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The Content of Gender Stereotypes Embedded in Language Use

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Abstract

Gender stereotypes have endured despite substantial change in gender roles. Previous work has assessed how gender stereotypes affect language production in particular interactional contexts. Here, we assessed communication biases where context was less specified: written texts to diffuse audiences. We used Latent Semantic Analysis (LSA) to computationally quantify the similarity in meaning between gendered names and stereotype-linked terms in these communications. This revealed that female names were more similar in meaning to the proscriptive (undesirable) masculine terms, such as *emotional*.

Keywords

gender, stereotypes, gender stereotypes, sex roles, language, latent semantic analysis

In society, there are status differences between groups. Historically men have had higher status and greater access to resources and positions of power than women. While the past century has shown significant progress toward gender equality, substantial inequalities remain (e.g., Moss-Racusin et al., 2012; Steffens & Viladot, 2015). Gender is also one of the earliest intergroup distinctions that humans recognize (Wingate & Palomares, 2018). Within social psychology, and social identity and self-categorization theories (Turner & Reynolds, 2011) in particular, it is argued that the world in which we live is "group-structured," and, given that the human mind is a

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product of these social processes, so too are our beliefs and practices (e.g., cognitions, communication, behavior; Turner & Oakes, 1997).

Group differences can affect the way people categorize themselves and others and the characteristics or stereotypes they associate with one group compared to another (Steffens & Viladot, 2015; Turner & Oakes, 1986). Stereotypes are cognitive structures that contain certain beliefs and expectations about the traits and behaviors of members of a social group (Koenig et al., 2011; Steffens & Viladot, 2015; White & White, 2006; Wingate & Palomares, 2018). Although gender stereotypes are complex, two key dimensions that characterize them are warmth/communion versus competence/agency/assertiveness (Eckes, 2002; Fiske et al., 2002; Menegatti & Rubini, 2017; Palomares, 2012; Steffens & Viladot, 2015). Stereotypes can be *prescriptive* (e.g., men *ought* to be competent) and proscriptive (e.g., women *ought not* show agency), not just descriptive, and these over-generalizations are applied to individuals, such that individuals who violate these stereotypes can be penalized for doing so (Prentice & Carranza, 2002; Steffens & Viladot, 2015). Gender stereotypes are not fixed, but are dynamic over time (Eagly et al., 2020). However, despite substantial changes in gender roles, gender stereotypes still endure, as evidenced on both explicit (Haines et al., 2016; López-Sáez et al., 2008) and implicit metrics (Lewis & Lupyan, 2020).

Language is a pervasive part of human experience, and virtually every aspect of daily life relies on communication with others (Giles et al., 2010). Language is also the primary semiotic system by which we transmit social and cultural norms and attitudes, and by implication is likely to contribute to the maintenance of existing beliefs about the characteristics and differences between certain groups (Holtgraves & Kashima, 2008; Kashima et al., 2014). Patterns of language use have also been hypothesized to perpetuate stereotypes, protecting them against counterexamples. That is, for in-group members, positive qualities are typically described in more abstract terms that link to enduring traits, whereas negative qualities are typically described in more concrete terms that link to situational factors. The reverse is true for out-group members. In this way, positive views of in-group members and negative views of out-group members can be maintained in the face of specific behavior that goes against these views. For example, if there is a stereotype of an outgroup being stingy, then positive outgroup behavior can be explained within a concrete context (e.g., giving money), without altering or inducing more abstract categorization (e.g., as generous) (Maass et al., 1989).

Gender stereotypes manifest in language (Menegatti & Rubini, 2017; Newman et al., 2008; Steffens & Viladot, 2015). For example, the magnitude of gendered pronoun usage in books at different points in history has been linked to women's societal status in the United States (Twenge et al., 2012). Further, while there is typically considerable similarity in how men and women produce language, there can be subtle differences whereby they can conform to stereotypes with respect to language production, such as women producing more affiliative language (Leaper & Ayres, 2007). Whether these stereotypical behaviors manifest depend on context (e.g., intergroup vs. intragroup interaction) (Leaper & Ayres, 2007; Palomares, 2008, 2009; Wingate & Palomares, 2018). For example, women have been found to produce more tentative language when discussing a masculine topic with men, but not when discussing this topic with women (Palomares, 2009).

