank	Dice	LL	Dice	LL	Dice	LL	Dice	LL
1	sexy	perfume	sexy	shoot	figure	fitness	figure	sports
2	perfume	fragrance	figure	man	sports	lose weight	sexy	model
3	fragrance	lipstick	Victoria	fan	fitness	train	beauty	goddess
4	lipstick	female	angel	girl	lose weight	muscle	fitness	muscle
5	bleach	rose	secret	boy	train	lose weight	model	man
6	rose	eresse	hot	Taiwan	Body	model	muscle	boy
7	dresse	Show	supermodel	show	muscle	diet	goddess	fan
8	aroma	aroma	special	advertise	lose weight	weight	photo album	feel
9	underwear	aroma	shoot	like	diet	yoga	hot	South Korea
10	show	grace	goddess	feel	model	maintain	boy	suit

	性感				身材			
	Vogue		*GQ*		*Vogue*		*GQ*	
rank	Dice	LL	Dice	LL	Dice	LL	Dice	LL
1	性感	香水	性感	拍攝	身材	健身	身材	運動
2	香水	香氛	身材	男人	運動	減肥	性感	模特兒
3	香氛	唇膏	維多利亞	粉絲	健身	訓練	美女	女神
4	唇膏	女性	天使	女孩	減肥	肌肉	健身	肌肉
5	淡香精	玫瑰	秘密	男生	訓練	瘦身	模特兒	男人
6	玫瑰	禮服	火辣	台灣	身體	模特兒	肌肉	男生
7	禮服	展現	超模	演出	肌肉	飲食	女神	粉絲

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8	香氣	香調	特輯	廣告	瘦身	體重	寫真集	覺得
9	內衣	香氣	拍攝	喜歡	飲食	瑜珈	火辣	韓國
10	展現	優雅	女神	覺得	模特兒	維持	男生	西裝

Table 12. Co-occurrence words of sexy(性感) and body shape(身材).

As for Table 13, consumerism in *Vogue* has been advocated when it comes to terms related to relationships. In contrast, *GQ* talks about the exact topic itself. Happiness in *Vogue* links to life, emotions, and relationships. *GQ* shares some similarities in this case.

	relationships				happy			
	Vogue		*GQ*		*Vogue*		*GQ*	
rank	Dice	LL	Dice	LL	Dice	LL	Dice	LL
1	emotion	metropolis	relationships	love	happy	happiness	happy	Mcdonald's
2	other side	brand	other side	relationships	life	love	Nakada Yingshou	work
3	single	should	fortune	cause	matter	alone	Mcdonald's	album
4	venus	skin	love	matter	sad	mood	sake	life
5	relation	be able to	in love	friend	feel	real	mood	seishu
6	this week	happiness	separate	girl	us	real	album	matter
7	maybe	body	cause	be together	alone	always	pressure	time
8	constellation	specialty	single	easy	happiness	find	co., ltd.	mood
9	love	launch	relation	marriage	real	other side	matter	real
10	need	fashion	be together	problem	mood	world	happy	pressure

rank	感情	快樂

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	Vogue		*GQ*		*Vogue*		*GQ*	
	Dice	LL	Dice	LL	Dice	LL	Dice	LL
1	感情	都會	感情	愛情	快樂	幸福	快樂	麥當勞
2	對方	品牌	對方	關係	人生	愛情	中田英壽	工作
3	單身	應該	財運	事業	事情	一個人	麥當勞	專輯
4	金星	肌膚	愛情	事情	悲傷	情緒	清酒	人生
5	關係	能夠	戀愛	朋友	覺得	真正	情緒	清酒
6	這周	幸福	分手	女生	我們	真的	專輯	事情
7	也許	身體	事業	交往	一個人	一直	壓力	時間
8	星座	專業	單身	容易	幸福	發現	有限公司	情緒
9	愛情	推出	關係	婚姻	真正	對方	事情	真的
10	需要	時尚	交往	問題	情緒	世界	開心	壓力

Table 13. Co-occurrence words of relationships(感情) and happiness(快樂).

Discussion

The analysis shows that gender-targeted magazines contain similar themes of content, but each magazine has its specific focus. Word embedding models support that there is gender bias within gender-targeted magazines, however, there are various directions in different themes.

