Erschienen in: Human Resource Management ; 60 (2021), 4. - S. 499-516
https://dx.doi.org/10.1002/hrm.22031

Distance matters! The role of employees' age distance on the effects of workforce age heterogeneity on firm performance

Kim De Meulenaere[1] **Florian Kunze**[2]

[1]Faculty of Business & Economics, Department of Management, University of Antwerp, Antwerp, Belgium

[2]Organizational Studies, University of Konstanz, Konstanz, Germany

Correspondence
Kim De Meulenaere, Department of Mangement, Faculty of Business & Economics, University of Antwerp, Prinsstraat 13, 2000 Antwerp, Belgium.
Email: kim.demeulenaere@uantwerpen.be

Funding information
Research Foundation Flanders (FWO), Grant/Award Number: 12Z7519N

Abstract

Age heterogeneity in Western workforces is increasing, generating potential informational benefits as well as harmful age-based social categorizations. When can firms benefit from age heterogeneity? Building on the categorization-elaboration model, we propose the average age distance between employees as a fundamental contingency. Using a longitudinal archival sample of 3,336 Belgian firms (2012–2015), we find that firms with a high level of age heterogeneity are less productive when employees' average distance is great (Study 1). Through an online experiment with 260 US participants, we show that employees in age-heterogeneous workforces are less willing to engage in inter-age cooperative contact and knowledge exchange under a great level of average age distance (Study 2). Our findings support that great distances foster age-based social categorizations that undermine the productive information elaborations between employees of different ages. This broadens our knowledge on the implications of workforce age diversity and helps organizations understand *when* they can(not) reap the productivity benefits of their age-diverse workforce. Moreover, this study's theory and implications are relevant to other types of diversity for which both heterogeneity and distance are meaningful constructs. We also discuss the practical implications of this study.

KEYWORDS

age distance, age heterogeneity, firm performance, inter-age cooperative contact, inter-age knowledge exchange

1 INTRODUCTION

The demographic trend of the aging population in most developed countries (OECD, 2008; PRP, 2015) inevitably affects firms' age distributions. As the share of older workers increases, the general age composition is evolving from an age pyramid structure to a rectangular age distribution with equal representation of younger, mid-aged, and older employees. Thus, the levels of age heterogeneity in organizations—that is, the extent to which workforces are characterized by an equal distribution of all age groups—are historically high and still on the rise (De Meulenaere, Boone, & Buyl, 2016; Kunze, Boehm, & Bruch, 2011, 2013; Wegge, Roth, Neubach, Schmidt, & Kanfer, 2008). Never before have people of so many different ages been interacting in the workspace, all with their unique knowledge, experience and values (King & Bryant, 2017; Parry & Urwin, 2011).

This age heterogeneity has the potential to spur employee creativity and efficiency and, therefore, workforce performance through *information-elaboration* processes involving exchange of unique age-specific knowledge, skills, and perspectives (De Meulenaere et al., 2016; Horwitz & Horwitz, 2007; Van Knippenberg, De Dreu, & Homan, 2004; Williams & O'Reilly, 1998). At the same time, *social categorization* processes can occur that increase age-based subgrouping, leading to reduced inter-age relations and hampered workforce productivity (Kunze et al., 2013; Tajfel & Turner, 1979). Currently, the existing research does not convincingly answer *when* workforce age heterogeneity generates a net positive effect on employee and firm performance. Previous studies so far mostly considered the negative perspective of age diversity (e.g., Kunze et al., 2011; Leonard, Levine, & Joshi, 2004; Timmerman, 2000) and, at best, considered moderators that can keep the harmful consequences in check (Kunze et al., 2013). As the positive effects are rarely addressed in empirical research (Boehm & Kunze, 2015), more and more scholars have encouraged research on contingencies enabling firms to reap the benefits of age diversity (e.g., Boehm & Dwertmann, 2015; Burmeister, van der Heijden, Yang, & Deller, 2018; Jungmann, Wegge, Liebermann, Ries, & Schmidt, 2020; Li, Chu, Lam, & Liao, 2011).

In this study, we address this research need by building on the categorization-elaboration model (Van Knippenberg et al., 2004), which proposes that the social categorization and information-elaboration effects of age heterogeneity do not occur in isolation but mutually interact. Following this reasoning, we introduce *age distance*—that is, the average distance between all employees' ages within a firm—as a fundamental moderator in the effect of workforce age heterogeneity on employee inter-age behaviors and firm performance. It reflects how far apart employees in age-heterogeneous workforces are on average (Bezrukova, Jehn, Zanutto, & Thatcher, 2009), affecting *both* the information-elaboration and social categorization processes associated with workforce age heterogeneity. More specifically, a greater distance between employees in an age-heterogeneous workforce (e.g., an age-heterogeneous workforce with employees aged 20–60 years versus one with members aged 30–40 years) goes along with a wider assortment of information, knowledge, and experiences and thus enlarges the potential for productive information elaborations. However, when age distances in age-diverse workforces become too large, this also makes age differences more salient (Bezrukova et al., 2009; Pelled, 1996), fostering age-based categorizations and harming inter-age relations. Thus, using the categorization-elaboration model (Van Knippenberg et al., 2004), we propose that workforce age heterogeneity can positively impact employees' inter-age behaviors and firm performance as long as the average age distance between employees is not too extensive.

To examine the interplay between workforce age heterogeneity and age distance, we performed two subsequent and complementary studies. Using a representative and longitudinal archival sample of 3,336 Belgian firms (2012–2015), we first investigate the interaction between workforce age heterogeneity and employees' average age distance in predicting workforce labor productivity (Study 1). For a refined testing of our theoretical argument, we executed an online experiment with 260 US participants, focusing on two important indicators of age-based social categorization and information-elaboration effects as outcomes: employees' inter-age cooperative contact and knowledge exchange (Study 2).

Our theory and findings contribute to the literature in many ways. It extends the age diversity literature by examining when age diversity benefits workforce productivity, as opposed to the traditional focus of scholars studying how the negative effects can be tempered (Kunze et al., 2011, 2013; Van Knippenberg et al., 2004). We do so by studying the impact of age heterogeneity and examining employees' age distance as a key moderator. Both distributional features simultaneously shape the social landscape of age-diverse workforces (De Meulenaere et al., 2016; Harrison & Klein, 2007), but their collective impact on firm performance has been systematically neglected in previous research (Gonzalez, 2016; Rupert, Blomme, Dragt, & Jehn, 2016). This study also contributes by providing support for the categorization-elaboration model of diversity (Van Knippenberg et al., 2004), which was designed precisely to emphasize that the net effect of workforce diversity results from an interplay between beneficial informational and harmful categorization effects (Lee & Kim, 2020). Our finding that age distance undermines the potential positive benefits of age heterogeneity should not only bring theoretical clarification to the field of age diversity research but also provide firms with better knowledge *if* and *when* the mix of young and old within their workforce can improve their firm productivity.

2 THEORY AND HYPOTHESES DEVELOPMENT

2.1 Implications of workforce age diversity

Research on workforce demographic diversity in general (Harrison & Klein, 2007; Williams & O'Reilly, 1998) and age diversity in particular (De Meulenaere et al., 2016; Kunze et al., 2013; Wegge et al., 2008) has conceptualized that age heterogeneity can affect employee behaviors and workforce performance both positively and negatively. Positively through the exchange of the rich pool of age-based perspectives, experiences, and competencies—*the information/decision making perspective* (Horwitz & Horwitz, 2007), negatively through age-based subgrouping processes that stimulate age-based stereotyping, discrimination, and reduced workforce cohesion—*the social categorization perspective* (Byrne, 1971; Hogg & Terry, 2000).

Whereas previous research (e.g., De Meulenaere et al., 2016; Kunze et al., 2013; Wegge et al., 2008) has typically treated these positive and negative effects as independent, in this article, we follow the categorization-elaboration model (Van Knippenberg et al., 2004) to integrate them into one coherent model. More specifically, as the age-based categorizations lead to firm members being cut off from the valuable resources (e.g., knowledge and other task-relevant resources) held by coworkers of other ages (Carton & Cummings, 2012; Meyer, Shemla, Li, & Wegge, 2015), this undermines the inter-age elaboration of relevant information and perspectives. These processes ultimately hamper firms in reaping the productivity-enhancing informational benefits of workforce age heterogeneity (Lee & Kim, 2020). In what follows, we theoretically explain how employees' average age distance influences these effects.

2.2 The role of age distance

From the information/decision-making perspective (Horwitz & Horwitz, 2007; Williams & O'Reilly, 1998), it can be derived that a greater age distance brings more potential benefits of age heterogeneity. The wider the distance between employees of different ages, the wider the assortment of valuable knowledge, experiences, networks, and skills. Consider two firms that both have their employees evenly distributed over 10 different age groups, one in which employees' ages range from 20 to 60, while the ages in the second firm range from 30 to 40 years old. While the degree of age heterogeneity is the same in both firms, they differ in how far apart the age groups are from one another. The first acquires knowledge from recently graduated young individuals with advanced and timely technological skills as well as from older employees who have accumulated in-depth knowledge and firm-specific problem-solving skills over their career (De Meulenaere et al., 2016; Parry & Urwin, 2011). In contrast, the second firm has relatively similar levels of age-based experience and types of knowledge, offering less diverse knowledge and experience to the firm. The *potential* for information elaborations leading to valuable outcomes like knowledge synergies, creativity and more efficient decision-making is, thus, higher in firms with greater average age distance compared with those with a small age distance, as the former have a richer pool of viewpoints and skills (Harrison & Klein, 2007).

However, building on the categorization-elaboration model (Van Knippenberg et al., 2004), we argue that this greater potential for informational benefits may not be realized, precisely because of the age distance. The greater the employees' age distance, the more likely employees are confronted with substantial age gaps between groups of colleagues, and the more salient age differences between firm members become. Theses age differences strengthen the identification of employees with similar coworkers and their alienation toward "the others" who are assumed to have different or even conflicting values, beliefs, and opinions and are considered less trustworthy (Carton & Cummings, 2012; De Meulenaere et al., 2016; Gibson & Vermeulen, 2003). Hence, the greater the distance, the more employees may feel psychologically distant toward coworkers of other ages, reducing their knowledge-related interactions. If age-heterogeneous employees are very distant from one another, this may also lower their formal and informal communication due to low levels of shared and implicit understanding in the form of norms, work-related jargon, and rules about appropriate judgments (Weber & Camerer, 2003). This further complicates positive inter-age interactions and the exchange of relevant information and knowledge within a workforce (Bezrukova et al., 2009; Zanutto, Bezrukova, & Jehn, 2011). Finally, great age distances also reinforce the widely held age stereotypes toward the oldest and youngest employees, setting the stage for age-based discrimination within the workforce (Posthuma & Campion, 2009). As multiple studies have shown that age discrimination lowers individuals' commitment to organizational goals (Snape & Redman, 2003), increases employees' job withdrawal (Griffin, Bayl-Smith, & Hesketh, 2016), and creates tensions in the workplace (Redman & Snape, 2006), it follows naturally that it also hinders the productive information-elaboration processes between employees of different ages (Kunze et al., 2011, 2013).