In this paper, we sought to extend the results of the previous studies by determining whether gender stereotypes manifest in general language use, where the communication was not created in the presence of a single particular interactional partner, but instead was intended to be published for a large group of recipients (e.g., the contents of books). We employed a computational measure of association, Latent Semantic Analysis (LSA), which quantifies degree of similarity in meaning of two terms in corpora. We quantified the similarity in meaning between gendered names and prescriptive and proscriptive gender stereotype-linked terms. It was hypothesized that the gender associations would be observed in language use patterns, as evidenced by prescriptive masculine descriptors being more similar in meaning to male names than female names, and prescriptive feminine descriptors being more similar in meaning to female names than male names. We did not have a priori predictions about how proscriptive terms would relate to male versus female names, but included them to assess whether they had gender-biased associations.

Method

Name Selection

To operationalize gender, we selected the 100 most commonly given female and male baby names in the US from 1960s (Social Security Administration, n.d.).[1] Gender and sex and not synonymous. Instead, sex is a biological attribute, whereas gender is a social construct of what it means to be a man versus a woman (e.g., Lonergan & Palomares, 2020).[2] Here the focus was on gender, whereas baby names are most likely determined by a person's sex, which does not always covary with gender. We acknowledge this, and emphasize we used baby names as a proxy for gender.

Associations between concepts computed using LSA are influenced by frequency of occurrence. Thus, we controlled for the frequency of the names included in our analyses.[3] To obtain the frequency values for each name, we used Google Ngram, a publicly available database of millions of digitized books (Michel et al., 2011). We recorded the case-insensitive frequency of use of each of the names over the 50 most recent years available in the database at the time of data collation (1958–2008). This frequency variable was natural log transformed to correct for the distributional skew that occurs for words in natural language (Baayen, 2008), and then centered to improve interpretability (Tabachnick & Fidell, 2013).

Descriptor Selection

We used the results of previous research on explicit gender stereotypes to identify the content of gender stereotypes. That is, attributes (descriptors, characteristics) that embodied stereotypical feminine and masculine traits were selected from Prentice and Carranza (2002). They asked participants to identify items that were prescriptive (i.e.,

Table 1. Six Selected Desirable and Undesirable Feminine and Masculine Descriptors.

Female-prescriptive	Female-proscriptive	Male-prescriptive	Male-proscriptive
Warm	Rebellious	Athletic	Emotional
Kind	Stubborn	Dependable	Impressionable
Loyal	Controlling	Ambitious	Yielding
Sensitive	Cynical	Assertive	Superstitious
Friendly	Promiscuous	Decisive	Shy
Clean	Arrogant	Disciplined	Moody

characteristics that people of this gender *should* embody) and proscriptive (i.e., characteristics that people of this gender should *not* embody) of men and women in US society. We selected the top six intensified prescriptions and proscriptions for men and women from Prentice and Carranza (2002), which can be seen in Table 1. There were two exceptions. First, we excluded items that consisted of multiple words (e.g., *interest in children*), since these would be problematic in the LSA. Second, although Prentice and Carranza (2002) treated *warm and kind* as a single item, we treated them as separate items.

Latent Semantic Analysis (LSA)

LSA is a technique developed in computational linguistics that employs singular value decomposition to calculate a metric of the relationship or similarity of meaning between concepts, which disregards word order and syntactic structure (Dumais, 2005; Landauer et al., 1998). It is one method of computing *distributed semantic representations*, which show empirical relationships with human behavioral data (Pereira et al., 2016). In using LSA we do not claim we are modeling human stereotypes; rather, we use it to obtain objective metrics of similarity in meaning between two words within a set of texts.

