Proceedings of the 57th Hawaii International Conference on System Sciences | 2024

Unraveling the Impact of Visual Cues in Online Portraits on Workers' Employability in Digital Labor Markets

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Abstract

Online portraits constitute a pervasive and critical signal in digital labor markets in that workers can boost their employability by manipulating select visual cues embedded in these portraits. Consequently, we attempt to unravel how visual cues embedded in workers' portraits within digital labor markets can collectively influence constituent dimensions of employability. Notably, we advance a non-verbal cues classification model that differentiates among demographic, physical appearance, image quality, and non-verbal behavioral cues as focal determinants affecting one's employment status, the number of job offers received, and rehiring probability. Employing computer vision and deep learning algorithmic techniques to analyze the online portraits and personal information of 53,950 workers on Upwork.com, we demonstrate that visual cues embedded in profile portraits exert a significant effect on workers' employability in digital labor markets.

Keywords: Visual cues, non-verbal classification model, deep learning, digital labor market.

1. Introduction

Economic globalization and the disruptive impact of the COVID-19 pandemic on onsite work have culminated in the proliferation of digital labor platforms (Li, Mo, & Zhou, 2022). Digital labor platforms facilitate remote collaboration in completing a wide range of tasks by connecting employers with workers worldwide, which range from lifestyle pursuits like fortune-telling to professional activities such as programming, translation, and video production. Indeed, by 2021, 36% of the workforce in the United States were online workers (Segal, 2021). Likewise, Upwork's (one of the largest digital labor platforms) total service volume was estimated at USD $3.3 billion in 2021 (Barbosa, 2022). However, despite the phenomenal growth of digital labor markets, information asymmetry remains an elusive challenge confronting such markets (Uhlmann & Silberzahn, 2014): Employers have to make hiring decisions based solely on informational cues provided by workers. Consequently, it is common for digital labor platforms to mandate workers to post portraits of themselves to alleviate information asymmetry. These online portraits embed visual cues that could dictate hiring decisions.

Past studies have discovered that employers are inclined to draw inferences about the personality traits of job applicants from visual cues and that these traits are deterministic of the latter's employability (Martín-Raugh, Leong, Roohr, & Chen, 2023). For example, employers tend to favor job applicants who hold eye contact and speak louder because they are likely to be perceived as extroverts. In the same vein, job applicants who gesture more and speak fluently also have a greater probability of being selected because they are viewed as intelligent. Apart from personality inferences, prior research has found that specific visual cues could also positively affect hiring decisions. For example, perceived beauty can positively impact the employability of job applicants by bolstering their attractiveness (Leung et al., 2020), whereas wearing glasses may positively influence hiring decisions by inducing employers' perception of intelligence (Wei & Stillwell, 2017). Nevertheless, at the same time, studies have revealed that visual cues related to demographics (e.g., ethnicity and gender) may also amplify biases and discrimination in the hiring process (Hannák et al., 2017; Leung et al., 2020).

Given the countervailing effects of visual cues in online portraits, we advance an integrated framework to account for the confluence of these visual cues on employment. Particularly, based on the integrated framework, we attempt to address the dearth of research on the impact of visual cues in online employment by differentiating among demographic, physical

URI: https://hdl.handle.net/10125/106460
978-0-9981331-7-1

appearance, image quality, and non-verbal behavioral cues as focal determinants driving one's employment status as well as the number of job offers received and rehiring probability. In so doing, we not only acknowledge the inevitability that visual cues embedded in online portraits are presented simultaneously to viewers such that it is impossible to disentangle the effect of one visual cue by disregarding others, but we also depart from previous work that shares a tendency to investigate the effects of each visual cue in isolation. Additionally, because measuring visual cues in past studies relies extensively on subjective evaluation, we further devise a methodological approach for automatically extracting visual cues from online portraits. This approach is developed to cater to contemporary digital labor platform environments where workers have extreme flexibility in adding and updating their portraits, thereby giving rise to a plethora of online portraits to analyze. Taken together, we endeavor to offer an answer to the following research question: **How do visual cues embedded in workers' online portraits affect their employability?**

To answer the above research question, we construct a non-verbal cue classification model, which embodies multiple visual cues, to systematically investigate how the joint effects of multiple types of cues shape online workers' employability. Running a Python script to obtain data from 53,950 workers at Upwork.com, we employed computer vision and deep learning algorithmic techniques to detect and extract visual cues from online portraits. Task complexity and text features supplied by workers, as identified through Natural Language Processing (NLP), are included as control variables. We then conduct logistic and least squares regression on the impact of visual cues on employment decisions, number of jobs, and reemployment probability to validate our research model.

