Bias in candidate sourcing communication: Investigating stereotypical gender- and age-related frames in online job advertisements at the sectoral level☆

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ARTICLE INFO

ABSTRACT

Job advertisements hold a wealth of knowledge for the public relations field about complex internal and external organizational dynamics. They reflect enduring social and sectoral cultural proclivities and associated stereotypes about workers. We examine the presence of stereotypical frames in job advertisements from sectors with varying gender and age social group composition. Guided by social categorization framing and the stereotype content model, we operationalize stereotypical warmth- and competence-related frames in candidate sourcing communication. Automated content analysis was conducted on a dataset of online job ad sentences ($n = 308,583$) from 16,135 job ads. Results indicate warmth-related frames are most observed in ads from female-dominated (vs. male-dominated) sectors and younger-dominated (vs. older-dominated and mixed-age) sectors. Conversely, competence-related frames are most observed in ads from male-dominated (vs. female-dominated and mixed-age) sectors and older-dominated (vs. younger-dominated and mixed-age) sectors. We additionally find candidate gender stereotypes may supersede age stereotypes in hiring contexts. Implications are discussed in light of socialization and structuralist forces and their influence on organizational communication in homogeneous and heterogeneous sectors.

1. Introduction

Scholars have long documented the influence of interpersonal bias in candidate sourcing, particularly with regard to job seekers' gender and age (Beattie & Johnson, 2012; Heilman, 2012; Paleari et al., 2019). In this study, we examine the presence of these biases in a crucial candidate sourcing communication device: job advertisements. Job ads are often overlooked in public relations research, yet they hold a wealth of knowledge for scholars and practitioners in the field. They represent the first touchpoint communication to an important stakeholder segment, namely prospective employees (Rynes, 1989). They also contain value-related information about "ideal" candidates (Kelly et al., 2010), a construction borne out of an interplay between internal and external organizational relations and cultures (Cheney & Christensen, 2004; Kuhn et al., 2008, 2019). Drawing on well-established research on gender and age bias in hiring within the field of public relations and beyond (Aldoory & Toth, 2002; Burn et al., 2019, 2023; Castilla & Rho, 2023; Pedriana, 2004), we investigate the presence of social group

stereotypical frames in job ads from varying sectors and focus on pan-cultural and enduring gender and age group stereotypes; warmth- and competence-related stereotypes (Fiske, 2017; Strinić et al., 2020). The present study thus explores the extent to which *job advertisements from gender- and age-homogeneous and heterogeneous sectors are framed in terms of warmth- and competence-related stereotypes*.

We move beyond previous work in three ways. First, we diverge from examining explicit textual indicators of bias such as individual words or job requirements. Instead, we employ *social categorization framing* (Yang, 2015) to explore latent stereotypes in text indicative of biases that are not obvious but are nonetheless impactful. As overt use of biased language is atypical in organizational communication, we contend that theory-driven examinations of latent content are vital for discussions around bias in sourcing communication. Second, we investigate the presence of stereotypical frames in sourcing communication through the *stereotype content model* (SCM; Fiske et al., 2002), which defines universal and generalizable warmth- and competence-related stereotypes, thus allowing comparison across gender and age social groups. Third, our study builds on prior research examining the presence of gender and age stereotypes in job ads at the individual job level (van Selm & van den Heijkant, 2021) and the broader occupation level (Gaucher et al., 2011), however, we diverge by investigating stereotypes in job ads at the sectoral level, a research area for which we find limited scholarly work (with the exception of Garcia-Retamero & López-Zafra, 2006, as cited in Clarke, 2020). This research area is important to address as Gordon (1991) finds organizational cultures are highly influenced by the larger slow-changing sectoral culture and the biases ingrained within. We address this gap and examine sectors that are homogeneous and heterogenous in their gender and age composition, i.e., gender- and age-homogeneous vs. heterogeneous, and explore, to a limited degree, sectoral interaction effects.

For the public relations field, insights from this study underscore the necessity for organizations to consider alignment of all forms of organizational messaging with stated company values (Elving et al., 2013; Puncheva-Michelotti et al., 2018). Any perception of bias can cause reputational harm and affect efforts toward authentic and consistent diversity messaging, particularly when communicators do not account for salient organizational dynamics (Edwards & Fredriksson, 2017; Furnham, 2012). Moreover, we contend that examining the influence of sectoral culture on communication is needed. Communication within organizations that share a sectoral culture "embody and reflect the cultural proclivities of the organization in which they feature" (Brown & Starkey, 1994, p. 808), and these proclivities manifest as communicated indicators of social group belongingness to said sectors (Arredondo et al., 2022). Thus, finding sector-wide shared frames elucidates the contexts under which sourcing communication may propagate and reinforce considerably enduring stereotypes; sector-level perceptions about workers and their work (Bhargava & Theunissen, 2019; Cheney et al., 2008; Fröhlich & Peters, 2007).

1.1. Theoretical framework

This paper takes a framing approach to examine latent stereotypes in job ads. Specifically, we leverage a type of frame defined through its emphasis on stereotypical characteristics of different social groups: the *social categorization frame*. Here, the general concepts of framing theories inform expectations regarding how stereotypes would appear in text – as subtle rather than outright – and with what effect, but it does not dictate which stereotypes are present. Employing a framing approach therefore provides a springboard from which to investigate the presence of a

myriad of stereotype categorizations. We look toward the *stereotype content model* (SCM) dimensions of warmth and competence,[6] and as will be discussed in relevant sections, there are compelling advantages to setting up the two dimensions as the connecting theoretical thread. Thus, we utilize social categorization framing as a lens by which to locate latent warmth and competence stereotypes in job ads and explore their relationships to gender and age homogeneous and heterogeneous sectors.

1.1.1. Framing theory and stereotypical frames

Framing has been utilized by public relations researchers to examine organizational communication and how it simultaneously constructs, reflects, and reinforces social realities (Lim & Jones, 2010). The purpose of framing a message is to constrain audiences to desired and meaningful interpretations by directing attention to information judged to be important by message senders, covertly alluding to assessments made by the latter (Hallahan, 1999). Frames thus make salient some aspects or subset of possible realities about a subject, consequently defining the subject for audiences (Entman, 1993). In practice, framing is done through strategic "selection, emphasis, exclusion, and elaboration" (Reese et al., 2001, p. 10). These strategies create explicit *framing devices*, or condensed symbols that allude to the core idea of the frame (Gamson & Modigliani, 1989). Frames often distill complex ideas, e.g., organizational values and norms, and framing devices serve to link these ideas to audiences' pre-existing cognitive schema (Baden & Stalpous-kaya, 2020). When framing is successful, audiences use expectations and associations to make inferences about the message subject and "to impute meaning not manifested in the message itself" (Hallahan, 1999, p. 208). This latent and non-neutral meaning conveyed by a frame is its *reasoning device* (Entman, 1993; van Gorp, 2005).

Within framing theory, stereotypes are a powerful framing device underscored by culturally-embedded reasoning devices (van Gorp, 2005), i.e., they draw on culturally shared cognitive schemata. Thus, the use of stereotypes as framing devices directs attention to culturally contextualized assessments of social groups, their roles, and their distance from the reader. Applied to candidate sourcing communication, stereotypes-as-framing-devices draw on societal, sectoral, and organizational cultures (Lim & Jones, 2010) and their associated reasoning devices are then interpreted by job seekers in light of these. Indeed, research shows that culture is reflected in organizational communication (Brown & Starkey, 1994) and that job seekers look for culture-related information in job advertisements to assess a job's fit (Pacelli et al., 2023).

Expounding on the use of stereotypes in framing, Yang (2015) presents a typology of stereotypical frame genres differentiated through their effects on cognition and the degree and pathways by which they make salient the perceived social distance between categories, i.e., self-to-other differences. *Social categorization frames* in particular are germane to the current study as their usage centers around ownership of cultural objects such as social roles or certain jobs and sectors. By emphasizing the belongingness of cultural objects to select social groups, social categorization frames activate distinct social identities, otherization, and make salient the social distance between groups. This frame genre thus conveys the reasoning that "certain groups are out-groups and their members are not qualified for ingroup activities" (Yang, 2015, p. 261). Likewise, social categorization frames activate self-stereotyping and lead to ingroup members assuming characteristics stereotypically associated with their category, increasing conformity and deindividuation (Brown & Gaertner, 2003). Social categorization frames in job ads inform readers about the social groups deemed ideal

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[6] By competence, we do not refer to job-specific competencies such as job performance or job-specific skills and knowledge (New, 1996); rather, we refer to a concept established in interpersonal psychology concerned with perceptions of social groups and an assessment of their ability.

for a job, i.e., dominant or ingroup, and how candidates from different social groups may be comparatively assessed, leading candidates to self-select or self-eliminate.

1.1.2. Stereotype content model (SCM)

As we have explored social categorization frames and their effects on communication receivers, we now discuss stereotypes that are transferable from societal cultures to sectoral ones. Specific stereotypes about both gender and age categories can vary across time, cultures, and within different strata of the same culture. One model that circumvents this unclarity is the *stereotype content model* (SCM) as it is suitable for investigating pancultural, superordinate, and broad-level stereotypes, particularly concerning gender and age stereotypes (Fiske, 2017; Strinić et al., 2020). Developed by Fiske et al. (2002), the SCM sets up a framework to comparatively and systematically investigate stereotype content across multiple social groups (Kroon et al., 2018; van Selm & van den Heijkant, 2021). Due to its generalizability, the SCM has been routinely used in studies on worker perceptions (Hofhuis et al., 2016) and computational stereotype- and bias-detection (Nicolas et al., 2020).

The SCM differentiates stereotype content along two perceptual dimensions: *warmth* and *competence* (Cuddy et al., 2009). Perceived warmth concerns assessments of intent; help vs. harm, whereas perceived competence concerns assessments of ability; able vs. unable (for a list of traits, see Bruckmüller & Abele, 2013; Hummert, 1990). Assessments of groups along these two dimensions form the core of social group stereotypes, including self-stereotypes. According to the SCM, women and older individuals are linked to warmth traits but perceived as low in competence whereas men and younger individuals are linked to competence traits but perceived as low in warmth (Cuddy et al., 2005; Eagly, 1997; Fiske et al., 2002; van Selm & van den Heijkant, 2021).[7] The current paper limits its scope to gender and age groups as Fiske (2017) posits warmth and competence stereotypes related to gender and age are cross-culturally shared to a great extent compared to other social categories.

Concerning intersectionality, research consistently finds multiple social group memberships have complex effects on warmth and competence perceptions (Bye et al., 2022; Nicolas et al., 2017). Strinić et al. (2020) found warmth and competence stereotypes are not additive, but rather can be offset when considering the unique interactions between an individual's full scope of group memberships. For intersectional gender and age stereotypes, some scholars find that gender stereotypes supersede age stereotypes (Andreoletti et al., 2015; Turner & Castellano, 1990) whereas others find age stereotypes are more pronounced (Bassili & Reil, 1981; Kite et al., 1991). Moreover, some studies find that men are advantaged as the association of competence with younger individuals extends exclusively to them (Martin et al., 2019) while others find women become advantaged as they age, scoring high on both warmth and competence when displaying self-sufficiency (Vale et al., 2020). Considering these findings, we opt for an exploratory approach and examine whether the interaction of gender and age sectoral composition influences the stereotypical framing of job ads. We thus explore the extent to which *the interaction of sectoral gender and age composition influence the framing of job advertisements in terms of warmth- and competence-based stereotypes*.

1.2. Extant literature in organizational studies and hypotheses

1.2.1. Stereotype construction in the context of work

Although the stereotype content model is primarily established in the fields of group-based psychology, the dimensions of warmth and competence are often broached in organizational and public relations

scholarship. Aldoory and Toth (2004) and Fröhlich and Peters (2007) discuss two perspectives that give rise to stereotypes about organizational leaders, namely socialization and structuralism, however, these approaches are also applicable to understanding how stereotypes become ascribed to workers from various social groups and encoded in sectors of various social group compositions.

Briefly, the socialization approach posits that socialization leads to the cultivation of somewhat immutable social group-congruent traits that account for differences in work styles, both actual and perceived. Women supposedly exhibit warmth-related traits, and men exhibit competence-related traits. The structuralist approach, conversely, posits that industry-wide contexts and demands inform which worker traits are expected and desirable. Although work is generally conceptualized in competence-related terms, warmth-related traits are deemed necessary for success in several contexts such as relationship-building in public relations (Aldoory & Toth, 2002; Fröhlich & Peters, 2007; Grunig et al., 2013).