Here, therefore, we used LSA scores as a way of quantifying the association in language or similarity in meaning between each of the names and each of the descriptors. For the present study, the LSA estimates were calculated online using a web-based computational tool, where we selected the topic space of general reading up to a 1-year college level, using the maximum number of factors available. This semantic space consists of more than 92,000 terms from English-language texts, novels, newspaper articles, and other information (Landauer et al., 2007). To clarify, these texts are the materials that form the basis of our LSA measure, and then within this (high-dimensional) space, the similarity in meaning of any two terms can be quantified. Importantly, this means that the analyzed content reflects a large array of communicated material by a variety of authors to a large array of intended recipients—quite different to the context of one person speaking to another in intragroup or intergroup contexts.

Similarity scores (which can range between −1 and +1) between each name and each descriptor were obtained via pairwise comparison in term-to-term space. Larger

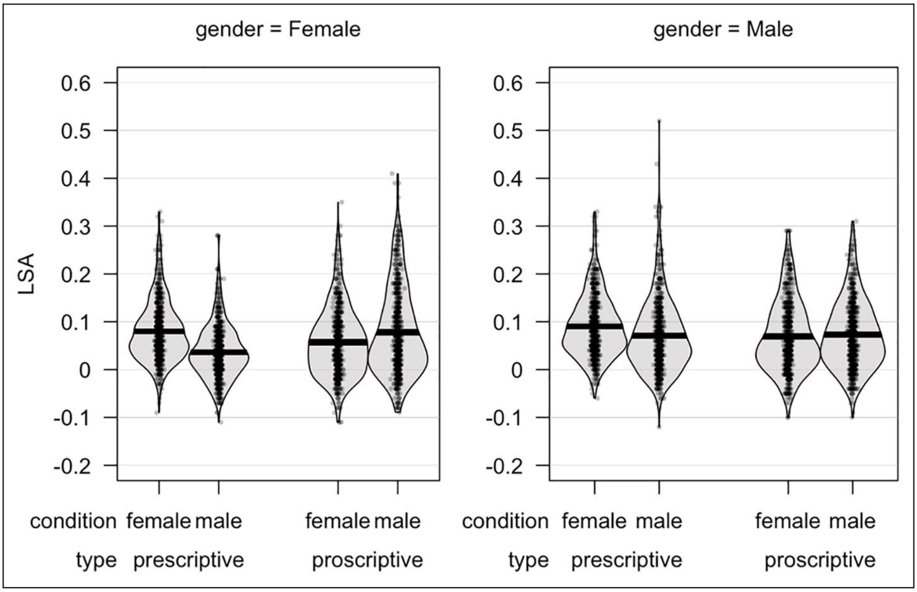

Figure 1. Pirate plots LSA similarity score as a function of gender of name and gender of descriptor.

Note. This figure shows that female names were more similar to prescriptive female descriptors than male descriptors, but more similar to male proscriptive than prescriptive descriptions. The pattern appears to hold for males, although the difference across the gendered descriptors is smaller in magnitude.

values indicate greater similarity in meaning. For example, the LSA similarity score between *assertive* and *Michael* is 0.08, whereas between *assertive* and *Lisa* is 0.05. This means that within the analyzed texts, *Michael* is more similar in meaning to the word *assertive* than is *Lisa*.

Results

Our data and analysis code are available on the Open Science Framework: https://osf.io/bxr3s/. Figure 1 presents pirate plots of the data for Female (left panel) and Male (right panel) names by descriptor type (prescriptive vs. proscriptive) and condition (female vs. male terms). Pirate plots show a combination of the raw data, the central tendency (i.e., the mean, as indicated by the solid black bar), the inference band around the mean, and the (smoothed) data density (indicated by the shaded gray area) (Phillips, 2018).

