Age Discrimination, HR Managers, and Eye-tracking: Evidence from a Lab-in-the-Field Experiment

by

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Abstract: Age discrimination can have negative effects on both individuals being discriminated against and on government programs and the economy, as potentially productive workers are unable to find work. This paper explores age discrimination at the hiring level in a lab-in-the-field experiment in which we go to Human Resources (HR) fairs and conferences and ask HR managers to rate resumes for an administrative assistant I position. While they rate the resumes, we track their eyes using a Tobii X2-60. After they have rated resumes, we ask them a series of questions to elicit explicit and implicit discrimination against older workers. We find evidence of quadratic age discrimination against older workers. Similarly, participants spend less time looking at resumes of older workers. Participants who hold stereotypes that older workers are less enterprising, less able to handle physically taxing jobs, and less likely to undergo training are more likely to exhibit these discriminatory behaviors. Although there is suggestive evidence that participants who explicitly prefer working with 45 year olds to 65 year olds using a Bogardus social distance task also rate resumes differently by age, this evidence is not robust to specification choice. Finally, there is no evidence that the Implicit Association Test (IAT) for age has any relation to how HR managers rate resumes by age.

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Introduction

Although employed older workers, on average, have better economic outcomes than employed younger workers, unemployed older people face greater difficulties finding work than do unemployed younger people (e.g., Diamond and Hausman 1984; Hirsch, Macpherson, and Hardy 2000; US Bureau of Labor Statistics 2012). One reason for these difficulties is age discrimination at the hiring level (Lahey 2008). This hiring discrimination can have profound negative consequences on the quality of life for those who are not financially, mentally, or emotionally ready to retire (Nelson 2002). Additionally, already stressed public programs such as Social Security, Medicare, and Disability suffer when older job seekers cannot find work (Burtless and Quinn 2001, 2002; Diamond and Orszag 2002).

Significant research (Albert et al. 2011; Bendick et al. 1996, 1999; Carlsson & Eriksson, 2019; Drydakis et al., 2018; Lahey 2008; Lahey and Oxley forthcoming; Neumark et al., 2019 see Finkelstein et al., 1995 for a meta-analysis of laboratory work) demonstrates that in field and laboratory settings, employers and laboratory subjects favor resumes from younger job applicants over those from older job applicants. Lahey and Oxley (forthcoming) find that patterns of age discrimination are different for Black compared to White applicants. However, reasons for hiring discrimination based on age are still open questions.

First, we further document differential treatment by age in a laboratory setting. Then we explore the open question of why there is differential treatment against older workers through testing participants for ageism using measures from different areas of social science, by including specific resume items intended to ameliorate discriminatory tendencies from a levels-based statistical discrimination framework, and by using eye-tracking to determine where they look, although we do not go into detail on that aspect in this draft. Eye-tracking methodology records eye movements and measures where the eye fixates and for how long. This technology allows us to explore what study participants find relevant to their resume screening in a natural setting that mimics how human resource managers screen resumes.

Laboratory experiments complement field experiments by allowing the researcher more control, as well as allowing for the testing of hypotheticals that do not exist under field conditions. Lahey and Oxley (forthcoming) used a professional student population to test questions of age discrimination in a laboratory environment. However, students may not behave the same way that professionals do with regards to age discrimination, especially when the student population is limited to younger ages. The experiment in this paper uses HR professionals recruited through HR-specific associations, conferences, and fairs to elicit their hiring preferences. The experiment used is a realistic one—participants were told we were interested in learning about how HR managers view resumes. They were then shown 40 resume pdfs in standardized formats and asked to rate them. Participants told us this was not unlike how screening for entry-level positions works at larger firms.

We first find, as have previous studies (Lahey 2008, Lahey and Oxley *forthcoming*), that there is a quadratic relationship between age and the rating given to resumes. With each year of age as indicated on resumes by date of high school graduation, participants give lower ratings to resumes, thought this decrease flattens out sometime in the mid-fifties and there may even be an uptick in resume ratings in the mid-60s. Similarly we find that participants spend less time looking at resumes by age indicated on the resume, though there is no uptick at later ages. Only participants over the age of 60 were helped by additional computer training, suggesting that this ageist stereotype does not hold for people in their 50s or younger. Clerical training helps those in the older and younger portions of the age spectrum in our study.

Participants with explicitly stated negative stereotypes about older workers being less enterprising, less able to handle physically demanding tasks, and less likely to undergo training are more likely to show discrimination against older workers in their resume ratings. Explicitly stated positive stereotypes towards older workers such as loyalty, being meticulous and having better social skills seem to have no positive effects on resume rating. Combining explicit stereotypes into four factors, the factors for capability and “other” appear to have the largest effect on ratings by age. Using a Bogardus Social Distance scale to determine participant's comfort working with individuals in different age groups produces suggestive evidence that discomfort leads to lower ratings by age, but these results are not consistently significant depending on specification. Finally, the Implicit Association Test on aging does not predict resume ratings by age, possibly because the IAT for aging is not set up for the work environment.

II Measurement Instruments

Is There Age Discrimination?

We first provide a measure of discrimination determined by how participants rate resumes for an entry-level clerical position in which resume content has been randomly varied. Thus, each unique resume includes different combinations of ages indicated by the listed date of high school graduation and other resume items. Participants rated the resumes on a 1 to 7 "Hireability" scale, with 7 indicating most hireable. We also track their eye movements as they view resumes, so we can determine how long they spend viewing each resume and each part of the resume.

Equation (1) provides a measure of how resumes are treated by the age indicated on each resume:

$$Hireability_r = \beta_1 * Age_r + \beta_2 * Age_r^2 + \gamma_p + \alpha_r + \varepsilon_r \tag{1}$$

As noted before, $Hireability_r$ indicates the rating that the participant gave each unique resume on a (1-7) Likert scale with 7 being most hireable. Age_r is the age indicated on the resume by date of high school graduation. γ_p is a vector of participant fixed effects. α_r is a constant and ε_r an error term. The coefficients β_1 and β_2 determine the relationship between age and ratings and in addition to providing these coefficients we will provide graphs of the relationship between age and rating to help visualize the shape of the quadratic by age. We will also use equation (1) with *Time spent on resume*, *Time spent on a resume part,* and *Count of fixations on a resume part* to determine if there are differences by age for these measures.

Why is there Discrimination?

