Age Inclusive Human Resource Practices, Age Diversity Climate, and Work Ability: Exploring Between- and Within-Person Indirect Effects

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Abstract

To address the challenges imposed by demographic change, organizations have become increasingly interested in maintaining and improving employees' work ability across the working lifespan. Based on signaling and social exchange theories, we present a study that investigates the indirect influence of age inclusive human resource practices on work ability through age diversity climate. Using a six-wave longitudinal study of n = 355 employees, we model between- and within-person mediated effects using a random intercept cross-lagged panel model. The results of this analysis partially support our mediation hypothesis. Specifically, we found evidence that age diversity climate mediates the influence of age inclusive human resource practices on work ability at the between-, but not at the within-person level of analysis. These findings have implications for the development of human resource practices that benefit employees at various ages.

Keywords: human resource practices; age diversity climate; work ability; longitudinal study

Age Inclusive Human Resource Practices, Age Diversity Climate, and Work Ability: Exploring Between- and Within-Person Indirect Effects

In the context of demographic change, understanding the role that organizations play in supporting employees across the lifespan is of growing importance. Answering calls to study how human resource (HR) practices contribute to pro-diversity climates, research has considered linkages between age inclusive human resource practices (AIHRP) and age diversity climate (ADC; Böhm, Kunze, & Bruch, 2014). Specifically, Böhm et al. (2014) demonstrate that, at the company level of analysis, AIHRP are positively related to ADC which, in turn, have a positive influence on performance and a negative influence on turnover through perceptions of social exchange. AIHRP are those organizational practices that foster employees' knowledge, skills, and abilities, motivation and effort, as well as opportunities to contribute -- *irrespective of age* (see Böhm et al., 2010). Furthermore, Böhm et al. (2014) defined ADC as "…perceptions of the fair and nondiscriminatory treatment of employees *of all age groups* with regard to all relevant organizational practices, policies, procedures, and rewards" (p. 671, emphasis added). Thus, both AIHRP and ADC are conceptualized as relevant and potentially beneficial to employees of all ages, across the entire work lifespan, and not just to "older" workers.

With the present study, we aim to address four interrelated goals, each of which contributes to the objectives of (a) extending previous empirical research that has considered links between AIHRP and ADC (Böhm et al., 2014) and (b) developing more dynamic theorizing about relationships between HR policies, organizational climate, and occupational wellbeing. First, whereas past research has primarily considered cross-sectional relationships between AIHRP, ADC, and work outcomes, we examine such relationships over time using a six-wave longitudinal research design conducted across 18-months. In doing so, we model and empirically separate between- and within-person relationships, which cannot be parsed in cross-sectional research designs. Consistent with best practice recommendations (Dormann & Griffin, 2015), we chose a relatively short time lag (i.e., three months) between measurement waves to optimally detect meaningful effects of AIHRP on ADC and work ability.

Second, extending research that has focused on predicting performance and withdrawal behavior, we consider work ability as an outcome of AIHRP and ADC via longitudinal mediation tests. Work ability entails employees' perception of their ability to continue working in their current job, given the characteristics of the job and their personal resources (e.g., health; Ilmarinen, Gould, Järvikoski, & Järvisalo, 2008). Modeling ADC as a mediating mechanism between AIHRP and work ability is important, because this extends research that has directly linked more general HR practices to other work outcomes, such as job attitudes (Kooij, Jansen, Dikkers, & de Lange, 2010). Moreover, despite obvious benefits, there is relatively little research linking climate variables to employee health and wellbeing outcomes (Schulz, Zacher, & Lippke, 2017). To some extent, this observation is tied to a lack of formal theory linking organizational climate to employee wellbeing (see Schneider, Erhart, & Macey, 2013), thus our study also serves to build novel theorizing about such relationships.

Third, we consider perceptions of ADC both inter- and intra-individually, thus extending research that has construed such climate perceptions as collective constructs to the individual level of analysis (i.e., "psychological climate," see Parker et al., 2003). Finally, this study addresses two calls by Böhm et al. (2014) to expand research on ADC to (a) individual-level outcomes and (b) to develop multilevel models of the effects of ADC. To this end, it has been recently suggested that "…age-inclusive human resources practices may also be beneficial to the performance and wellbeing of older workers as well as their employing organizations through their effects on age diversity climate" (Cadiz, Rineer, & Truxillo, 2019, p. 281).Our study answers the calls by Böhm et al. (2014) and, thus, represents the first effort to begin addressing this research question. Importantly, our study was conducted at the between- and within-person levels of analysis, and our measures likewise reflect individual level perceptions.

Next, we review research that has previously investigated AIHRP, ADC, and work ability in more detail. Then, we outline the theoretical rationale, based on signaling (Ostroff & Bowen, 2000; Connelly et al., 2011) and social exchange theories (Blau, 1964), to support our hypotheses.

Age Inclusive Human Resource Practices (AIHRP) and Age Diversity Climate (ADC)

Whereas research has focused on how age differentially dictates the effectiveness of general HR policies (i.e., without reference to age specifically, such as the provision of performance appraisals; Kooij et al., 2013), AIRHP represent those policies which would be most beneficial to most employees across the entirety of their working lifespans (i.e., rather than focusing on how general HR policies policies may be differentially relevant to workers of different ages). An existing body of evidence has found positive relationships between AIHRP and ADC at different levels of analysis. As alluded to previously, Böhm et al. (2014) studied the influence of AIHRP on firm-level outcomes (i.e., performance and turnover) via ADC. Drawing upon Kopelman's climate model of firm productivity (Kopelman, Brief, & Guzzo, 1990) and Cox's (1994) model of cultural diversity in organizations, this study found that AIHRP positively affects firm-level performance and (reduced) turnover via ADC and collective perceptions of social exchange. Similarly, however at the dyad-level of analysis, Burmeister, van der Heijden, Yang, and Deller (2018) drew upon the relational model of HR management (Mossholder, Richardson, & Settoon, 2011) to study links between AIHRP and knowledge sharing via ADC.

This study finds that AIHRP are positively associated with age-diversity climate, which, subsequently, positively influence knowledge sharing processes.

Despite the growing evidence for positive relationships between AIHRP and ADC, no studies have considered person-level (i.e., concurrent between- and within-person) effects of AIHRP and ADC. Moreover, despite research that has linked AIHRP to ADC, no studies have considered occupational health and wellbeing outcomes (such as work ability) of AIHRP via ADC. These observations are symptomatic of a more general gap in our understanding of how structural (e.g., HR policies) and psychological (i.e., perceived work climate) factors influence employee wellbeing. Indeed, although research has found links between features of organizational climate and employee health (e.g., Arnetz, Lucas, & Arnetz, 2011), there exists a lack of formal theory to guide such research efforts. Thus, our study contributes to an extended understanding of these relationships, and should likewise inform the extension and formalization of theories to include explicit predictions about the indirect relationships between HR policies and employee wellbeing via psychological climate (e.g., Zacher, Kooij, & Beier's, 2018, conceptualization of "active aging" at work implicates HR policies, resulting climates, and health and wellbeing for employees).

Work Ability

Work ability refers to employees' perceived ability to continue in their current job role, considering the characteristics and demands of that role, against their available personal resources, and especially including health (Ilmarinen, 2009; Ilmarinen & Ilmarinen, 2015). Recently, Rudolph and McGonagle (2018) have argued that understanding the antecedents of work ability is important, because it represents an important health-related outcome that has bearing on more distal work-related processes (e.g., workforce disengagement; departure). Given previous research that has linked AIHRP and ADC to turnover (Böhm et al., 2014), we would argue that work ability is an import, proximal, and person-level variable to consider in this linkage. Moreover, understanding the antecedent conditions that lead to change in work ability is important to design interventions that effectively promote work ability and work longevity (see Cadiz, Brady, Rineer, & Truxillo, 2018). We use the term "interventions" broadly here, as we think it would be reasonable to argue that the adoption of AIHRP represent more-or-less formal attempts by organizations to intervene in ways that improve the quality of the work environment at least partial to the benefit of health-related outcomes, such as work ability. Speaking to this, Brady (2016) offers meta-analytic evidence for relationships between features of the work environment (e.g., job demands and resources) and work ability. Importantly here, perceptions of injustice (i.e., those which AIHRP would be geared towards reducing) are negatively related to work ability (r_{xy} = -.29). This evidence serves as a basis to begin building hypotheses about relationships between AIHRP and work ability (See also Brady, Truxillo, Cadiz, & Rineer, 2019).

Conceptually, work ability is understood to exist and develop across different levels of analysis, and to have an ecological grounding (e.g., refer to Ilmarinen's, 2009, "house model" of work ability) that considers influences from one's work environment and work organization. While largely heuristic, this model suggests that the development of work ability is a dynamic process. Thus, understanding both the stable and dynamic components of work ability is especially important in efforts to understand its etiology. Importantly, in a daily diary study, Rudolph and McGonagle (2018) demonstrate that as much as 44% of the day-to-day variability in work ability occurs within-person, and concurrently call for research to consider within-person predictors of work ability across longer timeframes.