In practice, the two theoretical approaches are jointly and reciprocally influential. The interplay between ascribing certain traits to social groups and the presence of context-specific demand for said traits is central to parsing how certain social groups and their associated stereotypes become valorized as congruent with a role or within a context. Industry-wide contexts and demands are further tied to sectors as Gordon (1991) finds that organizations within the same sector share challenges, requirements, and societal expectations. These factors lead to a homogenization of culture as knowledge and norms, including communication norms, are shared to ensure survival. Consequently, stereotypes constructed under the joint approach become encoded in sectoral culture and reproduced in communication within it. It must be noted however that sectoral demands, and which of these are considered fundamental to fulfill, are equally constructed and malleable (Clair, 1996); the now male-dominated information technology (IT) sector was once female-dominated (Little, 1999) due to data-entry skills being the principal sector-wide demand. Another consideration of note is whether a heuristic emerges between dominant social groups and respective sectors, linking the two and forgoing actual demands. Insights may be found when comparing homogeneous and heterogeneous sectors. Stereotypical frames in job ads from homogeneous sectors may indicate a link exists between dominant group traits and sectors, regardless of actual sectoral demands. Conversely, job ads from heterogeneous sectors may shed light on relevant contextual demands and preferred communication frames when appealing to diverse audiences.

1.2.2. Gender stereotypes in sectors

The stereotypical attribution of warmth and competence to women and men also forms the basis for stereotypes about female and male workers (Froehlich et al., 2020) and is further generalizable to gendered occupational domains (Strinić et al., 2021). He et al. (2019) found a positive correlation between warmth and competence perception associated with different occupations and the respective level of gender segregation, thus suggesting applicability and transferability of the gendered SCM-congruent stereotypes to work contexts. Smith et al. (2019) found that positive attribute assignments to female and male leaders were aligned with the SCM and Rudman and Glick (2001) found implicit stereotyping led to discriminatory hiring of competent female candidates when job descriptions emphasized warmth. Both studies point to social gender stereotypes influencing worker stereotypes, and consequently hiring, in line with the SCM.

Considering the reviewed literature, we expect similar differences in the presence of warmth- and competence-related stereotypical frames in job ads at the sectoral level. Specifically, we expect associations between sectors and gendered warmth and competence worker stereotypes to influence how job advertisements are crafted:

Hypothesis 1. Job advertisements from female-dominated sectors are more likely to contain warmth-related frames compared to job

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[7] For transgender, genderqueer, and gender-nonconforming individuals, stereotypes vary and are highly dependent on endorsement of gender essentialist beliefs (Gallagher & Bodenhausen, 2020).

advertisements from male-dominated sectors **(H1a)** or mixed-gender sectors **(H1b)**.

Hypothesis 2. Job advertisements from male-dominated sectors are more likely to contain competence-related frames compared to job advertisements from female-dominated sectors **(H2a)** or mixed-gender sectors **(H2b)**.

1.2.3. Age stereotypes in sectors

Stereotypical attribution of warmth and competence to workers from different age groups also aligns with the general stereotypes of individuals in those categories. Kroon et al. (2018) found that both corporate and news media portray older workers as trustworthy, involved, and committed (warmth characteristics) but lacking in aptitudes related to productivity, adaptability, and technological skills (competence characteristics). Krings et al. (2011) also found that good-naturedness, amicability, and sincerity formed the content of warmth-related stereotypes for older workers while capability, efficiency, and skill formed the content of competence-related stereotypes for younger workers.

In job ads, different contextual factors seem to be at play. van Selm and van den Heijkant (2021) found hard abilities requirements for general job seekers were more pronounced compared to soft abilities requirements for older workers. This emphasis on competence was also noted in a study by Abrams et al. (2016) where role congruity between a job's age-type and an older candidate's stereotyped characteristics did not increase older candidate selection. Findings point to an undervaluing of older workers' warmth characteristics and indicate warmth perceptions may function differently in the context of age-typed recruitment.[8] Thus, age stereotypes, particularly in relation to older candidates' competence perceptions, may be more nuanced in the context of hiring. Nonetheless, as social stereotypes about older individuals likely form the basis for older-worker stereotypes, we expect that sectors and their dominant group age stereotypes manifest in job advertisements as age-congruent warmth- and competence-related frames:

Hypothesis 3. Job advertisements from sectors dominated by older workers are more likely to contain warmth-related frames compared to job advertisements from sectors dominated by younger workers **(H3a)** or mixed-age sectors **(H3b)**.

Hypothesis 4. Job advertisements from sectors dominated by younger workers are more likely to contain competence-related frames compared to job advertisements from sectors dominated by older workers **(H4a)** or mixed-age sectors **(H4b)**.

1.2.4. Intersectional gender and age stereotypes in sectors

Studies on intersectional worker stereotypes paint a complex picture (Hall et al., 2018; Rosette et al., 2018; Salter et al., 2021) and findings conflict regarding the link between workers' intersectional group memberships and their warmth and competence stereotypes. In work domains, men and older individuals are overall stereotyped positively (Kornadt et al., 2013), suggesting older men are at an advantage compared to other groups (Neumark et al., 2019). However, other studies find older men are disadvantaged, particularly for lower-status jobs (Ruggs et al., 2014), or that no significant hiring differences exist (Kite et al., 2005). For women, Vale et al. (2020) find that in day-to-day life, older women displaying stereotype-incongruent competence saw no decrease in their warmth perceptions whereas Chatman et al. (2022)

find older female professionals, i.e., those in stereotype-incongruent roles, are perceived as low in warmth. Given the conflicting evidence, the present study takes an exploratory approach to examining the effects of interactions between gender- and age-segregated sectors on job ad framing via the above-mentioned research question. As will be discussed in the methods section, we perform an exploratory analysis due to data limitations, however, we nonetheless present findings to promote future research.

2. Method

To assess the presence of warmth- and competence-related frames in job ads, we employ *supervised content analysis*, a two-stage approach (see Fig. 1) that relies on human-annotated text to train an automated classifier (van der Meer, 2016). The first stage is quantitative manual content analysis to categorize job ads based on the presence of warmth- and competence-related frames in a sentence. We employed holistic singular assessment (Burscher et al., 2014; David et al., 2011) to arrive at a binary coding for the two variables where warmth and competence were coded separately as either present or absent in a sentence. In the second stage, human-annotated job ad sentences were used to train automated machine learning classifiers on warmth and competence separately. Trained classifiers were then evaluated on several metrics specific to binary automated classification tasks. These metrics compare
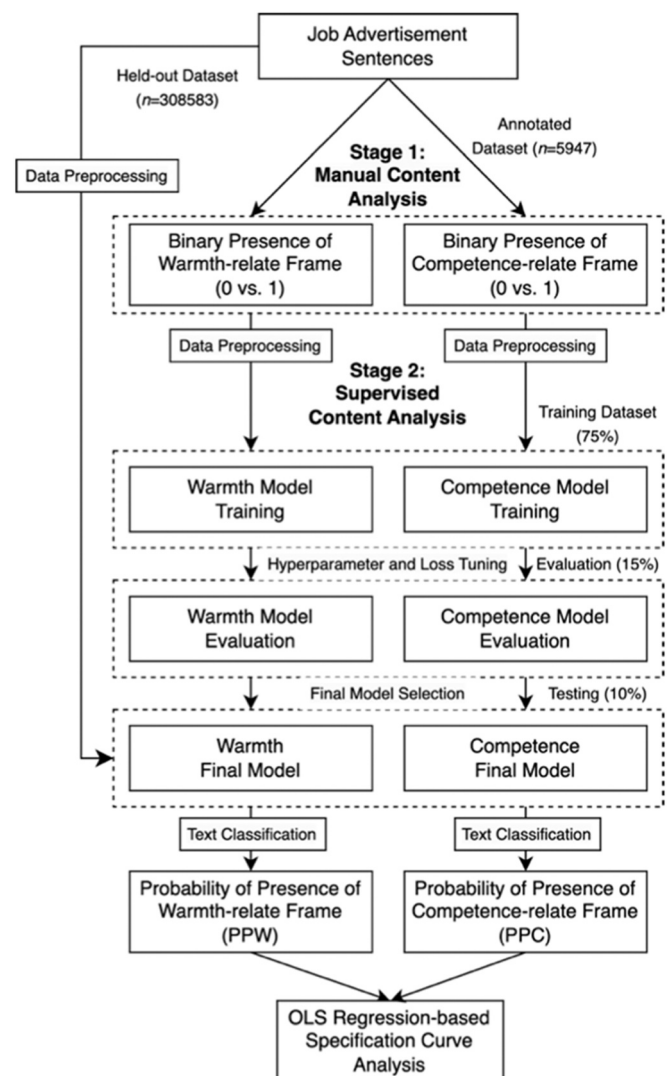
Fig. 1. Two-stage procedure for supervised content analysis.

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[8] It is also possible that certain characteristics of older workers such as higher knowledge-sharing motivations afford to them perceptions of competence (Burmeister et al., 2020). Moreover, seniority perceptions are linked to competence stereotypes as well as candidate age, however, we do not expect job ads from older-dominated sectors to all offer senior positions.

classifier-labeled sentences to human-annotated ones, the latter being the benchmark. We selected the best-performing classifier for each dependent variable and used it to label the remaining job ads in our sample, i.e., the held-out dataset. Each sentence in the held-out dataset receives one probability score for warmth- and competence-related framing respectively. Finally, the classifier-labeled dataset was used in OLS regression-based specification curve analysis (SCA).

2.1. Data collection and sample

Job ads were collected based on searches for sector-keywords from three online job search platforms: LinkedIn.nl, Indeed.nl, and Glassdoor. nl.[9] Sector designations and sector-keywords were obtained from the International Standard Industrial Classifications, referred to as Standard Business Indicators (SBI; Centraal Bureau voor de Statistiek, 2018), which cites 19 total sectors. All 19 sectors were included, and 99 sector-keywords were used (excluding pluralization and alternative spellings); sector-keywords per sector *M*= 6.8, *SD*= 2.9. Table A3 provides sector gender and age group composition, designation, and an overview of sector classifications and sector-keywords is provided in the online repository.

All scraping, preprocessing, and analysis scripts used Python 3.10.[10] Data collection relied on accessing job search websites via browser automation and collecting HTML-tagged relevant data such as job titles and descriptions (for a list of collected website data, refer to the online repository). This process did not rely on Application Programming Interface (API) access as no API is provided by the platforms under study. A scrapping approach to online data collection has comparative benefits to API-based approach. Dongo et al. (2021) find that web scraping captures largely indistinguishable data and is more flexible than API extraction where data availability is at the discretion of data providers. In practice, web scrapping relies on parsing HTML tags for elements in web pages and extracting relevant data associated with each.[11]

To counter any data collection shortcomings, we applied stringent textual data validation scripts and removed malformed and duplicate data. Additionally, a portion of the cleaned job advertisements were manually examined before classification. We also only included English language job ads as validation of non-English job ads was not possible and, at the time of writing, multilingual automated content analysis tools were not widely available or reliable. Data collection ran from November 2020 until April 2021. The final sample comprised 16,135 job ads; word count *M*= 613.29, *SD*= 524.43, containing a total of 308,583; word count *M*= 17.66, *SD*= 16.44. Table 2 shows the job ads' sample distribution across sector designations.

2.2. Variables

2.2.1. Dependent variable

Probability of warmth- and competence-related frames presence in

sentence (PPW and PPC respectively). The dependent variable examined is the probability of presence of warmth- and competence-related frames (henceforth PPW and PPC respectively) in job ad sentences as indicated by the extent to which the two concepts are emphasized in the text. We obtained these probabilities from the trained automated classifier, and we used these instead of binary predictions.[12] We argue that the extent of emphasis is variable (vs. binary), thus probabilities provide a more fine-grained measure in addition to allowing for more robust linear modeling. Table 1 shows the descriptive statistics for the classifier-labeled warmth and competence probabilities on the job ad and sentence level.

2.2.1.1. Operationalization.
To operationalize warmth and competence, definitions from Fiske et al. (2002) were supplemented with insights from our codebook construction procedure and relevant research in social psychology and organizational communication (e.g., Bruckmüller & Abele, 2013; Gaucher et al., 2011; Krings et al., 2011; Kroon et al., 2018; van Selm & van den Heijkant, 2021). The operational definition for warmth-related frames centered around whether a sentence highlights people-orientation and features interpersonal and community-building elements. For competence-related frames, the definition relied on whether a sentence highlights task- and outcome-orientation and emphasizes technical and productivity-centric elements (see Codebook in online repository). Due to the operationalization and holistic coding procedure, both the presence of warmth- and competence-related frames are considered latent variables.

2.2.2. Independent variables
The independent variable is the categorization of sectors as demarcated by respective gender and age segregation. This variable is measured at two levels: (1) categorical designations of a given sector and (2) continuous percentages of each social group in a given sector (PPS).

2.2.2.1. Categorical dominant social group of sector.
On gender, sectors were categorized as (1) female-dominated, (2) male-dominated, or (3) mixed-gender. On age, sectors were categorized as (1) older-dominated, (2) younger-dominated, or (3) mixed-age. Note that these variables were dummy-coded for linear analysis. Table 2 shows the descriptive statistics for the categorical gender and age sector designations on the job ad and sentence level.