Topics and Gender

According to topics identified in fashion magazines, better-looking, fashion, and products & ads account for more than 50% of articles. Many of them are full of self-improving tips along with products that can help, outfits of celebrities when walking the red carpet, and annual sales of malls. These articles push readers to go shopping,

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and they imperceptibly turn consumerism into a way of empowering themselves. This phenomenon echoes postfeminism, as Gill (2007) summarized, a "distinctive sensibility" consists of themes such as femininity as a bodily party, more focus on individualism instead of structural inequality, more self-monitoring and on body especially, the changing emphasis from objectification to subjectification, among others. However, postfeminism itself and its links with fashion magazines also provoke various types of critique (Budgeon & Currie, 1995). For instance, scholars question the individualism logic behind this kind of personal achievement (Caldeira, 2020). Women work hard and achieve their career goals, so they should reward themselves by buying designer brands. Yet, the structural inequality still couldn't be shaken.

Also, there are discussions about fashion and lifestyle journalism. Some advertorials are paid content since magazines put labels under the article. Nevertheless, there are articles that look like advertisements but do not make any claim. It raises questions about "churnalism" which can be linked to journalism quality (Van den Bulck et al., 2017), since the phenomenon may reveal that journalists are not able to make high-quality reports due to working environments and working conditions, which is a true case in Taiwan (Chang & Massey, 2010; Lo et al., 2017). It's also worth noting that these two magazines are gradually decreasing their emphasis on fashion themselves. They turn into talking more about life and hobbies. Before, publishers could only boost sales of fashion outfits. Now, they have more diverse sources of commodities.

Bias and Gender

With word embedding models, the closest words related to gender vectors show that there are male celebrities appearing in *Vogue* and female celebrities appearing in *GQ*.

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Co-occurrence networks indicate men and women keep gazing at the other's bodies and their own. I would like to argue that there are vacillating forces within and between magazines at the same time.

The pervasiveness of male gaze on female bodies in fashion/lifestyle magazines has its long history. Breazeale (1994) reviewed the founding of another male lifestyle magazine established in the 1930s, Esquire. Founders of Esquire attempt to attract male audiences, since female lifestyle markets were already filled with competitors. The image of consumerism was deeply connected with femininity then, therefore, Esquire attacked women's taste in food, drinks, and home decoration to justify its focus on lifestyle content. Additionally, feared about people would link the magazine to homosexuality, "it was taken that the magazine would prominently feature erotically coded representations of women." (p.10) Actually, one of the topics identified by the topic model, which is Photo of Star & Model, feature "hot"(火辣) women in articles. These women vary from actresses to online influencers and even ordinary people, which are often called "Otaku's Goddess" in the local context (Chen, 2020). In the same time, men's magazines remind their readers to follow ripped actors and masculine models to be "sexy"(性感) and attract women. Scholars remarked that marketing motivations increase the appearance of male bodies, contributing to the fact that "men are being encouraged to gaze upon images of other men." (Patterson & Elliott, 2002) For instance, one article in GQ titled "Compare Korean famous hunks' shape of body"(韓國名品猛男 身材超級比一比). Moreover, researchers found that men's bodies can be used not only as an idealized image, but a desirable object which can be linked to greatness. Also, there are more diverse traits displayed, which are not limited to robust or reliable (Schroeder & Zwick, 2004).

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Similarly, *Vogue* urges the audience to control weights and reduce blubber. It shares celebrities' diet recipes and exercise tips. *Vogue* provides male bodies for its readers to consume as well. Audiences are provided with idealized and desirable bodies of the other gender and their own. There have been discussions about promoting products to female audiences by featuring male idols (Li, 2020). However, the power of female gaze, which argues that women can empower themselves through enjoying consuming male body, has also been questioned, just like the critique of consumerism (Benson-Allott, 2017). In the findings of this study, male gaze is clearer than female gaze. Almost all of the words closest to "she vectors" in *GQ* are what men gaze at or see as ideal traits of women, but its counterpart in *Vogue* is not all this kind.

As for the gender targeted by the magazine, scholars argue that, first, it promotes a better self for its audience, and second, this kind of better self is also linked with the other's gaze (for instance, see Goddard's work). Thus, it is not surprising that the words closest to "she vectors" in *Vogue* contain four words related to makeups, three words related to models/celebrities, and other words related to ideal traits. However, its counterpart in *GQ* shows a dissimilar pattern with things they want to have, actions they want to take, and ideal image they want to become.