Levels-based statistical discrimination (Phelps, 1972) occurs when one group has lower "quality" on average and these group characteristics influence how individuals are treated. To test for levels-based statistical discrimination, we include items that contradict specific stereotypes on a subset of resumes. If resumes with positive items that contradict negative stereotypes result in comparatively better ratings for the stereotyped group than the non-stereotyped group, that provides evidence for levels-based statistical discrimination based on that stereotype. We specifically test stereotypes of inactivity, lack of flexibility, weak computer skills, and need for/dislike of training using this method.

Ageist attitudes or beliefs can be explicit or implicit (Devine, 1989). We first study explicit attitudes on aging using a set of direct questions devised by Henkens (2005). Ageism is still, in many ways, socially acceptable in the U.S. (D'cruz & Banerjee, 2020; Lipnic, 2018). Many people do not think of positive or negative age stereotypes as stereotypes or as being problematic, and these stereotypes may even be increasing even though underlying improvements in health may make them less likely to mirror true conditions over time (Hanrahan et al., 2017; Levy, 2017; Palmore, 2015). Given these beliefs, people may be more likely to state explicit age stereotypes that they hold in a way that they would not be willing to state stereotypes that they hold about other groups such as Black people or women. Previous studies have shown high amounts of agreement with aging stereotypes such as 'older workers are less productive than younger workers' or 'older workers are less able to adapt to technological change than younger workers' (Finkelstein & Truxillo, 2013; Henkens, 2005; Ng & Feldman, 2012; Posthuma & Campion, 2007). A meta-analysis by Ng and Feldman (2012) determined that of six commonly stated ageist stereotypes, the only stereotype containing truth is that older adults are less interested in continuing education or training (Ng & Feldman, 2012), although this stereotype may be a self-fulfilling prophecy; lower expectations lead to less training being offered and lower quality training being given when it is offered (McCausland et al., 2015).

In our study, participants were asked to rate their agreement with explicitly held negative and positive stereotypes about older adults in the workforce, as adapted from Henkens (2005). Participants stated their agreement with 15 statements such as "older workers are less productive than younger workers" or "older workers are less able to adapt to technological change than younger workers" on a 5 point Likert scale with the edges indicating Strongly Disagree to Strongly Agree.[2] We coded these ratings from -2 to 2, with -2 indicating strong agreement with negative stereotypes against older workers or strong disagreement with positive stereotypes for older workers, and 2 indicating the reverse. A zero indicated neither agree nor disagree with the queried stereotype.[3]

Equation (2) demonstrates how we will determine which of these individual stereotypes interacts with the age term to change participant ratings. That is, we will be able to see if people who state they believe that workers are less likely to seek training give resumes lower ratings quadratic with age compared to those who do not state those beliefs.

$$Hireability_r = \beta_1 * Age_r + \beta_2 * Age_r^2 + \beta_3 * Item_p + \beta_4 * Item_p * Age_r + \beta_5 * Item_p * Age_r^2 + \gamma_p + \alpha + \varepsilon_r \quad (2)$$

[2] A full set of these statements can be found in Appendix Table 1.
[3] Means are available in Table 4 and will be discussed in more detail in the Results section.

Here $Hireability_r$ and Age_r are defined as before. $Item_p$ is the level of agreement with an individual ageist stereotype at the participant level, using the coding mentioned above such that positive values imply less ageism. A significant value on β_4 indicates that people who agree with that stereotype give different hireability ratings based on the age of the resume compared to people who disagree with that stereotype. A significant value on β_5 indicates that this difference varies quadratically with age.

In addition to studying the explicit stereotypes separately, we also combine the different stereotypes into four factors using factor analysis. Factor analysis creates new linearly weighted variables from the initial variables using singular value decomposition. Using a 0.35 cutoff, we are able to divide our 15 measures of stereotypes into 4 separate factors. Note that in our discussion, all individual stereotypes are coded such that more positive beliefs about age are associated with larger numbers regardless of how the question was originally asked; that means for example, that positive correlations with "less productive", and "having better social skills" mean a positive correlation with disagreeing with the former and agreeing with the latter. We label the first factor "Capability". This factor shows positive correlations with beliefs that older workers are less productive, dislike being assigned tasks by younger employees, are less interested in technological change, are less able to adapt to technological change, are less capable of doing physically taxing work, are less interested in training, are less able to keep up, and are less enterprising. This factor also shows negative correlations with the stereotypes that older workers are more loyal, reliable, meticulous, and careful than younger workers. We term the second factor "dependable". This factor is positively correlated with older workers being less productive, having better social skills, and being more loyal, reliable, and careful than younger workers. The third factor we term "slow" and it is negatively correlated with older workers being able to keep up with youngers and older workers being less enterprising than younger workers. Finally, we term our fourth factor "other". This factor includes a positive correlation with being less interested in technological change, and a negative correlation with being less creative and less able to do physically taxing jobs. Full factor analysis for the four factors can be found in Appendix Table 3. We use equation (2) with $Item_p$ denoting each factor rather than each individual stereotype with the interpretation of the coefficients as above.

We use a second measure of explicit age discrimination from the sociological literature, the Bogardus Social Distance Scale. This scale, developed originally in the 1900s to study anti-immigrant feelings, is a measure of the willingness to accept members from another group into the participant's interaction sphere (Bogardus 1933). It has been widely used since then to examine the perceived intimacy between groups, including willingness to work together (Auer, Bonoli, Fossati, & Liechti, 2018; for review see Wark & Galliher, 2007). In our study, we use it to explore the extent to which participants are willing to work with various age groups. In 25 questions, participants were asked to rate their willingness on a 5 point Likert scale to engage with individuals from various age groups (teenager, 25-year-old, 45-year-old, 65-year-old, 85-year-old) in the workplace in the role as a supervisor, as an employee, as a new hire for an important job, as a coworker, or as a partner on an important project. In post-processing, we coded their responses from -2, very unwilling, to 2, very willing. We then create a difference measure (45-65) by simply subtracting the rating for people age 65 to the rating for people age 45, and another difference measure that takes the mean of the ratings for age 25 and 45 and the mean of the ratings for age 65 and 85 and subtracts the two means. We again use equation (2) to explore how participants with different feelings for social distancing with $Item_p$ denoting the age difference measure for each question. The interpretation of the coefficients is the same as with explicit stereotypes.