2.2.2.2. Operationalization.
To arrive at a discrete categorical classification, an approach advocated by Hakim (1993) was utilized where a threshold is set to demarcate homogeneous and heterogeneous sectors (see for similar approaches Bettio et al., 2009). The threshold chosen for demarcating older- vs. younger-dominated sectors is 45 years as studies find employers assess candidates' age relative to other candidates and workers (van Selm & van den Heijkant, 2021). In practice, the approach entails setting a threshold percentage-point spread around the overall proportion of a selected reference group in the workforce. For example, if a threshold is set at 10 % for a workforce where the reference group comprises 40 % of all workers, then a sector with 30 % reference group members or less (40–10 %) is classified as not dominated by the reference group and a sector with 50 % reference group members or more (40 % + 10 %) is classified as dominated by the reference group.

In 2020, the Dutch workforce comprised 47.6 % female workers, 52.4 % male workers, 42.1 % older workers (=>45-years), and 57.9 %

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[9] These platforms were chosen as Indeed.nl was the most popular job search board in the Netherlands with a share of 44 % active job seekers followed by LinkedIn with 35 % whereas Glassdoor was popular with employers and provided English language support (Intelligence Group, 2020).

[10] GitHub repository link: https://github.com/noon-abdulqadir/Automating _Equity1_Code

[11] It must be noted that web scraping has drawbacks due to reliance on tag assignment and general website design.

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[12] To confirm a strong linear relationship between the presence of warmth- and competence-related frames in sentence binary predictions and probabilities, we conduction an OLS regression on the testing dataset with probabilities as dependent variable and predictions as independent variable; warmth $F(1, 592)= 1908$, $p = .00$, $R^2 = 0.76$, $b= 0.90$, $t = 43.68$, $p = .00$, 95 %CI [0.859,0.940], and competence $F(1, 592)= 10,620$, $p = .00$, $R^2 = 0.94$, $b= 0.83$, $t = 103.06$, $p = .00$, 95 %CI[0.814, 0.846].

Table 1

Descriptive statistics for probabilities of warmth- and competence-related frames presence in job advertisements and sentences.

Classifier-labeled Job Advertisements								
Stereotype-related frames	Job Advertisement				Sentence			
	M	*SD*	95 % Conf.	Interval	*M*	*SD*	95 % Conf.	Interval
Warmth Probability (PPW)	0.26	0.33	0.26	0.27	0.33	0.37	0.33	0.33
Competence Probability (PPC)	0.39	0.37	0.38	0.40	0.45	0.38	0.45	0.45

Table 2

Descriptive statistics for categorical gender and age dominant social group per sector.

Collected Dataset Job Advertisements								
Sectors	**Gender Categorical Designation of Sector**							
	Job Advertisement				Sentence			
	n	%	*M*	*SD*	*n*	%	*M*	*SD*
Female-dominated	3475	21.5	0.22	0.41	78,331	25.4	0.25	0.44
Mixed Gender	6301	39.1	0.39	0.49	117,398	38.0	0.38	0.49
Male-dominated	6359	39.4	0.39	0.49	112,854	36.6	0.37	0.48
Total	16,135	100.0	-	-	308,583	100.0	-	-

Sectors	**Age Categorical Designation of Sector**							
	Job Advertisement				Sentence			
	n	%	*M*	*SD*	*n*	%	*M*	*SD*
Older-dominated	3605	22.3	0.22	0.42	62,868	20.4	0.20	0.40
Mixed Gender	10,277	63.7	0.64	0.48	198,012	64.2	0.64	0.48
Younger-dominated	2253	14.0	0.14	0.35	47,703	15.5	0.15	0.36
Total	16,135	100.0	-	-	308,583	100.0	-	-

younger workers (Centraal Bureau voor de Statistiek, 2019; OECD, 2020). The reference group for categorizing sector segregation by gender is females, and for age, older workers were referenced. Following the ratios used by Hakim (1993) and Bettio et al. (2009), a threshold of 15 % demarcated gender-typed sector and 10 % demarcated age-typed sector. For gender, sectors were classified as male-dominated if they comprised 32.6 % women or less and female-dominated if they comprised 62.6 % women or more. For age segregation, sectors were classified as younger-dominated if they comprised 32.1 % older workers or less and older-dominated if they comprised 52.1 % older workers or more. Sectors that did not fall within these thresholds were classified as mixed in gender and age composition respectively. Table A3 provides sector gender and age group composition and designation.

2.2.2.3. Percentages of social group per sector (PPS). This variable is a continuous percentage share of workers in a sector belonging to different gender and age social groups (henceforth PPS). In line with the above operationalization, we set the threshold for demarcating older workers at 45-years. Table 3 shows the descriptive statistics for the percentages of gender and age groups per sector on the job ad and sentence level.

2.2.3. Control variable

2.2.3.1. Number of words per sentence. This variable is measured at a continuous interval level and is a count of the number of words (excluding non-alphanumeric characters) per sentence; range= 3–349, M= 17.66, SD= 16.44. Controlling for this covariate attenuates the effects of shorter sentences on the analysis model.

2.3. Procedure

2.3.1. Manual content analysis

As Fig. 1 shows, the first stage of supervised content analysis involves a quantitative manual content analysis. The manual labeling of the dependent variables focused on identifying the presence (1) or absence (0) of warmth and competence-related frames in job ads based on the operationalization presented above. The registration unit selected was job ad sentences. This unit was deemed suitable because coding an entire job as (not) containing warmth- and competence-related frames results in significant information loss and does not tap into the degree of emphasis.

We employed a holistic singular assessment approach to coding frames, an approach suited to examining latent constructs in domain-specific text, i.e., text with a set format and unique features such as job ads. The method entails the use of "predetermined definitions intend [ed] to capture more latent meanings in texts" (David et al., 2011, p. 332). First, primary coders familiar with the topic conduct a close reading of sample texts and relevant literature with predetermined frames in mind. The aim is for the primary coders to get a sense of the overall manner frames of interest appear in a given population of text and find typical and atypical examples of use. This process also included codebook construction wherein definitions, descriptions, and examples of frames are iteratively refined. Next, secondary coders are trained on a small sample of text using the constructed codebook. The codebook asks coders to indicate whether a frame is present or absent based on code-book definitions and examples, forgoing other indicator items, thus a singular assessment is made by coders. Here, coders provide feedback on and rationale for coding, and the codebook is further refined. In the case of the present study, this step included intercoder reliability assessment as well as coder retraining. Finally, coders annotate the remaining text sample, and reliability is measured.

Due to the approach's attributes, Burscher et al. (2014) found holistic singular assessment more suitable for subsequent supervised machine learning frame classification when compared to the traditional indicator-based approach. Moreover, David et al. (2011) found it comparable to other coding approaches if coders were trained adequately. Indeed, one advantage of supervised content analysis is its ability to capture latent content of text by finding shared syntactic characteristics (van der Meer, 2016). Holistic singular assessment coding leverages this advantage by forgoing syntax- or word-based classification rules and allowing classifiers to tacitly learn these rules from the training data. Table 4 provides example sentences from the human-annotated sample and their coding, and the online repository provides the codebook and

Table 3

Descriptive statistics for percentages of gender and age social group per sector.

Collected Dataset Job Advertisements								
Percentages per Sector (PPS)	**Gender Percentages per Sector (%)**							
	Job Advertisement				**Sentence**			
	M	**SD**	**95 % Conf.**	**Interval**	**M**	**SD**	**95 % Conf.**	**Interval**
Female	43.82	18.86	43.53	44.11	45.36	19.48	45.29	45.43
Male	56.13	18.89	55.84	56.42	54.59	19.51	54.52	54.66

Percentages per Sector (PPS)	**Age Percentages per Sector (%)**							
	Job Advertisement				**Sentence**			
	M	**SD**	**95 % Conf.**	**Interval**	**M**	**SD**	**95 % Conf.**	**Interval**
Older	40.61	10.23	40.45	40.76	40.85	10.11	40.81	40.89
Younger	59.26	10.14	59.10	59.41	59.05	9.98	59.02	59.09

Table 4

Example sentence and their coding based on emphasis on warmth and competence.

Sentence	Coding
As a senior member of the team, fostering collaboration and encouraging best practices in ways of working and knowledge sharing.	Warmth
The IT security team works closely together with the Risk Management department on the topics Information Security and Privacy.	Competence
Acquiring deep knowledge of IQVIA data sources, acting as an advisor to other members of the consulting team.	Both warmth and competence
The role is open for candidates based in remote locations in the Region Europe.	Neither warmth nor competence

its construction procedure.

A random sample of job ads was used for the final phase of manual coding.[13] Each secondary coder annotated individual sentences from 80 job ads over 5 weeks. Following removal of job ads used for coder retraining, reliability testing, and those used as examples in the code-book, the final dataset contained 117 job ads and a total of 5947 sentences; warmth $n_{sentences}$ present= 1615 (27.2 %), $n_{sentences}$ absent= 4332 (72.8 %), M= 0.27, SD= 0.44, and competence $n_{sentences}$ present= 2767 (46.5 %), $n_{sentences}$ absent= 3180 (53.5 %), M= 0.47, SD= 0.50. Intercoder reliability was tested on a sample of five job ads and scores were satisfactory for warmth; intercoder Krippendorff's α= 0.65, and competence; intercoder Krippendorff's α= 0.75.[14]

2.3.2. Automated content analysis

As mentioned, we employ a two-stage supervised approach to automated content analysis wherein human-annotated data is used as training data for automated classifiers (Fig. 1). In the current study, we compare several classifiers that fall into two broad categories: (1) traditional supervised classifiers and (2) transformer-based fine-tuned classifiers. Traditional classifiers rely on statistical or neural architecture to analyze frequencies of words (e.g., bag-of-words approach) and their patterns of occurrence, known as word co-occurrence, within the training dataset (Hellsten et al., 2010). The rationale for using traditional classifiers for frame analysis rests on their ability to identify syntax characteristics (or lack thereof) to categorize text. Thus, supervised traditional classifiers are able to code latent variables in line with human coding of these variables (van der Meer, 2016).

Transformer-based classifiers conversely use a large pre-trained base language model, known as a large language model (Devlin et al., 2018), as reference, and update the base model to align with training data characteristics. Note that language models come in various sizes and all contain a corpus of word representations and information on word co-occurrence; collectively known as word-embeddings (Kroon et al., 2022; Mars, 2022). Transformer classifiers that leverage large language models differ from other architectures as they additionally account for and update word order and importance simultaneously during training, making word-embeddings dynamic. This attention to both word order and importance, combined with the substantial amounts of training data used in pre-training, enables transformer-based classifiers to capture more reliably the semantic and syntactic relationships between word sequences beyond those present in the training dataset (Vaswani et al., 2017).

We compare the performance of 13 traditional classifiers and 3 transformer-based classifiers with English-language base models. We fine-tuned classifiers specifically for binary classification and each classifier was trained on one dependent variable, i.e., presence (vs. absence) of warmth- and competence-related frames respectively. We used the validation dataset to obtain binary classification performance metrics and selected the best-performing classifier for each dependent variable. For both warmth- and competence-related frames, transformer-based classifiers achieved the best overall scores; warmth GPT2 model, and competence BERT-base model. We note here that the final selected models, GPT2 and BERT, differ in that the former processes word sequences based on previous sequences whereas the latter processes word sequences based on both previous and following sequences (Ghojogh & Ghodsi, 2020).

The classifier selected for each dependent variable is then used to predict the target variable in the remaining unlabeled dataset. The prediction step also provides the dependent variable used in the present study, i.e., probabilities of the presence of warmth- and competence-related frames (PPW and PPC respectively). Table 1 shows the descriptive statistics of the classifier-labeled dataset. For an overview of models and relevant performance metrics, see online repository and for technical details of the procedure, see Appendix B, Technical Methodology.

2.4. Analysis method

To test our hypotheses, we employ specification curve analysis (SCA), a frequentist technique that "… consists of reporting the results for all (or a large random subset thereof) 'reasonable specifications'" (Simonsohn et al., 2020, p. 1208). Specifications here refer to all combinations of model variables that are theoretically relevant, statistically valid, and non-redundant. Further, variables with differing operationalization and/or measurement can be included simultaneously (see Frey et al., 2020). Given that the measurements of our independent variable not only correlate with each other but also among each other (viz., high

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[13] A pre-test conducted on 5 job ads showed a satisfactory Krippendorff's α for competence; α = 0.72, however, the intercoder reliability for warmth was low at α = 0.19, thus coders were retrained for an additional week and the codebook was further refined.

[14] David et al. (2011) found holistic singular assessment coding reliability scores are commonly low compared to other coding approaches. The authors achieved Krippendorff's α range between 0.60 and 0.85 and Cohen's κ range between 0.62 and 0.85, thus our scores are deemed satisfactory.

correlation and inverse proportionality between categorical sectors and PPS respectively), a single model could not account for all predictors. The SCA is suited for the current study as it reveals whether the results as a whole are (in)consistent with the null hypothesis (Simonsohn et al., 2015). The SCA has additionally been found to attenuate the effects of arbitrary research decisions, reduce selective analysis and reporting, and increase transparency (Jussim et al., 2022).