Stable and Dynamic Effects of AIHRP, ADC, and Work Ability

In our six-wave longitudinal study, we conceptualized both stable (between-person) and dynamic (within-person) effects of AIHRP on ADC and work ability. As a reflection of rather stable features of one's work environment, it is likely that AIRHP will, to some extent, exhibit relative stability over time, manifesting as relatively stable between-person effects. At the same time, work policies are not necessarily universally applied nor adhered to, even those that are more-or-less formalized and sanctioned by organizations (e.g., because of leaders' varying support for such polices; Buengeler, Leroy, & De Stobbeleir, 2018). Research has for some time considered how over time variation in perceptions of HR polices associated with various work outcomes (e.g., extra role behavior, Knies & Leisink, 2014; commitment, Morris, Lydka, O'Creevy, 1993; firm performance Saridakis, Lai, & Cooper 2017). In this tradition, we anticipate that especially perceptions of AIHRP will be likely to vary to some degree within-person and over time and have a concomitant influence on both ADC and work ability. Just as stable levels of AIHRP would likely relate to one's general sense of ADC and work ability, dynamics in AIHRP are likely to have an influence on work ability, and especially so through their influence on variation in ADC.

If, for example, employees perceive a positive "shift" in AIHRP over time (e.g., recognize that their employer has recently adopted more age-inclusive practices, broadly defined), this would serve as an indication that their organization is paying more attention to, and dedicating resources toward, those issues that are especially likely to influence employees' long-term employability and career success (e.g., their ability to balance job demands against functional capacities, such as is captured by work ability). To explain why such effects are likely to occur, we consider ADC as an intermediary (i.e., mediating) mechanism, under the assumption that any within-person dynamics in AIHRP (i.e., increases or decreases in perceived AIHRP) would especially manifest as increases (or decreases) in ADC, which would then affect subsequent levels of work ability. To further explain the basis for these arguments, we next turn our attention to theoretical justifications (based upon signaling and social exchange theories) to support our hypotheses.

Theory and Hypotheses

Making predictions about dynamic phenomena requires one to match theory to the appropriate level of analysis (Kozlowski & Klein, 2000). As suggested, past research at the firm- and dyad-level has variously hypothesized relationships between AIRHP and ADC from the climate model of firm productivity and the relational model of HR management, respectively. Because we posit relationships that exist at the between- and within-person levels of analysis, our theoretical model is grounded in signaling and social exchange theory, and is supported by earlier research that has linked HR policies to work climates (e.g., Den Hartog, Boselie, & Paauwe, 2004; Kopelman, Brief, & Guzzo, 1990). From the perspective of signaling theory (Ostroff & Bowen, 2000; Connelly et al., 2011), HR policies are important "signals" of an organization's intentions toward its employees. Organizational members interpret such signals, which inform a process of sensemaking wherein climate perceptions are formed. Likewise, social exchange theory (Blau, 1964) would predict that employees who perceive higher levels of AIHRP (e.g., opportunities for training and development for people of all ages) may in turn be more likely to act in ways that support age inclusivity at work in general, and may exhibit behaviors that contribute to a positive ADC (e.g., taking active steps to make sure that people from different age groups "fit in" and are accepted at work). Thus, to the extent that HR policies are age inclusive, employees are likely to form positive perceptions of their organization's ADC.

Hypothesis 1: Age inclusive HR practices are positively related to age diversity climate.

Likewise based on propositions from signaling theory (Ostroff & Bowen, 2000; Connelly et al., 2011) and social exchange theory (Blau, 1964), we argue that AIHRP are positively related to work ability (e.g., Tuomi, Vanhala, Nykyri, & Janhonen, 2004; McGonagle, Fisher, Barnes-Farrell, & Grosch, 2015). Employees who perceive that their organization implements AIHRP should be more likely to believe that they have sufficient resources to meet their work demands, as captured by work ability. Consistent with this assumption, previous research has drawn links between HR policies and (higher levels of) employee health and wellbeing (e.g., Guest, 2002; Kooij et al., 2013). In addition, research has more generally linked positive features of the work environment to work ability (e.g., Brady, 2016; Brady et al. 2019). Of particular note here, a recent study by Sousa, Ramos, and Carvalho (2019) finds a positive relationship between AIHRP and work ability.

Hypothesis 2: Age inclusive HR practices are positively related to work ability.

As suggested, we expect that these positive relationships will manifest at both the within- and between-person levels of analysis. That is to say that there will be unique, and independent effects of AIHRP on ADC and work ability reflecting both cross-temporal variability (within-person), and relative stability (between-person) over time. Again, we expect this to be the case based on signaling theory, as it is likely that perceptions of the how consistently (or, perhaps inconsistently) one perceives the application of AIHRP over time would have an influence on one's perceptions of ADC, and ultimately their work ability. Indeed, if one is receiving "mixed signals" about the value of, and formalized support for, age inclusiveness, this will likely affect perceptions of ADC and ultimately be reflected in work ability. Our longitudinal study allows us to tease apart these independent facets of this proposition.

In general, climate theories do not provide much guidance for the development of hypotheses about relationships between psychological climate (e.g., ADC) and employee wellbeing (e.g., work ability). Consequently, although research exists linking work climates to wellbeing (e.g., Arnetz et al., 2011), theoretical support for the linkage between psychological climates to employee health outcomes is rather scant. Moreover, although research has linked perceptions of supportive organizational climates to work ability (Feldt et al., 2009; Schulz et al., 2017), little research has linked age diversity climate specifically to work ability. Indeed, we could only locate one study (Rineer, 2015) that has investigated, and consequently demonstrated a positive relationship between age diversity climate and work ability. Rineer (2015) uses a resource-based argument to suggest that age diversity climate constitutes a contextual resource that benefits work ability, because it enhances desirable cognitive and affect states.

More broadly, research has indicated that similar psychological climate variables (e.g., safety climate, Clarke, 2010) are linked to employee health and wellbeing outcomes. Grounded in arguments regarding the influence of stress on health, Clarke (2010) argues that positive (negative) perceptions of the work environment lead to the experience of lower levels (higher levels) of stress and consequently increased (reduced) wellbeing. Extrapolating to the constructs presently considered, perceiving one’s work environment to have a positive (negative) age diversity climate is likely associated with higher (lower) indicators of one’s wellbeing, including work ability. Similarly, although conceptualized in a different domain (i.e., cultural diversity), Cox (1994) argues that diversity climates should have proximal influences on individual-level work outcomes (e.g., job performance) that have some bearing on one’s work ability (i.e., insomuch as one’s capacity to meet their work demands is by-and-large dependent on their capacity for acceptable levels of job performance). More recent empirical evidence likewise suggests that perceiving age discrimination at work (i.e., which would be indicative of a poor ADC) can have negative consequences for health and wellbeing (Marchiondo, Gonzalez, & Williams, 2019). Research has likewise shown evidence for relationships between perceptions of age diversity and employee health (Liebermann, Wegge, & Jungmann, 2013).

Hypothesis 3: Age diversity climates are positively related to work ability.

In terms of a theoretically grounded explanation linking AIHRP to work ability via ADC, we again borrow from signaling and social exchange theories. Specifically, from a signaling theory perspective, a positive ADC signals to employees that their participation in their organization is valued, regardless of their age. From this perspective, ADC could signal the expectation that employees will take steps to support their long-term employability (i.e., especially by leveraging resources afforded by their organization's AIHRP, such as seeking out training or development opportunities, or seeking out promotions to further their career). Similarly, social exchange theory would predict that employees who perceive that age diversity is valued by their organization become more committed to the prospects of long-term employability therein and are likewise more likely to invest in efforts to maintain their capacity to do so, perhaps by taking proactive steps towards bolstering their work ability. Collectively, these predictions ground our hypothesis of a mediated relationship, whereby the influence of AIHRP on work ability is transmitted by ADC.

Hypothesis 4: Age inclusive HR practices are positively and indirectly linked to work ability through age diversity climate.

Based upon the same rationale offered above, we expect that positive indirect relationships between AIHRP and work ability via ADC will manifest at both the within- and between-person levels of analysis. That is to say that there will unique, and independent mediated effects of AIHRP on work ability through ADC, reflecting both an over-time (within-person) causal process, and one that reflects the relative stability (between-person) of this process, over time.