In sum, the perceived gap between "us" and "them" widens with the distance between age-heterogeneous employees (Bezrukova et al., 2009), reinforcing the in-group versus out-group dynamics that disrupt valuable inter-age behaviors and attitudes like interaction, cohesion, trust, and cooperation. According to the categorization-elaboration model, such harmed inter-age relations undermine the effective elaboration of age-specific information and, in turn, jeopardize the realization of the potential performance benefits of age heterogeneity (Van Knippenberg et al., 2004). In contrast, under smaller average age distance, age gaps and extreme age differences are less likely, reducing the formation of age-based subgroups that foster social categorization processes and undermine the elaboration of information. Therefore, we hypothesize:

Hypothesis 1 *The impact of workforce age heterogeneity on firm-level labor productivity is negatively moderated by employees' average age distance, such that workforce age heterogeneity is less (more) likely to improve workforce labor productivity under great (vs. small) average age distance.*

3 STUDY 1

3.1 Data study 1

We constructed a linked employer–employee database by collecting data from two different sources in Belgium. First, from SDWorx Belgium, a payroll and HR consultancy company, we received employee-level information regarding ages and other demographics (e.g., gender) for a wide range of private Belgian organizations. The original database included individual information about more than two-and-a-half million employees from 38,035 firms over four consecutive years (2012–2015). This enabled us to calculate age heterogeneity and the average age distance for each firm in the database. To avoid bias in diversity calculations (Biemann & Kearney, 2010) and in line with other age diversity studies (De Meulenaere et al., 2016; Grund & Westergaard-Nielsen, 2008), we included firms that employed at least 20 people, resulting in a sample of 5,943 firms.

Second, from BEL-first, a publicly available administrative data warehouse that records the financial reports of all registered Belgian firms, we collected additional firm-level information, for example on firms' labor productivity, our outcome variable. This database comprised information on more than 16,000 firms with at least 20 employees between 2012 and 2015.

We included firm observations only when they were involved in both data sources, resulting in a final sample of 3,336 firms (2012–2015), which roughly represent 15% of the actual Belgian population of private firms with more than 20 employees. To check if the exclusion of firms is random, we compared the key organizational characteristics between our sample of firms and the population of private firms with more than 20 employees. Results (see Online Supplement [OS] 1) show that the two samples are highly similar regarding the average firm age and profits as well as the distribution over four broad industry categories (service, production, retail and wholesale, and the agrarian sector), with only a slight difference in the average firm size. Thus, we can conclude that our sample of firms is as good as random and that we have a fairly representative dataset of Belgian firms.

3.2 Measures study 1

3.2.1 Labor productivity

We measured labor productivity as the gross added value of the firm—defined as the total revenues of the firm without subsidies and costs of products and services—divided by the number of employees (De Meulenaere et al., 2016; Grund & Westergaard-Nielsen, 2008). We took the logarithm of this variable because it was extremely skewed to the right. Note that we found similar results when we replicated our analyses with the untransformed version of labor productivity, using the negative binomial regression technique that accounts for the skewness of the measure (see OS 2).

3.2.2 Workforce age heterogeneity

We followed Harrison and Klein (2007) and others (e.g., De Meulenaere et al., 2016; Ferrero-Ferrero, Fernández-Izquierdo, & Muñoz-Torres, 2015) and operationalized age heterogeneity by Blau's heterogeneity index of all employees' ages within each firm, calculated as $Blau = 1 - \sum_{1}^{C} \pi_i{}^2$. C stands for the number of age categories to which employees can belong. We made an age category for each age between 15 and 64. Minimum age heterogeneity (*Blau* equals 0) occurs when all employees belong to the same age category. At maximum, *Blau* equals 0.98 (i.e., $1–1/C$, with $C = 50$ in our study), meaning that workforce members are evenly distributed over all 50 different age categories.

3.2.3 Age distance

We calculated the standard deviation (*SD*) of ages within the workforce because profound methodologic research on the characteristics of this measure (e.g., Roberson, Sturman, & Simons, 2007) has shown that it is particularly sensitive to the distance between unit members. Given that employees' ages can range from 15 to 64 years in our sample of firms, the maximum possible *SD* in our sample is 24.5 [(64–15)/2] (Harrison & Klein, 2007; Roberson et al., 2007). This value occurs when half of the firm members have the minimum age (i.e., 15 years in our sample) and the other half the highest age (64 years). *SD* thus indicates the degree to which extreme age differences and age gaps are present in the workforce. For this reason, it has been widely used as a measure of age separation, a particular distance-based conceptualization of age diversity (e.g., Harrison & Klein, 2007; Kunze et al., 2011, 2013). Given that the present study aims to address whether and how workforce age heterogeneity affects firm performance differently depending on whether (or not) large age gaps between the represented ages occur, we consider the *SD* highly appropriate for our conceptualization of age distance.

3.2.4 Controls

We control for several factors that may determine labor productivity and/or the effects of age diversity. First, we controlled for firm size, measured as the number of employees, as large firms may experience the effects of diversity more intensely or may have more resources to deal with the issues of age diversity (Boehm, Kunze, & Bruch, 2014b; De Meulenaere et al., 2016). Second, we added firm age as control because older firms are more likely to be age-diverse and because the age of the firm is related to the productivity level—that is, young firms largely have steeper increases but lower levels of productivity than older firms (De Kok, Brouwer, & Fris, 2005). Third, we controlled for the capital intensity (in terms of the fixed assets per employee), the share of white-collar workers, and the knowledge intensity of firms (measured as the share of employees with a bachelor or masters' degree). These factors all reflect the type of jobs that employees perform, which may influence how relevant the informational benefits of age diversity are to workforce productivity (Backes-Gellner & Veen, 2013). Fourth, as Belgium, our study context, is divided into three main regions with different legislation and cultures, we took into account the three region dummies (Flemish, Brussels, and Wallon region). Fifth, we followed previous age diversity studies (e.g., Wegge et al., 2008) and included the share of male employees. Further, as the frequency and intensity of the interactions between employees may depend on their presence in the firm (i.e., Lepak & Snell, 1999), we controlled for the share of part-time workers. Finally, we controlled for the year of observation (2012–2015) and the industry of the firm, by distinguishing between four main industry dummies: the primary (agrarian) sector, the secondary (production) sector, the tertiary sector (commercial services) and the quaternary sector (non-commercial sector).

3.3 Data analysis approach study 1

As our data comprises repeated measures over time, we used a panel regression design ("xtreg" in STATA) to determine the role of age distance in the workforce age heterogeneity–labor productivity link, with robust standard errors clustered per firm. We preferred a random effects above a fixed effects design because we are theoretically interested in the between-firm rather than the within-firm effects of workforce age heterogeneity (Bell & Jones, 2015). Also, our unbalanced panel dataset (i.e., only 46% of our firms is represented in each of the four observation years) complicates testing for within-firm effects. Several statistical tests provided strong support for our random effects design. First, Intraclass Correlation Coefficient (ICC) estimates indicate that there is very low variability in age heterogeneity at the within-firm level over the observation years (ICC1 = .98). The non-significant Bartlett's test for equal variances ($Chi^2 = 2.73$; $p = .436$) indicates that there is much more between-firm variability than within-firm variability. Finally, the Hausman test revealed a negative value for Chi^2 (–306.96), indicating that a fixed-effects approach would not be appropriate for our data. In addition to our random effects regressions, we also ran our analyses with the maximum-likelihood technique (see OS 3). This enabled us to confirm the robustness of our results and to perform the likelihood ratio (LR) test, which offers us a valuable statistical test for each model's fit (Nakagawa & Schielzeth, 2013).

3.4 Results study 1

Table 1 illustrates the mean, standard deviation, and the pairwise correlations between all variables used in the analyses. Table 2 presents the coefficients resulting from our random effects regression analyses. We mean-centered the variables, which is particularly important for the variables that are included in our interaction (i.e., age distance and age heterogeneity) to avoid unnecessary multicollinearity between the product of the variables.

Model 1 reveals that firm size ($B = .04$; $p = .001$), firm age ($B = .04$; $p = .001$), capital intensity ($B = .08$; $p < .001$), knowledge intensity ($B = .07$; $p < .001$), the share of white-collar workers ($B = .60$; $p < .001$), and the share of men ($B = .17$; $p = .001$) positively relate to labor productivity. The share of part-time workers is negatively associated with labor productivity ($B = -.29$; $p < .001$). Model 2 indicates that employees' average age distance is negatively associated with labor productivity, however the effect size is small and only significant at the .10 level ($B = -.01$; $p = .061$). In Model 3, we tested for the first-order effect of age heterogeneity and found that it was positively associated with labor productivity ($B = 1.10$; $p = .033$). This is in line with previous theory (Harrison & Klein, 2007) and findings (De Meulenaere et al., 2016; Ferrero-Ferrero et al., 2015) on the differential effects of different diversity types, claiming that diversity as heterogeneity is considered the type of diversity with most potential to induce positive effects.

Finally, and most importantly, Model 4 analyzed how employees' average age distance moderates the impact of workforce age heterogeneity. Our results are in line with Hypothesis 1, showing a negative and significant interaction coefficient ($B = -.38$; $p = .003$), implying that the positive impact of age heterogeneity on labor productivity reduced as employees' age distance increased. Figure 1 illustrates the interaction.

For a meaningful interpretation of the interaction, we performed a post hoc simple slopes analysis. Table 3 shows the effects of age heterogeneity for different conditional values of age distance between 2 and 16 (i.e., the full range of age distance values in our data). It reveals that when age heterogeneity increases by 1%, labor productivity increases by 3.48% when the average age distance is 2, but only by 1.97% when the distance is 6, and by 1.21% for a distance of 8. For high values of age distance and, more specifically, for values greater than 8.40, the impact of age heterogeneity failed to be significant at the .05 level. This means that age heterogeneity is positively related to firm performance only in firms in which the average distance between employees' ages is not too excessive.

3.5 Robustness analyses

We ran several robustness checks of our findings and report the regression coefficients for the interaction effect between age distance and age heterogeneity in the Online Supplement (see OS 4). First, we checked for potential reversed causality by controlling for firms' labor productivity level in the previous year and for firms' growth in their level of labor productivity compared to last year. As the parameter estimates reveal a similar pattern of findings as in our baseline analyses, this is a reassuring indication that there is no reversed causality bias in our findings.

Second, we did not take the average age as a control in our baseline analyses as we would not capture the pure effect of an age-heterogeneous workforce anymore (the older employees in highly age-diverse workforces would be taken into account to a lower degree). But there are many reasons to assume that the underlying social categorization and information-elaboration processes associated with age distance and age heterogeneity unfold differently when the pool of employees consists of mainly older or younger employees. For example, age differences may become more salient as the share of older workers grows (i.e., ageist stereotypes and age bias have been found particularly strong toward older people). Therefore we checked if our findings were robust by including the average age of the workforce as control, which was the case.