Besides, the correlation result between AGSS dataset and word embeddings models verify that gender bias revealed in fashion magazines are a replication of societal bias (Kozlowski et al., 2020). Though the media should be neutral and unbiased, the hidden attitudes inherited from daily lives impact the articles. Both Word-Embedding Association Tests and Embedding Coherence Test again confirm the same results. Compared with the CKIP model, which is trained based on relatively gender-neutral corpus, gender-targeted magazines show their within-corpus bias.

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With McNemar's Chi-squared and cross-corpus ECT tests, these magazines show different directions of gender bias across them. Previously, researchers found that fashion and lifestyle journalism operate in a similar logic as our daily lives, but most works focus on the strength and types of gender bias. Kozlowski et al. (2022) have done interesting work that adopt topic modeling and other text analysis techniques. They scrutinize and compare magazines between targeted genders. I go further by examining the subtle differences of gender bias with the power of word embeddings. The observations of directions of bias and co-occurrence words indicate that there are intertwining factors behind magazines, or the fight between objectivity and subjectivity (Malik, 2005). Both genders have to cater to the gaze of others, but it is evident that women need to push themselves harder by doing fitness or decorating themselves.

The conclusion of the study is that fashion/lifestyle magazines do contain gender bias respectively. However, it does not fully echo the results of gendered occupation bias or sexualized body bias, which may be due to the goal of magazines is empowering consumers by promoting values such as shopping and enjoying sex - no matter the audiences are males or females.

Contributions

There are several contributions I want to mention here. First, I systematically compare gender bias between gender-targeted sources. I not only present within bias but also between bias, and the latter is relatively rare in previous research. Also, instead of focusing on the prediction accuracy of models, I make conversations with magazines research, feminism, and gender studies. Second, I combine inductive research and deductive approaches, providing a way to fully examine bias revealed in word embedding models. Additionally, I added the part of the reliability test on gender

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vectors and embedding models to prevent suffering from measurement bias such as those mentioned in Du et al. (2021). Most of the research in the media field does not execute this kind of test. However, there is a need to inspect the word lists and models considering that there are cultural differences (Kurpicz-Briki, 2020). Word lists and pre-existing embedding models used by previous researchers may not suit local context or selected corpus. Third, there are not many journalism research applied word embeddings with traditional Chinese. Thus, resources are relatively scarce compared with the English word embedding model. In addition to referring to research based on simplified Chinese corpus, I integrate several traditional Chinese resources such as the CKIP model, translated word lists, then manually inspected them. Future researchers can rely on these works if they target traditional Chinese texts. Fourth, I propose using paired McNemar's Chi-square tests and cross-corpus-ECT tests to compare bias between corpus. To my best knowledge, there aren't other researchers examining between biases with these kinds of techniques.

There are limitations in this study as well. The first limitation is about the sample chosen. I only include online articles extracted from two fashion magazines. Future research could pay attention to other genres of journalism such as sports magazines or other channels such as social media. Second, it would be great to dig deeper into interesting cases happening in Taiwan such as online gender wars happening in social media and forums (Yu, 2016). It may have a spilling effect in established media. However, I rely more on automated and scalable approaches and have to make some sacrifices. Third, the thematic word lists used in this article are mainly related to the research interests of this article such as body, consumption, and sex. However, there may be other unanticipated words that contain hidden bias. Researchers can consider a more systematic way to detect gender bias in all dimensions.

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Appendix

appendix 1: word lists of gender vectors

A. the list based on Bolukbasi et al. (2016)

   a. “she vectors”: "女性", "女人", "女孩", "姐妹", "她", "她的", "女兒"

   b. “he vectors”: "男性", "男人", "男孩", "兄弟", "他", "他的", "兒子"

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B. the list based on Dev & Phillips (2019)

a. “she vectors”: "女人", "女兒", "她", "女性", "女孩", "她自己", "媽媽", "母親"

b. “he vectors”: "男人", "兒子", "他", "男性", "男孩", "他自己", "爸爸", "父親"

C. the list based on Garg et al. (2018)

a. “she vectors”: "他", "兒子", "他的", "爸爸", "父親", "男人", "男孩", "他自己", "男性", "女性", "兄弟", "叔叔", "伯伯", "姪子"

b. “he vectors”: "她", "女兒", "她的", "媽媽", "母親", "女人", "女孩", "她自己", "女性", "女性", "姐妹", "阿姨", "嬸嬸", "姪女"

