AI Personality Extraction from Faces: Labor Market Implications

by

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Background: Personality and AI in Labor Market Screening

Personality and Labor Market Screening + AI



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Today's Personality Tests Raise the Bar for Job Seekers

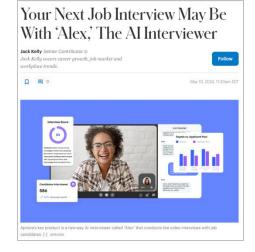
More companies use assessments to hire, with fewer willing to take a chance on anyone who doesn't measure up

By Lauren Weber Follow Updated April 14, 2015 11:13 pm ET

Top AI recruiting tools and software of 2025

Al continues to spread to every corner of recruiting and talent acquisition. Here's the latest on Al tools from GenAl to smart chatbots and agents, plus details on 13 products.

Find My Fit helps candidates identify roles that best match their potential by quickly assessing their skills, interests and personality.



Recruiting is costly

AI is getting involved in <u>screening</u>, <u>shortlisting</u>, and <u>selection</u>:

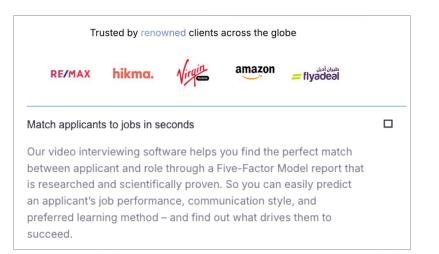
- Resume Screening
- Behavioral and Skills Assessments
- AI Video Interviews
- Predictive Analytics
- Cultural Fit and Personality Matching

Personality and Faces

- Early usage of personality extraction from videos: HireVue said its video-based algorithmic assessments provide "excellent insight into attributes like social intelligence (interpersonal skills), communication skills, personality traits, and overall job aptitude." (2019)
- Black box: HireVue experienced a lot of pushback.

Other firms engaging in similar behavior:





Regulation on AI use in Hiring

• American Privacy Rights Act failed:

WSJ PRO

Patchwork of State Privacy Laws Remains After Latest Failed Bid for Federal Law

Conflicting state privacy laws create unnecessary costs and confusion, companies say

- Current regulations in US:
 - Illinois: Artificial Intelligence Video Interview Act (2019)
 - Maryland: Facial Recognition Law (2020)
 - $\,\circ\,$ New York: Automated Employment Decision Tools (AEDT) Law (2023)
 - $\,\circ\,$ Colorado: Colorado Artificial Intelligence Act(2024)
- EU: The EU Artificial Intelligence Act (AI Act) (2024)

Ethics Considerations

We assess the Photo Big 5 predictive power, but are *not* advocating for usage in labor market screening

• Personality extraction from faces is Fundamental Statistical Discrimination

• Inferences made from immutable characteristics

A fundamental question:

Among people of same gender and race, is it ethical to screen out those whose faces predict greater agreeableness?

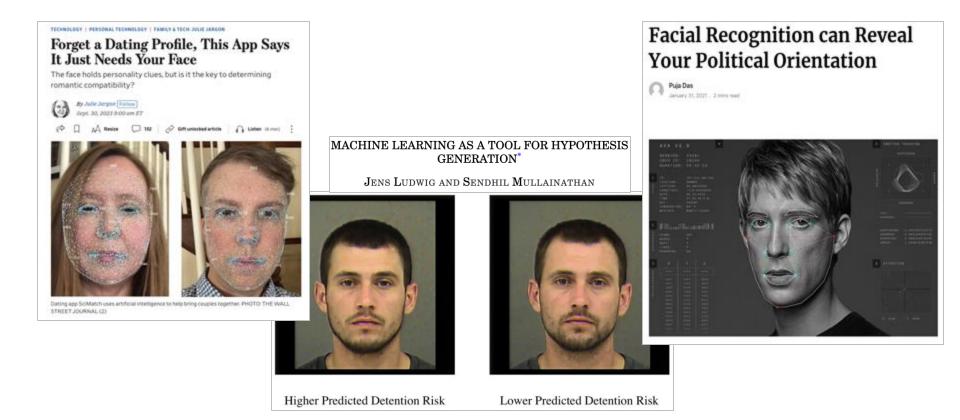
- Violation of autonomy and respect for individuals
- Removes incentives to improve personality
- Inequality of opportunity

Our Paper

Academic Motivation

- Human capital—skills, knowledge, and personality—is a critical determinant of labor market success
- Personality often has larger explanatory power than other individual characteristics Labor market (e.g., Barrick and Mount, 1991; Nyhus and Pons, 2005; Heckman et al., 2006; Mueller and Plug, 2006; Almlund et al., 2011); education (e.g., Heckman and Rubinstein, 2001; Heckman et al., 2011); health (e.g., Roberts et al., 2007; Kern and Friedman, 2014); crime (e.g., Cunha et al., 2006); financial investments (e.g., Jiang et al., 2024)
- Key obstacle: Personality remains difficult to *measure at scale*
 - Lack of large-scale personality surveys coupled with individual (employment) outcomes
 - Survey-based measures susceptible to manipulation
- > Photo Big 5 is accessible for large datasets with other observable characteristics.