Third, we observe a strong correlation between age heterogeneity and firm size (corr = .71, see Table 1). This can be logically explained as firms with fewer employees have lower chances to have all age groups represented (e.g., a firm with 20 employees can have maximally 20 different ages represented). Whereas Biemann and Kearney (2010) have suggested the use of a size-corrected measure of heterogeneity, we consciously chose not to do so as we wanted to examine whether the variance in firms' levels of labor productivity can be explained by the extent to which they have *all* ages equally represented. Nevertheless, we did test whether our findings were robust without firm size as control as well as by using the size-corrected measures of age heterogeneity and age distance, which was the case, making us confident that our findings are not biased by our conceptualization of age heterogeneity.

3.6 Discussion study 1

Study 1 shows that workforce age heterogeneity positively affects workforce labor productivity but less so with increasing age distance. The positive impact disappeared for large values of age distance. This finding supports our expectation that workforce age heterogeneity can only stimulate the exchange of age-based informational resources (knowledge, experiences, skills) if the relations between employees of different ages are not harmed, which is more likely to happen in age-heterogeneous firms with great age distances (i.e., gaps or extreme age differences) between employees. As the data used for Study 1 did not allow us to measure and to test for these underlying informational and social-categorization effects, we conducted a vignette experiment in Study 2.

4 STUDY 2

In Study 2, we examine the interplay between workforce age heterogeneity and the average age distance in predicting two indicators of

TABLE 1 Descriptive statistics and bivariate correlations between variables used in the analyses

Variable	μ	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Labor productivity (log)	4.42	0.59	–																	
2. Firm size (log)	4.04	0.83	**.13**	–																
3. Firm age (log)	3.08	0.73	**.06**	**.16**	–															
4. Capital intensity (log)	3.32	2.07	**.40**	**.14**	**.16**	–														
5. Knowledge intensity	0.38	0.38	**.32**	.01	**–.13**	–.01	–													
6. Region: Brussels	0.11	0.31	**.09**	**.03**	**–.03**	–.01	**.19**	–												
7. Region: Flemish	0.75	0.43	.01	–.01	**.03**	.01	**–.10**	**–.61**	–											
8. Region: Walloon	0.14	0.35	**–.10**	–.01	–.01	–.00	**–.04**	**–.14**	**–.71**	–										
9. Industry: Primary	0.01	0.08	**–.03**	**.03**	–.00	**.04**	**–.05**	–.01	**–.03**	**.05**	–									
10. Industry: Secondary	0.37	0.48	**–.05**	**.14**	**.13**	**.11**	**–.32**	**–.16**	**.10**	.01	**–.06**	–								
11. Industry: Tertiary	0.59	0.49	**.10**	**–.13**	**–.10**	**–.12**	**.33**	**.15**	**–.03**	**–.09**	**–.10**	**–.92**	–							
12. Industry: Quaternary	0.03	0.18	**–.11**	**–.03**	**–.07**	–.00	**–.03**	**.03**	**–.18**	**.19**	–.01	**–.14**	**–.22**	–						
13. White collars (%)	0.60	0.36	**.33**	**–.06**	**–.16**	–.01	**.66**	**.23**	**–.13**	**–.05**	**–.09**	**–.52**	**.50**	**.09**	–					
14. Gender (% men)	0.69	0.25	–.00	**.05**	**.08**	**.06**	**–.24**	**–.10**	**.10**	**–.04**	**.02**	**.36**	**–.25**	**–.30**	**–.49**	–				
15. Part time (%)	0.16	0.16	**–.15**	–.01	–.01	**–.09**	**–.06**	**–.03**	**–.04**	**.07**	.00	**–.22**	**.06**	**.42**	**.14**	**–.61**	–			
16. Age distance	9.80	1.69	**–.13**	**–.03**	**.18**	**.03**	**–.31**	**–.09**	.05	.01	**.02**	**.13**	**–.15**	**.07**	**–.27**	**.07**	**.12**	–		
17. Age heterogeneity	0.95	0.02	**.08**	**.71**	**.23**	**.16**	**–.14**	**–.04**	**–.00**	**.03**	**.04**	**.18**	**–.20**	**.02**	**–.19**	**.05**	**.05**	**.37**	–	
18. Age distance × age heterogeneity	9.28	1.64	**–.04**	**–.09**	**–.15**	**–.12**	**.13**	**.05**	**–.02**	–.02	.00	**–.09**	**.10**	–.02	**.12**	.01	**–.07**	**–.47**	**–.46**	–

Note: Source data of SDWorx Belgium, an HR consultancy firm with expertise in HR, payroll, and tax and legal activities; financial data from annual reports retrieved from BEL-first. n = 3,336; correlations for which $p < .05$ are in bold.

TABLE 2 The interplay of workforce age heterogeneity and average age distance in predicting labor productivity

Predictor	Model 1 *B* (*SE*) (*z*; *p*)	Model 2 *B* (*SE*) (*z*; *p*)	Model 3 *B* (*SE*) (*z*; *p*)	Model 4 *B* (*SE*) (*z*; *p*)
Intercept	0.02 (0.02) (1.36; *.174*)	0.02 (0.02) (1.36; *.174*)	0.02 (0.02) (1.37; *.170*)	0.03 (0.02) (1.59; *.113*)
Firm size	**0.04 (0.01)** (3.24; *.001*)	**0.04 (0.01)** (3.25; *.001*)	0.02 (0.01) (1.29; *.198*)	0.03 (0.01) (1.77; *.076*)
Firm age	**0.04 (0.01)** (3.46; *.001*)	**0.05 (0.01)** (3.62; *.000*)	**0.05 (0.01)** (3.53; *.000*)	**0.04 (0.01)** (3.43; *.001*)
Capital intensity	**0.08 (0.01)** (14.69; *.000*)	**0.08 (0.01)** (14.73; *.000*)	**0.08 (0.01)** (14.71; *.000*)	**0.08 (0.01)** (14.61; *.000*)
Knowledge intensity	**0.07 (0.02)** (4.19; *.000*)	**0.06 (0.02)** (4.07; *.000*)	**0.06 (0.02)** (4.09; *.000*)	**0.06 (0.02)** (4.07; *.000*)
Brussels region	0.03 (0.04) (0.79; *.431*)	0.03 (0.04) (0.75; *.451*)	0.03 (0.04) (0.78; *.436*)	0.03 (0.04) (0.77; *.441*)
Walloon region	**−0.08 (0.02)** (−3.83; *.000*)	**−0.08 (0.02)** (−3.88; *.000*)	**−0.08 (0.02)** (−3.94; *.000*)	**−0.09 (0.02)** (−3.97; *.000*)
Primary sector	−0.06 (0.08) (−0.77; *.441*)	−0.07 (0.08) (−.80; *.426*)	−0.07 (0.08) (−0.80; *.425*)	0.06 (0.08) (−0.71; *.479*)
Tertiary sector	**−0.07 (0.02)** (−3.17; *.002*)	**−0.07 (0.02)** (−3.18; *.001*)	**−0.06 (0.02)** (−3.15; *.002*)	**−0.06 (0.02)** (−3.10; *.002*)
Quaternary sector	**−0.26 (0.06)** (−4.49; *.000*)	**−0.26 (0.06)** (−4.42; *.000*)	**−0.26 (0.06)** (−4.47; *.000*)	**−0.26 (0.06)** (−4.37; *.000*)
White collars (%)	**0.60 (0.03)** (18.61; *.000*)	**0.60 (0.03)** (18.14; *.000*)	**0.60 (0.03)** (18.13; *.000*)	**0.60 (0.03)** (18.11; *.000*)
Gender (% men)	**0.17 (0.05)** (3.37; *.001*)	**0.17 (0.05)** (3.39; *.001*)	**0.17 (0.05)** (3.44; *.001*)	**0.17 (0.05)** (3.53; *.000*)
Part time (%)	**−0.29 (0.06)** (−4.69; *.000*)	**−0.28 (0.06)** (−4.51; *.000*)	**−0.28 (0.06)** (−4.51; *.000*)	**−0.28 (0.06)** (−4.50; *.000*)
Age distance		−0.01 (0.00) (−1.87; *.061*)	**−0.01 (0.00)** (−2.72; *.006*)	**−0.01 (0.00)** (−3.26; *.001*)
Age heterogeneity			**1.10 (0.52)** (2.14; *.033*)	0.53 (0.55) (0.96; *.335*)
Age heterogeneity × age distance				**−0.38 (0.13)** (−3.00; *.003*)
Chi^2	**1,046.82**	**1,052.79**	**1,057.68**	**1,067.22**
LR test (model compared to)		**3.97 (1)**	**5.12 (2)**	**14.46 (2)** **9.35 (3)**

Note: Dependent variable: logarithm of labor productivity. Source data of SDWorx Belgium, an HR consultancy firm with expertise in HR, payroll, and tax and legal activities; financial data from annual reports retrieved from BEL-first. Robust standard errors, clustered for firm ID, are in parentheses. *t*-Statistics and precise *p*-values are also in parentheses. Significant results are in bold. All variables are mean-centered to avoid multicollinearity. Observation years are controlled for. n = 3,336.

age-based social categorization and information-elaboration effects on the individual level: inter-age cooperative contact and inter-age knowledge exchange. Following our theorizing findings in Study 1, we expect that age heterogeneity and distance will negatively influence one another in their impact on both outcomes.