Method

Data for this study came from a panel of n = 355 full-time employed German respondents (n = 222 males, n = 133 females; M_{age} = 44.02 years, SD_{age} = 11.82 years, range = 21 to 71 years; $M_{org.\ tenure}$ = 12.37 years, $SD_{org.\ tenure}$ = 10.76 years, range = <1 to 51 years). The age distribution of our sample is comparable to other studies investigating the role of age in the work context and allows conclusions to be drawen about the role of AIHRP, ADC, and work ability across the work lifespan (i.e., typically between 18 and 70 years; see Bohlmann, Rudolph, & Zacher, 2018). Respondents from multiple industries and occupations representing all 16 German states were invited to participate, and there were no quotas placed on our sampling strategy (e.g., for age, gender, industry, location.).Respondents worked on average M = 39.14 (SD = 4.08) hours/week. Considering highest levels of educational attainment, n = 26 (7.32%) of respondents held lower secondary school degrees, n = 97 (27.32%) held secondary school degrees, n = 74 (20.85%) held high school degrees, n = 26 (7.32%), and n = 132 (37.18%) held undergraduate or graduate university degree. Moreover, participants were employed in a wide array of industries, represented by a variety of job types (e.g., positions in education, research, skilled trades, and healthcare). On a scale ranging from 1 = “entry-level positions” to 7 = “highest achievable employment in your company,” the modal category was 4 (n = 114; 32.11%, M = 3.97, SD = 1.47). Additionally, n = 112 (31.55%) reported having supervisory responsibilities at work.

Respondent completed six surveys, each separated by a time lag of three months (i.e., as has been recommended to optimally detect meaningful effects, see Dormann & Griffin, 2015). Data were collected in July and October 2017 (T1, T2) and January, April, July, and October 2018 (T3-T6). We commissioned a panel management and online research company to recruit participants for this study. Participants were compensated by the company for their time. To ensure sample quality, the company recruits its participants using a variety of sources, from online communities and news portals to members-get-members campaigns, social media campaigns, and invitations after in-person interviews. All panelists register triple-opt-in and are deemed active according to ISO standards. This study was approved by BLINDED FOR PEER REVIEW University's Ethical Review Committee (No. 2019.06.25_eb_16, Study Title: Longitudinal Study on Work, Aging and Health). The data presented in this article were part of a larger data collection effort. So far, no other article based on this dataset has been published.

As is typical with longitudinal survey research, we observed some degree of attrition across the six waves of our study. Initially, n = 1,152 people began the survey, and n = 925 completed the Time 1 (T1) survey; complete T1 responders were then invited to participate in subsequent waves, with additional attrition noted over time (i.e., n_{T2} = 733; n_{T3} = 618; n_{T4} = 469; n_{T5} = 388). Ultimately, at T6, we observed n = 355 complete respondents, who constitute the panel considered in the analyses presented in support of our hypothesis tests, reported below.

Questions of selection bias emerge in longitudinal studies if the pattern of attrition over time is observed to be systematic (e.g., dependent upon other variables within one's model). To rule out this possibility, we conducted a series of independent samples t-tests, comparing T1 levels of AIHRP, ADC, and work ability between the n = 355 panel responders and the n = 570 "other" responders (i.e., those who provided responses to *at least* one time point; n_{total} = 925).

We observed no statistically significant differences between panel responders and “other” responders for AIHRP, $t_{(923)} = -0.27$, $p = .79$, $d_{\text{Cohen's}} = -0.02$, ADC, $t_{(923)} = -0.65$, $p = .516$, $d_{\text{Cohen's}} = -0.04$, and work ability, $t_{(933)} = 0.03$, $p = .98$, $d_{\text{Cohen's}} < 0.01$. Thus, we are confident that, at least with respect to average T1 differences on our focal constructs, attrition was not an overwhelming concern.

To strengthen our confidence in this conclusion, we likewise followed the advice of Goodman and Blum (1996) and specified a model, in which we regressed the pattern of attrition onto substantive variables measured at T1. To do accomplish this, we specified a multinomial logistic regression model in which patterns of attrition (i.e., a six-level categorical variable, representing “T1 only responders,” “T1 and T2 responders,” etc.) were regressed onto participant’s T1 levels of AIHRP, ADC, and work ability. Full results of this analysis are available from the first author, however, in summary, this model did not fit significantly “better” than a null model (i.e., an “intercept only” model, specified without any predictors; $\chi^2_{(15)} = 23.244$, $p = .079$).

We also conducted a supplementary attrition analysis, considering whether participant demographics (i.e., age, gender, and organizational tenure) predicted attrition over time, using the same multinomial logistic regression framework described above. In summary, we found evidence that gender, but not age or organizational tenure, accounted for patterns of attrition over time in our sample. However, we noted that the amount of variance explained by gender in such patterns was quite small (i.e., < 3.0%; $R^2_{\text{McFadden-Adjusted}} = 0.02$). Collectively, we take this as evidence that initial levels of the substantive variables considered in our focal analyses cannot differentiate patterns of attrition over time in our sample, and demographic factors account for only small amounts of variance in such patterns, which further bolsters our confidence that selection bias, in the form of systematic attrition and with respect to observed variables, was not a large issue here. Still, to bolster confidence in our conclusions, we chose to construe gender as a covariate (among others) in a sensitivity analysis, described below.

Measures

Age inclusive human resource practices. We measured AIHRP with the five-item scale developed and validated by Böhm et al. (2014). Example items include, "With how much intensity does your company … offer equal access to training and further education for all age groups?" and "…offer equal opportunities to be promoted, transferred, and to make further career steps irrespective of one's age?" Responses on these five items were collected on a scale anchored with 1 = "very low intensity" and 5 = "very high intensity." Across all six time points, the average coefficient alpha was $\bar{\alpha}$ = .92 (*S.D.* = .01, Range .89 to .94), suggesting adequate reliability.

Age diversity climate. We measured ADC with the four-item scale developed and validated by Böhm et al. (2014). Example items include, "Our company makes it easy for people from diverse age groups to fit in and be accepted" and "Where I work, employees are developed and advanced without regard to the age of the individual." Responses on these five items were collected on a scale anchored with 1 = "strongly disagree" and 5 = "strongly agree." Across all six time points, the average coefficient alpha was $\bar{\alpha}$ = .92 (*S.D.* = .02, Range .89 to .92), suggesting adequate reliability.

Work ability. We measured work ability with the four-item scale developed and validated by McGonagle et al. (2015). The items are "How many points would you give your current ability to work?" and "Thinking about the [physical, mental, interpersonal] demands of your job, how do you rate your current ability to meet those demands?" Responses on these items were collected on a scale anchored with 0 = "cannot currently work at all" and 10 = "work ability at its lifetime best." Across all six time points, the average coefficient alpha was $\bar{\alpha}$ = .93 (*S.D.* = .01, Range .92 to .94), suggesting adequate reliability.

Analyses

Selig and Preacher (2009) outline an approach to testing mediated effects in fully crossed and lagged longitudinal research designs. This approach is an extension of the standard two-variable cross-lagged panel model (CLPM; see Liu, Mo, Song, & Wang, 2016) to three variables, representing independent, mediating, and outcome variables, respectively, and with each measured across time. In addition to specifying such a model here, we additionally adopt the more recent random-intercept cross-lagged panel model (RI-CLPM) introduced by Hamaker, Kuiper, and Gasman (2015). Unlike a standard CLPM, the RI-CLPM has the advantage of parsing between- and within-person variance across time. Because they cannot model person-level (i.e., between-person) effects, traditional CLPMs have been criticized for inflating within-person (cross-lagged) relationships, by conflating within-person with between-person sources of variance (e.g., Berry & Willoughby, 2017). Organizational research has previously adopted the RI-CLPM to effectively parse within-person with between-person sources of variance (e.g., Bednall, Rafferty, Shipton, Sanders, & Jackson, 2018). The RI-CLPM is an appropriate analytic approach for testing our hypotheses using longitudinal data, as we assume that our focal constructs vary at both the between-person (i.e., interindividual differences) and the within-person level (i.e., intraindividual changes over time). The RI-CLPM allows us to concurrently examine these, as well as cross-lagged, potential reverse, reciprocal, and indirect effects, making it an optimal strategy for our analysis.

Results

Descriptive statistics and correlations among the study variables can be found in Table 1.