The data were modeled using linear mixed effects models in R v.4.0.3 (R Core Team, 2014) using the *lme4* package (Bates et al., 2015), with *p*-values obtained from the “lmerTEST” function. We first analyzed the full data set with the three independent variables (sum coded to allow for ANOVA-like interpretations) and log-transformed frequency (centered) in a fully factorial model and a maximal random effects structure as justified by the design (following Barr et al., 2013), but the model did not converge. The final model contained our fully-crossed independent variables, random intercepts for name and descriptor, and a random slope for gender in descriptor. The four-way interaction between name gender, descriptor type, descriptor gender, and name frequency was significant ($\beta = 2.681e^{-3}$, $SE(\beta) = 7.393e^{-4}$, $t = 3.627$, $p < .001$). We thus further explored this interaction by analyzing the data separately by name gender.

Male Names

We followed the same modeling approach as above. The final model contained a factorial combination of descriptor type, descriptor gender, and log-transformed frequency, and random intercepts for name and descriptor type. The three-way interaction was significant ($\beta = -3.898e^{-3}$, $SE(\beta) = 1.053e^{-3}$, $t = -3.70$, $p < .001$), and is plotted in Figure 2.

Figure 2 (top panel) shows that male names are associated with more female prescriptive and proscriptive descriptors as name frequency increases. Although the prescriptive/proscriptive difference appears to be larger at lower frequencies, a follow-up analysis showed the interaction was not significant ($\beta = -0.002$, $SE(\beta) = 0.001$, $t = -1.64$, $p = .104$). In contrast, there was a cross-over interaction between frequency and descriptor type for male descriptors ($\beta = 5.425001e^{-3}$, $SE(\beta) = 1.569001e^{-3}$, $t = 3.46$, $p < .001$), such that low frequency names were more strongly associated with proscriptive terms, which changed direction as names become higher in frequency. In other words, the least commonly-used male names from the list were more similar in meaning to the undesirable male attributes, which reversed as name frequency increased, such that the most commonly-used male names had stronger similarity to desirable male attributes.

Female Names

The final model contained a factorial combination of descriptor type, descriptor gender, and log-transformed frequency, and random intercepts for name and descriptor type. There was one result of interest: a marginal descriptor type by descriptor gender interaction ($\beta = -1.621e^{-2}$, $SE(\beta) = 9.094e^{-3}$, $t = 1.783$, $p = .09$). However, plots of the data (Figure 3) suggested a cross-over interaction (i.e., greater use of female prescriptive terms to describe females [top panel], but also greater use of male proscriptive terms [bottom panel]), and inspection of the 95% confidence interval of the estimate showed that it only just contained zero (−0.0008, 0.033). Thus, since this effect tested our hypothesis that female names would be more likely to be associated with prescriptive female descriptors, we explored this interaction.

Figure 3 (top panel) shows that female names were more similar in meaning to female prescriptive than proscriptive terms, although an analysis of these data only show an effect of frequency ($\beta = .017$, $SE(\beta) = 0.002$, $t = 7.88$, $p < .001$), such that similarity to both descriptor types increased with name frequency. In contrast, the bottom panel shows that females names were consistently more similar to male proscriptive terms, a difference that became larger as name frequency increased (frequency $\times$ descriptor