Inter-age cooperative contact refers to the positive, face-to-face interactions between employees of different ages, for example, by having conversations about work-related or private matters or by eating lunch together (King & Bryant, 2017; Pettigrew & Tropp, 2008). In theory, inter-age contact can only arise in age-heterogeneous workforces and not in age-homogeneous workforces, as people can interact with colleagues of other ages only if they are present in the firm. Hence, we expect a positive baseline effect of workforce age heterogeneity on employees' inter-age cooperative contact. As a result, when increasing levels of age heterogeneity do not augment the frequency of inter-age cooperative contact, this indicates damaged relations between employees of different ages and, thus, the occurrence of harmful age-based social categorization effects. More specifically, research on intergroup contact (Pettigrew & Tropp, 2008) suggests that the lack of such cooperative contact between age groups hinders employees from getting to learn members of out-groups and to empathize with them, which keeps age-based

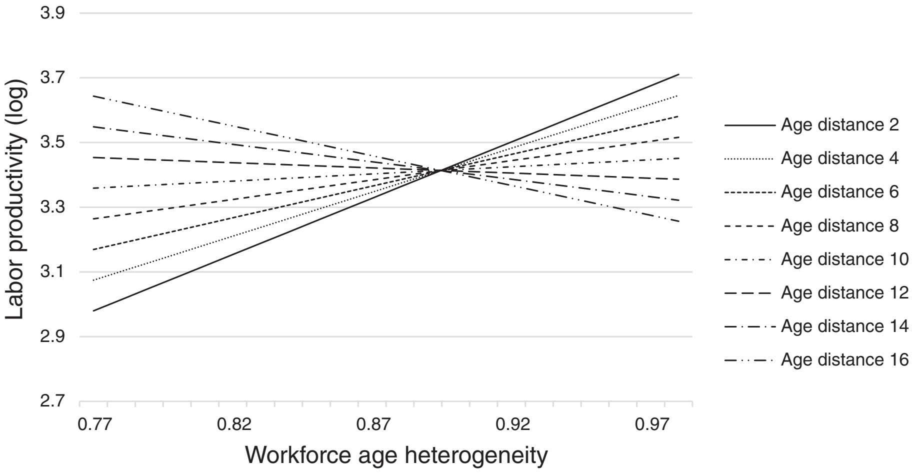

FIGURE 1 The impact of workforce age heterogeneity on workforce labor productivity (log) for different values of employees' average age distance in the firm

TABLE 3 Simple slopes of the effect of age heterogeneity on labor productivity for different values of employees' average age distance

Age distance	$B_{AgeHeterogeneity}$	*SE*	*z*	*p* > |*z*|	95% Conf. Interval	
2	**3.48**	0.96	3.63	**.000**	1.60	5.37
4	**2.73**	0.76	3.59	**.000**	1.24	4.22
6	**1.97**	0.60	3.27	**.001**	0.79	3.15
8	**1.21**	0.52	2.32	**.021**	0.19	2.24
8.40	**1.02**	0.52	1.96	**.050**	0.00	2.05
10	0.46	0.56	0.81	.416	−0.64	1.55
12	−0.30	0.69	−0.44	.663	−1.66	1.05
14	−1.06	0.88	−1.21	.228	−2.78	0.66
16	−1.82	1.09	−1.66	.096	−3.96	0.32

prejudices on the out-group prevailing (King & Bryant, 2017). Building on our prior theorizing, age heterogeneity will be less likely to engender more inter-age cooperative contacts under great average age distance than under small distance, as great distance encourages age-heterogeneous employees to cluster themselves in age-based subgroups that are reluctant to interact with one another. In contrast, increasing levels of age heterogeneity may well augment the frequency of inter-age cooperative contact if the average age distance remains small, as the formation of age-based categorizations is less likely in a setting in which age distances between employees are small on average:

Hypothesis 2 *Workforce age heterogeneity is less (more) likely to increase inter-age cooperative contact if employees' age distance is great* (versus *small).*

Inter-age knowledge exchange refers to the processes in which employees of different ages exchange knowledge, experiences, and information with one another (Burmeister et al., 2018; Gerpott, Lehmann-Willenbrock, & Voelpel, 2017). Building on the categorization-elaboration model we assume that the exchange of age-unique information is the critical process through which the benefits of workforce age heterogeneity can be realized (Burmeister et al., 2018; Van Knippenberg et al., 2004). We expect a positive baseline effect of workforce age heterogeneity on the frequency of employees' inter-age knowledge exchange because interactions between employees of different ages are theoretically possible only in age-heterogeneous and not in age-homogenous firms. The greater workforce age heterogeneity, the more potential for valuable inter-age knowledge exchanges. However, as previously theorized, we expect that the exchange of information between employees of different ages is jeopardized by the age distance between these individuals. As increasing age heterogeneity is less likely to augment the frequency of inter-age interactions if employees' age distance is great (see Hypothesis 2), it follows that the positive effect of age heterogeneity on the inter-age exchange of valuable informational resources will be less likely to be realized under great distance:

Hypothesis 3 *Age heterogeneity is less (more) likely to trigger inter-age knowledge exchange if employees' age distance is great (vs. small).*

4.1 Methods study 2

4.1.1 Sample and procedure

We conducted a two-by-two (2 × 2) factor, between-subjects experimental design, manipulating workforce age heterogeneity (high/low) and the average age distance between employees (great/small). This resulted in four scenarios that we presented to our respondents (one scenario per respondent) through an online survey.

We collected data from 400 US employees (randomly assigned across the four scenarios), using Amazon's M-Turk online platform. The criteria for inclusion in the experiment were that participants should be native US citizens and have working experience. Being aware of the strengths (e.g., high internal consistency; Buhrmester, Kwang, & Gosling, 2011) and the pitfalls of online collected information (Cheung, Burns, Sinclair, & Sliter, 2017), we included responses only when we could guarantee the validity of the information retrieved. We did so by excluding the responses of participants who (a) invested more/less time than two times the standard deviation of the average completion time; (b) failed the attention checks that we included at three specific points in the questionnaire (e.g., "if you are paying attention, please click 4"); and (c), at the end of the survey, could not recall what has been questioned. As the samples of in- and excluded respondents were highly comparable regarding the share of men, the average age, the share of white-collar workers and the share of full-time working employees (see OS 5), we are confident that the exclusion of respondents was non-random. After removing the 136 invalid responses, we had a final sample of 260 participants: 61 in the high heterogeneity × great distance scenario; 70 in the high heterogeneity × small distance scenario; 65 in the low heterogeneity × great distance scenario; and 64 in the low heterogeneity × small distance scenario. In addition, 116 respondents were male, 143 female, and one indicated to be neither male or female (i.e., gender category "other"). The mean age was 39.86 (*SD* = 10.01).

Our respondents were told they were among the 100 members of a firm. We briefly described and graphically depicted the organization's age distribution (see Figures 2a–d) and mentioned that they belonged to the age category closest to their actual age. Each scenario represented a distinct age distribution, in which the level of age heterogeneity (high/low) and the distance between members' ages (great/small) were manipulated.

4.2 Manipulations study 2

4.2.1 Age heterogeneity

We based our age heterogeneity manipulation on our measure in Study 1 and on previous research (Rabl & Triana, 2014). High age heterogeneity implies many different age categories over which employees are evenly distributed. Figures 2a,b illustrate our high heterogeneity firms, both having 20 age categories, each represented by five employees. Note that this level of age heterogeneity corresponds with a Blau index of .95. Low age heterogeneity implies that only few age categories are represented and/or that the represented age groups are not equally sized. Figures 2c,d illustrate the two low heterogeneity scenarios, one (Figure 2c) with limited heterogeneity as the (few) represented age categories are far from equally sized (Blau equals .57) and one (Figure 2d) with no heterogeneity at all (Blau is zero, as there is only one age category represented). Even though the Blau values of .57 and zero seem to be highly different at first sight, they both refer to very low levels of heterogeneity (Rabl & Triana, 2014). This is also emphasized by the fact that the minimum value for Blau in our administrative data set (representing real values of organizational age heterogeneity) used for Study 1 is .76. We acknowledge that the latter manipulation (Figure 2d) is an extreme and unrealistic representation of low age heterogeneity, but it enabled us to successfully manipulate high versus low age heterogeneity in combination with high versus low age distance.

To evaluate whether the age heterogeneity manipulation was successful, we asked the respondents, based on a scale of 1 ("not at all varied in age") to 7 ("very varied in age"), to what extent they perceived the organization as diverse regarding age. As intended, respondents in the "high heterogeneity" scenarios perceived significantly more diversity in age (*M* = 5.24; *SD* = 1.79) as compared with respondents in the "low diversity" scenarios (*M* = 2.53; *SD* = 1.76; *F*[479.86] = 151.66; *p* = .000).

4.2.2 Age distance

We based our age distance manipulation on the standard deviation (*SD*) of employees' ages, in line with our age distance measure in Study 1. The larger *SD*, the greater the average distance between employees' ages. As the fictitious firms in our scenarios can have firm members aged between 18–64, the maximum *SD* equals 23 (i.e., [64–18]/2), which would arise when half of the firm members are 18 years old, and the other half is 64 years old (Harrison & Klein, 2007; Roberson et al., 2007). Given that such distribution does not at all reflect high heterogeneity, it is theoretically impossible to create a scenario representing maximum values for both age heterogeneity *and* age distance. As a result, our high distance manipulations correspond with *SD* values of 13.29 and 9.73 (Figures 2a,c, respectively), whereas the low distance scenarios represent *SD* values of 5.77 and 0 (Figures 2b,d, respectively).

As part of the manipulation check, we asked participants to what extent they perceived great age differences in the firm on a scale of 1 to 7. In line with our intentions, respondents in the "great distance" scenarios perceived significantly more differences in age (*M* = 4.73; *SD* = 1.88) as compared with the "small distance" participants (*M* = 2.45; *SD* = 1.72; *F*[338.29] = 104.66; *p* = .000). Thus, we can consider our distance manipulation successful.

4.3 Outcome measures and controls study 2

4.3.1 Cooperative inter-age contact

We built on the workplace intergenerational climate scale (WICS) developed by King and Bryant (2017), which aims to evaluate individuals' perspectives and attitudes toward employees of different ages at work. It is a multidimensional scale, comprising a subscale for *intergenerational cooperative contact*. We slightly adapted the items, as we wanted to measure inter-*age* contact and not inter-