Confirmatory Factor and Measurement Invariance Analyses

Before specifying models to test our hypotheses, we first specified a series of CFA models to (a) demonstrate the appropriateness of separating measures of our focal constructs, and (b) explore the equivalence of these measures across the six time points of our study. To the first point, we specified five CFA models based on T1 data to explore the factor structure of AIHRP, ADC, and work ability. We specified and contrasted the fits of one 1-factor model (i.e., combining AIHRP, ADC, and work ability), three 2-factor models (i.e., combining measures of AIHRP and ADC, AIHRP and work ability, and ADC and work ability), and one 3-factor model (i.e., specifying AIHRP, ADC, and work ability as separate constructs). Given observed deviations from normality, these and all subsequent models reported here were specified with a robust maximum likelihood estimator (i.e., \`MLR\` in \`lavaan\`, Rosseel, 2012). Unless otherwise noted (i.e., for tests of indirect effects, described below), we report robust (i.e., Huber-White) standard errors for parameter estimates (Freedman, 2006), and Yuan-Bentler scaled test statistics (Yuan & Bentler, 2000). All tests of nested models are based upon Satorra-Benter scaled difference tests (Satorra & Bentler, 2001), and we likewise report appropriately scaled variants of supplementary fit indices (i.e., CFI, TLI, and RMSEA). In summary, the three-factor model had the best fit to the data ($\chi^2_{(62)}$ = 207.33, CFI = .96, TLI = .95, RMSEA = .07, SRMR = .04), and no other model that we specified fit the data well. We additionally considered a series of multilevel CFA models, which differentiated between- and within-person variability in these constructs. Mirroring the conclusions drawn from the T1 CFA models, a three-factor model had the best fit to the data ($\chi^2_{(124)}$ = 514.81, CFI = .96, TLI = .95, RMSEA = .04, $SRMR_{Within}$ = .02, $SRMR_{Between}$ = .05), and no other model that we specified fit the data well. All together, these results suggest that conceptualizing these three measures separately in our subsequent models is appropriate. Table 2 summarizes the fit of these CFA models.

To the second point, we ran a series of measurement invariance analyses, based upon the suggestions of Vandenberg and Lance (2000) and Putnick and Bornstein (2016). Specifically, for each substantive measure, we fit three measurement models across all six time points. First, a model was specified to allow the same factor structure to be imposed across time (i.e., configural invariance). Second, a model was specified in which the factor loadings were constrained to be equal across time (i.e., "weak factorial" or "metric" invariance). Finally, the third model specified factor loadings and intercepts that were constrained to be equal across time (i.e., "strong factorial" or "scalar" invariance). Across these models, we observed changes in chi-square ($\Delta\chi^2$), and changes in CFI and RMSEA as evidence of (in)variance. For all models, except for AIHRP (for which only evidence for weak factorial invariance was observed), strong measurement invariance was upheld (see Table 3). Thus, we are confident that our models are invariant, at least with respect to the factor structures that represent each latent variable over time. Further supporting conclusions of such invariance over time, ΔCFI and ΔRMSEA observed across all models were no less than .01 and no greater than .015, respectively (Chen, 2007; Cheung & Rensvold, 2002; see Table 3).

Hypothesis Tests

To test our hypotheses, we considered three competing structural equation (SEM) models. Of note, as the RI-CLPM is a generalization of the CLPM, all models presented here could be specified by placing constraints on the more general RI-CLPM by variously fixing or freeing parameters (e.g., those parameters defining random intercepts). To simplify model specification, manifest variables representing scale-level means of AIHRP, ADC, and work ability at each time point were used in this analysis. Also serving parsimony, all over-time parameters (i.e., autoregressive and cross-lagged effects) were specified to be time-invariant in each of the models described next. We justified this decision based upon comparing the fit of an unconstrained (i.e., time variant, with respect to auto-regressive and cross-lagged pathways) version of our focal RI-CLPM to a constrained (i.e., time invariant, with respect to the same parameters) version of this model (i.e., described in more detail below). In summary, the time invariant model did not fit the data significantly differently than the time variant model ($\Delta\chi^2_{(38)}$ = 50.99, p = .08), thus justifying the restriction of over-time parameters to equality. Where relevant, we imposed different patterns of constraints on the over-time parameters to allow for the specification of mediated effects. Bootstrapping is a common practice for ascertaining asymptotically-appropriate standard errors to facilitate statistical significance testing of mediated effects. However, bootstrapping is not possible when using the `MLR` estimator in `lavaan`. Thus, we apply the Monte Carlo method to assessing mediation here (MCMAM; MacKinnon, Lockwood, & Williams, 2004; Preacher & Selig, 2012), each estimated with 5,000 re-samples. We describe our model specification process in more detail, below.

First, we specified a CLPM (Model 1), with time invariant auto-regressive and cross-lagged paths between AIHRP, ADC, and work ability. Of note, the CLPM is essentially a restricted form of the RI-CLPM described below, in which the random intercepts for each substantive variable assessed over time are not estimated (i.e., fixed at, and assumed to be, zero). Second, we re-specified this CLPM (Model 2), relaxing restrictions on the cross-lagged parameters to allow for an over-time mediated effect to be modeled (i.e., see Selig & Preacher, 2009). Specifically, to identify ‘a’ and ‘b’ paths for testing this process, we constrained time adjacent cross-lagged parameters (i.e., a-paths linking AIHRP at time t to ADC at time t+1, b-paths linking ADC at t+1 to work ability at t+2). We likewise specified 'direct' paths (i.e., c'-paths linking AIHRP at time *t* to work ability at time *t*+2; see Figure 2).

Third, we specified our focal RI-CLPM (Model 3) following specifications suggested by Hamaker and colleagues (i.e., Hamaker, Kuiper, & Grasman, 2015). The most important difference between this model and the second CLPM model tested is that the RI-CLPM estimates random intercepts for each substantive variable measured over time (i.e., AIHRP, ADC, and work ability; see Figure 1). This specification allows for the separation of between- from within-person effects in this model; relationships among random effects are interpreted as unique between-person effects, whereas auto-regressive and cross-lagged effects are interpreted as unique within-person effects. As before, this model was specified to allow for an over-time within-person mediated effect (i.e., in terms of adjacent cross-lagged parameters, as described in our description of Model 2, above). Moreover, to simultaneously capture the between-person mediated effect, we additionally specified directional parameters between random intercepts, linking between-person AIHRP to work ability via ADC. Figure 1 depicts those parameters derived from this model that are most relevant to the hypotheses tested here.

Fit indices for all three of these models can be found in Table 4. Model 3, the RI-CLPM that concurrently specified between- and within-person mediated effects, fit the data best ($\chi^2_{(142)}$ = 169.59, p = .06, CFI = .99, TLI = .99, RMSEA = .02, SRMR = .04), and fit significantly better than Model 1 ($\Delta\chi^2_{(8)}$ = 411.75, p = <.001) and Model 2 ($\Delta\chi^2_{(6)}$ = 380.200, p = <.001). As such, we focus primarily on this Model 3 here, however note important patterns in the results of the other models, where relevant. Table 5 summarizes the relevant parameter estimates for Model 3.

With respect to our hypothesized relationships, recall that Hypothesis 1 offers that AIHRP are positively related to ADC (i.e., the "a-path" of our model), Hypothesis 2 suggests that AIHRP are positively related to work ability (i.e., the “c′-path” of our model), and Hypothesis 3 proposes that ADC is positively related to work ability (i.e., the “b-path” of our model). Finally, combining these predictions, Hypothesis 4 considers whether ADC mediates the relationship between AIHRP and work ability. Both Model 2 and Model 3 specify mediated effects, so we consider these relationships in turn. Of note, we report unstandardized (i.e., raw metric) coefficients, *B*, for all parameter estimates described below.

First, if we consider the mediated effect specified in Model 2 (momentarily suspending judgement about the fit of this model to the data), we noted significant “a-path” ($B = 0.14$, $SE_B = .03$, $p = < .001$) and “b-path” ($B = 0.22$, $SE_B = .05$, $p = < .001$) relationships, but not “c′-path” relationships ($B = -0.01$, $SE_B = .04$, $p = .759$). Moreover, the indirect effect was statistically significant ($B_{ab} = 0.030$; MCMAM 95% CI: 0.013 *to* 0.049). These findings suggest support for our hypotheses. However, because this model does not separate the within- versus between-person nature of this mediated effect, the nature of this effect is quite obfuscated (i.e., cannot be unambiguously attributed to either between- or within-person sources of observed variance). Thus, we next consider parameters from the RI-CLPM (Model 3), which appropriately separates between- from within-person sources of observed variance.

Second, considering the interpretation of relevant within-person parameters from the RI-CLPM (Model 3), cross-lagged parameters reflect whether within-person changes in one variable are predicted by the deviation from one’s own expected scores on another variable assessed earlier in time. Within this model, neither the “a-path” ($B = 0.06$, $SE_B = .04$, $p = 0.15$), the “b-path” ($B = -0.03$, $SE_B = .08$, $p = 0.75$) nor the “c′-path” were statistically significant ($B = < 0.01$, $SE_B = .05$, $p = .95$) (see Table 5). Additionally, the within-person indirect effect was likewise not statistically significant ($B_{ab} = -0.001$; MCMAM 95% CI: -0.017 *to* 0.007).