Although participants may be more likely to explicitly to state ageist stereotypes than they would be racist stereotypes, there may still be some unwillingness to fully state negative beliefs about older workers. Additionally, some beliefs may not be explicitly known to the participant. They may have implicit age attitudes that influence their rating of workers without them being consciously aware of these attitudes. Implicit bias measurement is most commonly measured using Implicit Association Tests (IAT).[4] In the IAT, images of faces are paired with either positive or negative words, and the relative reaction times for the participant to pair faces with those words illuminates their beliefs about groups represented by the faces (Greenwald, McGhee, & Schwartz, 1998; Greenwald, Nosek and Banaji 2003; Nosek, Greenwald and Banaji 2007). Researchers have developed IATs for a variety of groups, including one that compares older and younger people (Malinen & Johnston, 2013; Mohammed et al., 2019; Ruiz et al., 2015). Combined with resume audit studies for hiring, researchers have shown the IAT to predict discrimination against obese job seekers and against Arab-Muslim men (Agerström & Rooth, 2011; Rooth, 2010).

The version of the IAT for age asked participants to pair photos of younger or older adults with either positive or negative characteristics (See Appendix Figure 1). We scored latencies in response time using the mean difference between practice and test blocks as in Greenwald et al. (2003), with higher d scores indicating preference for associating younger faces with positive characteristics and older faces with negative characteristics. Participants who made an incorrect pairings, such as pressing the "positive or younger" key for a negative word or for

[4] The use of the IAT is not without controversy (Rothermund & Wentura, 2004).

an older face, were not allowed to advance to the next screen until the correct key had been pressed.

Another method of eliciting implicit biases is to use eye-tracking to track where participants' eyes are viewing. In post-processing we divided resumes into specific "Areas of Interest" (AOI) in order to measure the amount of time spent on each resume section. These AOI are virtual boxes that surround the fixed parts of the resume and include Name, Address, Employment history, Years associated with employment history, Education, Year associated with high school graduation, Other (which includes items such as training, statements of flexibility, and volunteer work), and Outside (which includes everything on the page not in another AOI). An example of this partition can be seen in Appendix Figure 2. This draft will not go into detail about these results.

III Method

67 human resources professionals were recruited at Human Resource conferences and through HR professional associations to participate in this study. Table 1 shows summary statistics for the participants who were 80% female, 84% White, 16% Black, and 18% Hispanic. The bulk, 40%, had a Bachelor's degree, while 18% had some college, 22% had some post-graduate education, and 20% had a graduate degree. The average age was 44 and the modal income (62%) was over $100K. Because Lahey, Weaver, and Oxley (2020) finds that students with public and non-profit training are less discriminatory than those without such training, we limit our sample for this study to full-time for-profit professionals, leaving 50 HR professionals total.

After consenting to participate in the study, participants calibrated with the eye-tracker, a Tobii X2-60, which involved looking at a ball on the screen. Following that, they were asked to imagine they were an HR manager and given a description of an Administrative Assistant I position. They were then shown 5 randomly drawn example resumes representative of a previous position. Following that, they were shown 40 randomly generated resumes and asked to rate each in turn on a 1-7 Likert scale, with 7 denoting the most "hireable". Then, in results we will not be discussing in this paper, they were shown their top five rated resumes and asked to determine the top two, then top one resume. Next they were given an Implicit Association Test for age (Project Implicit, n.d.), then a battery of questions from a Bogardus Social Distancing exercise for age and work, then an explicit age stereotype survey, then finally they were asked about their own demographic characteristics. On average, each participant took a little over 30 minutes to complete the study and was compensated $50 for their time.

Resumes were created with Lahey and Beasley's (2009) program using inputs taken from actual resumes to create unique resumes for each participant. Thus for the 50 participants, there are 2000 uniquely created resumes. Because participants treat resumes with Black names differently by age than they do resumes with "White" names (Lahey and Oxley *Forthcoming*), we limit the resumes in this study to those whose names do not indicate any specific race, and thus are likely to be assumed White. In total, we have a sample of 1,809 resumes across 50 participants, and 1,766 resumes with complete eye-tracking information. The resumes indicate age by high school graduate year, and also provide information on up to 10 years of recent previous work experience, high school, additional training, volunteer experience, and a statement on flexibility. With the exception of age which varies uniformly between 35-75 years, we chose demographic information to match that of high school graduates working in clerical positions in the 2012 American Community Survey (ACS)(Ruggles, et al., 2020). Thus the resumes in our sample are 50% female and 12% Hispanic with an average age of 56.5 years.

IV Results

Table 1 presents summary statistics for resume ratings and time spent on the resumes. On average, participants gave all resumes a rating of 4.72 out of 7 in terms of "hireability." They spent about 16 seconds on each resume, which is in line with previous results from student samples and from discussions with HR professionals (Lahey 2008, Lahey and Oxley forthcoming, Lahey and Weaver 2020).

Evidence of Age Discrimination in Resume Ratings

Figure 1 shows the relationship between age as indicated on the resume and the Likert rating for that resume using a local weighted regression estimate, or *lowess* smoother in Stata. Here we can see that as the age indicated on the resume increases, the resume rating decreases until the mid-50s when it flattens out, and then has a gentle increase starting sometime in the early to mid-60s. This pattern is similar to the one found for similar resumes in the student sample studied in Lahey and Oxley (forthcoming). The slight increase at older ages is also found with interview requests, at least for women in Boston and St. Petersburg, FL, in the correspondence audit in Lahey 2008.