D. the test on three lists and explanation

a. GQ result

ID	term	Chinese	human-labeled	dictionary 01	dictionary 02	dictionary 03
1	flirtatious	嬌媚	female	female	female	female
2	charming	嫵媚	female	female	female	female
3	pretty	俏麗	female	female	female	female
4	plump	豐腴	female	female	female	female
5	coquettish	嬌羞	female	female	female	female
6	handsome	帥氣	male	male	male	male
7	exquisite	精壯	male	female	male	female
8	mighty	威武	male	male	male	male
9	hansome	英俊	male	male	female	female
10	unusual	壯碩	male	male	male	male

b. Vogue result

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ID	term	Chinese	human-labeled	dictionary 01	dictionary 02	dictionary 03
1	flirtatious	嬌媚	female	female	female	female
2	charming	嫵媚	female	female	female	female
3	tenderness	柔媚	female	female	female	female
4	virtuous	賢淑	female	female	female	female
5	pretty	俏麗	female	female	female	female
6	robust	健壯	male	male	male	male
7	handsome	帥氣	male	male	male	male
8	exquisite	精壯	male	male	male	male
9	hansome	英俊	male	male	male	male
10	unusual	壯碩	male	male	male	male

c. Explanation: Term 1 to Term 5 are the most female-skewed human-labeled adjectives. Term 6 to Term 10 are the most male-skewed human-labeled adjectives. I calculated the distance between three lists of gender vectors and each keyword. Then I get the learning score by deducting the male score from the female score.

For the *GQ* model, the result shows that all three lists correctly identify female-skewed adjectives. List 3 has two errors, and List 1 and List 2 have one error. For the Vogue model, the result shows that all three lists correctly both identify female-skewed adjectives and male-skewed adjectives.

Since List 1 and 2 break even, I use the simpler one, which is List 1, as my gender vectors.

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appendix 2: topic model

A. adjectives from (Zhu & Liu, 2020)'s AGSS

"知名","有趣","時髦","帥氣","實在","大膽","健康","可愛","瘋狂","熱情","自信","美麗","細膩","漂亮","恐怖","認真","積極","幽默","幸福","貼心","大方","快樂","聰明","專注","主動","活潑","溫柔","無聊","幸運","偉大","平凡","普通","敏感","富有","溫和","隨意","邪惡","嚴格","嚴肅","親切","俏皮","馬虎","驕傲","堅強","高貴","穩重","圓潤","專心","細心","嚴謹","友善","冷靜","不幸","執著","可靠","尊貴","樂觀","敏銳","清純","平靜","從容","任性","真誠","爽快","孤獨","斯文","謹慎","善良","純真","長壽","鎮定","天真","無畏","豐滿","無情","謙虛","冷酷","怪異","正經","高明","真摯","邋遢","古怪","偏執","開朗","客氣","拘謹","吝嗇","難看","健壯","忠誠","踏實","稱職","機智","嫵媚","英勇","堅韌","高大","直率","自私","仁愛","強健","貪婪","俗氣","膚淺","剛毅","幼稚","殘暴","俏麗","老實","友好","冷漠","精壯","壯碩","貪心","純潔","勇猛","自卑","俊美","辛勞","純情","野蠻","高尚","嚴厲","懶惰","熱心","稚嫩","強硬","靈巧","豐腴","小氣","愚蠢","固執","圓滑","扭捏","硬朗","精明","威風","清秀","慎重","頑皮","豪爽","平庸","滑稽","柔弱","正派","勤奮","剛強","臃腫","刻苦","淘氣","冷淡","囂張","謙遜","世故","無私","隨和","慷慨","顯赫","軟弱","平和","輕浮","乖巧","呆板","自大","矜持","粗魯","謙卑","可笑","俊俏","放蕩","輕狂","秀氣","拖拉","狂妄","高傲","英俊","可惡","嬌貴","正直","羞澀","張狂","笨拙","豪放","虔誠","機靈","死板","孤僻","懶散","狹隘","溫順","勤勞","麻木","率真","狡猾","嬌媚","浮躁","威嚴","陰險","專一","風風火火","冷冰冰","冷峻","文靜","自滿","憔悴

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","心急","直爽","落寞","老練","仁慈","倔強","忠貞","慈悲","開明","好客","潑辣","辛勤","凶狠","文雅","矯健","聰慧","自負","虛弱","頑強","聰穎","懵懂","俊秀","魯莽","苗條","懦弱","率直","迷糊","放浪","堅忍","豁達","多愁善感","勤快","苛刻","用功","刻薄","急躁","狠心","嬌羞","老成","溫厚","儒雅","果敢","孤傲","剛烈","窮困","猖狂","纖弱","和善","勢利","散漫","憨厚"