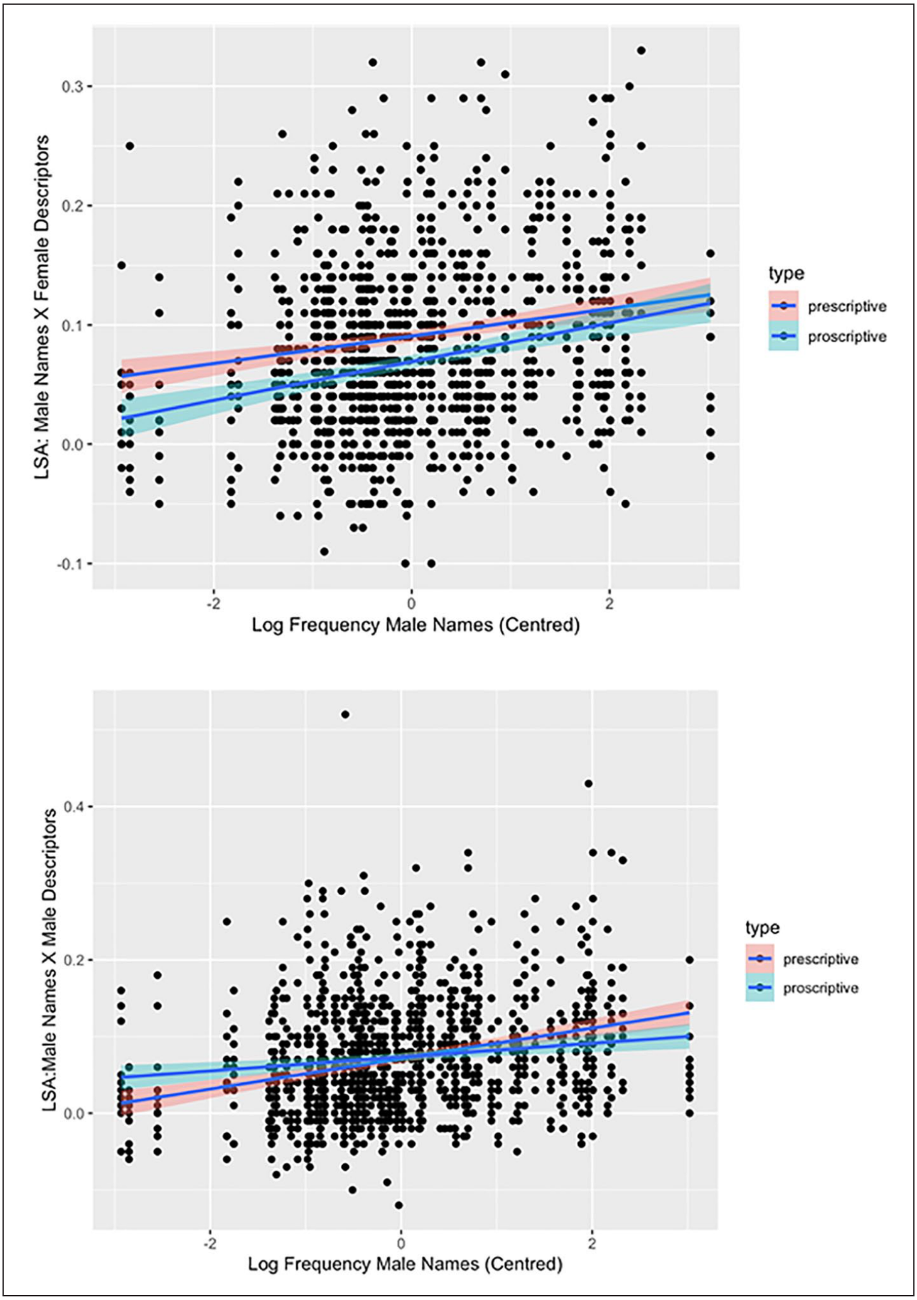

Figure 2. LSA similarity scores between male names and gendered descriptors (top: female, bottom: male) as a function of male name frequency.