Considering the interpretation of relevant between-person parameters from the RI-CLPM (Model 3), directional relationships between the latent variable representing random intercepts reflect whether between-person differences in one construct are associated with between-person differences in another construct, irrespective of the within-person effects. Within this model, the "a-path" ($B = 0.037$, $p < 0.001$), "c′-path" ($B = - 0.96$, $SE_B = .22$, < 0.00), and the "b-path" ($B = 1.494$, $p < 0.001$) were each statistically significant. Notably, this evidence can be taken as partial support for Hypotheses 1, 2, and 3 respectively. Moreover, supporting evidence for between-person mediation, the indirect effect was also statistically significant ($B_{ab} = 0.198$; MCMAM 95% CI: 0.948 *to* 1.711), suggesting that inter-personal perceptions of ADC translate AIHRP into work ability. Thus, Hypothesis 4 was likewise partially supported as well. This model explained $R^2 = 25.60\%$ of the between-person variance in work ability, and about $R^2 = .01\%$ of the within-person variance in work ability.

Supplemental Analyses

To understand why we observed between-person, but not within-person mediated effects of AIHRP on work ability through ADC, we ran a series of supplemental analyses to better understand the nature of between- and within-person variability in these variables, and to address the possibility of more systematic linear and non-linear changes in these variables over time. We specified these follow-up analyses using a mixed effects (i.e., "random coefficients"; see Bliese & Ployhart, 2002) modeling framework (i.e., via the `lme4` package for R; Bates, Maechler, & Bolker, 2011), as it allows for a parsimonious and intuitive means of decomposing variance explained (i.e., R^2) into unique between- and within-person contributions. Of note, when parameterizing time in a substantive way, such models are equivalent to the approach of growth modeling using scale-level indictors in an SEM framework (Bliese & Ployhart, 2002). Table 6 presents the between- and within-person correlations among the variables AIHRP, ADC, and work ability, as well as ICC_1 and ICC_2 estimates. We specified three models, each of which considered work ability as the outcome. Prior to specification, we person mean centered AIHRP and ADC into orthogonal within- and between-person variance components (see Bolger & Laurencau, 2013, pp. 77-78). Each model specified a respondent-level random effect to account for the nesting of observations within-person and over time, and all predictors were entered into these models as fixed effects.

First, to understand the role that AIHRP plays in explaining variability in work ability, we regressed work ability onto between- and within-person AIHRP, and the interactions of time and time^2 with between- and within-person AIHRP. Time was parameterized as 0,1,3,4,5, such that the intercept represents initial, or “time one” levels. Moreover, in this model time and time^2 were specified as orthogonal power polynomials. Second, we followed this model up, this time treating ADC as the predictor, again regressing work ability onto between- and within-person ADC, and the interactions of time and time^2 with between- and within-person ADC. These two models are described fully in Table 7. In summary, unique between-and within-person effects of AIHRP and ADC were observed in both models; higher levels of both between- and within-person AIHRP and ADC were positively associated with work ability. This suggests that both peoples’ average levels of AIHRP and ADC, as well as variability (i.e., positive and negative deviations from average levels) around those average levels over time, have appreciable bearing on the prediction of work ability. However, we noted no systematic effects of time, or conditional effects of time-by-predictors in either model. Thus, there were no systematic temporal patterns (linear or quadratic trajectories) associated with these effects.

We additionally conducted an analysis that considered chronological age as a moderator of time-by-AIHRP and time-by-ADC effects on work ability. In summary of this model, although we do not find evidence that age moderates time-by-AIHRP or time-by-ADC effects on work ability, we do find that within-person variability in AIHR interacts with age to predict work ability. The nature of this effect is such that the work ability of relatively older workers seems to especially benefit from increases (i.e., positive deviations from average levels) in AIHRP. These analyses are presented in our online appendix (https://osf.io/gr8j3/, See Table A1-2, and Figure A1).

Third, given that no systematic main or conditional effects of time or time^2 were observed in either model described immediately above, we ran a model in which work ability was regressed on between- and within-person AIHRP and ADC concurrently, as a means of decomposing the relative contributions of between- and within-person AIHRP and ADC to the prediction of work ability. From this model we derived estimates of pseudo-R^2 using formulae provided by Snijders and Bosker (2012); these estimates represent the amount of variance explained in work ability at the between- and within-person levels of analysis. To parse the unique contributions of these predictors at both levels of analysis, we conducted a multilevel dominance analysis, following the suggestions of Luo and Azen (2012). This model is elaborated in Table 8.

In summary, this model explained R^2=14.28% of the within-person, and R^2= 19.47% of the between-person variance in work ability. At the within-person level of analysis, 89.67% of this explained variance was attributable to between-person predictors, whereas at the between-person level of analysis 99.99% of the explained variance was attributable to between-person predictors. Thus, although both within- and between-person levels of AIHRP and ADC contribute meaningfully to the prediction of work ability over time, overwhelmingly these relationships are accounted for by between-person predictors (i.e., person average levels). Considering the individual dominance weights further, the strongest single predictor of work ability was between-person ADC, which accounted for R^2=10.02% of the within-person and R^2=15.24% of the between-person variance in work ability observed here.

We also noted that between-person AIHRP and ADC are strongly correlated (r_{xy} = .84; see Table 6) and that the direction of the partial regression coefficient representing AIHRP "sign changes" compared to its zero-order counterparts (see Tables 7 and 8). Importantly, this observation cannot be solely attributed to the strength of this correlation, as the largest variance inflation factor observed here was *VIF* = 3.30 (see Table 8), suggesting that multicolinearity is not of principal concern. We also note that the direction of this relationship has little bearing on variance explained estimates (i.e., R^2), and as such is not of consequence to our dominance analysis. Nonetheless, the associated parameter estimates, among between-person levels of AIHRP and ADC and work ability should be interpreted with some caution, either as an artifact of an underlying simultaneous relationship between these predictors that manifest as a suppressor effect, or perhaps as an indicator of some unmeasured, omitted "third variable" that underlies both relationships. Speculatively, it is likely that as people perceive higher levels of AIHRP, they also tend to experience more favorable ADCs. As such, AIHRP and ADC tend to co-occur with one another, and this relationship is relatively stable over time (i.e., as this is reflected in the strength of this relationship at the between-person level of analysis). Thus, these supplemental analyses should serve as a call for future research to further unpack the complexities of these relationships, and especially focus on the emergence of ADC over time. We provide additional thoughts on this matter in our discussion, below.

Finally, we considered whether age moderated the effects of individual AIHR policies (i.e., the five items that comprise the AIHRP scale) on work ability. In summary of this model, we found no evidence that any age-by-AIHR policy interaction predicted work ability, which suggests that there are no appreciable age-differentiated effects of individual AIRHPs to speak of. For complete results of this analysis, please refer to our online appendix (https://osf.io/gr8j3/; See Table A3).

Sensitivity Analysis

We additionally conducted a sensitivity analysis to the robustness of our findings to three covariates, each construed at T1. Specifically, we considered health (i.e., as assessed by the SF-12 physical component score; Ware, Kosinksi, & Keller, 1996) and organizational tenure as covariates in this analysis. Additionally, given that our supplemental attrition analysis suggested that gender could differentiate patterns of attrition, we also considered it as a covariate. In summary of this analysis, adding Time 1 health, organizational tenure, and gender as covariates to the RI-CLPM significantly *reduced* the fit of the model to the data when compared to the fit of our focal model (i.e., the inclusion of covariates increased the χ^2 relative to the model without covariates: $\boldsymbol{\Delta}\chi^2_{(51)} = 70.00$, p = .04). More importantly, the parameter estimates were substantively equivalent in this model, compared to our focal model. Accordingly, we consider the results of our focal model to be a better representation of these data, and our results to be robust (i.e., not sensitive) to the inclusion of these covariates.

Discussion

Based on signaling (Ostroff & Bowen, 2000) and social exchange theories (Blau, 1964), we proposed that when employees perceive that their organization implements AIHRP, they should be more likely to believe that their organization is capable and willing to invest into their knowledge, skills, and abilities, motivation, and opportunities to contribute, irrespective of their age (Böhm et al., 2010). These beliefs, in turn, should increase the likelihood that they perceive that their organization treats employees of all age groups in a fair and nondiscriminatory way (i.e., ADC; Böhm et al., 2014). Moreover, we argued that high levels of both AIHRP and ADC should be linked to higher perceived work ability, because employees feel that the HR practices and age-related climate of their organization enable them to meet their work demands and to continue working at any age. Finally, we hypothesized that ADC transmits the positive effect of AIHRP on work ability, both at the between- and at the within-person level of analysis. In general, our hypotheses received mixed support, with evidence favoring relationships at the between- but not the within-person level in our statistical models. Considering between- and within-person correlations, which represent the zero-order effects, there were positive correlations observed between AIHRP, ADC, and work ability at both levels of analysis. Beyond these correlations, however, our RI-CLPM suggests that the effects of AIHRP on work ability are partially explained by ADC, but only at the between-person level of analysis (i.e. suggesting largelyi interindividual differences across time). Given that tests for our hypotheses are embedded in this larger model, we thus conclude partial support for Hypotheses 1-4. Corroborating this, our follow-up mixed effects models suggest that, although AIHRP and ADC both have independent between- and within-person effects on work ability, a majority of the variance that is explained in work ability is attributable to relatively stable, between-person, rather than dynamic, within-person influences of ADC.