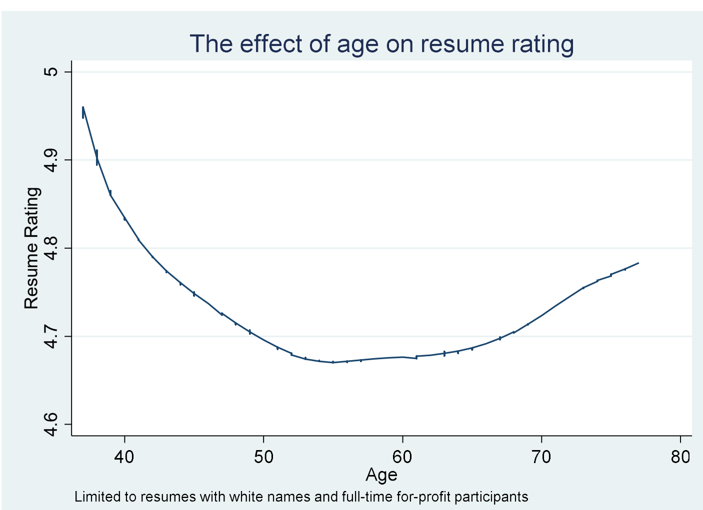


Figure 1

This figure suggests a quadratic relationship with resume ratings and age. Table 2 formalizes this relationship using Equation (1). Columns (1) and (2) show the coefficients on the age and age^2 terms for the resumes in our sample. Both terms are significant at the five percent level, with the coefficient of age around -0.06 and the coefficient of the age^2 term around 0.005 or 0.006 depending on specification. Columns (3) – (6) repeat these regressions separating the resumes by those with female names and those with male names, and while these regressions are at most significant at the 10% level, possibly because the sample size drops to around 900 observations (clustered on 50 participants), their coefficients are similar to those for the whole sample. One deviation from previous work (Lahey and Oxley forthcoming, Neumark et al., 2019) is that the results appear to be stronger for the resumes with male names than for those with female names, but that effect may be a result of increased error given the smaller sample sizes rather than a real phenomenon. The coefficients by gender do not differ from each other significantly (results available from the authors).

We next turn to how long people spend viewing the resumes. In general, people spend more time viewing things that they like (Holmqvist et al., 2011; Lahey and Oxley forthcoming), and we find the same in our experiment, as shown in Figure 2, which plots the ratings that participants give resumes against the amount of time in seconds they spend viewing said resumes. There is an almost linear relationship between the two in our sample.

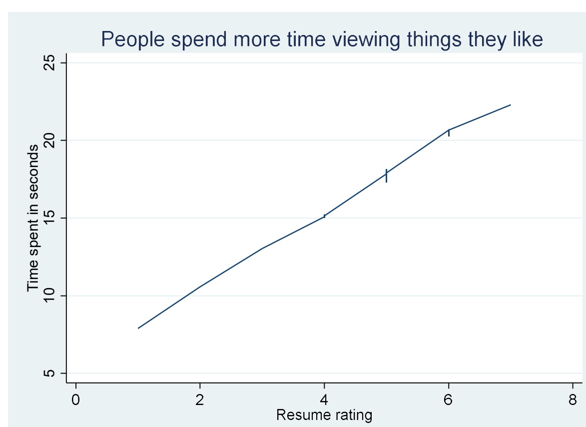


Figure 2

Plotting the relationship between the ages indicated on the resumes and the number of seconds spent on the resumes using a *lowess* smoother results in Figure 3. Here we see a decrease in the number of seconds from almost 18 seconds per resume to 15.5 seconds until around age 55 when the amount of time spent flattens out. Unlike the resume ratings results, there is no increase in time spent at older ages.

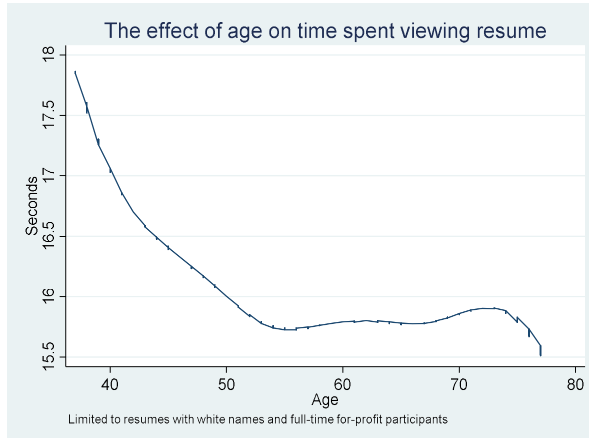
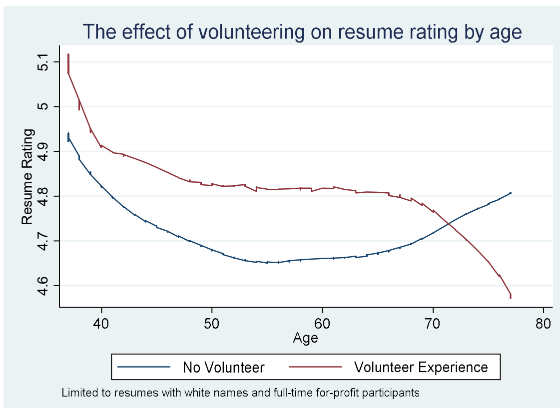


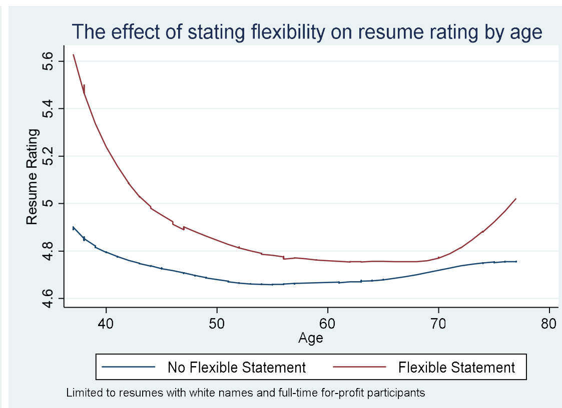
Figure 3

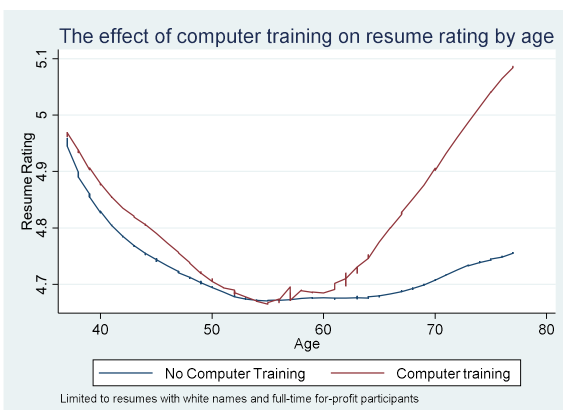
Table 3, column 1, Panel I uses Equation (1) to model Figure 3 as a quadratic and finds marginally significant results for the coefficients of age and age^2. Panel II repeats this exercise with the count of fixations on each resume across all areas of interest, but only the age term is significant and the age^2 term switches sign from positive to negative. From Figure 3, it is not clear that the true shape is a quadratic, but it does appear that there is a negative relationship between the age indicated on the resume and the time spent on the resume overall.