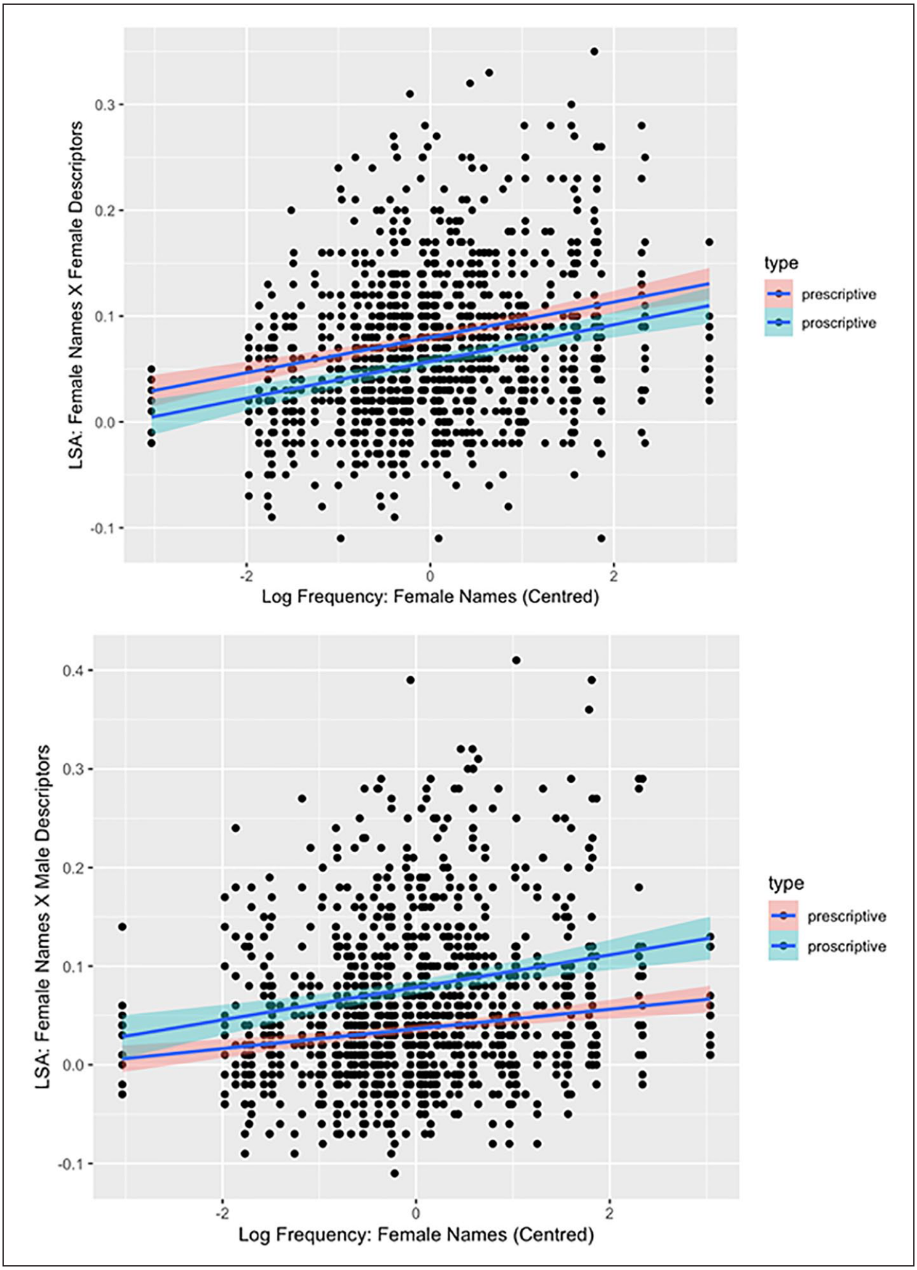

Figure 3. LSA similarity scores between female names and gendered descriptors (top: female, bottom: male) as a function of female name frequency.

interaction: $\beta=-3.258e^{-3}$, $SE(\beta)=1.546e^{-3}$, $t=-2.11$, $p=.035$). This means that female names (e.g., Lisa or Tamara) were more similar in meaning to the undesirable male attributes (e.g., emotional) than the desirable ones (e.g., assertive), with the effect becoming stronger for the more popular female names (e.g., Lisa).

Discussion

In this paper, we tested whether gender stereotypes were present in general language use where communication was from a variety of writers to a large audience. We employed LSA to quantify the similarity in meaning between gendered names and gender stereotypical terms. In most cases, systematic gender biases were not apparent. However, there is evidence in the data to suggest that female names suffered an undesirability bias when it came to male descriptors, such that they showed greater similarity with the proscriptive (i.e., undesirable) male descriptors *emotional*, *impressionable*, *yielding*, *superstitious*, *shy*, and *moody*, than with prescriptive male descriptors *athletic*, *dependable*, *ambitious*, *assertive*, and *decisive*. Male names did not consistently exhibit this bias. In fact, for high frequency male names (e.g., Michael), male names were more similar in meaning to the desirable male descriptors.