These findings contribute to the literature on HR practices and employee age in several important ways. First, signaling and social exchange theories have been used previously to explain the effects of HR practices and organizational climate on employee outcomes, such as job attitudes and performance (Ostroff & Bowen, 2000). Additionally, several empirical studies have examined associations between HR practices, climate, employee age, and occupational well-being exist (e.g., Schulz et al., 2017). However, the application of signaling and social exchange theories to predict age- and health-related constructs, such as ADC and work ability, is novel. Our findings suggest that these theories can be used to explain variation in interindividual differences in ADC and work ability perceptions over time. Employees seem to differ in their reactions to AIHRP in terms of ADC and work ability. We argue that this occurs because they perceive AIHRP as a signal from their organization, suggesting that its employee are valued and invested in, independent of their age. Perceiving such signals, in turn, contributes to a social exchange process, wherein employees rate their organization more favorably in terms of ADC and also perceive their own ability to meet various demands of their jobs more favorably. Given our findings here, additional research is needed to examine the mechanisms and boundary conditions of these relationships, especially those that are more directly tied to signaling and social exchange processes. For instance, future studies could additionally examine perceived organizational support (Eisenberger, Huntington, Huchison, & Sowa, 1986) as a competing mediator in parallel to ADC, as well as individual differences in equity sensitivity (Sauley & Bedeian, 2000) as a moderator operating jointly with age.

Second, the observation of between-person effects of ADC might suggest that ADC, as a feature of psychological climate (Schneider et al., 2013), has to emerge in a way that is homologous to the emergence of other unit-level climate variables. This observation may also indicate a new venue for psychological “climate strength” research, specifically the notion that *less* within-person variability may be indicative of stronger psychological climates (see Schneider, Salvaggio, & Subirats, 2002). Third, our results show that more stable between-person effects of AIHRP, and especially ADC "matter more" than individual idiosyncratic effects of either for the prediction of work ability. This observation underscores the suggestion that organizations must be particularly attuned to those features that consistently contribute to a positive ADC (not least of which is, according to the evidence presented here, AIHRP). Indeed, our results suggest that enduring qualities of one's perceived work environment are especially important predictors of work ability.

Finally, this is the first study linking AIHRP to ADC and work ability at both the between- and within-person levels and should thus serve to inspire future research. Generally, more research is needed to explore the between- and within-person implications of these and related constructs. We note that, although between-person effects abound, that there is an appreciable degree of within-person variance in all three variables (AIHRP, ADC, and work ability) left to be explained (e.g., see the ICC_1 values in Table 6, which suggest that up to 50% of the observed variability in work ability occurs within-person; see also Rudolph & McGonagle, 2018). Keeping these ideas in mind, we discuss further the theoretical and practical implications of this work.

Theoretical and Practical Implications

In terms of theoretical development, this study has at least four notable implications. First, we extend theorizing on AIHRP and ADC, which has mainly focused on company level conceptualizations of these constructs and their respective outcomes (e.g., firm-level performance and turnover). We argue and find support for the idea that perceptions of the organizational practices (AIHRP) by employees have a more proximal effect on the individual outcome of work ability. To build a bridge between this and past research on these topics, it would be interesting for future research to theorize and examine organizational level, team level, and individual level factors -- especially those related to health and wellbeing -- in one study. Thus, future theorizing should also adopt a multilevel perspective that, in addition to the micro level, additionally includes the meso levels of the organization and, potentially, the team.

Second, and related to the previous point, future multilevel perspectives on age-related organizational practices and climates should consider that these constructs seem to vary primarily at the between-person level as compared to the within-person level. This does not imply that future theorizing on variability and change in these constructs over time is not needed. On the contrary, future theorizing should focus on the nature and meaningfulness of shifts in average levels of ADC and work ability due to AIHRP over time, as compared to average intraindividual changes over time. In this regard, associations among employees' perceptions of AIHRP, ADC, and work ability seem to differ from more dynamic phenomena in the work context, such as more transient affective and well-being responses to work events that manifest as daily hassles (e.g., interruptions; Sonnentag, 2015).

Third, we contribute to theorizing on work ability, which has traditionally been examined in relation to age and aging at work (see Ilmarinen & Ilmarinen, 2015). Arguably, the "upper level" of the "house" of work ability (i.e., those broader contextual factors associated with the work context and the "work community"; Ilmarinen, 2009) have been by-and-large neglected in past research. In the present study, we show that individuals' perceptions of organizational age-related practices and climates, notable features of the work context and the work community, matter for the prediction of work ability. Future theorizing in this area could translate the "floors" and "interior design" of the "house" of work ability into more specific individual and contextual variables that are part of a testable ecological process model of work ability (see also

McGonagle, Fisher, Barnes-Farrel, & Grosch, 2015. Our findings suggest that AIHRP and ADC would be relevant antecedents in such a model.

Finally, research on age-focused organizational practices and climates is still in its infancy (e.g., Kunze & Toader, 2019). Our study provides evidence that AIHRP and ADC have positive effects on work ability for workers from all age groups, and not just among relatively older (or younger) workers. Still, in order to further develop theories linking AIHRP and ADC to employee or organizational outcomes, it will be important to demonstrate that these specific age-related practices and climates have unique and incremental contributions above-and-beyond relevant established and alternative practices (e.g., so-called "high-performance human resources practices"; Sun Aryee, & Law, 2007) and team and organizational climates (e.g., "team health climate," Schulz et al., 2017; "organizational climate for successful aging," Zacher & Yang, 2016).

In terms of practical implications, our findings can be translated into useful advice to organizations that are interested in maintaining and improving employees' work ability in times of demographic change, especially increased age diversity. To enhance employees' perceptions of AIHRP, organizations should take steps to implement policies and practices such as age-neutral recruitment and selection processes, the provision of training and career development opportunities for employees of all age groups, as well as fair and nondiscriminatory leadership. Organizational also need to clearly communicate such efforts to employees (Böhm et al., 2014; Böhm & Dwertmann, 2015). Indeed, beyond adopting age inclusive policies and practices, organizations need to ensure that employees are aware of and utilize them. The beneficial effects of AIHRP on work ability that we observe occur in part because of their influence on ADC. Therefore, organizations must also take steps to ensure that the implementation of age inclusive policies and practices leads to individual and shared employee perceptions that employees of all ages are treated in a fair and nondiscriminatory way (see also Böhm et al. 2014). This requires frequent and effective communication between management, supervisors, and employees about the nature and potential benefits of AIHRP, as well as support with accessing, interpreting, and using available information regarding these practices (Böhm et al., 2014; Pugh, Dietz, Brief, & Wiley, 2008). These efforts to enhance ADC should, in turn, help to enhance employees' work ability, which has been shown to be associated with several important labor force outcomes, such as reduced absenteeism, delayed retirement, and reduced disability leave (McGonagle et al., 2016).

Limitations and Directions for Future Research

Although our six-wave longitudinal study has distinct advantages, especially compared to typical cross-sectional research designs, there are some limitations of this work that we hope will inspire future research in this area. First, we did not observe significant "change" effects at the within-person level of analysis over time. It is important to note that such time-graded within-person effects (i.e., trajectories) are by no means a requirement for studying within-person processes (Singer & Willet, 2003). However, it would be interesting for future studies to consider timeframes that are longer, as perhaps it takes more than 18-months for these effects to manifest as significant change trajectories. Relatedly, we also focused on three-month intervals between observations, so it is also possible that this gap needs to be altered (e.g., 6 or 12 months) for such effects to be captured (see Dormann & Griffin, 2015, for considerations regarding optimal time lags in panel studies).

Second, we did not study the onset of the implementation of AIRHP within organizations, nor the conditions that would give rise to their onset. For example, it could be that the effects of AIHRP take time to manifest, and perhaps ADC manifests differently among different organizations. It could also be that organizations implement AIHRP as remediation for instances of age discrimination, rather than as a proactive strategy for enhancing worker wellbeing. Thus, our heterogeneous sample might be occluding certain effects (we do note, however, that Böhm et al., 2014, use a heterogeneous sample across multiple organizations). To address questions about onset of AIHRP and properties of ADC relevant to specific contextual features, future research should consider regression discontinuity designs conducted within single organizations. Moreover, as suggested above, future studies should consider moderators of the links between AIHRP, ADC, and employee outcomes, such as leadership behavior or equity sensitivity.