The method entails performing numerous regression analyses on different specifications and the results are displayed in graphic format. The specification curve within the specification panel shows unstandardized coefficients of all the tested regression models along with their confidence intervals (error bars), color-coded to indicate model significance. A gray error bar indicates a non-significant model whereas a blue or red error bar indicates significance. A red error bar indicates a negative coefficient whereas a blue bar indicates a positive one. All included variables are listed at the bottom of the panel. Information about a single model is read vertically; a dash in a variable's row, i.e., a decision, indicates the variable was included in the model that gave the coefficient aligned directly above the dash. Simonsohn et al. (2020) advise reporting overall statistical inference for SCA by reporting the (1) share of significant results for a particular variable, i.e., the number of significant results in specifications that include the variable over all other specifications that include the variable, and (2) the aggregate of significant results for a particular variable by averaging p-values of all specification that include the variable to obtain a z-value for said variable (Stouffer's Z).[15] Singular regression models can also be retrieved and reported.

Upon assessing multicollinearity, a very high VIF was found between all independent variables; range= 1.00–21445712511288.08. Removing homogeneous sector categories improved VIF scores; range= 1.00–1.79.[16] In total, 2 dependent variables, 10 independent variables (excluding constant), and one control variable were used for each SCA model resulting in 40 specifications (Figs. 2–4). We performed SCA via a Python library provided by Turrell (2022) and used OLS regression with continuous probabilities of warmth and competence predictions (PPW and PPC respectively) regressed on dummy-coded sector categories and continuous percentages of social group per sector (PPS) as independent variables. The SCA provides results for single regression, so we additionally conducted a multiple regression analysis that includes all variables except heterogeneous (mixed) categorical sectors for comparison (see Tables A1 and A2).

Finally, we conduct an exploratory OLS regression-based SCA to test gender and age sector interaction effects on the PPW and PPC in job ads. This is due to limitations around overlap between gender and age categorical designations of sectors, e.g., all female-dominated sectors are mixed in age composition, and all younger-dominated sectors are mixed in gender composition (see Table A3). For this reason, we opt to test interaction effects using only the continuous PPS as the independent variable, and we include the above-mentioned control variable. A high correlation was found between the interaction variables; VIF range= 1.01–301.90. In total, 2 dependent, 4 independent (excluding constant), and one control variable were used for each SCA model resulting in 16 specifications. Fig. 5 shows the exploratory SCA panel.

3. Results

The overall SCA panel (Fig. 2) shows the presence of warmth- and

competence-related frames vary widely among sectors. For warmth, the SCA share of significant results was 19 out of 20 specifications; $p = .00$; aggregate p-values $Z_{Stouffer}= 80.19$, $p = .00$, R^2 range= 0.126–0.129 (i. e., when modeling predictors separately, the sector from which a job ad originated explains between 12.6 % to 12.9 % of variance in PPW), RMSE range= 0.341–0.342, $F_{Full}(9, 308,573)= 5158.27$, $p_{Full}= .00$, $R^2_{Full}= 0.131$ (i.e., when modeling predictors jointly, the sector from which a job ad originated explains between 13.1 % of variance in PPW), $RMSE_{Full}= 0.341$. For competence, the SCA share of significant results was 19 out of 20 specifications; $p = .00$; aggregate p-values $Z_{Stouffer}= 71.57$, $p = .00$, R^2 range= 0.100–0.101 (i.e., when modeling predictors separately, the sector from which a job ad originated explains between 10.0 % to 10.1 % of variance in PPC), RMSE range= 0.358–0.359, $F_{Full}(9, 308,573)= 4041.81$, $p_{Full}= .00$, $R^2_{Full}= 0.105$ (i.e., when modeling predictors jointly, the sector from which a job ad originated explains between 10.5 % of variance in PPC), $RMSE_{Full}= 0.358$.

There is a significant positive association between the presence of warmth-related frames (PPW) in job ads and female-dominated sectors and between the presence of competence-related frames (PPC) and male-dominated sectors. We also note a negative association between the presence of competence-related frames (PPC) and female-dominated sectors and the presence of warmth-related frames (PPW) and male-dominated sectors. This is consistent with the gender-typed sector hypotheses, however, age-typed sectors' SCA results are not consistent with our hypotheses. Younger-dominated sectors are not only positively associated with the presence of warmth-related frames (PPW), but also negative association with presence of competence-related frames (PPC). Strikingly, older-dominated sectors are negatively associated with presence of warmth-related frames (PPW) and a positive association with presence of competence-related frames (PPC). These associations can be further explored in Fig. 3 (SCA for categorical sectors) and in Fig. 4 (SCA for PPS). Tables A1 and A2 show all SCA regression statistics including the full multiple regression analysis.[17]

For gender-typed sectors, we expect that job ads from female-dominated sectors are more likely to contain warmth-related frames when compared to ads from male-dominated sectors (H1a) and mixed-gender sectors (H1b). For warmth, the SCA share of significant results for female-dominated and higher female-worker-PPS sectors was 3 out of 4 specifications; $p = .05$; aggregate p-values $Z_{Stouffer}= 29.36$, $p = .00$, and share for male-dominated and higher male-worker-PPS was 4 of 4; $p = .00$; $Z_{Stouffer}= 55.54$, $p = .00$. Job ads from female-dominated sectors; $\beta = 0.032$, $t = 28.06$, $p = .00$, 95 %CI[0.0112,0.0167], and higher female-worker-PPS; $\beta = 0.000$, $t = 28.06$, $p = .00$, 95 %CI [0.0008,0.0009], had higher PPW compared to job ads from male-dominated sectors; $\beta = -0.086$, $t = -32.50$, $p = .00$, 95%CI [− 0.044,− 0.039], and higher male-worker-PPS; $\beta = -0.000$, $t = -28.14$, $p = .00$, 95 %CI[− 0.0010,− 0.0008], thus H1a is supported. Conversely, job ads from female-dominated sectors had lower PPW compared to job ad sentences from mixed-gender sectors; $\beta = 0.061$, $t = 23.41$, $p = .00$, 95 %CI[0.0272,0.0322], thus H1b is rejected. On average, job ads from female-dominated sectors are 3.2 % more likely to contain warmth-related frames, job ads from male-dominated sectors are 8.6 % less likely to contain warmth-related frames, and job ads from mixed-gender sectors are 6.1 % more likely to contain warmth-related frames.

Next, we expect that job ads from male-dominated sectors are more likely to contain competence-related frames when compared to ads from female-dominated sectors (H2a) and mixed-gender sectors (H2b). For competence, the SCA share of significant results for male-dominated and high male PPS was 4 of 4; $p = .00$; $Z_{Stouffer}= 47.66$, $p = .00$, and share for

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[15] Note that the SCA test statistics are reported for the dependent variables as well as for every hypothesis' relevant specification separately, i.e., all specifications that include the hypotheses' relevant independent, dependent, and control variables.

[16] Note that the multicollinearity test did not include the PPS variables as those naturally correlate with the dummy coded homogeneous sectors variables as well as each other.

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[17] We report regression coefficients for models that include the control variable and do not include heterogeneous categorical sectors in full multiple regression model due to multicollinearity.
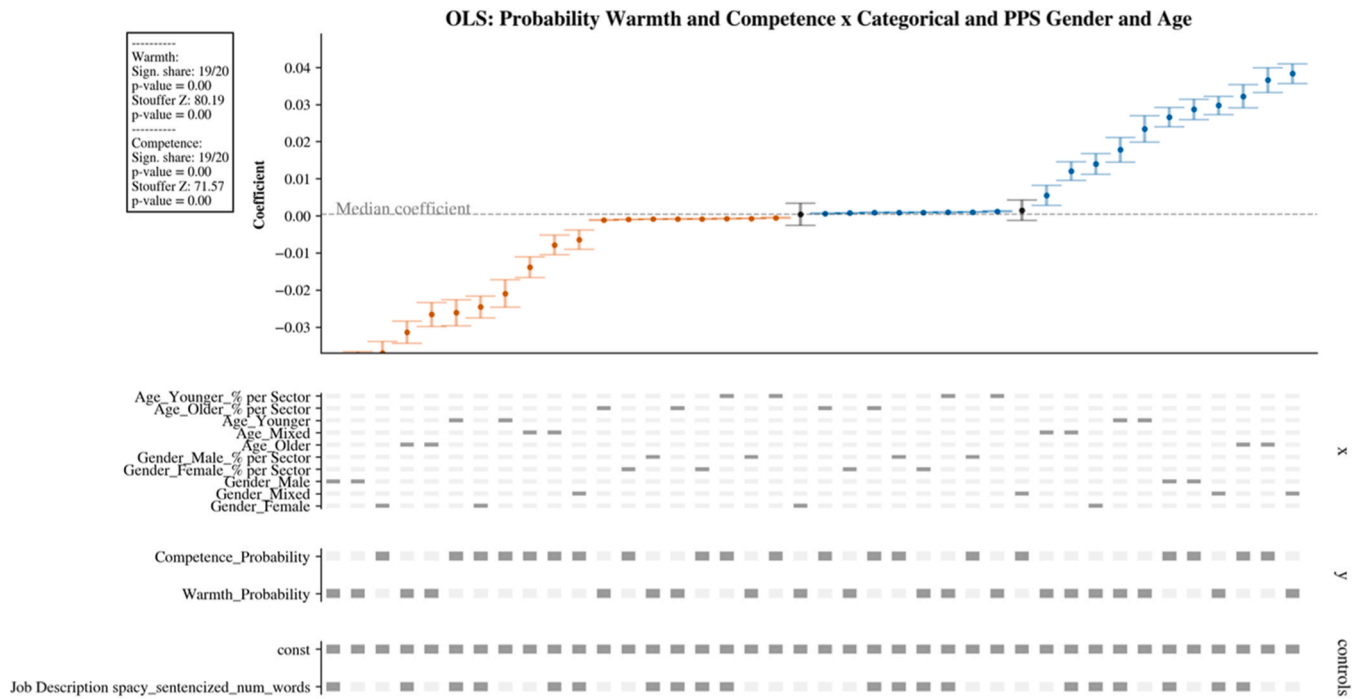
Fig. 2. Overall OLS regression-based specification curve. Note. Dependent variable: Probability of Warmth- and Competence-Related Frames Presence in Sentence (PPW and PPC respectively). Independent variables: (1) Categorical Dominant Social Group of Sector and (2) Percentages of Social Group per Sector (PPS). Control variable: Number of Words per Sentence.
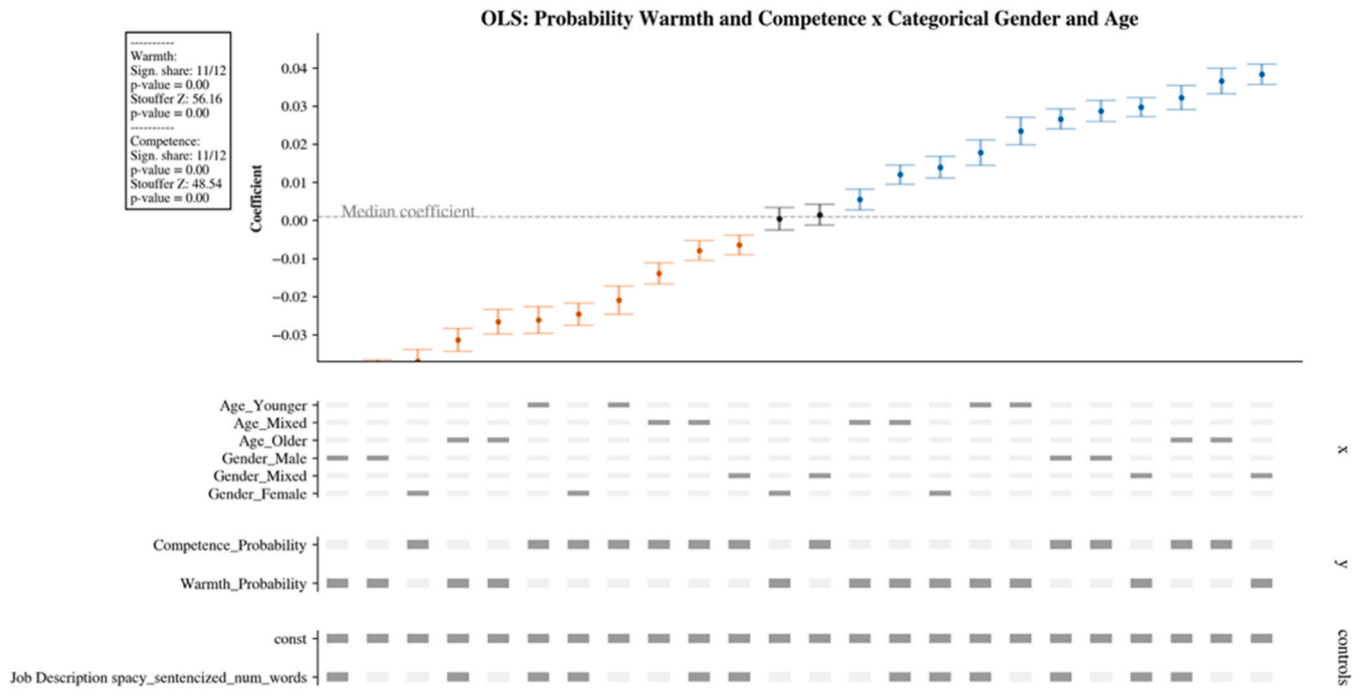