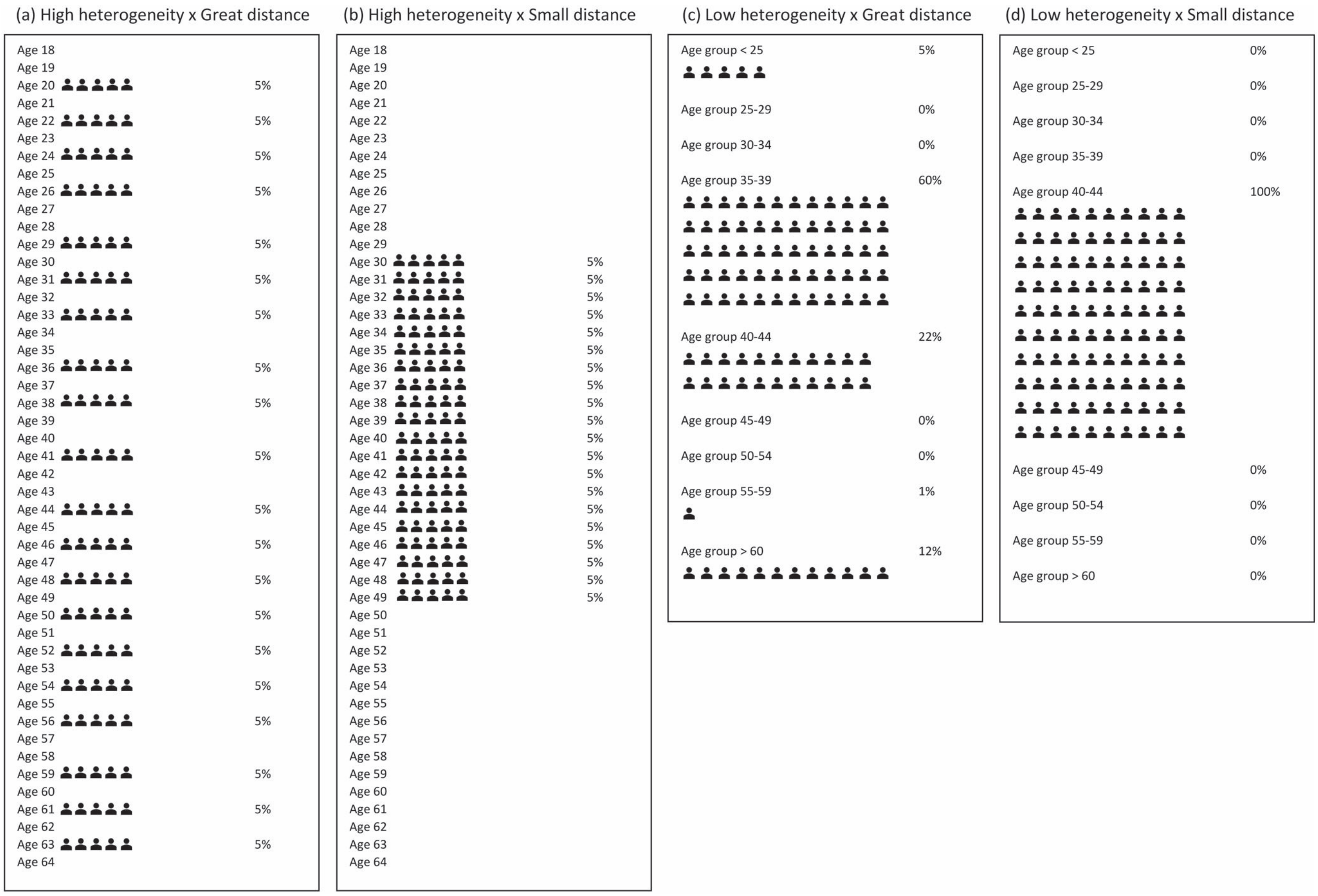

FIGURE 2 (a) High age heterogeneity × great age distance. (b) High age heterogeneity × small age distance. (c) Low age heterogeneity × great age distance. (d) Low age heterogeneity × small age distance

generational contact. The respondents were asked to indicate on a scale of 1 ("never") to 6 ("very frequently") how often they would engage in four particular interactions with employees of other ages in the fictitious organization they have been assigned to. More specifically, they were asked how often they would have conversations with co-workers outside their age group; have conversations with co-workers outside their age group relating to things other than work; talk with co-workers outside their age group about their personal life; and eat meals with co-workers outside their age group during the workday. To construct the scale of inter-age cooperative contact, we calculated the mean over the four items for each respondent. The Cronbach's alpha coefficient for this scale was .91.

4.3.2 Inter-age knowledge exchange

Building on the knowledge exchange scale developed by Reinholt, Pedersen, and Foss (2011), we asked respondents how frequently (1 – "never" to 6 – "very frequently") they would *exchange* their knowledge with colleagues that do not belong to their age group and *use* knowledge from colleagues of other age groups if they shared their knowledge. The reliability coefficient alpha for this two-item scale was .90.

4.3.3 Controls

In line with the recommendations of Becker (2005) and Wang, Sparks, Gonzales, Hess, and Ledgerwood (2017), we do not take into account the control variables that were available in our database (that is, gender, white vs. blue-collar and age). Neither of these controls significantly affects our outcome variables (positive inter-age contact and inter-age knowledge exchange). As suggested and empirically shown by Wang et al. (2017), including these controls would inflate Type 1 errors. Note, however that the pattern of results is robust for the in- or exclusion of these controls in the empirical model (see OS 6a and OS 6b).

4.4 Data analysis approach study 2

To test for the moderating impact of employees' age distance on the relationship between workforce age heterogeneity on the one hand

and inter-age cooperative contact and knowledge exchange on the other, we performed OLS regressions using the PROCESS macro in SPSS (Hayes, 2017).

4.5 Results study 2

Table 4 shows the descriptive statistics and correlations of the variables used in Study 2. Based on the theoretical interplay between the mechanisms, we expected that high levels of inter-age cooperative contact are associated with high levels of inter-age knowledge exchange, which is indicated by the high correlation between the constructs (*corr.* = .77; $p = .000$).

Consistent with our assumptions, Model 1 in Table 5 shows a positive first-order effect of age heterogeneity on inter-age cooperative contact ($B = .70$; $p < .0005$). Model 2 shows a positive impact of age distance, too ($B = .47$; $p = .001$). In line with Hypothesis 2, Model 3 indicates that the positive effect of age heterogeneity on inter-age cooperative contact is reduced by employees' age distance, as shown by the negative interaction effect ($B = -1.05$; $p < .001$). Table 6, where we displayed the conditional effects of age heterogeneity for the great versus small distance scenarios separately, further indicates that the beneficial effect of age heterogeneity completely disappeared under great distance. Figure 3 illustrates the interaction.

Model 1 in Table 7 reveals a positive first-order effect of age heterogeneity on inter-age knowledge exchange ($B = .66$; $p < .001$), which is in line with our assumptions. Model 2 reveals a positive first-order impact of age distance ($B = .62$; $p < .001$). Model 3 offers support for Hypothesis 3 by revealing a negative interaction effect between age heterogeneity and age distance in predicting inter-age knowledge exchange ($B = -1.01$; $p < .001$). Further, we find that the positive effect exists only for the small distance scenarios (see Table 8 for the simple slopes). Figure 4 illustrates the interaction.

4.6 Discussion study 2

By means of an online experiment, in Study 2, we examined the moderating role of employees' age distance in the effects of workforce age heterogeneity on two important inter-age outcomes—cooperative contact and knowledge exchange—that relate to age-based social categorization and information-elaboration effects and, thus, are assumed to embody the underlying mechanisms in the relationship between age heterogeneity and firm performance (Study 1). Through these experimental results, we find additional support for the expectation that increasing age heterogeneity is more likely to engender age-based social categorization effects that hamper valuable age-based informational processes in workplaces in which the average age distance between employees is great. These findings are a complementary addition to the findings of Study 1, where we revealed a negative effect of age distance on the age heterogeneity–firm performance relationship.

TABLE 4 Minima, maxima, means, *SD*s, and intercorrelations of variables used in the analyses

Variable	Min	Max	Mean	*SD*	1	2	3	4
1. Age heterogeneity	0	1	0.50	0.50	—			
2. Age distance	0	1	0.48	0.50	−0.04	—		
3. Positive inter-age contact	1	6	4.12	1.22	**0.29**	**0.18**	—	
4. Inter-age knowledge exchange	1	6	4.55	1.25	**0.27**	**0.24**	**0.77**	—

Note: $n = 260$; correlations for which $p < .01$ are in bold.

TABLE 5 The moderating role of age distance on the effect of age heterogeneity on positive inter-age contact

Predictor	Model 1 *B* (*SE*) (*t*; *p*)	Model 2 *B* (*SE*) (*t*; *p*)	Model 3 *B* (*SE*) (*t*; *p*)
Intercept	**3.77 (0.10)** (36.65; *.000*)	**3.53 (0.12)** (28.53; *.000*)	**3.29 (0.14)** (23.43; *.000*)
Age heterogeneity	**0.70 (0.15)** (4.82; *.000*)	**0.72 (0.14)** (5.04; *.000*)	**1.18 (0.19)** (6.10; *.000*)
Age distance		**0.47 (0.14)** (3.30; *.001*)	**0.95 (0.20)** (4.83; *.000*)
Age heterogeneity × age distance			**−0.96 (0.28)** (−3.45; *.001*)
F	**23.27**	**17.53**	**16.16**
R^2	**.08**	**.12**	**.16**

Note: $n = 260$; significant results are in bold.

TABLE 6 Simple slopes of the effect of age heterogeneity on positive inter-age contact for great versus small age distance

Age distance	$B_{AgeDiversity}$	SE	t	p > |t|	95% Conf. Interval	
Small	**1.18**	0.19	6.10	**.000**	0.80	1.56
Great	0.22	0.20	1.10	.271	−0.17	0.61

Note: n = 260; significant results are in bold.

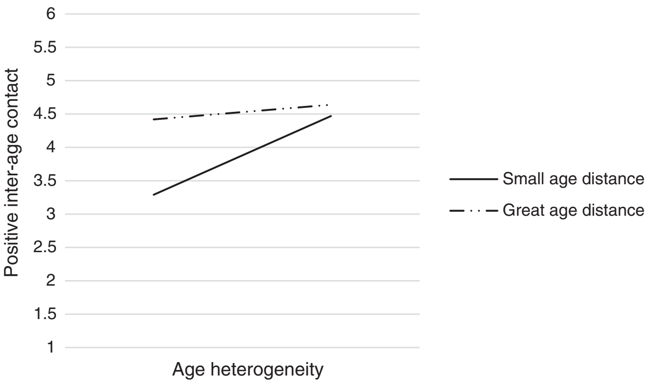

FIGURE 3 The moderating role of age distance on the effect of age heterogeneity on positive inter-age contact. *Note*. Dependent variable: The frequency at which respondents would engage in positive inter-age contact 1-never; 2-very rarely; 3-rarely; 4-occasionaly; 5-frequently; 6-very frequently)

5 GENERAL DISCUSSION AND CONCLUSION

In this study, we examined the moderating role of age distance on the impact of workforce age heterogeneity—that is, the degree to which firms have rectangular age distribution implying that all ages are equally represented—on workforce performance. Building on the categorization-elaboration model (Van Knippenberg et al., 2004), we assumed that age distance evokes age-based social categorization effects that undermine the productive elaboration of information across age-heterogeneous employees. Two different, complementary studies provided strong support for this assumption. Study 1, an archival study based on 3,336 Belgian firms (2012–2015), showed that employees' age distance diminished the positive relationship between age heterogeneity and labor productivity. The productivity advantage of age heterogeneity even completely vanished in firms with great age distance, that is, for distance values larger than 8.40. As the median distance was 9.86 in our sample, this means that employees' age distance was too great to enable for the performance benefits of age heterogeneity in more than half of the firms in our dataset. Study 2, an online vignette experiment with 260 US participants, revealed that firm-level age heterogeneity has a positive first-order impact on employees' inter-age cooperative contact and knowledge exchange, but only in firms with small age distance. Thus, though there is more potential for informational synergies in age-heterogeneous workforces with great age distance because the distance broadens the pool of age-based knowledge, experience, and other informational resources, our findings indicate that this potential cannot be realized when age differences are too large. Under large age distance, increasing age heterogeneity does not increase employees' positive interactions with other ages during work (Study 2). As this implies that the exchange of valuable, age-specific knowledge between coworkers of different ages neither becomes more frequent (Study 2), it naturally follows that firms cannot benefit from the potential productivity-enhancing effect of age heterogeneity under great distance (Study 1).