AI facial recognition has entered `mainstream'



This paper

- Apply **AI-photo-personality analysis** to LinkedIn data on MBAs
- Evaluate the **predictive power** of the **'Photo Big 5' for labor market** outcomes
- Why MBAs?
 - Industry participants argue personality traits and soft skills important for MBAs
 - Survey and task-based personality measures already heavily used in hiring and job screening

Preview of results

Photo Big 5:

- Significantly predicts school rank, compensation, job seniority, job transitions
- Has predictive power comparable to race, attractiveness, and educational background
 - Bottom to top quintile of 'desirable' personality
 = 64%-122% of Black-White compensation gap
- **Correlated** with survey-based measures of personality
- **High incremental predictive power** to GPAs and test scores

Methodology and Data

Big Five personality traits

- The five factors are:
 - Openness to experience (curiosity, aesthetic sensitivity, imagination)
 - o Conscientiousness (organization, productiveness, responsibility)
 - o Extraversion (sociability, assertiveness, energy level)
 - o Agreeableness (compassion, respectfulness, trust)
 - Neuroticism (anxiety, depression, emotional volatility)
- The five factors are:
 - **Labels** reflecting distinct personality dimensions each encompassing a broad range of specific characteristics

AI personality extraction from faces

Use **ML algorithm** developed by Kachur, Osin, Davydov, Shutilov, Novokshonov (2020): Assessing the big five personality traits using real-life static facial images. Nature Scientific Reports 10 (1), 8487

- 12,447 volunteers submitted photos + took a Big 5 personality survey
- Extract facial features from self-submitted images
- Train a cascade of artificial neural networks (ANNs) on survey-based measures of Big 5 traits
- Algorithms were trained separately for male and female faces

Why might face be associated with personality?

- 1. Genetics contribute to both face and personality
 - Craniofacial characteristics can be predicted with DNA (e.g., Claes et al. 2014)
 - Recent studies have attributed 40-60% of personality traits to genetic factors. Consistent across different cultures and age groups (e.g., Bouchard and McGue 2003, Vukasovic and Bratko 2015, Gupta et al. 2024)

Yale school of medicine	How Genes Shape Personality Traits: New Links Are Discovered	The Big Five and novel loci
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- 2. Pre- and postnatal hormones affect both facial shape and personality (e.g., Lefevre 2013 and Penton Voak 2004)
- 3. Perceived facial shape by self and others could affect personality and vice versa (e.g., "Quasimodo complex" in Masters and Greaves 1967)

KODSN (2020) examples

Humans can perceive personality traits from each other's faces with some accuracy Combined images created based on differences in **survey** responses

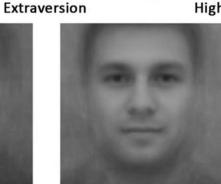


Low



High







Low

Neuroticism





High

Method stability

The results are **not** (or **very slightly**) affected by:

- Clothes
- Makeup/haircut
- Resolution of the photo (as long >30 pixels between eyes)
- Facial expression



Personality extraction from faces: Accuracy

Accuracy:

- Correlations between self-reported and predicted scores:
 - **0.14** (openness; women) to **0.36** (conscientiousness; men).
 - 7 out of 10 correlations are > 0.2.

Benchmarks:

- Compared to 0.30 to 0.41 for peers and -0.01 to 0.29 for strangers (Connolly et al., 2007)
- "correlations between *behavioral task measures* of personality and *questionnaire measures* seldom, if ever, exceeded 0.3" (Almlund, Duckworth, Heckman, Kautz, 2011)

> **Note**: true personality is latent

Data

- 1. Large-scale dataset of education and employment history from LinkedIn & Photos (*Revelio Labs*)
- 2. Smaller dataset of several top 10 US MBA programs' entrance screening and academic performance measures
- Photo age and race (Guenzel, Borgschulte, Liu, Malmendier (2024), Deepface/Revelio)
- Attractiveness score (*Liang*, *Lin*, *Jin*, *Xie*, *Li*, 2018)
- Face blurriness, glasses recognition, emotional expression (*Microsoft Face API*)
- Probability of Photoshop (*Wang, Wang, Owens, Zhang, Efros, 2019*)

LinkedIn Sample

LinkedIn Data (Revelio Labs)