B. occasions from Dev & Phillips (2019)

"導演","編輯","代表","演員","主角","藝術家","大師","歌手","攝影師","老闆","老師","學生","藝人","爸爸","記者","編劇","專家","作家","運動員","教練","總統","作者","殺手","員工","醫生","廚師","警察","教授","大使","青少年","戰士","顧問","律師","造型師","經紀人","插畫家","經理","太空人","隊長","畫家","科學家","店主","舞者","漫畫家","負責人","公關","士兵","導師","偵探","軍人","詩人","部長","講師","商人","射手","使者","音樂家","管家","大亨","鼓手","企業家","水手","學者","刺客","船長","工人","官員","助手","護士","服務生","傳教士","檢察官","魔術師","業主","神父","公民","流氓","分析師","理髮師","修女","哲學家","總理","農夫","法官","治療師","作曲家","漁夫","議員","物理學家","發明家","上校","牙醫","消防員","酒保","勞工","替補","妓女","院長","政客","指揮官","職員","政治家","囚犯","委員","主婦","校長","和尚","聖人","管理員","女僕","地主","人類學家","保鏢","男爵","牧師","看守","發起人","木匠","門徒","外科醫生","主教","保姆","消防隊員","研究員","官僚","考古學家","辯護律師","教徒","國會議員","數學家","參議員","天文學家","監護人","外交官","會計","屠夫"

C. word lists related to fashion magazines (self-constructed)

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a. parts of body: "身體","背","肌","大腿","胸","乳","奶","臀","手臂","腿","手指","事業線","馬甲線","臉","鼻","眼","耳","嘴","手腕","牙齒"

b. shape of body: "胖","肥", "瘦","減重","減肥","減脂"

c. sex: "性慾","情慾","性愛","前戲","上床","高潮","保險套","敏感帶","情趣","避孕","自慰","體位"

d. love: "愛情","交往","單身","曖昧","感情","伴侶","對象"

e. love - negative: "渣","渣男","渣女","劈腿","偷吃","分手","前任","出軌","約砲","搭訕"

f. workout: "健身","健身房","重訓","運動","鍛練","鍛鍊"

g. self: "自己","自信","值得","擁有","主體","需求","自我","關係","成長","主動","被動","完整","犧牲","探索"

h. work: "工作","職場","辭職","應徵","履歷","求職","外商","管理","事業","專業","企業","公司","薪水","辦公室","職涯"

i. people: "家人","朋友","家庭","父母","孩子","親戚"

j. shopping: "消費","購買","下單",

k. source of values: "地位","成就","名聲","成功","競爭","價值"

l. sexy: "性感"

D. Explanation

Not all models contain all words that appear in the word lists. Thus, when calculating distances between each word and gender vectors, I take the intersection of word lists between models to make sure that they share the same word list basis.

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appendix 3: word lists of WEAT test

A. subjects based on Jiao (2021)

a. math: "數學", "代數", "幾何", "微積分", "等式", "計算", "數字", "加法"

b. art: "詩", "藝術", "跳舞", "文學", "小說", "交響樂", "戲劇", "雕塑"

c. science: "科學", "技術", "物理", "化學", "愛因斯坦", "實驗", "天文"

B. the emphasis on life based on Lewis & Lupyan (2020)

a. career: "執行長", "管理", "專業", "企業", "薪水", "辦公室", "生意", "事業"

b. family: "家","父母","兒童","家人","婚姻","婚禮","親戚"

C. Explanation

There are other testing word lists such as flowers and insects. However, many of these words do not appear in these two magazines. Thus, I only compare subjects and the emphasis on life word lists.

appendix 4: Complete result of direction difference

A. Times of adjectives' direction difference between *GQ* and *Vogue*. "negative" indicates the bias is directed toward females for a particular word, and "positive" indicates the bias is directed toward females.

GQ/Vogue	female	male
female	54	93
male	31	79

B. Times of occupations' direction difference between *GQ* and *Vogue*. "negative" indicates the bias is directed toward females for a particular word, and "positive" indicates the bias is directed toward females.

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GQ/Vogue	female	male
female	13	72
male	4	47

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