5.1 Theoretical contributions

This study's theory and findings contribute meaningfully to the literature on workforce diversity in general and age diversity in specific. First, as argued by Van Knippenberg et al. (2004), one of the most critical flaws in diversity research is that it "has paid insufficient attention to [...] important moderators of group information processing, as the process underlying the positive effects of diversity" (p. 1009). As a result, "it remains unclear which contingency factors make it work" (Guillaume, Dawson, Otaye-Ebede, Woods, & West, 2017:276). This also applies to age diversity research in particular, which has so far mainly studied the negative implications of age diversity and the moderators that help to reduce the drawbacks (Joshi & Roh, 2009). By focusing on the potential informational *benefit* of workforce age heterogeneity and revealing that it depends on the distance between employees' ages whether this potential will be realized, our study extends the current research on firm-level age diversity and diversity in general, which has put the search for moderators of the positive effects of (age) diversity high on the research agenda (Guillaume et al., 2017; Van Knippenberg et al., 2004).

Doing so, this article is, to our knowledge, the first to integrate the categorization-elaboration model (Van Knippenberg et al., 2004) in age diversity research. Whereas prior studies (e.g., De Meulenaere et al., 2016; Ferrero-Ferrero et al., 2015; Kunze et al., 2011, 2013) have acknowledged that age diversity can evoke both positive and negative effects, none of them incorporated the view that both effects co-occur and interact. Our findings support that they, indeed, co-occur and that it depends on employees' age distance whether age-based information elaboration processes outweigh social categorization processes or vice versa, ultimately determining the "net" effect of age diversity. As a result, this study extends our current knowledge on the implications of workforce age diversity and provides support for the categorization-elaboration model of Van Knippenberg et al. (2004).

Second, while past research has emphasized that compositional characteristics of firms' age structure (e.g., distribution type and firm size) influence the effects of workforce age diversity (De Meulenaere

TABLE 7 The moderating role of age distance on the effect of age heterogeneity on inter-age knowledge exchange

Predictor	Model 1 *B* (*SE*) (*t*; *p*)	Model 2 *B* (*SE*) (*t*; *p*)	Model 3 *B* (*SE*) (*t*; *p*)
Intercept	**4.22 (0.11)** (39.75; .000)	**3.91 (0.13)** (30.99; .000)	**3.64 (0.14)** (25.56; .000)
Age heterogeneity	**0.66 (0.15)** (4.42; .000)	**0.69 (0.15)** (4.72; .000)	**1.20 (0.20)** (6.07; .000)
Age distance		**0.62 (0.15)** (4.29; .000)	**1.15 (0.20)** (5.74; .000)
Age heterogeneity × age distance			**−1.05 (0.28)** (−3.72; .000)
F	**19.50**	**19.62**	**18.35**
R^2	**.07**	**.13**	**.18**

Note: *n* = 260; significant results are in bold.

TABLE 8 Simple slopes of the effect of age heterogeneity on inter-age knowledge exchange for great versus small age distance

Age distance	$B_{AgeDiversity}$	*SE*	*t*	*p* > |*t*|	95% Conf. Interval	
Small	**1.20**	0.20	6.07	**.000**	0.81	1.58
Great	0.14	0.20	0.70	.485	−0.26	0.54

Note: *n* = 260; significant results are in bold.

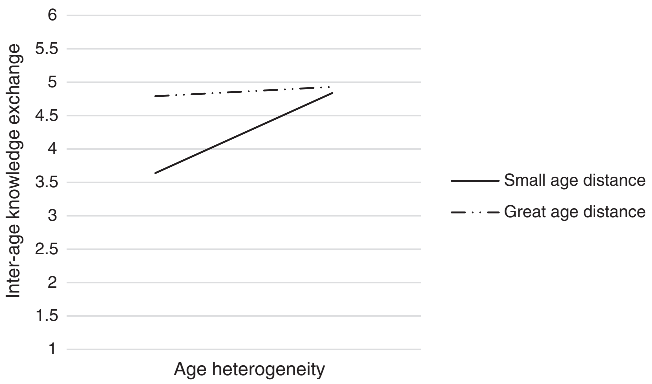

FIGURE 4 The moderating role of age distance on the effect of age heterogeneity on inter-age knowledge exchange. *Note*. Dependent variable: The frequency at which respondents would exchange knowledge with employees of other ages (1-never; 2-very rarely; 3-rarely; 4-occasionaly; 5-frequently; 6-very frequently)

et al., 2016; Ferrero-Ferrero et al., 2015; Guillaume et al., 2017), it suffers from two major flaws. First, prior studies have mostly investigated the first-order effect of a distance-based construct of age diversity (i.e., separation), reflecting the degree to which age gaps are present in the workforce. As separation most likely triggers the negative, social categorization effects of age diversity, this may well explain the dominant-negative effect predicted and found in previous studies (e.g., De Meulenaere et al., 2016; Harrison & Klein, 2007; Kunze et al., 2011, 2013). Age heterogeneity, as another key characteristic of age diversity, remains widely understudied, while theoretical (Harrison & Klein, 2007) and limited empirical evidence (De Meulenaere et al., 2016; Ferrero-Ferrero et al., 2015) has shown that it enables for the information-elaboration benefits of age diversity. By focusing on age heterogeneity, we contributed to the literature by adding evidence on the potential positive effects of diversity in general and age diversity in specific. Second, prior research has ignored that distributional characteristics like age heterogeneity and distance can co-occur and jointly affect firm performance (Gonzalez, 2016; Harrison & Klein, 2007; Thatcher & Patel, 2012). This is unfortunate because, while high levels of age heterogeneity denote that there are many different ages evenly represented in a firm (Harrison & Klein, 2007), they do not reveal *how* different firm members are from one another. Our findings show that this difference determines how intense the age-based social categorizations are that undermine the information-elaboration processes triggering the positive effects of age heterogeneity (De Meulenaere et al., 2016; Van Knippenberg et al., 2004). By ignoring the role of age distance, we would have falsely concluded that more age heterogeneity is always better for inter-age employee relations and workforce performance. In line with Harrison and Klein (2007), we suggest that our findings are relevant beyond the context of *age* diversity, too. For all variables for which both distance and heterogeneity are meaningful (like age, tenure, number of children, number of diplomas, etc.), future scholars should consider the joint impact of both distributional characteristics to gain a better understanding of the implications of diversity.

Third, our findings can also add knowledge to the rapidly growing literature on diversity and inclusion in age-diverse workforces (Nishii, 2013; Shore et al., 2011; Shore, Cleveland, & Sanchez, 2018). Inclusion scholars postulate that only when workforce members perceive they can identify with others in the firm and, at the same time, deliver a unique contribution can firms reap the benefits of workforce diversity. In line with this idea, Boehm, Kunze, et al. (2014b) found that inclusive HR practices relate to a pro-diversity climate that facilitated the beneficial effects of organizational age diversity. Our findings seem to indicate that a balance between similarities and dissimilarities in employees' ages is, indeed, important to reap the benefits of age-diverse workforces. In particular, there should be enough differences in age (i.e., the level of age heterogeneity should be sufficiently high) to enable for valuable information-elaborations. Still, they should neither be too large (i.e., the average age distance cannot be too great), as this would hinder employees from identifying and interacting with colleagues of different ages to realize these informational processes. As such, our results suggest that the age structure of the workforce, in terms of heterogeneity and distance in age, might influence the firm's climate for inclusion. We thus also add important knowledge to the inclusion literature, which still requires adequate theoretical grounding and empirical tests on how to achieve organizational inclusion (Shore et al., 2018).

5.2 Practical implications

Beyond conceptual contributions, our study provides important implications for practitioners. Most importantly, we show that there are boundaries to the beneficial effects of workforce age heterogeneity. Great differences in age alienate employees from one another such that they refrain from engaging in positive interactions through which they can exchange and combine their unique sources of knowledge and experience. Practitioners might infer from this finding two important implications.

First, firms could *avoid large gaps* in the age structure of their workforce to reap the productive knowledge benefits of age heterogeneity. If recruits “fill the gaps,” that is, they belong to age categories that have been underrepresented before, they will have intermediate ages between the age categories that are already represented. This reduces the average age distance between all employees, makes age gaps smaller, and enables newcomers to play a bridging role between younger and older employees, all facilitating the elaboration of information across employees of different ages. To do so, firms could engage in targeted recruitment to influence their workforce's age structure (Casper, Wayne, & Manegold, 2013). More specifically, as employees of different ages are motivated by different incentives (Kooij, De Lange, Jansen, Kanfer, & Dikkers, 2011), organizations targeting an under-represented age cohort could advertise their vacancies by emphasizing the HR practices that appeal to this cohort. Examples are promotion opportunities for younger employees, family-friendly policies for employees in their early 30s, and stability practices (like job security) for older recruits (Kooij et al., 2011).

While not all firms have the appropriate budget to restructure their workforce, we propose as the second practical implication that firms should efficiently *manage existing age gaps* in age-heterogeneous workforces. Within this line of reasoning, the rapidly growing literature on (age) inclusive management may offer inspiring insights (Boehm, Dwertmann, et al., 2014a; Boehm, Kunze, et al., 2014b; Kunze et al., 2013; Nishii, 2013; Shore et al., 2018). The principle of age-inclusive management is that firms will benefit from age diversity only when workforce members of different ages feel treated as insiders, while at the same time, they feel valued for their unique knowledge and contributions. Accordingly, age inclusion in the workplace can be generated in different ways—that is, through age-inclusive HR-practices, leadership, and organizational climates (Mitchell et al., 2015; Nishii, 2013; Shore et al., 2018). They are considered critical elements of employee management that reinforce each other in fostering the informational benefits of workforce age heterogeneity while suppressing the social drawbacks (Boehm & Dwertmann, 2015).

An example of an *age-inclusive HR practice* is the provision of training and education to managers on how to deal with an age-diverse workforce (Boehm, Dwertmann, et al., 2014a; Boehm, Kunze, et al., 2014b). From a signaling and sense-making perspective (Connelly, Certo, Ireland, & Reutzel, 2011) such a practice would signal employees that a firm values the unique contributions of all age groups. Employees, in turn, would interpret this as an age-inclusive behavioral guideline, such that they will be more likely to behave positively toward colleagues of different ages (Boehm, Dwertmann, et al., 2014a; Boehm, Kunze, et al., 2014b). *Leaders* can act in an age-inclusive way by focusing on accepting, valuing, and explicitly using the age-based differences of employees within the workforce, for example, by allowing employees of all ages in the decision-making process (Boehm & Dwertmann, 2015; Mitchell et al., 2015). Finally, by explicitly pronouncing an *organizational age-inclusive climate*, firms may signal to their employees that they are inclusive to employees of all ages (Boehm, Dwertmann, et al., 2014a). One way firms can explicitly pronounce an age-inclusive climate is by stating it on the website. For example, Google mentions the following: “Google is committed to creating a diverse and inclusive workforce. Our employees thrive when we get this right. We aim to create a workplace that celebrates the diversity of our employees, customers, and users. We endeavor to build products that work for everyone by including perspectives from backgrounds that vary by race, ethnicity, social background, religion, gender, age, disability, sexual orientation, veteran status, and national origin” (Google Diversity, 2019).