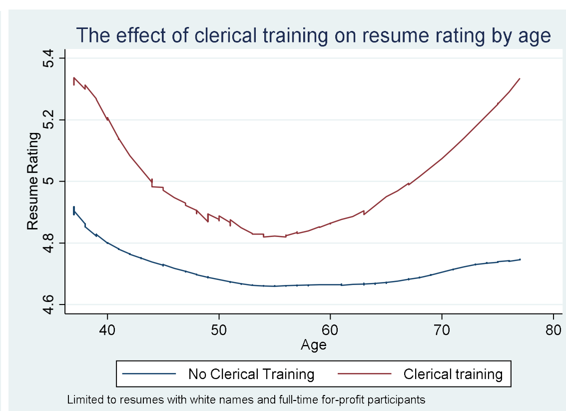
Statistical Discrimination

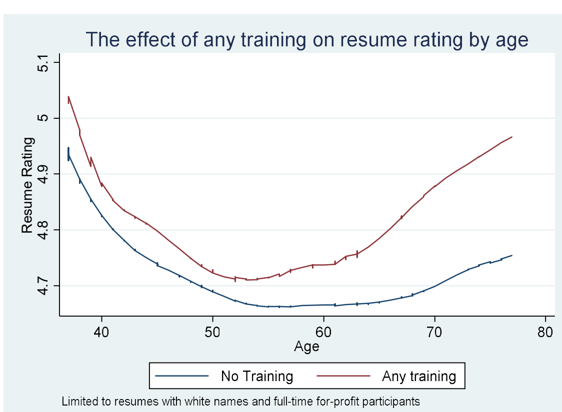
Figures 4a-4e plot resume ratings by age for resumes that do and do not include items that we randomly put into a subset of resumes to counteract specific stereotypes. Current volunteer experience at a local food-bank, HOA, or PTA was included to show that the applicant was active. A statement of flexibility (“I am flexible” “I embrace change”) serves two purposes: first, as a statement to be taken at face value to indicate that the worker is flexible and adaptive, and second, to test whether the statement has the negative effects by age found in Lahey (2008) when the AARP was recommending older job seekers put such statements on their resumes. We also included several types of recent training on a random subset of resumes including computer training to test if concerns about computer skills are a problem with older job applicants, specific clerical training to see if recent job-specific training helped older workers compared to younger workers, and finally less relevant training (for example, home health care aid classes) to see if it is just training itself that is important.











Figures 4a-4e

None of the relationships shown follow standard, testable, linear or quadratic patterns. All added resume items appear to improve ratings overall. However, the size of this increase in ratings varies across the age listed on the resume. For the most part, volunteering seems to help evenly across the age spectrum, at least until age 70 when it dips. Flexibility statements help younger workers and seem to mostly stop helping by age 60, though unlike in Lahey (2008) they never turn negative for older applicants. Computer training does not help applicants age 35-60 at all, but has an outsize impact on applicants older than that—that is, computer training does not seem to help people in Generation X or the tail end of the Baby Boom, but does help earlier boomers and the tail end of the Silent Generation. Clerical training helps all workers, but seems to help the youngest and oldest workers most. Overall any training helps those over age 60 the most.[5]

Explicit Bias

Our first measure of explicit bias is explicit stereotypes themselves. Table 4 sorts stereotypes by the mean of the -2 to 2 scale, where all stereotypes are coded such that positive numbers indicate less ageism. While none of these means are significantly different from zero, four of them present negative point values, indicating that on average the people in the sample were willing to state that they explicitly believe the negative stereotype presented. The first two of these both deal with technological change, suggesting that older workers are both less interested in (mean = -0.3284) and less able to adapt to (mean = -0.2687) technological change. The other two stereotypes with negative means are that older workers dislike having tasks assigned to them by younger workers (mean = -0.2388) and older workers are less capable of

[5] Interestingly, we also included military experience on a random subset of resumes, and it seems to help the cohorts that did not see any boots on the ground conflict, but hurts those who did (Desert Storm).

doing physically taxing work (mean = -0.0746). However, even though only four of these terms indicate negative explicit stereotypes on average, Figure 5 demonstrates that there is spread across all 15 stereotypes, with some participants strongly agreeing or disagreeing with each stereotype.

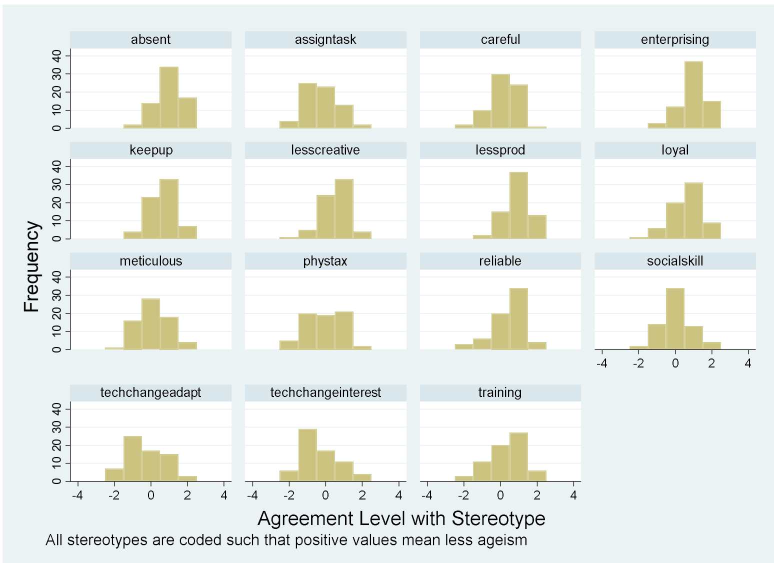


Figure 5

Given these differences across participants, we can use Equation (2) to compare how participants with different explicit beliefs by age rate resumes by age of the resume. Table 5 shows the five stereotypes that show significant or marginally significant interactions with the age and age^2 terms and Appendix Table 2 shows the ten regressions for which the age and age^2 stereotype interaction terms are not significant. These regressions have not been adjusted for multiple inference testing, but it is clear that only ability to adapt to technological change would survive such adjustment.