Fig. 3. OLS regression-based specification curve: categorical dominant social group of sector. Note. Dependent variable: Probability of Warmth- and Competence-Related Frames Presence in Sentence (PPW and PPC respectively). Independent variables: Categorical Dominant Social Group of Sector. Control variable: Number of Words per Sentence.

female-dominated and higher female-worker-PPS was 4 of 4; $p = .00$; $Z_{\text{Stouffer}} = 47.60, p = .00$. Job ad sentences from male-dominated sectors; $\beta = 0.055$, $t = 19.82$, $p = .00$, 95 %CI[0.0240,0.0292], and higher male-worker-PPS; $\beta = 0.000$, $t = 26.40$, $p = .00$, 95 %CI [0.0008,0.0009], had higher PPC compared to job ads from female-dominated sectors; $\beta = -0.056$, $t = -16.56$, $p = .00$, 95 %CI

$[-0.0275, -0.0217]$, and higher female-worker-PPS; $\beta = -0.000$, $t = -26.28$, $p = .00$, 95 %CI$[-0.0009, -0.0008]$, thus H2a is supported. Job ad sentences from male-dominated sectors had higher PPC compared to job ad sentences from mixed-gender sectors; $\beta = -0.013$, $t = -4.84, p = .00$, 95 %CI$[-0.0091, -0.0038]$, thus H2b is supported. On average, job ads from male-dominated sectors are 5.5 % more likely
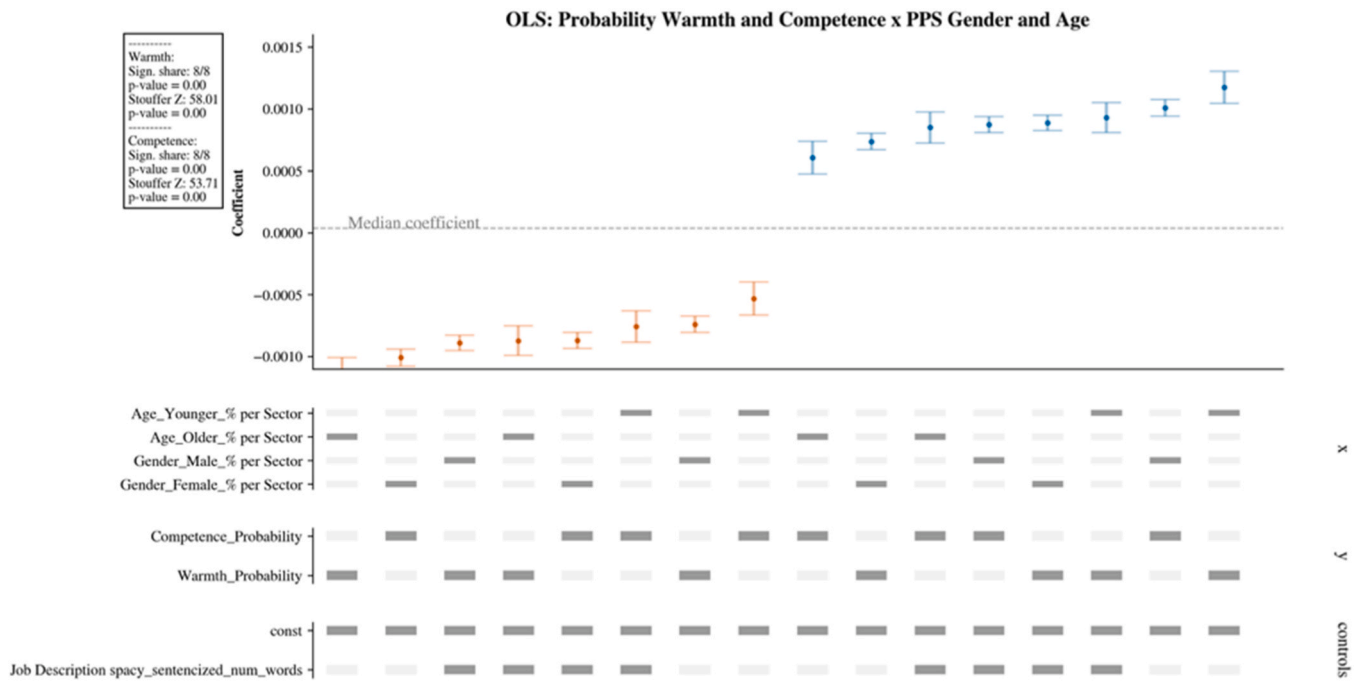
Fig. 4. OLS Regression-based specification curve: percentages of social group per sector (PPS). Note. Dependent variable: Probability of Warmth- and Competence-Related Frames Presence in Sentence (PPW and PPC respectively). Independent variables: Percentages of Social Group per Sector (PPS). Control variable: Number of Words per Sentence.
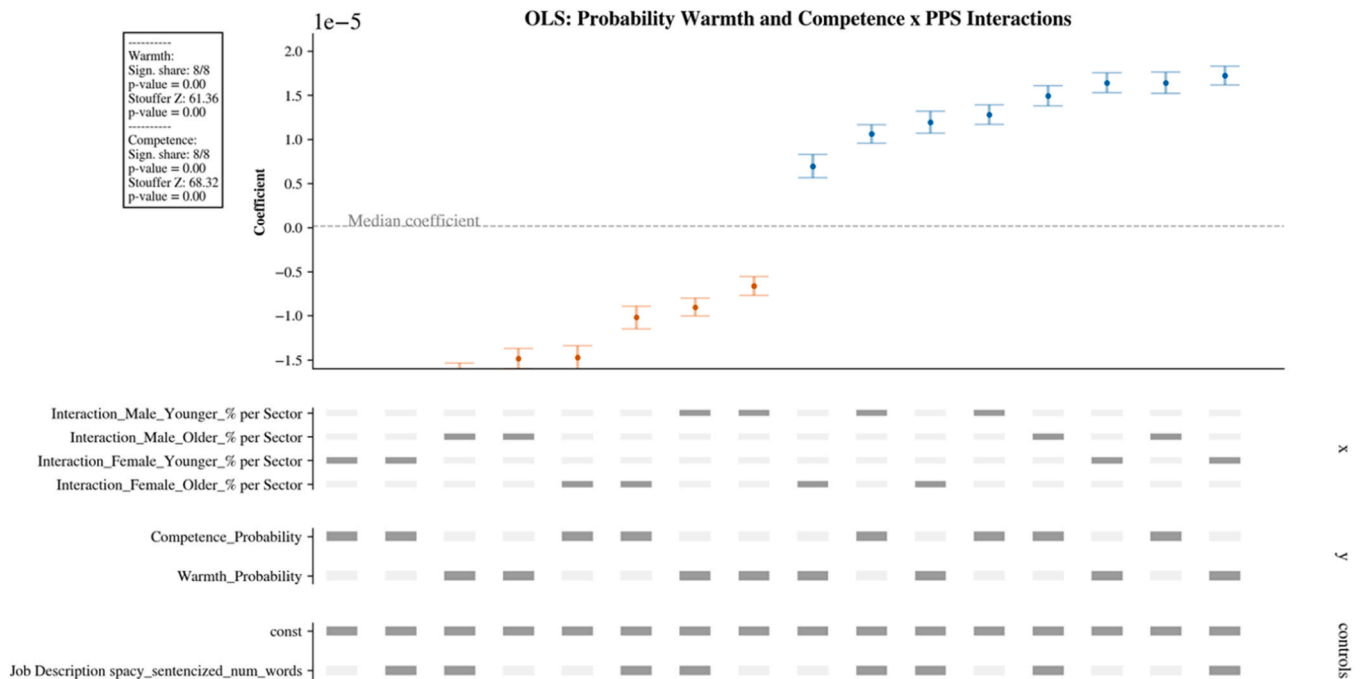

Fig. 5. Exploratory OLS regression-based specification curve: interactions of percentages of social group per sector (PPS). Note. Dependent variable: Probability of Warmth- and Competence-Related Frames Presence in. Sentence (PPW and PPC respectively). Independent variables: Interactions of Percentages of Social Group per Sector (PPS). Control variable: Number of Words per Sentence.

to contain competence-related frames, job ads from female-dominated sectors are 5.6 % less likely to contain competence-related frames, and job ads from mixed-gender sectors are 1.3 % less likely to contain competence-related frames.

For age-typed sectors, we expect that job ads from older-dominated sectors are more likely to contain warmth-related frames when compared to ads from younger-dominated sectors (H3a) and mixed-age

sectors (H3b). For warmth, the SCA share of significant results for older-dominated and higher older-worker-PPS was 4 of 4; $p = .00$; $Z_{\text{Stouffer}} = 34.16$, $p = .00$, and share for younger-dominated and higher younger-worker-PPS was 4 of 4 $p = .00$; $Z_{\text{Stouffer}} = 27.94$, $p = .00$. Job ad sentences from older-dominated sectors; $\beta = -0.077$, $t = -20.50$, $p = .00$, 95 %CI[$- 0.0344, - 0.0284$], and higher older-worker-PPS; $\beta = -0.000$, $t = -14.30$, $p = .00$, 95 %CI[$- 0.0010, - 0.0008$], had

lower PPW compared to job ads from younger-dominated sectors; $\beta = 0.049$, $t = 10.43$, $p = .00$, 95 %CI[0.0145,0.0211], and higher younger-worker-PPS; $\beta = 0.000$, $t = 15.03$, $p = .00$, 95 %CI [0.0008,0.0010], thus we reject H3a. Job ad sentences from older-dominated sectors also had lower PPW compared to job ad sentences from mixed-age sectors; $\beta = 0.025$, $t = 9.35$, $p = .00$, 95 %CI [0.0095,0.0145], thus H3b is rejected. On average, job ads from older-dominated sectors are 7.7 % less likely to contain warmth-related frames, job ads from younger-dominated sectors are 4.9 % more likely to contain warmth-related frames, and job ads from mixed-gender sectors are 2.5 % more likely to contain warmth-related frames.

Next, we expect that job ads from younger-dominated sectors are more likely to contain competence-related frames when compared to ads from older-dominated sectors (H4a) and mixed-gender sectors (H4b). For competence, the SCA share of significant results for younger-dominated and higher younger-worker-PPS was 4 of 4; $p = .00$; $Z_{Stouffer} = 22.50$, $p = .00$, and share for older-dominated and higher older-worker-PPS was 4 of 4; $p = .00$; $Z_{Stouffer} = 31.92$, $p = .00$. Job ad sentences from younger-dominated sectors; $\beta = -0.072$, $t = -14.63$, $p = .00$, 95 %CI[$-0.0296, -0.0226$], and higher younger-worker-PPS; $\beta = -0.000$, $t = -11.71$, $p = .00$, 95 %CI[$-0.0009, -0.0006$], had lower PPC compared to job ads from older-dominated sectors; $\beta = 0.080$, $t = 20.09$, $p = .00$, 95 %CI[0.0291, -0.0353], and higher older-worker-PPS; $\beta = 0.000$, $t = 13.32$, $p = .00$, 95 %CI [0.0007,0.0010], thus H4a is rejected. Job ad sentences from younger-dominated sectors also had lower PPC compared to job ad sentences from mixed-age sectors; $\beta = -0.016$, $t = -5.84$, $p = .00$, 95 %CI [$-0.0105, -0.0052$], thus H4b is rejected. On average, job ads from younger-dominated sectors are 7.2 % less likely to contain competence-related frames, job ads from older-dominated sectors are 8.0 % more likely to contain competence-related frames, and job ads from mixed-gender sectors are 1.6 % less likely to contain competence-related frames.

To test the robustness of our results, we conducted an SCA with specification variables aggregated on the job ad level. Fig. A2 shows the SCA panel with relevant test statistics. The results confirm our findings and show effects similar in direction to those achieved at the job ad sentence level. For warmth, the SCA share of significant results was 18 out of 20 specifications; $p = .00$; aggregate p-values $Z_{Stouffer} = 45.73$, $p = .00$, R^2 range= 0.002–0.021 (i.e., when modeling predictors separately, the sector from which a job ad originated explains between 0.2 % to 2.1 % of variance in PPW), RMSE range= 0.175–0.177, $F_{Full}(9, 16,125) = 75.84$, $p_{Full} = .00$, $R^2_{Full} = 0.041$ (i.e., when modeling predictors jointly, the sector from which a job ad originated explains between 4.1 % of variance in PPW), RMSE$_{Full} = 0.173$. For competence, the SCA share of significant results was 18 out of 20 specifications; $p = .00$; aggregate p-values $Z_{Stouffer} = 40.32$, $p = .00$, R^2 range= 0.004–0.021 (i.e., when modeling predictors separately, the sector from which a job ad originated explains between 0.4 % to 2.1 % of variance in PPC), RMSE range= 0.183–0.184, $F_{Full}(9, 308,573) = 4041.81$, $p_{Full} = .00$, $R^2_{Full} = 0.033$ (i.e., when modeling predictors jointly, the sector from which a job ad originated explains between 3.3 % of variance in PPC), RMSE$_{Full} = 0.182$.