These three managerial actions toward age inclusion—that is, age-inclusive HR practices, leadership, and organizational climates—could be very effective in overcoming or at least mitigating the disrupting effect of age gaps in realizing the potential benefits of workforce age heterogeneity. Note, however, that research on the actual success of age-inclusive management in age-diverse workforces needs more research attention (Boehm, Dwertmann, et al., 2014a; Boehm, Kunze, et al., 2014b; Shore et al., 2018).

5.3 Limitations and directions for future research

As with most empirical research, our study has several limitations. First, we tested our main hypothesis in a large archival sample of Belgian firms, which allowed us to base our results on objective information on the independent variables (age heterogeneity and distance) and the dependent variable (firm performance). We also collected additional data in an experimental design, which enabled us to make more robust, causal inferences. However, even though we build our arguments on solid and empirically validated theories, such as social categorization theory, information/decision-making theory, and (age) diversity research (De Meulenaere et al., 2016; Kunze et al., 2011, 2013; Van Knippenberg et al., 2004; Williams & O'Reilly, 1998), we were not able to test for our implicit assumption that inter-age cooperative contact and knowledge exchange improve workforce performance because our two data sets could not be combined. Moreover, as our vignette study builds on an extreme representation of firms with low age heterogeneity and low age distance, one can argue that its external validity is limited. Therefore, we believe it is worthwhile to test our theoretical mechanisms more thoroughly in future research to support the causality further and to improve the external validity of our findings (Miller & Triana, 2009).

As a first step in this direction, we performed two additional exploratory analyses using our administrative database of Study 1. We first performed a split-sample analysis of the interplay between workforce age heterogeneity and age distance for two subsamples of firms within our data: one covering the 25% of firms with the lowest share of full-time workers ("part-time firms") and one representing the 25% of firms with the highest share of full-time workers ("full-time firms"). Note that the part-time firms had at least 21% of part-time employees, whereas the full-time firms subgroup had at least 93% of full-time employees. Employees in part-time firms interact less with their coworkers than in full-time firms. Thus, they have less time and opportunities to get to know one another and to go beyond the surface-level characteristics of age (Lepak & Snell, 1999). Following our theoretical arguments, we would expect that the undermining effect of age distance in age-heterogeneous workforces is stronger in part-time firms than in full-time firms. Second, we also compared our interaction effect between the subgroups of firms with the 25% lowest and the 25% highest levels of knowledge intensity. The 25% lowest knowledge-intensive firms all had zero employees with a bachelor or master's degree. The 25 highest knowledge-intensive firms had 75% or more employees with such a degree. The higher firms' knowledge intensity, the more they rely on social capital—that is, the interactions and collaborations among employees in the workplace (Datta, Guthrie, & Wright, 2005; Von Nordenflycht, 2010). In consequence, knowledge-intensive firms require more co-worker collaboration than firms with low levels of knowledge intensity. Thus, we would expect that the undermining effect of great age distances in age-heterogeneous workforces is weaker in firms with a higher share of knowledge intensity. Our regression coefficients support our assumptions (see OS 7 and OS 8). The undermining effect of age distance is only present in the subgroup of part-time firms ($B = -.61$; $p = .008$) but not for the full-time subgroup ($B = -.23$; $p = .234$) for which the first-order effect of age heterogeneity prevails ($B = 1.97$; $p = .020$; see OS 7). Similarly, the moderating effect of age distance only occurs for the firms with low levels of knowledge intensity ($B = -.48$; $p = .013$) but not for highly knowledge-intensive firms ($B = -.21$; $p = .371$) for which positive effect of age heterogeneity dominates ($B = 2.76$; $p = .004$; see OS 8). In sum, these exploratory analyses reveal that when employees do not (need to) interact with their coworkers, which makes superficial age differences more salient, the undermining social categorization processes will be more likely to unfold. Whereas these findings add valuable support for our assumptions on the mechanisms underlying the interaction effect of workforce age heterogeneity and age distance on firm performance, we still encourage future researchers to examine the proposed mechanisms.

Second, our theoretical argumentation and the testing in Study 2 is focused on within-organizational knowledge exchange as the main mechanism between the positive effects of age heterogeneity and firm productivity (which is also in line with the CEM of Van Knippenberg et al., 2004). Still, other potential mechanisms should be explored in future studies. One option might be to investigate if age diversity increases performance via the congruence with an age-diverse customer base. Although there is at best mixed evidence for such employee/customer relational diversity effects (Dwyer, Orlando, & Shepherd, 1998; Leonard et al., 2004), we encourage exploring them further as another potent mechanism or additional moderator for the interaction between age heterogeneity and age distance, especially for service companies in which employees may interact intensely with customers. Furthermore, age heterogeneity, especially in combination with large age distance, might also prevent the development of a cohesive culture, which has been put forward as an important predictor of performance (Evans & Dion, 2012; Harrison, Price, & Bell, 1998). In consequence, we would encourage inspecting workforce cohesion as another competitive mediator in future studies.

Third, our experimental testing in Study 2 also has several drawbacks that might be addressed in future studies. As mentioned above, our manipulation created rather extreme and artificial conditions, which can be improved by more nuanced manipulation of more lenient situations of age heterogeneity and distance. Additionally, we only used M-Turk respondents, which are more diverse than other samples (e.g., students) often used in empirical research, but still represent a specific population (Keith, Tay, & Harms, 2017). Ideally, further studies might, therefore, replicate our findings with real-group manipulations (e.g., different age-related staffing of experimental and control groups) in laboratories or even better company settings.

Fourth, there is growing awareness among diversity scholars that the context in which employees work determines how the implications of diversity unfold (Guillaume et al., 2017; Johns, 2006; Joshi & Roh, 2009). In line with their arguments, we should acknowledge that age-based category differences are social constructs that might be perceived as major in some social settings and non-existent in others. The extent to which age distances stimulate age-based categorizations mitigating the benefits of workforce age heterogeneity may, thus, differ across firms. Therefore, we encourage future studies to explore additional contextual moderators. We already found in our further exploratory analyses that the mitigating effect of age distance in age-heterogeneous workforces is weaker in firms with more full-time workers and in more knowledge-intensive firms. In addition, it may also be weaker in organizations operating in large cities than in firms located in rural areas because diversity is more the norm in large city environments. Further, one can argue that a great age distance may be particularly disruptive when more older employees (e.g., older than 50 years) are involved, as these are particularly ageist and wanting to mix with their age peers only. In contrast, a great age distance may be less disruptive when more very young employees (e.g., younger than 25 years) are present. For a very young workforce, it may be even valuable for firms to have the recent knowledge and technological skills of younger employees complemented by the experience of much older employees. Note that with our data, we were able to empirically confirm this latter assumption (see OS 9), underscoring the importance of exploring these potential asymmetries of our findings in future research (Gonzalez, 2016). Finally, we also acknowledge that some firms may benefit more from age heterogeneity than others, depending on the type of employees' knowledge and skills. For example, high-tech firms often rely on the most recent technological know-how that younger employees tend to acquire. Therefore, they might benefit more from moderate (instead of high) levels of age heterogeneity around a low average age. We believe that it is highly valuable to explore these complexities in future research.

In sum, our study took an important step in examining when the positive, informational benefits of workforce age heterogeneity arise. At the same time, it also calls for more research on the underlying mechanisms and on the contingencies that influence the moderating role of age distance in the impact of workforce age heterogeneity.

ACKNOWLEDGMENT

This research was supported by the Research Foundation Flanders (FWO), grant numbers 12Z7519N (Postdoctoral Research Fellowship).

ORCID

Kim De Meulenaere https://orcid.org/0000-0002-5503-0317
Florian Kunze https://orcid.org/0000-0002-2583-6221

REFERENCES

Backes-Gellner, U., & Veen, S. (2013). Positive effects of ageing and age diversity in innovative companies–large-scale empirical evidence on company productivity. *Human Resource Management Journal*, *23*, 279–295.

Becker, T. E. (2005). Potential problems in the statistical control of variables in organizational research: A qualitative analysis with recommendations. *Organizational Research Methods*, *8*, 274–289.

Bell, A., & Jones, K. (2015). Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data. *Political Science Research and Methods*, *3*, 133–153.

Bezrukova, K., Jehn, K. A., Zanutto, E. L., & Thatcher, S. M. (2009). Do workgroup fault lines help or hurt? A moderated model of fault lines, team identification, and group performance. *Organization Science*, *20*, 35–50.

Biemann, T., & Kearney, E. (2010). Size does matter: How varying group sizes in a sample affect the most common measures of group diversity. *Organizational Research Methods*, *13*, 582–599.

Boehm, S. A., & Dwertmann, D. J. (2015). Forging a single-edged sword: Facilitating positive age and disability diversity effects in the workplace through leadership, positive climates, and HR practices. *Work, Aging and Retirement*, *1*, 41–63.

Boehm, S. A., & Kunze, F. (2015). Age diversity and age climate in the workplace. In P. M. Bal, D. T. A. M. Kooij, & D. M. Rousseau (Eds.), *Aging workers and the employee-employer relationship* (pp. 33–55). New York, NY: Springer.

Boehm, S. A., Dwertmann, D. J., Kunze, F., Michaelis, B., Parks, K. M., & McDonald, D. P. (2014a). Expanding insights on the diversity climate–performance link: The role of workgroup discrimination and group size. *Human Resource Management*, *53*, 379–402.

Boehm, S. A., Kunze, F., & Bruch, H. (2014b). Spotlight on age-diversity climate: The impact of age-inclusive HR practices on firm-level outcomes. *Personnel Psychology*, *67*, 667–704.

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science*, *6*, 3–5.

Burmeister, A., van der Heijden, B., Yang, J., & Deller, J. (2018). Knowledge transfer in age-diverse coworker dyads in China and Germany: How and when do age-inclusive human resource practices have an effect? *Human Resource Management Journal*, *28*, 605–620.

Byrne, D. E. (1971). *The attraction paradigm*. New York: Academic Press.

Carton, A. M., & Cummings, J. N. (2012). A theory of subgroups in work teams. *Academy of Management Journal*, *37*, 441–470.

Casper, W. J., Wayne, J. H., & Manegold, J. G. (2013). Who will we recruit? Targeting deep-and surface-level diversity with human resource policy advertising. *Human Resource Management*, *52*, 311–332.

Cheung, J. H., Burns, D. K., Sinclair, R. R., & Sliter, M. (2017). Amazon mechanical Turk in organizational psychology: An evaluation and practical recommendations. *Journal of Business and Psychology*, *32*, 347–361.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management*, *37*, 39–67.

Datta, D. K., Guthrie, J. P., & Wright, P. M. (2005). Human resource management and labor productivity: Does industry matter? *Academy of Management Journal*, *48*, 135–145.

De Kok, J., Brouwer, P., & Fris, P. (2005). Can firm age account for productivity differences? Scales Research Reports N200421, *EIM Business and Policy Research*.

De Meulenaere, K., Boone, C., & Buyl, T. (2016). Unraveling the impact of workforce age diversity on labor productivity: The moderating role of firm size and job security. *Journal of Organizational Behavior*, *37*, 193–212.