In order to make more sense of the 15 different explicit stereotypes, we combine them into 4 different factors using factor analysis as described in Section II. We term Factor 1 “capability”, Factor 2 “dependable”, Factor 3 “slow”, and Factor 4 “other.” Table 6 presents results using Equation (2) and finds that participants who explicitly state stereotypes in concordance with the "capability" factor have a marginally significant interactive effect with age as indicated on resume. Those whose statements correspond with the "other" factor have a significant interactive effect with age and age^2.

A second measure of explicit age discrimination is that of Social Distance (Bogardus 1938, Wark and Galliher 2007) which measures bias against an outgroup. For the most part, as demonstrated in Figure 6, participants in our sample are, on average, willing to work with workers of all ages across a number of work roles. The only exception with this sample is that people prefer not to have a teenage supervisor.[6]

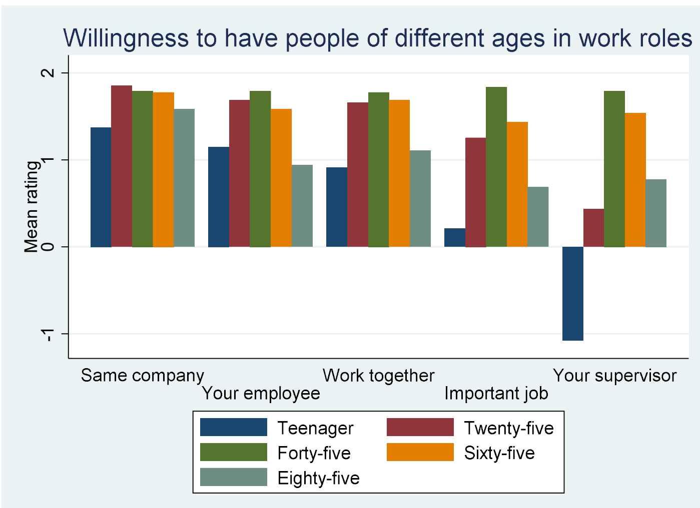


Figure 6

Using Equation (2), we treat the difference between how each participant rates their willingness to work with a 45 and 65 year old in a specific role (results combining 25 and 45 and 65 and 85 year olds are available from authors). Results are presented in Table 7. None of the interactions with age are significant for any of the roles except for "Same Company," and these results are being driven by a small number of participants given that the average value for "Same Company" is close to the high of 2. These results suggest that Bogardus Social Distance measures are not highly correlated with resume ratings by age.

[6] In John and Lahey (2020), we show that the student sample is more wary of teenagers and 85 year olds across several of these work roles.

Implicit Bias

A frequently used measurement of implicit bias is the IAT. In a departure from our measures of explicit bias, more positive numbers using our IAT signal *more* rather than less ageism in order to keep our results comparable with previous such studies using the same aging IAT. These studies usually find evidence of mild implicit discrimination, with a roughly normal distribution centered somewhere between 0.5 and 1 (Project Implicit, n.d.; John and Lahey, 2020; Malinen & Johnston, 2013; Nosek et al., 2007; Xu et al., 2020). Figure 7 demonstrates the results from this study which follow this same pattern.

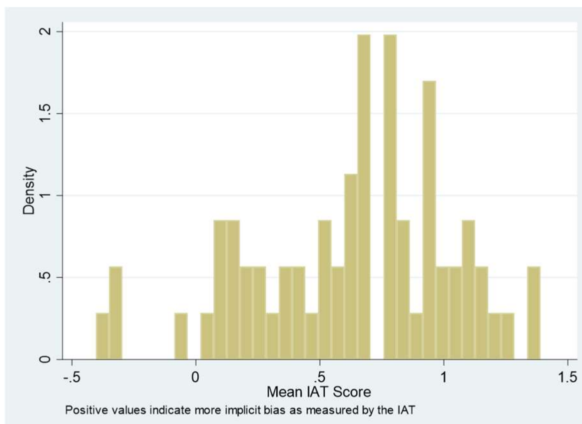


Figure 7

We again use equation (2) to interact our measure of IAT with the age and age^2 measures indicated on the resumes. Results are available in Table 8. None of the terms in these regressions are significant at conventional levels. In addition, the magnitudes are such that for most scores within the ageist range, as the IAT gets larger, the larger the preferences for those in the middle of the age range rather than either end. Figure 8 plots the additional effect of the IAT*Age Interaction terms for IAT ratings of 0, 0.5, 1, and 1.5. It is highly plausible that the age IAT is not appropriate for measuring implicit bias or attitudes for job applicants in this study given that the IAT was not created with the idea of work in mind (unlike the IAT for women and work, which is separate than the IAT for women alone), and the ages in the pictures appear to be both younger and older than the ages in our sample, rather than the continuous series of ages shown in the resumes presented to participants.

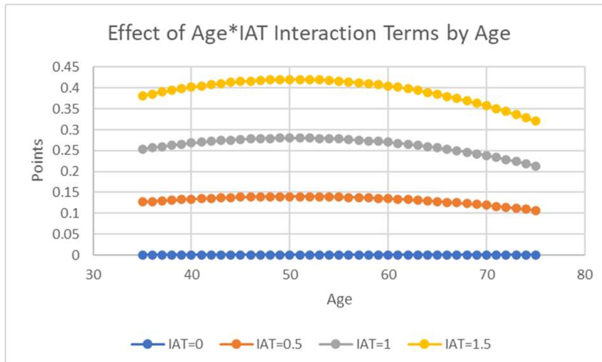


Figure 8

V Conclusion

This paper presents the results of an experiment in which we showed resumes with randomized inputs including age, indicated by date of high school graduation, to HR professionals. We demonstrate that resumes are treated differently by age and that this pattern is quadratic. Time spent on resumes shows similar patterns by age as rating.

Participants express different levels of stereotypes about older workers. We show that stereotypes about computer training seem to be limited to those over the age of 60 and that concerns about training more generally show up both explicitly and in the revealed ratings of participants. Combining several stereotypes together using factor analysis, we show that there are underlying concerns about the general capability of older workers that affect resume ratings by age.

Most people are willing to work with older workers in different roles. Only the small number of people who do not want to work at the same company as older workers show statistically different ratings outcomes by age using the Bogardus Social Distance scale. The implicit bias test for aging does not seem to be related to ratings for older workers, though it may not be a good tool to measure implicit bias for these age groups or in the workplace.