Content analysis studies often report small effects, particularly when investigating latent constructs in text (Perloff, 2013; Valkenburg & Peter, 2013). However, we find that employing SCA helps determine the consistency of results while allowing comparison of highly correlated predictors. The SCA panels and test statistics show differential effects exist between sectors, particularly homogeneous ones, albeit small. Moreover, the direction of effects when comparing categorical sector designations and PPS are consistent in direction. Below, exploratory analysis results further highlight that differences exist and add context to the counter-expectations findings on age-typed sectors.

3.1. Exploratory analysis

We conducted an exploratory SCA examining the interaction effects between the percentage of gender social group per sector and age social group per sector (PPS) on probabilities of warmth and competence (Fig. 5). For warmth, the SCA share of significant results was 8 out of 8 specifications; $p = .00$; $Z_{Stouffer} = 61.36$, $p = .00$, R^2 range= 0.127–0.129 (i.e., when modeling predictors separately, the sector from which a job ad originated explains between 12.7 % to 12.9 % of variance in PPW), RMSE range= 0.341–0.342, $F_{Full}(5, 308,577) = 9172.85$, $p_{Full} = .00$, $R^2_{Full} = 0.129$ (i.e., when modeling predictors jointly, the sector from which a job ad originated explains between 12.9 % of variance in PPW), RMSE$_{Full} = 0.342$. For competence, the SCA share of significant results was 8 out of 8 specifications; $p = .00$; aggregate p-values $Z_{Stouffer} = 68.32$, $p = .00$, R^2 range= 0.100–0.102 (i.e., when modeling predictors separately, the sector from which a job ad originated explains between 10.0 % to 10.2 % of variance in PPC), RMSE range= 0.358–0.359, $F_{Full}(5, 308,577) = 7228.97$, $p_{Full} = .00$, $R^2_{Full} = 0.105$ (i.e., when modeling predictors jointly, the sector from which a job ad originated explains between 10.5 % of variance in PPC), RMSE$_{Full} = 0.358$. We must note that the coefficients and confidence intervals for the exploratory SCA are negligible, however, a trend emerges in terms of the direction of effects that can inform future research.

For warmth, the highest PPW was observed in higher younger-female-PPS; $\beta = 0.000$, $t = 31.85$, $p = .00$, 95 %CI [0.000019,0.000023], followed by higher older-female-worker-PPS; $\beta = 0.000$, $t = 18.87$, $p = .00$, 95 %CI[0.000008,0.000014], as the regression coefficients and confidence intervals are positive numbers. The lowest PPW was observed in higher older-male-worker-PPS; $\beta = -0.000$, $t = -29.69$, $p = .00$, 95 %CI[$-0.000021, -0.000016$], followed by higher younger-male-worker-PPS; $\beta = -0.000$, $t = -17.67$, $p = .00$, 95 %CI[$-0.000012, -0.000008$]. On average, job ads from sectors with higher percentage of younger-female workers were most likely to contain warmth-related frames, followed by sectors with higher percentage of older-female workers. Job ads from sectors with higher percentage of older-male workers were least likely to contain warmth-related frames, followed by sectors with higher percentage of younger-male workers.

For competence, the highest PPC was observed in higher older-male-worker-PPS; $\beta = 0.00$, $t = 25.71$, $p = .00$, 95 %CI[0.000017,0.000022], followed by higher younger-male-worker-PPS; $\beta = 0.00$, $t = 19.84$, $p = .00$, 95 %CI[0.000015,0.000020]. The lowest PPC was observed in higher younger-female-worker-PPS; $\beta = 0.00$, $t = 25.71$, $p = .00$, 95 %CI[0.000017,0.000022], followed by higher younger-male-worker-PPS; $\beta = 0.00$, $t = 19.84$, $p = .00$, 95 %CI[0.000015,0.000020]. On average, job ads from sectors with higher percentage of older-male workers were most likely to contain competence-related frames, followed by sectors with higher percentage of younger-male workers. Job ads from sectors with higher percentage of younger-female workers were least likely to contain competence-related frames, followed by sectors with higher percentage of younger-male workers.

Taken together, these findings show that warmth- and competence-related framing of job ads aligns with gender stereotypes more so than age stereotypes. This may suggest that, in the context of candidate sourcing, gender stereotypes supersede age stereotypes, however, these findings must be interpreted with caution given the small effect sizes.

4. Discussion

In conducting this study, we set out to examine the stereotypical frames present in job advertisements, as indicated by the differential emphasis on warmth and competence, and to empirically investigate the link between the presence of such frames and sectoral gender and age social group composition. We examine stereotype propagation in job advertisements and put forth an operationalization of broad-level

gender- and age-related stereotypical frames that are compatible with the axioms of the social categorization framing (Yang, 2015) and stereotype content model (SCM; Fiske et al., 2002). As per the operationalization, warmth in the occupational domain is communicated by emphasizing an orientation towards people, team and community building, and strong interpersonal characteristics. Occupational competence, conversely, is conveyed by emphasizing productivity, performance on tasks, measurable outcomes, and the display of technical acumen.

Our findings show that the social group composition of sectors influences the extent to which stereotypes appear in communication targeting prospective employees, however, we note the small effects achieved in analysis and advise caution in interpretation. Nonetheless, these effects are most observed in sectors with homogeneous worker gender and age composition such that stereotypes of the dominant social group are reproduced in sourcing communication. For gender, we find that job ads from female-dominated sectors emphasize warmth when compared to male-dominated sectors but not when compared to mixed-gender sectors. Job ads from these sectors also de-emphasized competence compared to other gender-typed sectors. Conversely, ads from male-dominated sectors emphasize competence, indicating the differences in effects stem chiefly from the framing of ads from male-dominated sectors.

Emphasis on competence in job ads from male-dominated but not female-dominated sectors aligns with social categorization framing (Yang, 2015) and various studies highlighting differential competence-related gendered social expectations (Biernat & Fuegen, 2001). Although organizational communicators tend to define competence via job-specific competencies related to candidate skills and knowledge (New, 1996), social and group psychology research shows that the concept goes beyond task-based assessments. Competence under the SCM is a perception of ability and is considered essential to the male social group. In job ads from male-dominated sectors, competence is emphasized to signal ownership of the sector and reflect sectoral cultures that assess workers and potential candidates primarily through stereotype-congruent competence.

Framing job ads through competence can also function as a vetting strategy that, although may help target sourcing efforts, makes salient social distance and constructs a barrier-to-entry for candidates from social groups stereotyped as low in competence. Indeed, studies cite cultural barriers in male-dominated industries as an obstacle to diversifying sectors (Bridges et al., 2020). Efforts to promote inclusivity and attract a diverse candidate pool to male-dominated sectors may thus be hampered as stereotypical sourcing communication primes candidates to negatively assess their fit and prompt self-elimination. Conversely, job ads from female-dominated sectors de-emphasized competence in line with the SCM yet were not more likely to contain warmth-related frames compared to mixed-gender sectors. A degree of sectoral ownership is indeed conveyed in these ads, however, may not be perceived as a barrier-to-entry as candidates encounter ads comparable in warmth framing from mixed-gender sectors. Female-dominated sectors may thus be successful in communicating inclusivity and attracting diverse candidates compared to male-dominated sectors despite the actual gender composition of these sectors.

With regards to the relationship between age-stereotypical job ad framing and sectoral segregation, our findings show an effect opposite to our expectations. Job ads from older-dominated sectors emphasized competence compared to ads from other age-typed sectors. Job ads from younger-dominated sectors, also against our expectations, emphasized warmth. These results are not in line with studies about older individuals, however, age-related warmth stereotypes may not be as readily transferable to the context of hiring and recruitment despite older individuals being stereotyped as warm. Indeed, Krings et al. (2011) found that when explicitly evaluating candidates for hiring as opposed to a context-free evaluation, older job seekers were perceived as less warm than their younger counterparts. It must be noted that job

descriptions are more representative of prescriptive (vs. descriptive) stereotypes, i.e., stereotypes about what a social group should or should not do (Rudman & Glick, 2001). Thus, older individuals and workers may be perceived as warm whereas older *candidates*, due to expectations regarding career progression, may be expected to possess experience, knowledge-sharing motivations, or rich social capital that are incongruent with stereotypical age perceptions (Burmeister et al., 2020). Additionally, candidate age, occupational seniority, and competence stereotypes are indeed correlated. There may be more job ads for senior positions coming from older-dominated sectors, however, our census data collection lends some assurance that job ads collected from these sectors are representative of all occupational status levels.

Notwithstanding, the strength of the association between the presence of competence-related frames in job ads and older-dominated sectors shows that there exists a more complex relationship. Results from exploratory analysis on the interaction of sectoral gender and age composition may shed light on one possible explanation: that gender stereotypes may supersede age stereotypes in the hiring context. Job ads from sectors with a high percentage of male workers of all ages were likely to contain more competence-related framing whereas those from sectors with high percentages of female workers of all ages were likely to contain more warmth-related framing. This aligns with research on intersectional stereotypes, particularly Andreoletti et al. (2015) finding warmth and competence gender stereotypes hold up across lifespan. However, our findings also show that job ads from sectors with a high percentage of older-female workers and those with a high percentage of younger-male workers had coefficients closer to each other compared to their counterparts (see Fig. 5). The attenuation of framed gender stereotypes in ads from older-female and younger-male sectors suggests that, although gender stereotypes prevail, they are offset to some extent by age stereotypes (Strinić et al., 2020).[18]

Findings on age-typed sectors can also signal a shift in occupational attitudes towards age and may prove beneficial for both older and younger workers. In the long run, adopting less stereotypical framing in job ads targeting older individuals will ensure inclusivity towards an aging workforce with recent increases in retirement age (Axelrad & Luski, 2022). Moreover, the significant positive relationship between younger-dominated sectors and the presence of warmth-related frames is possibly a reflection of changing attitudes among younger workers who value open communication, life-long learning, team-orientation, and prioritize social aspects of work (Myers & Sadaghiani, 2010). We note here that a shift in attitudes among younger workers is one possible explanation, however, an investigation into whether social stereotypes of age groups have undergone a similar shift can bolster this explanation.

4.1. Limitations

As with any endeavor, this study has some limitations of note. Regarding sector categorization, we measured occupational segregation via an index devised by Hakim (1993) deemed suitable for various reasons including its consideration for part-time workers and its categorical level of measurement. However, we found that the threshold set at 45 years of age following recommendations from extant literature was not conducive to our study as it did not align with normative views on age. We advise future researchers to be cognizant of this and utilize age thresholds developed to examine hiring-related age ingroup-stereotypes (as opposed to stereotypes relative to outgroups). We also acknowledge

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[18] We note the stronger emphasis on warmth in job ads from younger-male-dominated sectors relative to older-male-dominated sectors and on competence in job ads from older-female-dominated sectors relative to younger-female-dominated sectors. This suggests the association of warmth with younger-dominated sectors and competence with older-dominated sectors holds merit.

the presence of confounding factors for age-typed sectors. Most salient are period and birth cohort effects as incorporating these may alter the results of analysis significantly (Lois, 2020), however, we are limited in the cross-sectional nature of the data available to us from the Dutch Central Bureau of Statistics (CBS). Moreover, the organization provides age segments per sector which does not inform us about birth cohort status. Future researchers are advised to consider longitudinal designs to disentangle period and cohort effects from age.

4.2. Implications

Underpinning the present study are compound dynamics related to enduring sectoral cultures and their relationship to the larger societal culture. Stereotypes about candidates and workers emerge from these dynamics, however, they are difficult to parse. We look towards a paradigm that helps disentangle these forces and accommodates both the socialization and structuralist approaches to understand their reciprocal effect on worker stereotypes. A joint approach posits stereotypes of dominant social groups in sectors as well as the contextual demands of said sectors mutually construct stereotypes of ideal workers (Aldoory & Toth, 2004). We contend that these stereotypes are reflected, reinforced, and reproduced in framed communication targeting job candidates (Brown & Starkey, 1994; Pacelli et al., 2023).

Our results support the effects of socialization in homogeneous sectors where social group-congruent stereotypical frames are observed, notwithstanding contextual demands. These findings are also in line with the stereotype content model (SCM; Fiske et al., 2002) and provide evidence that for gender groups, some transferability of social stereotypes to hiring contexts occurs. We also find evidence for the structuralist approach in gender-heterogeneous sectors as these sectors favor emphasizing warmth. As discussed, this could be due to contextual demands in these sectors as no clear socialization-based incentives exist to emphasize warmth. Mixed-gender sectors may choose to engage in communication that highlights warmth-related facets of work, thus implicitly recognizing employees' desire for interpersonal connections and the need for interpersonally skilled workers.