Finally, although our study uses a time lagged complete panel design, which helps assuage concerns about temporal precedence and endogeneity, broadly defined, we do note that there are potential omitted variables to account for in understanding the linkage between AIHRP, ADC and work ability. For example, organizations that have AIHRP in place might also be more likely to adopt health and wellbeing promoting HR policies, more generally. Perhaps it could be the latter that is really driving the effects of AIHRP and work ability in this case. Similar arguments could be made for "organizational health climates" or the way in which climates are translated to employees via "healthy leadership" (Rudolph, Murphy, & Zacher, 2019). As suggested previously, these issues can be addressed in future research by demonstrating evidence for the unique and incremental validity of AIHRP and ADC above-and-beyond broader HR practices and other related climate variables when predicting wellbeing.

Conclusion

This study contributes to the literature on HR practices, age, and wellbeing by showing that employees' perceptions of their organization's age diversity climate mediate the influence of age inclusive human resource practices on work ability at the between-person level of analysis (i.e., observed differences in these variables between employees, over time), but not at the within-person level of analysis (i.e., observed changes in these variables within employees, over time). Our findings have implications for the development and implementation of human resource practices that benefit the occupational health and wellbeing of employees at various ages. These finding further underscore the need to for theories of HR management and climate to integrate predictions about individual-level wellbeing and emphasize the important of adopting multi-level deigns to better understand how organizational practices impact on employees' work ability.

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Table 1. Descriptive Statistics and Intercorrelations Among Study Variables

		Mean	S.D.	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.
1.	T1 AIHRP	2.66	1.02	(.89)																	
2.	T2 AIHRP	2.66	1.07	.63	(.93)																
3.	T3 AIHRP	2.76	1.02	.56	.60	(.92)															
4.	T4 AIHRP	2.73	1.05	.54	.57	.61	(.93)														
5.	T5 AIHRP	2.76	1.04	.55	.60	.62	.64	(.92)													
6.	T6 AIHRP	2.82	1.07	.52	.58	.53	.59	.64	(.94)												
7.	T1 ADC	3.19	1.04	.68	.48	.55	.53	.51	.41	(.91)											
8.	T2 ADC	3.14	1.01	.57	.76	.56	.54	.56	.53	.66	(.90)										
9.	T3 ADC	3.16	0.99	.54	.54	.76	.60	.62	.51	.67	.70	(.91)									
10.	T4 ADC	3.13	1.02	.48	.53	.58	.79	.61	.54	.63	.65	.73	(.92)								
11.	T5 ADC	3.21	0.97	.47	.47	.52	.55	.74	.54	.62	.61	.67	.67	(.82)							
12.	T6 ADC	3.23	1.05	.48	.49	.52	.58	.63	.76	.55	.62	.66	.68	.70	(.92)						
13.	T1 WA	8.04	1.76	.17	.08	.13	.12	.15	.18	.28	.23	.27	.23	.24	.25	(.94)					
14.	T2 WA	8.07	1.67	.14	.17	.14	.22	.15	.19	.26	.33	.27	.28	.29	.29	.55	(.92)				
15.	T3 WA	8.04	1.64	.10	.02	.15	.19	.12	.11	.24	.19	.29	.30	.22	.24	.61	.62	(.92)			
16.	T4 WA	8.09	1.80	.11	.11	.13	.24	.21	.17	.24	.26	.25	.39	.27	.35	.52	.57	.69	(.94)		
17.	T5 WA	8.07	1.78	.09	.02	.06	.17	.22	.13	.24	.19	.23	.28	.30	.28	.55	.58	.60	.54	(.93)	
18.	T6 WA	8.12	1.72	.14	.09	.11	.20	.16	.23	.26	.25	.26	.30	.28	.41	.55	.58	.62	.65	.62	(.93)

Note. $N = 355$, T = time, AIHRP = age inclusive human resource practices, ADC = age diversity climate, WA = work ability. $r_{xy} \geq |.11|$ are $p < .05$. Values in the diagonal are coefficient alpha (reliability) estimates.

Table 2. Summary of Confirmatory Factor Analysis (CFA) Model Fit Indices

Time 1 CFAs	χ^2	**df**	**p-value**	**CFI**	**TLI**	**AIC**	**BIC**	**RMSEA**	**95% CI**	**SRMR**	
Three Factor	159.87	62	< .001	0.96	0.95	12598.94	12711.23	0.07	0.06 - 0.08	0.04	
Two Factor: AIHRP + ADC vs. WA	392.13	64	< .001	0.86	0.83	12914.12	13018.67	0.12	0.11 - 0.13	0.07	
Two Factor: AIHRP + WA vs. ADC	1014.14	64	< .001	0.60	0.52	13802.23	13906.77	0.20	0.20 - 0.21	0.19	
Two Factor: ADC + WA vs. AIHRP	985.98	64	< .001	0.62	0.53	13758.16	13862.70	0.20	0.19 - 0.21	0.18	
One Factor	1185.71	65	< .001	0.53	0.44	14086.89	14187.57	0.22	0.21 - 0.23	0.20	
Multilevel CFAs	χ^2	**df**	**p-value**	**CFI**	**TLI**	**AIC**	**BIC**	**RMSEA**	**95% CI**	**SRMR$_W$**	**SRMR$_B$**
Three Factor	514.81	124	< .001	0.96	0.95	68289.05	68691.18	0.04	0.04 - 0.04	0.02	0.05
Two Factor: AIHRP + ADC vs. WA	1326.49	128	< .001	0.87	0.84	69528.01	69907.48	0.07	0.06 - 0.07	0.06	0.08
Two Factor: AIHRP + WA vs. ADC	3505.32	128	< .001	0.63	0.55	73228.17	73607.65	0.11	0.11 - 0.11	0.15	0.22
Two Factor: ADC + WA vs. AIHRP	3435.95	128	< .001	0.64	0.56	72944.29	73323.77	0.11	0.11 - 0.11	0.14	0.20
One Factor	4212.34	130	< .001	0.55	0.46	74318.72	74686.88	0.12	0.12 - 0.12	0.16	0.21

Note. AIHRP = age inclusive human resource practices, ADC = age diversity climate, WA = work ability, SRMR$_W$ = SRMR within, SRMR$_B$ = SRMR between

Table 3. Summary of Measurement Invariance Tests

AIHR	χ^2	**df**	**CFI**	**RMSEA**	**AIC**	**BIC**	**Δχ2**	**Δdf**	**p**	**ΔCFI**	**ΔRMSEA**
Configural Invariance	1371.10	385.00	0.91	0.07	24829.00	25255.00					
Weak Invariance	1392.70	405.00	0.91	0.07	24811.00	25159.00	28.03	20	0.11	0.003	0.001
Strong Invariance	1422.30	425.00	0.90	0.07	24800.00	25072.00	34.63	20	0.02	0.003	0.001
ADC	χ^2	**df**	**CFI**	**RMSEA**	**AIC**	**BIC**	**Δχ2**	**Δdf**	**p**	**ΔCFI**	**ΔRMSEA**
Configural Invariance	864.39	233.00	0.93	0.07	19102.00	19455.00					
Weak Invariance	876.94	245.00	0.92	0.07	19091.00	19397.00	17.61	12	0.13	0.002	0.001
Strong Invariance	881.25	257.00	0.92	0.07	19071.00	19331.00	5.01	12	0.96	0.000	0.001
WA	χ^2	**df**	**CFI**	**RMSEA**	**AIC**	**BIC**	**Δχ2**	**Δdf**	**p**	**ΔCFI**	**ΔRMSEA**
Configural Invariance	734.31	233.00	0.95	0.05	26836.00	27188.00					
Weak Invariance	745.50	245.00	0.95	0.05	26823.00	27129.00	8.76	12	0.72	0.000	0.001
Strong Invariance	757.82	257.00	0.95	0.05	26811.00	27071.00	13.66	12	0.32	0.001	0.001

Note. AIHRP = age inclusive human resource practices, ADC = age diversity climate, WA = work ability.