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Table 1. Summary statistics.

	Mean	SD
Resume Characteristics		
Female	0.50	
Hispanic	0.12	
Age	56.54	11.91
Participant Characteristics		
Female	0.80	
White	0.84	
Asian	0.02	
Black	0.16	
Hispanic	0.18	
Some College	0.18	
Bachelors Degree	0.40	
Some Post Grad	0.22	
Graduate Degree	0.20	
Income 31-70K	0.14	
Income 71-100K	0.24	
Income > 100K	0.62	
Age	44.21	11.44
Ratings		
Likert (1-7)	4.72	1.40
Eye-tracking		
Seconds spent: Total	16.04	9.18
Outside	0.43	0.77
Employment history	6.12	4.84
Name	0.11	0.21
High school	0.47	0.71
Years employed	0.83	1.11
Graduation year	0.06	0.16
Other	0.22	0.52
Education	0.27	0.37

Notes: There are 1,809 resumes for the non-eye-tracking statistics and 1,766 resumes for the eye-tracking statistics, other than seconds spent total which has 1,774 resumes.

Table 2. Baseline Results by Age - Whites, For Profit, and Full Time Only

	Likert rating (1-7)					
	All		Female		Male	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.0645**	-0.0632**	-0.0493	-0.0441	-0.0778*	-0.0735*
	(0.0303)	(0.0287)	(0.0431)	(0.0427)	(0.0434)	(0.0391)
Age squared	0.0006**	0.0005**	0.0004	0.0004	0.0007*	0.0007*
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Observations	1,809	1,809	900	900	909	909
Subject FE?	No	Yes	No	Yes	No	Yes

Notes: * Statistically significant at 10 percent level; ** at 5 percent level; *** at 1 percent level. Each column represents the results from a separate OLS regression. Standard errors corrected for clustering on the participant level are reported in parentheses. Female and Male refer to the gender indicated on the resume. A Likert score of 7 denotes most hireable.

Table 3: Duration and Count in Areas of Interest - White, For Profit, and Full Time Only

	All (1)	Outside (2)	Emp hist (3)	Name (4)	Address (5)	Yrs Emp (6)	Grad Yr (7)	Other (8)	Education (9)
		Panel I: Duration							
age	-0.3441*	0.0182	-0.1730	0.0027	-0.0049	0.0035	-0.0017	-0.0054	0.0121
	(0.1778)	(0.0151)	(0.1080)	(0.0048)	(0.0140)	(0.0212)	(0.0037)	(0.0128)	(0.0078)
age squared	0.0028*	-0.0002	0.0015	0.0000	0.0000	0.0000	0.0000	0.0001	-0.0001
	(0.0015)	(0.0001)	(0.0009)	(0.0000)	(0.0001)	(0.0002)	(0.0000)	(0.0001)	(0.0001)
		Panel II: Count							
age	-1.019*	0.0930	-1.051**	0.0145	-0.0700	0.0156	-0.0004	-0.0619	0.0409
	(0.6014)	(0.0731)	(0.5060)	(0.0245)	(0.0676)	(0.0955)	(0.0166)	(0.0653)	(0.0406)
age squared	-0.0087	-0.0009	0.0090**	-0.0001	0.0006	-0.0002	0.0000	0.0006	-0.0003
	(0.0052)	(0.0007)	(0.0044)	(0.0002)	(0.0006)	(0.0008)	(0.0002)	(0.0006)	(0.0004)

Note: Universe limited to resumes for whites, for profit, and full time only. Robust standard errors are clustered on subject. There are **1,766** observations. Duration is number of seconds spent viewing. Count denotes number of fixations using the Tobii X2-60 eye-tracker.

Table 4. Stereotypes

Question Type	Mean	SD
Tech Change Interest	-0.3284	1.0501
Tech Change Adapt	-0.2687	1.0672
Assign Task	-0.2388	0.9389
Physically taxing	-0.0746	1.0197
Social Skills	0.0448	0.8779
Meticulous	0.1194	0.8965
Careful	0.1791	0.8151
Training	0.3284	1.0059
Reliable	0.4478	0.9093
Less Creative	0.5075	0.7857
Loyal	0.6119	0.8869
Keep Up	0.6418	0.7528
Less Productive	0.9104	0.7330
Enterprising	0.9552	0.7674
Absent	0.9851	0.7686

Notes: There are 50 participants. All stereotypes are coded such that positive values mean less ageism and range from -2 to 2.

Table 5: Likert ratings for stereotypes with interacted age effects

item =	Enterprising	Phystax	Reliable	Adapt Tech	Training
	(1)	(2)	(3)	(4)	(5)
item*age	0.0707*	0.0436*	-0.0624*	-0.0373*	-0.0928***
	(0.0354)	(0.0220)	(0.0346)	(0.0214)	(0.0290)
item*age squared	-0.0005*	-0.0004*	0.0005*	0.0003*	0.0008***
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
item	-2.1374**	-1.1887*	1.7076*	0.9418	2.4837***
	(1.0428)	(0.6272)	(0.9737)	(0.6152)	(0.8166)
age	-0.1305***	-0.0655**	-0.0385	-0.0531*	-0.0967***
	(0.0419)	(0.0299)	(0.0361)	(0.0290)	(0.0286)
age squared	0.0011***	0.0006**	0.0003	0.0004*	0.0008***
	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)

Notes: Robust standard errors clustered on participant. There are 1,809 observations.

Table 6: Likert ratings for stereotype factors with interacted age effects

item =	Capable	Dependable	Slow	Other
	(1)	(2)	(3)	(4)
item*age	-1.4172*	0.0368	0.7959	-2.0240**
	(0.7092)	(1.0372)	(0.9526)	(0.7984)
item*age squared	0.0522**	-0.0019	-0.0251	0.0739**
	(0.0247)	(0.0376)	(0.0332)	(0.0300)
item	-0.0005**	0.0000	0.0002	-0.0007**
	(0.0002)	(0.0003)	(0.0003)	(0.0003)
age	-0.0643**	-0.0644**	-0.0635**	-0.0561*
	(0.0297)	(0.0295)	(0.0303)	(0.0298)
age squared	0.0005**	0.0006**	0.0005**	0.0005*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)

Notes: Robust standard errors clustered on participant. There are 1,809 observations.