For public relations practitioners, these findings present interesting lines of inquiry regarding the use of non-neutral framing in organizational communication and the conditions under which such framing may convey divergent meanings; does the presence or absence of a dominant group in an occupational domain redefine frames and their meaning? Here, we stress the importance of considering the dynamics at play and how they may construct stereotypes. Although both socialization and structuralist forces are omnipresent, thought should be given to which of the two is more salient to communication receivers. For instance, when structuralist forces are forefront, warmth-related framing may signal inclusivity and appeal to the heterogeneous segments of the public. Indeed, research supports the positive influences of warmth display on organizational virtue, reputation, and overall performance (Chun, 2017). However, when social roles are salient, the use of any stereotypical framing may reinforce existing societal biases and activate self-stereotyping. Our findings on age-typed sectors – that job ad framing runs counter to age stereotypes – may additionally point to a rejection of age-related stereotypes in the workplace. Stereotypical communication in this context may repel workers, narrow candidate pools, and even harm organizational reputation. Ultimately, our findings underscore that the success of any organizational communication efforts must be grounded in an understanding of macro-level forces, their influences, and the salient social roles communication receivers occupy.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.pubrev.2024.102456.

References

Abrams, D., Swift, H. J., & Drury, L. (2016). Old and unemployable? How age-based stereotypes affect willingness to hire job candidates. *Journal of Social Issues, 72*(1), 105–121. https://doi.org/10.1111/josi.12158

Aldoory, L., & Toth, E. (2002). Gender discrepancies in a gendered profession: A developing theory for public relations. *Journal of Public Relations Research, 14*(2), 103–126. https://doi.org/10.1207/S1532754XJPRR1402_2

Aldoory, L., & Toth, E. (2004). Leadership and gender in public relations: Perceived effectiveness of transformational and transactional leadership styles. *Journal of Public Relations Research, 16*(2), 157–183. https://doi.org/10.1207/s1532754xjprr1602_2

Andreoletti, C., Leszczynski, J. P., & Disch, W. B. (2015). Gender, race, and age: The content of compound stereotypes across the life span. *The International Journal of Aging and Human Development, 81*(1–2), 27–53. https://doi.org/10.1177/0091415015616395

Arredondo, P., Miville, M. L., Capodilupo, C. M., & Vera, T. (2022). Organizational culture and climate: historic systemic barriers for women. In P. Arredondo, M. L. Miville, C. M. Capodilupo, & T. Vera (Eds.), *Women and the challenge of STEM professions: thriving in a chilly climate* (pp. 41–61). Springer International Publishing. https://doi.org/10.1007/978-3-030-62201-5_3.

Axelrad, H., & Luski, I. (2022). Actual retirement age: A European cross-country analysis. *Ageing International, 47*(3), 534–558. https://doi.org/10.1007/s12126-021-09435-9

Baden, C., & Stalpouskaya, K. (2020). Maintenance of news frames: How US, British and Russian news made sense of unfolding events in the Syrian chemical weapons crisis. *Journalism Studies, 21*(16), 2305–2325. https://doi.org/10.1080/1461670X.2020.1843066

Bassili, J. N., & Reil, J. E. (1981). On the dominance of the old-age stereotype. *Journal of Gerontology, 36*(6), 682–688. https://doi.org/10.1093/geronj/36.6.682

Beattie, G., & Johnson, P. (2012). Possible unconscious bias in recruitment and promotion and the need to promote equality. *Perspectives: Policy and Practice in Higher Education, 16*(1), 7–13. https://doi.org/10.1080/13603108.2011.611833

Bettio, F., Verashchagina, A., Mairhuber, I., & Kanjuo-Mrčela, A. (2009). *Gender segregation in the labour market: Root causes, implications and policy responses in the EU*. Publications Office of the European Union Luxembourg.

Bhargava, D., & Theunissen, P. (2019). The future of PR is 'fantastic', 'friendly' and 'funny': Occupational stereotypes and symbolic capital in entry-level job advertisements. *Public Relations Review, 45*(4), Article 101822. https://doi.org/10.1016/j.pubrev.2019.101822

Biernat, M., & Fuegen, K. (2001). Shifting standards and the evaluation of competence: Complexity in gender-based judgment and decision making. *Journal of Social Issues, 57*(4), 707. https://doi.org/10.1111/0022-4537.00237

Bridges, D., Wulff, E., Bamberry, L., Krivokapic-Skoko, B., & Jenkins, S. (2020). Negotiating gender in the male-dominated skilled trades: A systematic literature review. *Construction Management and Economics, 38*(10), 894–916. https://doi.org/10.1080/01446193.2020.1762906

Brown, A. D., & Starkey, K. (1994). The effect of organizational culture on communication and information*. *Journal of Management Studies, 31*(6), 807–828. https://doi.org/10.1111/j.1467-6486.1994.tb00640.x

Brown, R., & Gaertner, S. L. (Eds.). (2003). *Blackwell handbook of social psychology: Intergroup processes*. Blackwell Publishers Ltd. https://doi.org/10.1002/9780470693421.

Bruckmüller, S., & Abele, A. (2013). The density of the big two how are agency and communion structurally represented? *Social Psychology, 44*(2), 63–74. https://doi.org/10.1027/1864-9335/a000145

Burmeister, A., Wang, M., & Hirschi, A. (2020). Understanding the motivational benefits of knowledge transfer for older and younger workers in age-diverse coworker dyads: An actor–partner interdependence model. *Journal of Applied Psychology, 105*(7), 748–759. https://doi.org/10.1037/apl0000466

Burn, I., Button, P., Corella, L. F. M., & Neumark, D. (2019). *Older workers need not apply? Ageist language in job ads and age discrimination in hiring*. National Bureau of Economic Research. https://doi.org/10.3386/w26552

Burn, I., Firoozi, D., Ladd, D., & Neumark, D. (2023). Stereotypes of older workers and perceived ageism in job ads: Evidence from an experiment. *Journal of Pension Economics & Finance, 22*(4), 463–489. https://doi.org/10.1017/S1474747222000270

Burscher, B., Odijk, D., Vliegenthart, R., de Rijke, M., & de Vreese, C. H. (2014). Teaching the computer to code frames in news: Comparing two supervised machine learning approaches to frame analysis. *Communication Methods & Measures, 8*(3), 190–206. https://doi.org/10.1080/19312458.2014.937527

Bye, H. H., Solianik, V. V., Five, M., & Agai, M. S. (2022). Stereotypes of women and men across gender subgroups. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.881418

Castilla, E. J., & Rho, H. J. (2023). The gendering of job postings in the online recruitment process. *Management Science*. https://doi.org/10.1287/mnsc.2023.4674

Centraal Bureau voor de Statistiek. (2018). *Standard industrial classifications (Dutch SBI 2008, NACE and ISIC) [Database]*. Centraal Bureau voor de Statistiek (CBS).

Centraal Bureau voor de Statistiek. (2019). *The sustainable development goals in the Dutch context 2019*. Statistics Netherlands.

Chatman, J. A., Sharps, D., Mishra, S., Kray, L. J., & North, M. S. (2022). Agentic but not warm: Age-gender interactions and the consequences of stereotype incongruity perceptions for middle-aged professional women. *Organizational Behavior and Human Decision Processes, 173*, Article 104190. https://doi.org/10.1016/j.obhdp.2022.104190

Cheney, G., & Christensen, L. T. (2004). Organizational identity: Linkages between 'internal' and 'external' organizational communication. *Organizational identity: A reader* (pp. 510–557). Oxford University Press.

Cheney, G., Zorn, T. E., Planalp, S., & Lair, D. J. (2008). Meaningful work and personal/social well-being organizational communication engages the meanings of work. *Annals of the International Communication Association, 32*(1), 137–185. https://doi.org/10.1080/23808985.2008.11679077

Chun, R. (2017). Organizational virtue and performance: An empirical study of customers and employees. *Journal of Business Ethics, 146*(4), 869–881. https://doi.org/10.1007/s10551-016-3262-z

Clair, R. P. (1996). The political nature of the colloquialism, "a real job": Implications for organizational socialization. *Communication Monographs, 63*(3), 249–267. https://doi.org/10.1080/03637759609376392

Clarke, H. M. (2020). Gender stereotypes and gender-typed work. In K. F. Zimmermann (Ed.), *Handbook of labor, human resources and population economics* (pp. 1–23). Springer International Publishing. https://doi.org/10.1007/978-3-319-57365-6_21-1.

Cuddy, A. J. C., Fiske, S. T., Kwan, V. S. Y., Glick, P., Demoulin, S., Leyens, J.-P., Bond, M. H., Croizet, J.-C., Ellemers, N., Sleebos, E., Htun, T. T., Kim, H.-J., Maio, G., Perry, J., Petkova, K., Todorov, V., Rodríguez-Bailón, R., Morales, E., Moya, M., … Ziegler, R. (2009). Stereotype content model across cultures: Towards universal similarities and some differences. *British Journal of Social Psychology, 48*(1), 1–33. https://doi.org/10.1348/014466608×314935

Cuddy, A. J. C., Norton, M. I., & Fiske, S. T. (2005). This old stereotype: The pervasiveness and persistence of the elderly stereotype. *Journal of Social Issues, 61*(2), 267–285. https://doi.org/10.1111/j.1540-4560.2005.00405.x

David, C., Atun, J., Legara, E. F., & Monterola, C. (2011). Finding frames: Comparing two methods of frame analysis. *Communication Methods and Measures, 5*, 329–351. https://doi.org/10.1080/19312458.2011.624873

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding. *CoRR, abs/1810.04805*. ⟨http://arxiv.org/abs/1810.04805⟩.

Dongo, I., Cadinale, Y., Aguilera, A., Martínez, F., Quintero, Y., & Barrios, S. (2021). Web scraping versus Twitter API: A comparison for a credibility analysis. *Proceedings of the 22nd International Conference on Information Integration and Web-Based Applications & Services*, 263–273. https://doi.org/10.1145/3428757.3429104

Eagly, A. H. (1997). Sex differences in social behavior: Comparing social role theory and evolutionary psychology. *The American Psychologist, 52*(12), 1380–1383. https://doi.org/10.1037/0003-066X.52.12.1380.b

Edwards, L., & Fredriksson, M. (2017). Forum: Inconsistency and communication in organizations. *Management Communication Quarterly, 31*(3), 467–472. https://doi.org/10.1177/0893318917699886

Elving, W. J. L., Westhoff, J. J. C., Meeusen, K., & Schoonderbeek, J.-W. (2013). The war for talent? The relevance of employer branding in job advertisements for becoming an employer of choice. *Journal of Brand Management, 20*(5), 355–373. https://doi.org/10.1057/bm.2012.21

Entman, R. M. (1993). Framing: Toward clarification of a fractured paradigm. *Journal of Communication, 43*(4), 51–58. https://doi.org/10.1111/j.1460-2466.1993.tb01304.x

Fiske, S. T. (2017). Prejudices in cultural contexts: Shared stereotypes (gender, age) versus variable stereotypes (race, ethnicity, religion). *Perspectives on Psychological Science, 12*(5), 791–799. https://doi.org/10.1177/1745691617708204

Fiske, S. T., Cuddy, A. J. C., Glick, P., & Xu, J. (2002). A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. *Journal of Personality and Social Psychology, 82*(6), 878–902. https://doi.org/10.1037/0022-3514.82.6.878

Frey, R., Richter, D., Schupp, J., Hertwig, R., & Mata, R. (2020). Identifying robust correlates of risk preference: A systematic approach using specification curve analysis. *Journal of Personality and Social Psychology*. https://doi.org/10.1037/pspp0000287

Froehlich, L., Olsson, M. I. T., Dorrough, A. R., & Martiny, S. E. (2020). Gender at work across nations: Men and women working in male-dominated and female-dominated occupations are differentially associated with agency and communion. *Journal of Social Issues, 76*(3), 484–511. https://doi.org/10.1111/josi.12390

Fröhlich, R., & Peters, S. B. (2007). PR bunnies caught in the agency ghetto? Gender stereotypes, organizational factors, and women's careers in PR agencies. *Journal of Public Relations Research, 19*(3), 229–254. https://doi.org/10.1080/10627260701331754

Furnham, A. (2012). The content of job advertisements. In A. Furnham (Ed.), *The talented manager* (pp. 70–72). Palgrave Macmillan UK. https://doi.org/10.1057/9780230369764_13.