- Focus on graduates of full-time MBA programs from top 110 business schools (US News 2023)
- Require non-missing undergrad graduation year & MBA graduation year (between 2000-2023) and at least one post-MBA (within 1 year of graduation) position listed on LinkedIn in the US:
 - Final Sample: 70,593 men and 26,316 women

School ranking and Photo Big 5

- Regress school ranking (1 is a `good' ranking) on Photo Big 5 and controls.
- Consistent prior literature on performance in post-secondary education & on standardized tests (Poropat, 2009 & Duckworth 2011)
- Photo Big 5 effect (Top20-Bottom20): going from 'undesirable' to 'desirable' personality

	School Ran	king $(1=$ highest)
	Men (1)	Women (2)
Agreeableness (z)	0.382^{***} (0.148)	-1.897^{***} (0.235)
Conscientiousness (z)	0.733^{***} (0.160)	0.853^{***} (0.237)
Extraversion (z)	-0.480^{***} (0.184)	-1.446^{***} (0.213)
Neuroticism (z)	-0.626^{***} (0.111)	$0.107 \\ (0.208)$
Openness (z)	0.308^{*} (0.182)	-0.024 (0.234)
Grad. Year FE	Yes	Yes
Race FE	Yes	Yes
Image Controls	Yes	Yes
Age Controls	Yes	Yes
LHS mean	35.582	37.982
R2	0.101	0.132
Observations	70,593	26,316
Big 5 Top20-Bottom20	2.616	6.588

1st Post-MBA Compensation

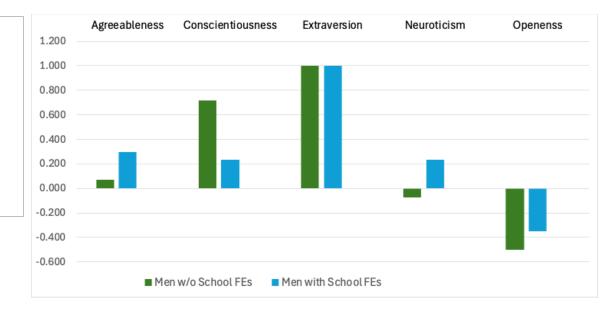
- Include controls: race, age at MBA (and squared), attractiveness, image blurriness, glasses dummy, emotional expression, lighting adjustment dummy, implied age in the photo, the probability of Photoshop
- Add School FE effects
- Photo Big 5 effect:

 4.3% (men), 4.7% (women)
 ▶ 122% and 64% of the Black-White gap
- Effects are **stable** if we control for O*NET job classifications from BLS

	(1) 0.001	en (2)	Wor	nen
		(2)	(0)	
A 11 ()	0.001		(3)	(4)
Agreeableness (z)				
	(0.003)			
Conscientiousness (z)	0.010^{***}			
	(0.003)			
Extraversion (z)	0.014^{***}			
	(0.003)			
Neuroticism (z)	-0.001			
	(0.002)			
Openness (z)	-0.007**			
	(0.003)			
Asian	0.079***			
	(0.007)			
Black	-0.016^{*}			
	(0.010)			
Hispanic	0.012			
	(0.013)			
Other Non-White	0.024^{***}			
	(0.006)			
Age at MBA	0.121^{***}			
	(0.004)			
Attractiveness Score (z)	0.028^{***}			
	(0.002)			
Grad. Year FE	Yes			
Image Controls	Yes			
Age at MBA ² School FE	Yes			
R2	0.100			
Observations	70,593			
Big 5 Top20-Bottom20	0.048			

Big 5 and Job Productivity: Prior Literature

- Display 'scaled' coefficients (|largest coefficient| = 1)
- Compare to prior literature on job productivity, also `scaled' (Barrick and Mount, 1991)



Post-MBA Compensation: Long-term effect

• The effect of personality on compensation is **present 5 years** after MBA

Photo Big 5 effect:

- **2.2%** (men), **2.4%** (women)
- Magnitude is **smaller** than for 1st job.
- Find **similar** similar results for **seniority**

	Δ 5yr	-1st Post-M	BA Comp	(log)
	M	len	Wo	men
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.003 (0.003)	$0.004 \\ (0.004)$	-0.000 (0.005)	$0.004 \\ (0.005)$
Conscientiousness (z)	$\begin{array}{c} 0.016^{***} \\ (0.004) \end{array}$	0.010^{**} (0.004)	-0.012^{**} (0.005)	-0.009^{*} (0.005)
Extraversion (z)	$0.002 \\ (0.004)$	-0.004 (0.004)	$0.004 \\ (0.005)$	-0.001 (0.005)
Neuroticism (z)	-0.000 (0.003)	$0.000 \\ (0.003)$	$0.006 \\ (0.005)$	$\begin{array}{c} 0.002 \\ (0.005) \end{array}$
Openness (z)	-0.004 (0.004)	-0.003 (0.004)	-0.007 (0.005)	-0.005 (0.005)
Asian		-0.039^{***} (0.010)		-0.021 (0.016)
Black		-0.021 (0.014)		-0.009 (0.030)
Hispanic		-0.033^{*} (0.019)		-0.046 (0.030)
Other Non-White		-0.023^{***} (0.007)		-0.030^{**} (0.013)
Attractiveness Score (z)		$0.003 \\ (0.003)$		-0.000 (0.005)
Grad. Year FE	Yes	Yes	Yes	Yes
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
School FE	No	Yes	No	Yes
R2	0.003	0.018	0.006	0.025
Observations	$47,\!049$	$47,\!049$	$15,\!913$	15,913
Big 5 Top20-Bottom20	0.044	0.022	0.040	0.024