Table 7: Likert ratings for prejudice with interacted age effects (45-65)

item =	Same Comp (1)	Your Employee (2)	Work Together (3)	Imp Job (4)	Your Super (5)
item*age	1.0690**	1.1893	-1.5174	0.6279	-0.6981
	(0.5158)	(1.1576)	(1.4532)	(1.7752)	(0.6828)
item*age squared	-0.0414**	-0.0471	0.0581	-0.0203	0.0312
	(0.0191)	(0.0429)	(0.0553)	(0.0648)	(0.0268)
item	0.0004**	0.0004	-0.0006	0.0002	-0.0003
	(0.0002)	(0.0004)	(0.0005)	(0.0006)	(0.0002)
age	-0.0699**	-0.0696**	-0.0570*	-0.0725**	-0.0624**
	(0.0303)	(0.0291)	(0.0339)	(0.0303)	(0.0305)
age squared	0.0006**	0.0006**	0.0005	0.0006**	0.0005**
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)

Notes: Robust standard errors clustered on participant. There are 1,809 observations.

Table 8: Effect of Implicit Bias Scores by Age

	Likert (1)	Likert (2)
IAT*age	0.0111	0.0205
	(0.0669)	(0.0692)
IAT*age squared	-0.0001	-0.0002
	(0.0006)	(0.0006)
IAT score	-0.0742	-0.0223
	(1.9290)	(1.9490)
age	-0.0719	-0.0759
	(0.0524)	(0.0540)
age2	0.0006	0.0007
	(0.0005)	(0.0005)
Observations	1,809	1,809
Subject FE?	No	Yes

Note: Robust standard errors clustered on participant.

Appendix Table 1: Stereotype statements

Older workers are less productive than younger workers.
Older workers are less creative than younger workers.
Older workers keep up just as well as younger workers.
Absenteeism is higher among older workers than among younger workers.
Older workers are just as enterprising as younger workers.
Older workers prefer not to be assigned tasks by younger workers.
Older workers are more loyal than younger workers.
Older workers are more reliable than younger workers.
Older workers are more meticulous than younger workers.
Older workers have greater social skills than younger workers.
Older workers are more careful than younger workers.
Older workers are less interested in technological change than younger workers.
Older workers are less able to adapt to technological change than younger workers.
Older workers are less capable of doing physically taxing work than younger workers.
Older workers are less interested in participating in training programs than younger workers.

Appendix Table 2: Likert ratings for stereotypes with interacted age effects

item =	Absent	Task	Careful	Keep Up	Creative	Less Prod	Loyal	Meticulous	Social Skill	Interest Tech Change
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
item*age	-0.0512	-0.0324	-0.036	0.0155	-0.0072	-0.0300	-0.0402	-0.0113	0.0463	-0.0361
	(0.0348)	(0.0291)	(0.0366)	(0.0389)	(0.0347)	(0.0290)	(0.0362)	(0.0263)	(0.0357)	(0.0241)
item*age squared	0.0004	0.0003	0.0003	-0.0002	0.0000	0.0003	0.0003	0.0001	-0.0004	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
item	1.4783	0.8964	0.921	-0.3947	0.2188	0.8343	1.2138	0.2582	-1.3356	0.9755
	(0.9836)	(0.8245)	(1.0126)	(1.0752)	(0.9700)	(0.8330)	(1.0123)	(0.7572)	(0.9937)	(0.6832)
age	-0.1105**	-0.0564*	-0.0588*	-0.0737*	-0.0666*	-0.0895**	-0.0376	-0.0650**	-0.0630**	-0.0516
	(0.0469)	(0.0284)	(0.0301)	(0.0392)	(0.0334)	(0.0365)	(0.0447)	(0.0304)	(0.0296)	(0.0316)
age squared	0.0009**	0.0005*	0.0005*	0.0006*	0.0006*	0.0008**	0.0003	0.0006**	0.0005**	0.0004
	(0.0004)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)

Notes: Robust standard errors clustered on participant. There are 1,809 observations.

Appendix Table 3: Factor analysis of stereotypes

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
Less productive	0.6153	0.3664	-0.0332	0.1611	0.4601
Less creative	0.3279	0.2650	-0.5777	-0.0243	0.4879
Absent	0.2351	0.3467	0.1700	0.1098	0.7835
Assign task	0.6398	0.0770	0.0750	0.2392	0.5218
Tech change interest	0.6351	0.0515	0.3455	0.1583	0.4496
Tech change adapt	0.7334	0.2043	0.1528	-0.0436	0.3951
Physically taxing	0.4414	0.1780	-0.4277	0.1633	0.5640
Training	0.5721	0.0374	0.0954	0.1430	0.6418
Keep up	0.4423	0.3415	0.0809	-0.3613	0.5507
Enterprising	0.3504	0.2503	0.0127	-0.6124	0.4394
Loyal	-0.4264	0.5270	-0.2624	0.1005	0.4615
Reliable	-0.5919	0.4180	-0.0156	-0.0019	0.4747
Meticulous	-0.4065	0.3216	0.2484	0.0097	0.6696
Social skills	-0.3293	0.4095	0.2267	0.0221	0.6720
Careful	-0.4606	0.4921	0.1327	0.1414	0.5081

Appendix Figure 1

[The participant will be relocated to another computer where the rest of the survey can be completed.

The Age Attitude Implicit Association Test (IAT) will be administered with the following stimuli:

Good Stimuli: *Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy*

Bad Stimuli *Agony, Terrible, Horrible, Nasty, Evil, Awful, Failure, Hurt*

In the next task, you will be presented with a set of words or images to classify into groups. This task requires that you classify items as quickly as you can while making as few mistakes as possible. Going too slow or making too many mistakes will result in an uninterpretable score. This part of the study will take about 5 minutes. The following is a list of category labels and the items that belong to each of those categories.

<u>Category Items</u>

Good Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy

Bad Agony, Terrible, Horrible, Nasty, Evil, Awful, Failure, Hurt

Old faces of Old people

Young faces of Young people

Keep in mind

- Keep your index fingers on the 'e' and 'i' keys to enable rapid response.
- Two labels at the top will tell you which words or images go with each key.
- Each word or image has a correct classification. Most of these are easy.
- The test gives no results if you go slow -- Please try to go as fast as possible.
- Expect to make a few mistakes because of going fast. That's OK.
- For best results, avoid distractions and stay focused.

Appendix Figure 2