Gallagher, N. M., & Bodenhausen, G. V. (2020). Lay theories guide mental representation of emerging social groups: Gender essentialism and stereotypes of transgender women and men. *PsyArXiv Preprints*. https://doi.org/10.31234/osf.io/t7yf9

Gamson, W. A., & Modigliani, A. (1989). Media discourse and public opinion on nuclear power: A constructionist approach. *American Journal of Sociology, 95*(1), 1–37. https://doi.org/10.1086/229213

Gaucher, D., Friesen, J., & Kay, A. C. (2011). Evidence that gendered wording in job advertisements exists and sustains gender inequality. *Journal of Personality and Social Psychology, 101*(1), 109–128. https://doi.org/10.1037/a0022530

Ghojogh, B., & Ghodsi, A. (2020). *Attention mechanism, transformers, BERT, and GPT: Tutorial and survey.* https://doi.org/10.31219/osf.io/m6gcn

Gordon, G. G. (1991). Industry determinants of organizational culture. *Academy of Management Review, 16*(2), 396–415. https://doi.org/10.5465/AMR.1991.4278959

Grunig, L. A., Hon, L. C., & Toth, E. L. (2013). *Women in public relations: How gender influences practice.* Routledge.

Hakim, C. (1993). Segregated and integrated occupations: A new approach to analysing social change. *European Sociological Review, 9*(3), 289–314. https://doi.org/10.1093/oxfordjournals.esr.a036682

Hall, E. V., Hall, A. V., Galinsky, A. D., & Phillips, K. W. (2018). MOSAIC: A model of stereotyping through associated and intersectional categories. *Academy of Management Review, 44*(3), 643–672. https://doi.org/10.5465/amr.2017.0109

Hallahan, K. (1999). Seven models of framing: Implications for public relations. *Journal of Public Relations Research, 11*(3), 205–242. https://doi.org/10.1207/s1532754xjprr1103_02

He, J. C., Kang, S. K., Tse, K., & Toh, S. M. (2019). Stereotypes at work: Occupational stereotypes predict race and gender segregation in the workforce. *Journal of Vocational Behavior, 115*, Article 103318. https://doi.org/10.1016/j.jvb.2019.103318

Heilman, M. E. (2012). Gender stereotypes and workplace bias. *Research in Organizational Behavior, 32*, 113–135. https://doi.org/10.1016/j.riob.2012.11.003

Hellsten, I., Dawson, J., & Leydesdorff, L. (2010). Implicit media frames: Automated analysis of public debate on artificial sweeteners. *Public Understanding of Science, 19*(5), 590–608. https://doi.org/10.1177/0963662509343136

Hofhuis, J., van der Zee, K. I., & Otten, S. (2016). Dealing with differences: The impact of perceived diversity outcomes on selection and assessment of minority candidates. *The International Journal of Human Resource Management, 27*(12), 1319–1339. https://doi.org/10.1080/09585192.2015.1072100

Hummert, M. L. (1990). Multiple stereotypes of elderly and young adults: A comparison of structure and evaluations. *Psychology and Aging, 5*(2), 182–193. https://doi.org/10.1037/0882-7974.5.2.182

Intelligence Group. (2020). *Top 10 job boards: "The playground of the employment agencies and US Tech giants".* Intelligence Group. ⟨https://intelligence-group.nl/en/news/top-10-job-boards-the-playground-of-the-employment-agencies-and-us-tech-giants⟩.

Jussim, L., Krosnick, J. A., & Stevens, S. T. (2022). *Research integrity: Best practices for the social and behavioral sciences.* Oxford University Press.

Kelly, E. L., Ammons, S. K., Chermack, K., & Moen, P. (2010). Gendered challenge, gendered response: Confronting the ideal worker norm in a white-collar organization. *Gender & Society, 24*(3), 281–303. https://doi.org/10.1177/0891243210372073

Kite, M. E., Deaux, K., & Miele, M. (1991). Stereotypes of young and old: Does age outweigh gender? *Psychology and Aging, 6*(1), 19–27. https://doi.org/10.1037/0882-7974.6.1.19

Kite, M. E., Stockdale, G. D., Whitley, B. E., Jr., & Johnson, B. T. (2005). Attitudes toward younger and older adults: An updated meta-analytic review. *Journal of Social Issues, 61*(2), 241–266. https://doi.org/10.1111/j.1540-4560.2005.00404.x

Kornadt, A. E., Voss, P., & Rothermund, K. (2013). Multiple standards of aging: Gender-specific age stereotypes in different life domains. *European Journal of Ageing, 10*(4), 335–344. https://doi.org/10.1007/s10433-013-0281-9

Krings, F., Sczesny, S., & Kluge, A. (2011). Stereotypical inferences as mediators of age discrimination: The role of competence and warmth. *British Journal of Management, 22*(2), 187–201. https://doi.org/10.1111/j.1467-8551.2010.00721.x

Kroon, A. C., Van Der Meer, T., & Vliegenthart, R. (2022). Beyond counting words: Assessing performance of dictionaries, supervised machine learning, and embeddings in topic and frame classification. *Computational Communication Research, 4*(2), 528–570. https://doi.org/10.5117/CCR2022.2.006.KROO

Kroon, A. C., Van Selm, M., ter Hoeven, C. L., & Vliegenthart, R. (2018). Reliable and unproductive? Stereotypes of older employees in corporate and news media. *Ageing and Society, 38*(1), 166–191. https://doi.org/10.1017/S0144686×16000982

Kuhn, T., Ashcraft, K. L., & Cooren, F. (2019). Introductory essay: What work can organizational communication do? *Management Communication Quarterly, 33*(1), 101–111. https://doi.org/10.1177/0893318918809421

Kuhn, T., Golden, A. G., Jorgenson, J., Buzzanell, P. M., Berkelaar, B. L., Kisselburgh, L. G., Kleinman, S., & Cruz, D. (2008). Cultural discourses and discursive resources for meaning/ful work: Constructing and disrupting identities in contemporary capitalism. *Management Communication Quarterly, 22*(1), 162–171. https://doi.org/10.1177/0893318908318262

Lim, J., & Jones, L. (2010). A baseline summary of framing research in public relations from 1990 to 2009. *Public Relations Review, 36*(3), 292–297. https://doi.org/10.1016/j.pubrev.2010.05.003

Little, J. C. (1999). The role of women in the history of computing. *1999 International Symposium on Technology and Society - Women and Technology: Historical, Societal, and Professional Perspectives Proceedings Networking the World (Cat No 99CH37005*, 202–205. https://doi.org/10.1109/ISTAS.1999.787332

Lois, D. (2020). Gender role attitudes in Germany, 1982-2016: An age-period-cohort (APC) analysis. *Comparative Population Studies - Zeitschrift Für Bevölkerungswissenschaft, 45*, 35–63. https://doi.org/10.12765/cpos-2020-02en

Mars, M. (2022). From word embeddings to pre-trained language models: A state-of-the-art walkthrough. Article 17. *Applied Sciences, 12*(17). https://doi.org/10.3390/app12178805

Martin, A. E., North, M. S., & Phillips, K. W. (2019). Intersectional escape: Older women elude agentic prescriptions more than older men. *Personality and Social Psychology Bulletin, 45*(3), 342–359. https://doi.org/10.1177/0146167218784895

Myers, K. K., & Sadaghiani, K. (2010). Millennials in the workplace: A communication perspective on millennials' organizational relationships and performance. *Journal of*

Business and Psychology, 25(2), 225–238. https://doi.org/10.1007/s10869-010-9172-7

Neumark, D., Burn, I., & Button, P. (2019). Is it harder for older workers to find jobs? New and improved evidence from a field experiment. *Journal of Political Economy, 127*(2), 922–970. https://doi.org/10.1086/701029

New, G. E. (1996). Reflections: A three-tier model of organizational competencies. *Journal of Managerial Psychology, 11*(8), 44–51. https://doi.org/10.1108/02683949610150051

Nicolas, G., Bai, X., & Fiske, S. T. (2020). Comprehensive stereotype content dictionaries using a semi-automated method. *European Journal of Social Psychology*.

Nicolas, G., de la Fuente, M., & Fiske, S. T. (2017). Mind the overlap in multiple categorization: A review of crossed categorization, intersectionality, and multiracial perception. *Group Processes & Intergroup Relations, 20*(5), 621–631. https://doi.org/10.1177/1368430217708862

OECD. (2020). *OECD labour force statistics 2020*. OECD. https://doi.org/10.1787/5842cc7f-en

Pacelli, J., Shi, T. (Terrence), & Zou, Y. (2023). Communicating corporate culture in labor markets: Evidence from job postings (SSRN Scholarly Paper 4235342). ⟨https://doi.org/10.2139/ssrn.4235342⟩.

Paleari, F. G., Brambilla, M., & Fincham, F. D. (2019). When prejudice against you hurts others and me: The case of ageism at work. *Journal of Applied Social Psychology, 49*(11), 704–720. https://doi.org/10.1111/jasp.12628

Pedriana, N. (2004). Help wanted NOW: Legal resources, the women's movement, and the battle over sex-segregated job advertisements. *Social Problems, 51*(2), 182–201. https://doi.org/10.1525/sp.2004.51.2.182

Perloff, R. M. (2013). Progress, paradigms, and a discipline engaged: A response to lang and reflections on media effects research. *Communication Theory, 23*(4), 317–333. https://doi.org/10.1111/comt.12024

Puncheva-Michelotti, P., Hudson, S., & Jin, G. (2018). Employer branding and CSR communication in online recruitment advertising. *Business Horizons, 61*(4), 643–651. https://doi.org/10.1016/j.bushor.2018.04.003

Reese, S. D., Jr, O. H. G., & Grant, A. E. (2001). *Framing public life: Perspectives on media and our understanding of the social world.* Routledge.

Rosette, A. S., Ponce de Leon, R., Koval, C. Z., & Harrison, D. A. (2018). Intersectionality: Connecting experiences of gender with race at work. *Research in Organizational Behavior, 38*, 1–22. https://doi.org/10.1016/j.riob.2018.12.002

Rudman, L. A., & Glick, P. (2001). Prescriptive gender stereotypes and backlash toward agentic women. *Journal of Social Issues, 57*(4), 743–762. https://doi.org/10.1111/0022-4537.00239

Ruggs, E. N., Hebl, M. R., Singletary Walker, S., & Fa-Kaji, N. (2014). Selection biases that emerge when age meets gender. *Journal of Managerial Psychology, 29*(8), 1028–1043. https://doi.org/10.1108/JMP-07-2012-0204

Rynes, S. L. (1989). Recruitment, job choice, and post-hire consequences: A call for new research directions. In M. D. Dunnette, & L. M. Hough (Eds.), *Handbook of industrial and organizational psychology* (Vol. 2, pp. 399–444). Consulting Psychologists Press.

Salter, N. P., Sawyer, K., & Gebhardt, S. T. (2021). How does intersectionality impact work attitudes? The effect of layered group memberships in a field sample. *Journal of Business and Psychology, 36*(6), 1035–1052. https://doi.org/10.1007/s10869-020-09718-z

Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2015). Specification curve: Descriptive and inferential statistics on all reasonable specifications. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2694998

Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2020). Specification curve analysis. *Nature Human Behaviour, 4*(11), 1208–1214. https://doi.org/10.1038/s41562-020-0912-z

Smith, D. G., Rosenstein, J. E., Nikolov, M. C., & Chaney, D. A. (2019). The power of language: Gender, status, and agency in performance evaluations. *Sex Roles, 80*(3), 159–171. https://doi.org/10.1007/s11199-018-0923-7

Strinić, A., Carlsson, M., & Agerström, J. (2020). Multiple-group membership: Warmth and competence perceptions in the workplace. *Journal of Business and Psychology*. https://doi.org/10.1007/s10869-020-09713-4

Strinić, A., Carlsson, M., & Agerström, J. (2021). Occupational stereotypes: Professionals' warmth and competence perceptions of occupations. *Personnel Review*. https://doi.org/10.1108/PR-06-2020-0458

Turner, B. F. T., & Castellano, B. (1990). Through a glass, darkly: gender stereotypes for men and women varying in age and race. *Growing old in America* (4th ed.). Routledge.

Turrell, A. (2022). *Specification curve: V0.3.1*. Zenodo. https://doi.org/10.5281/zenodo.7264033

Vale, M. T., Bisconti, T. L., & Sublett, J. F. (2020). Benevolent ageism: Attitudes of overaccommodative behavior toward older women. *The Journal of Social Psychology, 160*(5), 548–558. https://doi.org/10.1080/00224545.2019.1695567

Valkenburg, P., & Peter, J. (2013). Five challenges for the future of media-effects research. *International Journal of Communication, 7*, 197–215.

van der Meer, T. G. L. A. (2016). Automated content analysis and crisis communication research. *Public Relations Review, 42*(5), 952–961. https://doi.org/10.1016/j.pubrev.2016.09.001

van Gorp, B. (2005). Where is the frame?: Victims and intruders in the Belgian press coverage of the asylum issue. *European Journal of Communication, 20*(4), 484–507. https://doi.org/10.1177/0267323105058253

van Selm, M., & van den Heijkant, L. (2021). In search of the older worker: Framing job requirements in recruitment advertisements. *Work, Aging and Retirement, 7*(4), 288–302. https://doi.org/10.1093/workar/waaa026

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems, 30*.

Yang, A. (2015). Building a cognitive-sociological model of stereotypes: Stereotypical frames, social distance and framing effects. *Howard Journal of Communications, 26*(3), 254–274. https://doi.org/10.1080/10646175.2015.1049757