Dwyer, S., Orlando, R., & Shepherd, C. D. (1998). An exploratory study of gender and age matching in the salesperson-prospective customer dyad: Testing similarity-performance predictions. *Journal of Personal Selling & Sales Management*, *18*, 55–69.

Evans, C. R., & Dion, K. L. (2012). Group cohesion and performance: A meta-analysis. *Small Group Research*, *43*, 690–701.

Ferrero-Ferrero, I., Fernández-Izquierdo, M. Á., & Muñoz-Torres, M. J. (2015). Age diversity: An empirical study in the board of directors. *Cybernetics and Systems*, *46*, 249–270.

Gerpott, F. H., Lehmann-Willenbrock, N., & Voelpel, S. C. (2017). A phase model of intergenerational learning in organizations. *Academy of Management Learning & Education*, *16*, 193–216.

Gibson, C., & Vermeulen, F. (2003). A healthy divide: Subgroups as a stimulus for team learning behavior. *Administrative Science Quarterly*, *48*, 202–239.

Gonzalez, J. A. (2016). Demographic dissimilarity, value congruence, and workplace attachment: Asymmetrical group effects. *Journal of Managerial Psychology*, *31*, 169–185.

Google Diversity. (2019). Retrieved from https://diversity.google.

Grund, C., & Westergaard-Nielsen, N. (2008). Age structure of the workforce and firm performance. *International Journal of Manpower*, *29*, 410–422.

Griffin, B., Bayl-Smith, P., & Hesketh, B. (2016). The longitudinal effects of perceived age discrimination on the job satisfaction and work withdrawal of older employees. *Work, Aging and Retirement*, *2*, 415–427.

Guillaume, Y. R., Dawson, J. F., Otaye-Ebede, L., Woods, S. A., & West, M. A. (2017). Harnessing demographic differences in organizations: What moderates the effects of workplace diversity? *Journal of Organizational Behavior*, *38*, 276–303.

Harrison, D. A., & Klein, K. J. (2007). What's the difference? Diversity constructs as separation, variety, or disparity in organizations. *Academy of Management Review*, *32*, 1199–1228.

Harrison, D. A., Price, K. H., & Bell, M. P. (1998). Beyond relational demography: Time and the effects of surface-and deep-level diversity on work group cohesion. *Academy of Management Journal*, *41*, 96–107.

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York: Guilford Publications.

Hogg, M. A., & Terry, D. I. (2000). Social identity and self-categorization processes in organizational contexts. *Academy of Management Review*, *25*, 121–140.

Horwitz, S. K., & Horwitz, I. B. (2007). The effects of team diversity on team outcomes: A meta-analytic review of team demography. *Journal of Management*, *33*, 987–1015.

Johns, G. (2006). The essential impact of context on organizational behavior. *Academy of Management Review*, *31*, 386–408.

Joshi, A., & Roh, H. (2009). The role of context in work team diversity research: A meta- analytic review. *Academy of Management Journal*, *52*, 599–627.

Jungmann, F., Wegge, J., Liebermann, S. C., Ries, B. C., & Schmidt, K. H. (2020). Improving team functioning and performance in age-diverse teams: Evaluation of a leadership training. *Work, Aging and Retirement*, *6*, 175–194.

Keith, M. G., Tay, L., & Harms, P. D. (2017). Systems perspective of Amazon Mechanical Turk for organizational research: Review and recommendations. *Frontiers in Psychology*, *8*, 1359.

King, S. P., & Bryant, F. B. (2017). The Workplace Intergenerational Climate Scale (WICS): A self-report instrument measuring ageism in the workplace. *Journal of Organizational Behavior*, *38*, 124–151.

Kooij, D. T. A. M., De Lange, A. H., Jansen, P. G. W., Kanfer, R., & Dikkers, J. S. E. (2011). Age and work-related motives: Results of a meta-analysis. *Journal of Organizational Behavior*, *32*, 197–225.

Kunze, F., Boehm, S. A., & Bruch, H. (2011). Age diversity, age discrimination climate and performance consequences – A cross organizational study. *Journal of Organizational Behavior*, *32*, 264–290.

Kunze, F., Boehm, S. A., & Bruch, H. (2013). Organizational performance consequences of age diversity: Inspecting the role of diversity-friendly HR policies and top managers' negative age stereotypes. *Journal of Management Studies*, *50*, 413–442.

Lee, H. W., & Kim, E. (2020). Workforce diversity and firm performance: Relational coordination as a mediator and structural empowerment and multisource feedback as moderators. *Human Resource Management*, *59*, 5–23.

Leonard, J. S., Levine, D. I., & Joshi, A. (2004). Do birds of a feather shop together? The effects on performance of employees' similarity with one another and with customers. *Journal of Organizational Behavior*, *25*, 731–754.

Lepak, D. P., & Snell, S. A. (1999). The human resource architecture: Toward a theory of human capital allocation and development. *Academy of Management Review*, *24*, 31–48.

Li, J., Chu, C. W. L., Lam, K. C., & Liao, S. (2011). Age diversity and firm performance in an emerging economy: Implications for cross-cultural human resource management. *Human Resource Management*, *50*, 247–270.

Meyer, B., Shemla, M., Li, J., & Wegge, J. (2015). On the same side of the fault line: Inclusion in the leader's subgroup and employee performance. *Journal of Management Studies*, *52*, 354–380.

Miller, T., & Triana, M. D. (2009). Demographic diversity in the boardroom: Mediators of the board diversity-firm performance relationship. *Journal of Management Studies*, *46*, 755–786.

Mitchell, R., Boyle, B., Parker, V., Giles, M., Chiang, V., & Joyce, P. (2015). Managing inclusiveness and diversity in teams: How leader inclusiveness affects performance through status and team identity. *Human Resource Management*, *54*, 217–239.

Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R2 from generalized linear mixed-effects models. *Methods in Ecology and Evolution*, *4*, 133–142.

Nishii, L. H. (2013). The benefits of climate for inclusion for gender-diverse groups. *Academy of Management Journal*, *56*, 1754–1774.

OECD (2008). Population dynamics and demographics. In *OECD environmental outlook to 2030* (pp. 65–73). Paris: OECD Publishing.

Parry, E., & Urwin, P. (2011). Generational differences in work values: A review of theory and evidence. *International Journal of Management Review*, *13*, 79–96.

Pelled, L. H. (1996). Demographic diversity, conflict, and work group outcomes: An intervening process theory. *Organization Science*, *7*, 615–631.

Pettigrew, T. F., & Tropp, L. (2008). How does intergroup contact reduce prejudice? Meta-analytic tests of three mediators. *European Journal of Social Psychology*, *38*, 922–934.

Posthuma, R. A., & Campion, M. A. (2009). Age stereotypes in the workplace: Common stereotypes, moderators, and future research directions. *Journal of Management*, *35*, 158–188.

PRP. (2015). Aging in the United States. *Population Bulletin*, *70*, 1–19.

Rabl, T., & Triana, M. D. R. (2014). Organizational value for age diversity and potential applicants' organizational attraction: Individual attitudes matter. *Journal of Business Ethics*, *121*, 403–417.

Redman, T., & Snape, E. (2006). The consequences of perceived age discrimination amongst older police officers: Is social support a buffer? *British Journal of Management*, *17*, 167–175.

Reinholt, M. I. A., Pedersen, T., & Foss, N. J. (2011). Why a central network position isn't enough: The role of motivation and ability for knowledge sharing in employee networks. *Academy of Management Journal*, *54*, 1277–1297.

Roberson, Q. M., Sturman, M. C., & Simons, T. L. (2007). Does the measure of dispersion matter in multilevel research? A comparison of the relative performance of dispersion indexes. *Organizational Research Methods*, *10*, 564–588.

Rupert, J., Blomme, R. J., Dragt, M. J., & Jehn, K. (2016). Being different, but close: How and when fault lines enhance team learning. *European Management Review*, *13*, 275–290.

Shore, L. M., Randel, A. E., Chung, B. G., Dean, M. A., Holcombe Ehrhart, K., & Singh, G. (2011). Inclusion and diversity in work groups: A review and model for future research. *Journal of Management*, *37*, 1262–1289.

Shore, L. M., Cleveland, J. N., & Sanchez, D. (2018). Inclusive workplaces: A review and model. *Human Resource Management Review*, *28*, 176–189.

Snape, E., & Redman, T. (2003). Too old or too young? The impact of perceived age discrimination. *Human Resource Management Journal*, *13*, 78–89.

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In H. Tajfel (Ed.), *The social psychology of intergroup relations* (pp. 33–47). Monterey, CA: Brooks/Cole.

Thatcher, S. M., & Patel, P. C. (2012). Group fault lines: A review, integration, and guide to future research. *Journal of Management*, *38*, 969–1009.

Timmerman, T. A. (2000). Racial diversity, age diversity, interdependence and team performance. *Small Group Research*, *31*, 592–606.

Van Knippenberg, D., De Dreu, C. K., & Homan, A. C. (2004). Work group diversity and group performance: An integrative model and research agenda. *Journal of Applied Psychology*, *89*, 1008–1022.

Von Nordenflycht, A. (2010). What is a professional service firm? Toward a theory and taxonomy of knowledge-intensive firms. *Academy of Management Review*, *35*, 155–174.

Wang, Y. A., Sparks, J., Gonzales, J. E., Hess, Y. D., & Ledgerwood, A. (2017). Using independent covariates in experimental designs: Quantifying the trade-off between power boost and type I error inflation. *Journal of Experimental Social Psychology*, *72*, 118–124.

Weber, R. A., & Camerer, C. F. (2003). Cultural conflict and merger failure: An experimental approach. *Management Science*, *49*, 400–415.

Wegge, J., Roth, C., Neubach, B., Schmidt, K. H., & Kanfer, R. (2008). Age and gender diversity as determinants of performance and health in a public organization: The role of task complexity and group size. *Journal of Applied Psychology*, *93*, 1301–1313.

Williams, K. Y., & O'Reilly, C. A. (1998). Demography and diversity in organizations: A review of 40 years of research. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior* (pp. 77–140). Greenwich, CT: JAI Press.

Zanutto, E. L., Bezrukova, K., & Jehn, K. A. (2011). Revisiting fault line conceptualization: Measuring fault line strength and distance. *Quality & Quantity*, *45*, 701–714.

AUTHOR BIOGRAPHIES

Kim De Meulenaere is an assistant professor of HRM, Organizational Behavior, and Organizational Development at the University of Antwerp (Department of Management, Faculty of Business & Economics). Her research focuses on organizational demography and diversity in general, with a particular interest in workforce age demography, the aging workforce, inclusive firms, and employee turnover.

Florian Kunze is a full professor and holder of the chair for Organizational Studies at the department for politics and public administration at the University of Konstanz. His research focuses on the demographic change in organizations, the design of effective leadership behaviors for individuals, teams and organizations and evidence-based human resource management. His research has been published in a wide variety of international journals such as the Academy of Management Journal, Journal of Management, and Journal of Applied Psychology.