Table 4. Summary of cross-lagged panel model (CLPM) and random intercepts CLPM (RI-CLPM) Fit Indices

Model	Description	χ^2	df	p	CFI	TLI	AIC	BIC	RMSEA	95% CI	SRMR
Model 3	RI-CLPM + Within & Between Mediated Effect	169.59	142	0.06	0.99	0.99	15901.56	16083.55	0.02	0.01 - 0.03	0.04
Model 2	CLPM + Mediated Effect	655.06	148	< .001	0.85	0.85	16527.39	16686.15	0.10	0.09 - 0.11	0.15
Model 1	CLPM	656.22	150	< .001	0.85	0.85	16523.67	16674.68	0.10	0.09 - 0.10	0.15

Table 5. Summary of Relevant Model 3 Parameter Estimates

Parameter Description	Parameters	Estimate	S.E.	95% CI
Auto Regressive Paths	AIHRP	0.10	0.05	0.00 - 0.20
	ADC	0.10	0.06	-0.02 - 0.22
	Work ability	0.04	0.04	-0.04 - 0.12
Reverse Cross-Lagged Paths	Reverse A-Path: Work ability ⟹ ADC	0.01	0.02	-0.02 - 0.05
	Reverse B-Path: ADC ⟹ AIHRP	0.03	0.06	-0.08 - 0.14
	Reverse C'-Path: Work ability ⟹ AIHRP	0.02	0.02	-0.02 - 0.06
Within-Person Cross-Lagged Mediation Paths	A-Path: AIHRP ⟹ ADC	0.06	0.04	-0.02 - 0.13
	B-Path ADC ⟹ Work ability	-0.03	0.08	-0.19 - 0.13
	C'-Path AIHRP ⟹ Work ability	< 0.01	0.05	-0.10 - 0.11
	Indirect Effect: A×B	< 0.001	0.01	-0.02 - 0.01
	Total Effect: C' + (A×B)	< 0.001	0.05	-0.10 - 0.11
Between-Person Mediation Paths	A-Path: AIHRP ⟹ ADC	0.89	0.04	0.82 - 0.96
	B-Path ADC ⟹ Work ability	1.49	0.21	1.08 - 1.90
	C'-Path AIHRP ⟹ Work ability	-0.96	0.22	-1.38 - -0.54
	Indirect Effect: A×B	1.33	0.20	0.95 - 1.71
	Total Effect: C' + (A×B)	0.37	0.10	0.17 - 0.57

Note. AIHRP = age inclusive human resource practices, ADC = age diversity climate.

Table 6. Between- and Within-Person Intercorrelations

		1.	**2.**	**3.**
1.	AIHRP	0.58/0.89	0.57	0.16
2.	ADC	0.84	0.65/0.92	0.20
3.	Work ability	0.22	0.40	0.50/0.90

Note. AIHRP = age inclusive human resource practices, ADC = age diversity climate. Between-person correlations are shown below the diagonal, within-person correlations are shown above the diagonal. ICC_1/ICC_2 values are depicted along the diagonal. All correlations at both levels of analysis are $p < .05$.

Table 7. Summary of Mixed Effects Models Predicting Work Ability

	AIHRP Model		**ADC Model**	
Predictors	*Estimates*	*95% CI*	*Estimates*	*95% CI*
(Intercept)	8.07	7.93 – 8.21	8.07	7.94 – 8.20
Time	0.41	-1.75 – 2.57	0.66	-1.47 – 2.79
$Time^2$	0.25	-1.90 – 2.41	-0.19	-2.32 – 1.94
Predictor Between	0.36	0.19 – 0.53	0.65	0.49 – 0.81
Predictor Within	0.27	0.19 – 0.34	0.38	0.29 – 0.46
Time × Predictor Between	-0.23	-2.78 – 2.32	1.17	-1.33 – 3.66
$Time^2$ × Predictor Between	0.51	-2.03 – 3.06	0.20	-2.30 – 2.69
Time × Predictor Within	1.10	-2.76 – 4.96	3.54	-0.68 – 7.76
$Time^2$ × Predictor Within	-0.91	-4.70 – 2.87	-1.42	-5.63 – 2.78
Random Effects				
σ^2	1.20		1.18	
τ_{00}	1.68		1.46	
ICC_1	0.58		0.55	
Observations	2130		2130	
Within R^2 / Between R^2	0.03 / 0.04		0.11 / 0.15	

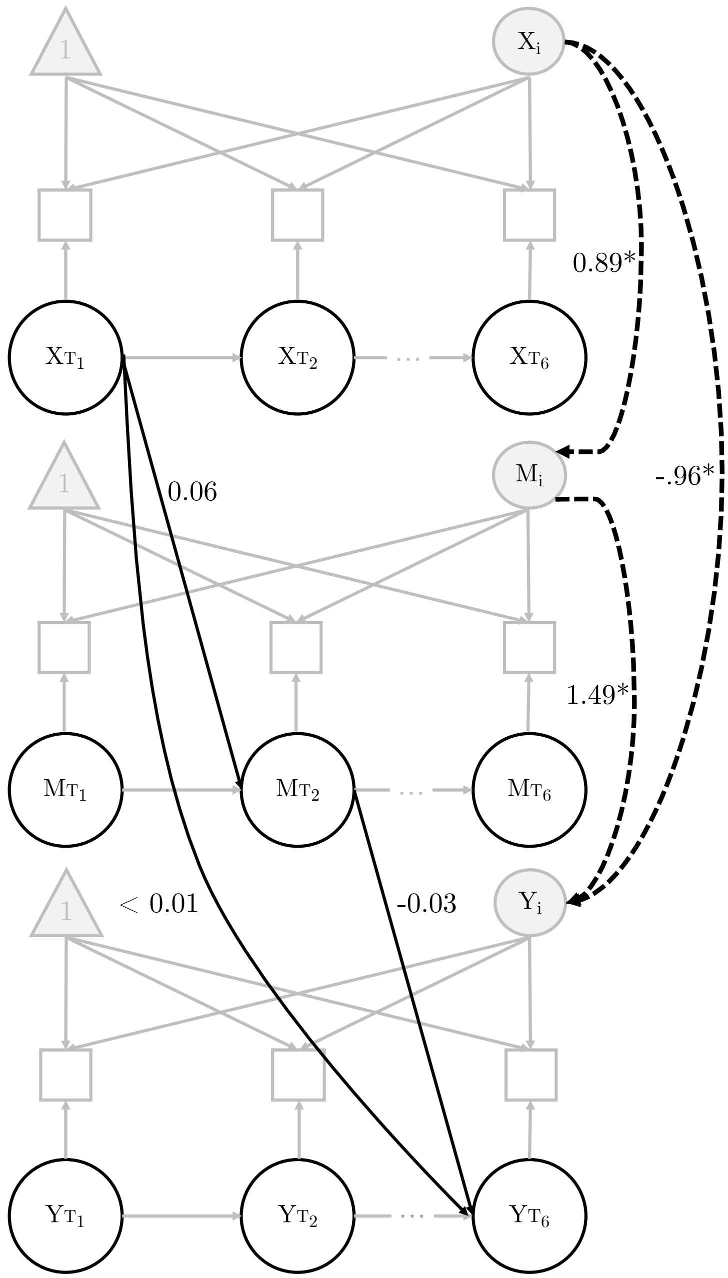
Note. AIHRP = age inclusive human resource practices, ADC = age diversity climate.

Table 8. Summary of Dominance Analysis for Work Ability

		Work Ability			
Predictors	*Estimates*	*95% CI*	*VIF*	Within R^2_{Dom}	Between R^2_{Dom}
(Intercept)	8.07	7.94 – 8.20	-	-	-
AIHRP Between	-0.62	-0.91 – -0.34	3.30	0.0279 / 2.79%	0.0424 / 4.24%
AIHRP Within	0.12	0.03 – 0.21	1.48	0.0050 / 0.50%	0.0000 / 0.00%
ADC Between	1.16	0.89 – 1.44	3.30	0.1002 / 10.02%	0.1523 / 15.23%
ADC Within	0.30	0.19 – 0.40	1.48	0.0097 / 0.97%	0.0000 / 0.00%
Random Effects					
σ^2		1.17			
τ_{00}		1.39			
ICC_1		0.54			
Observations		2130			
Within R^2 / Between R^2		0.14 / 0.19			

Note. AIHRP = age inclusive human resource practices, ADC = age diversity climate. VIF = variance inflation factor. Within & Between R^2_{Dom} = Raw metric dominance weights for within- and between person R^2, interpreted in “variance explained” units (e.g., AIHRP Between explains 0.0279 = 2.79% of the within-person variance explained in work ability). Within sources of variance, raw metric dominance weights sum to their respective “total” variance explained (e.g., Within R^2 = .0279 + .0050 + .1002 + .0097 = .1428 ≅ .14 or 14.28% of the within-person variance explained).

Figure 1. Summary of Relevant Parameters from the Random Intercepts Cross-Lagged Panel Mediation Model



Note. X_{T_1}-X_{T_6} represents measurement of age inclusive human resource practices (AIHRP) over time. M_{T_1}-M_{T_6} represents measurement of age diversity climate (ADC) over time. Y_{T_1}-Y_{T_6} represents measurement of work ability over time. X_i, M_i, & Y_i represent random intercepts (i.e., between-person effects) for AIHRP, ADC, and work ability, respectively. Solid (dashed) directional arrow represent within-person (between-person) parameter estimates. This figure was adapted from Hamaker et al. (2015) and Selig & Preacher (2009). Certain parameters have been omitted from this representation for sake of parsimony; see Table 5. *$p < .05$.