The remainder of this paper is organized as follows. In Section 2, we review extant literature on the classification of visual cues and their applications in online employment. Next, we introduce our research model in Section 3 and formulate hypotheses pertaining to the effects of visual cues on workers' employability in digital labor markets. Data collection and analytical procedures are described in Section 4. We then present the analytical results in Section 5. Finally, in Section 6, we discuss the implications of our empirical findings for theory and practice as well as highlight the limitations of our work from which future avenues for research could spawn.

2. Theoretical Foundation

2.1. Visual cues and online employment success

Past studies have explored the effect of visual cues on online employment success. Previous research has shown that demographic cues, such as gender, age, and race, can contribute to online discrimination and bias (Hannák et al., 2017; Leung et al., 2020), while specific facial features, such as expressions (J. Kim & Park, 2017), beauty, and use of make-up (Yang, Li, Li, & Yuan, 2022) can have a positive effect on online decision-making (Peng, Cui, Chung, & Zheng, 2020; Y. Li, Zhang, & Laroche, 2019). Beyond demographics and beauty, studies have shown that the person's distance from the camera in the image affects how the image is perceived (Kapidzic & Herring, 2015). For example, individuals shown in close-ups are perceived to be more intimate with the viewer (Pitcher, 2000), while people whose bodies are fully visible may be perceived as both physically and emotionally distant (Kapidzic & Herring, 2015). In addition, Van der Land et al. (2016) found that avoiding eye contact can reduce recruiters' perceived trust. It can be seen that these studies have addressed the impact of a few specific visual cues on employment success without a more systematic framework for analyzing different types of visual cues. Because of the multifaceted impact of a portrait on online decision-making, different results may be expected when different types of visual cues are investigated simultaneously. For example, when employers make online employment, the competition result between the positive effect of beauty and the negative effect of stereotype discrimination is still unclear. In the online job market context, there is still a dearth of research on how online portraits can be manipulated to achieve more favorable results. This will become a more pressing issue as cheap and easy-to-use generative AI tools (such as Dall-E and Midjourney for pictures) become widely available.

In earlier research on the impact of visual cues, the empirical data has most often been collected by conducting an experiment or a survey (Kuttal, Chen, Wang, Balali, & Sarma, 2021; Thompson, Braddy, & Wuensch, 2008). However, this approach has constraints when applied to platforms where the number of portraits is large. In addition to limits in the possible sample size, with this method using a questionnaire, the decision-making variable is measured as an intention rather than the actual behavior, which may influence the validity of the results. In this paper, we applied the non-verbal classification model to incorporate a full range of visual cues to comprehensively evaluate the effect of visual cues on employment success in the context of digital labor markets.

2.2. Non-verbal classification model

Non-verbal cues are defined as non-spoken or non-written subtle cues (Yuanqing Li, Xiao, & Wu, 2021). Tortoriello et al. (1978) defined non-verbal cues more specifically as the information exchanged through non-verbal means, including body languages, facial expression, gestures, eye contact, interpersonal distance, space, physical attraction, and paralinguistic cues, such as voice change, volume, speed, and conversation duration, as well as the use of silence and time. Demographic cues (e.g., gender, race, age) are also included in this definition. These indicators can systematically convey image information to perceivers.

De Meuse (1987) established a classification model of non-verbal cues, including two dimensions. The first dimension describes the nature of cues, including behavioral cues (e.g., facial posture) and non-behavioral cues (e.g., race). The second dimension describes how much the individual can or cannot control the cue. Whereas cues such as facial expression and make-up can be manipulated, cues such as gender or race are beyond individuals' control. In the framework of De Meuse (1987), three attribute regions are divided based on these two dimensions: demographics, personal appearance, and non-verbal behavior. Demographic cues refer to non-verbal cues not under the individual's control. Appearance cues are non-behavioral and subject to transient and frequent changes in the individual, whereas non-verbal behavior encompasses cues completely under the individual' control.

Although the classification model of non-verbal cues was advanced to scrutinize performance appraisal in employment contexts, its applications mainly focus on computer-generated images. For example, Cowell and Stanney (2005) designed an anthropomorphic computer character using a non-verbal cue classification model to increase the character's trustworthiness. Furthermore, Liew and Tan (2021) designed highly professional artificial agents using the classification model of non-verbal cues. There is still a lack of research applying this non-verbal cue classification model in the context of real people.

Through the literature review, we found that studies rarely consider the role of non-verbal cues in the context of online employment. In addition, relatively few studies directly investigate various non-verbal variables, and the existing studies only discuss a few non-verbal cues. Since non-verbal cues form an overall impression, it is necessary to conduct a comprehensive analysis of different types of cues to explore employment success under the combined effect of different types of non-verbal variables.

3. Research Model and Hypotheses

Our research model builds on De Meuse's taxonomy (De Meuse, 1987). We propose to augment the taxonomy with a new category of cues, which we have labeled as image quality cues and classified into the controllable non-behavioral module. Finally, we expanded behavioral features, including the degree of eye openness, distance from the camera, and head pose angle (See Figure 1).