Previous work has suggested that gender salience is an important moderating factor in whether gender stereotypes manifest in language, such that they may emerge only in contexts where gender is salient, such as a woman talking to a man (Palomares, 2009, 2012). This present work advances theory in demonstrating that gender stereotypes can still be evident in content generated for a large audience of intended recipients. Furthermore, our results are novel in that they reveal what is implied about men and women in the language of a large set of communications, highlighting the embeddedness of stereotype use in communication.

These results can be considered in the context of the social identity model of de-individuation (SIDE) (Reicher et al., 1995). This model was specifically developed to understand the social-psychological processes associated with de-individuation and group behavior. It is relevant here because it espouses that social identity can be salient even in the absence of an explicit inter-group or interactional context (Reicher et al., 1995). Authors could be connecting with imagined audiences through "assumed" shared understandings of social identities and gender relations. Despite the diffuse intended audience of the analyzed texts these gender stereotypic assumptions seem to be at work.

The approach that we employed here provided the opportunity to elucidate the presence of implicit semantic associations between gendered names and stereotypical evaluative terms conveyed in a large body of texts (i.e., a distributed semantic representation). That is, we did not explicitly ask people about their gender stereotypes (e.g., Eckes, 2002) or count the mere frequency of gendered pronouns in a large body of texts (e.g., Twenge et al., 2012). Further, we did not have to create artificial interactional scenarios in the laboratory to capture a snapshot of human language use (Palomares, 2009). To our knowledge, this is among the first studies to use computational techniques like LSA to elucidate the existence of gender stereotypes in human language use (see also Lewis & Lupyan, 2020). The use of computational tools to determine distributed semantic representations hold promise for the study of social processes, and an obvious next step would be to triangulate computational and behavioral data.

The present results suggest that some gender stereotypes are identifiable across large amounts of unrelated language. These stereotypes likely reflect knowledge systems and socialization processes in societies that may subtly reinforce perceived gender differences. Existing evidence indicates that stereotypes are malleable rather than fixed, and the effects of gender stereotypes on judgments appear to become less pronounced over time (Eagly et al., 2020; Steffens & Viladot, 2015). The finding here that there was substantial overlap in how male and female names were contextualized in language could be considered consistent with a weakening of gender stereotypes. However, the present study did not investigate *time* as a factor. This means that these findings do not speak to this issue directly, but it could be investigated in future research by submitting more recently-published texts to the analytic procedures applied here and assessing whether the gender-specific effects have reduced.

A number of ways of facilitating reduction in stereotypes have been suggested, including having a critical mass of appropriate role models that challenge stereotypes (Steffens & Viladot, 2015), changing the distribution of labor within the home and with child care (Crabb, 2015), and as potentially implied by the present research, changing language use patterns. Since gender stereotypes are firmly entrenched and can be damaging, it would seem that combining language changes with other approaches would be the most effective route to behavioral change.

In conclusion, we examined language use patterns in a large array of communicated material where there was not a single intended recipient, but instead the material was generated for publication and subsequent consumption by multiple recipients. Using LSA, it was found that in this material female names exhibited heightened similarity in meaning to proscriptive (undesirable) masculine stereotype descriptors, such as emotional and shy. Such methods offer new ways to study language use and social change because they can shed light on patterns of stability and malleability of gender stereotypes over time.

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Notes

1. The only names on the list that were excluded was the unusually-spelt Jeffery and Darryl, which did not yield any results in the LSA, and therefore was replaced with the next most popular male name.
2. We note that gender identity is not a binary construct, and it is valid for a person to have a gender identity that is neither male nor female. However, when it comes to *gender stereotypes*, male/female gender stereotypes are most commonly discussed in previous research, and the available birth name data did not explicitly include non-binary names, and thus we focused on male and female genders.
3. Note that descriptor frequency was not controlled since it served as a manipulated fixed effect in our analyses. That is, we tested the association between each name and the full range of descriptors.

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