Job Mobility

Men:

- Agreeableness is positive for tenure and negative for # of firms/industries/job categories
- **Conscientiousness** is **positive** for **tenure** and **positive** for **# of industries**
- Extraversion is negative for tenure and positive for # of firms/industries/job categories
- **Neuroticism** is **negative** for **tenure** and **negative** for **# of industries**
- **Openness** is **positive** for **tenure** and **negative** for **# of firms/industries/job categories**

Women:

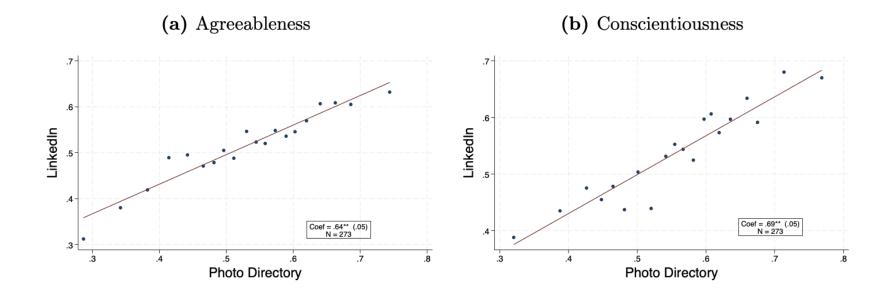
- **CEAN** are the same as for men
- **Openness** is **negative** for **tenure** and **positive** for **# of firms/industries/job categories**

Top MBA Programs Sample

Validating our measures

- Admission data & photo directories from several top MBA programs.
- Match to LinkedIn profiles
- ▶ 1,374 observations; 1,100 LinkedIn profiles; 273 MBA +LinkedIn photos.

Personality measures: LinkedIn vs. MBA photos



Survey and Photo Big 5

- Men: N = 544; Women: N = 380
- Map facets into Big 5.
- Men: Average correlation is 0.166; Women: Average correlation is 0.186

1st Post-MBA Salary

- Similar effects of Photo Big 5 to the full sample results.
- Undergraduate/MBA GPAs and GMAT only slightly affect the relationship between Photo Big 5 and the 1st post-MBA salary

	1st Post	t-MBA Co	mpensatio	on (log)
	Μ	en	Women	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.019	0.024	0.029	0.029
	(0.029)	(0.029)	(0.033)	(0.034)
Conscientiousness (z)	0.070^{**}	0.061^{*}	-0.039	-0.043
	(0.034)	(0.034)	(0.047)	(0.046)
Extraversion (z)	0.049	0.058	0.038	0.042
	(0.038)	(0.038)	(0.029)	(0.030)
Neuroticism (z)	0.002	0.002	0.031	0.030
	(0.023)	(0.023)	(0.035)	(0.034)
Openness (z)	-0.085**	-0.083**	-0.029	-0.028
	(0.035)	(0.035)	(0.035)	(0.037)
Undergrad GPA		-0.133**		-0.078
		(0.063)		(0.121)
GMAT Quant		-0.002		-0.002
		(0.002)		(0.003)
GMAT Verbal		0.002		-0.001
		(0.003)		(0.004)
MBA GPA		0.109		0.259^{**}
		(0.071)		(0.101)
Grad. Year FE	Yes	Yes	Yes	Yes
mage Controls	Yes	Yes	Yes	Yes
ge Controls	Yes	Yes	Yes	Yes
chool FE	Yes	Yes	Yes	Yes
R2	0.062	0.076	0.167	0.205
Observations	883	883	217	217
Big 5 Top20-Bottom20	0.217	0.217	0.155	0.161

Conclusion

- Explore a new methodology: leveraging machine learning techniques to infer Big 5 personality characteristics from individuals' images
 - This methodology circumvents the limitations of survey-based assessment: limited sample size and gaming of the survey.

• Current project finds that:

- Photo Big 5 have strong predictive power for future compensation/seniority
- Predictability remains strong after controlling for demographic characteristics, past labor and education history