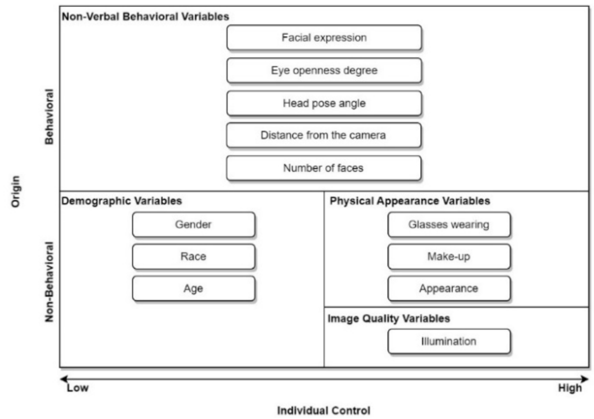

Figure 1. Classification Model of Non-Verbal Cues

In our adapted classification model of non-verbal cues, demographic cues include gender, race, and age. Physical appearance cues include glasses-wearing, make-up, and overall appearance. Non-verbal behavioral cues include facial expression, degree of eye openness, head pose angle, distance from the camera, and the number of faces in the portrait.

To study the impact of visual cues on employment success, we developed a research model depicted in Figure 2. Specifically, we explored the effects of four categories of non-verbal cues, namely demographic cues, physical appearance cues, image quality cues, and behavioral cues, on three categories of employment success: the employment decision, the number of jobs, and the reemployment probability.

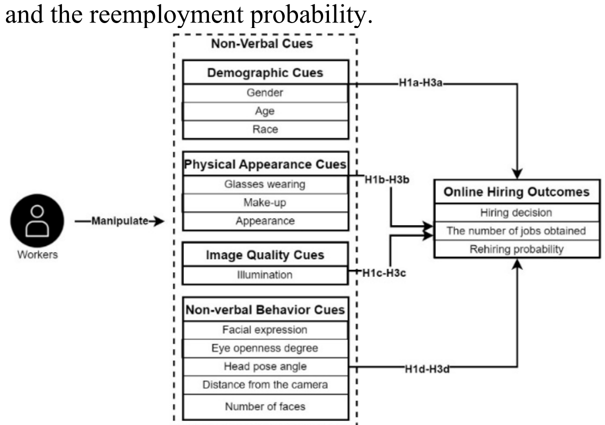

Figure 2. Research Model

Next, we summarize relevant research on the impact of visual cues on different types of employment success. First, several studies have suggested a possible link between visual cues and employment status. Troncoso and Luo (2020) studied the impact of the portraits on online recruitment outcomes. They found that workers who "looked fit for the job" were more likely to be employed, even when demographics and beauty have controlled for. Hemamou et al. (2019) investigated the impact of visual cues from candidates in asynchronous video job interviews on employment status. They showed that the four most important traits were blinking, lip expansion, jaw drop, and tight lips. Chen et al. (2018) automatically predicted the employment status based on the visual cues of candidates in asynchronous video interviews. We therefore hypothesize that:

Hypothesis 1: *Visual cues in the form of (a) demographic cues, (b) physical appearance cues, (c) image quality cues, and (d) non-verbal behavioral cues significantly affect employment status.*

Other studies have discussed the impact of visual cues on sales performance. For example, Walker and Raghunathan (2004) investigated whether and to what extent visual cues influence employers' first impressions of salespeople. They found that in employer-salesperson interactions, impressions based on visual cues could be directly obtained after exposure to a static image of salespeople. Moreover, the employer's judgment of visual cues is significantly related to the salesperson's success. The employer's initial impression of the target is formed based on the visual cues, which influence subsequent behavior towards the target. Kim et al. (2009) found that professional dress, friendly facial expressions, and attractive overall appearance of salespeople working in stores positively impacted sales. We therefore hypothesize that:

Hypothesis 2: *Visual cues in the form of (a) demographic cues, (b) physical appearance cues, (c) image quality cues, and (d) non-verbal behavioral cues significantly affect the number of jobs.*

Finally, some studies discussed the influence of visual cues on reemployment intention. Lee (2012) used reliability analysis, factor analysis, multiple regression analysis, and other methods to analyze the questionnaire data of 335 consumers. They found that body appearance, posture, and facial expression positively affected repurchase intention. Park et al. also emphasized that visual cues can influence service repurchase intentions (Park et al., 2014). We therefore hypothesize that:

Hypothesis 3: *Visual cues in the form of (a) demographic cues, (b) physical appearance cues, (c) image quality cues, and (d) non-verbal behavioral cues significantly affect reemployment probability.*

Based on these theoretical findings, we posit that four sub-cues of visual cues, namely, demographic cues, physical appearance cues, image quality cues, and non-verbal behavioral cues, can significantly affect employment status, the number of jobs, and the reemployment probability.

4. Methodology

4.1. Data collection

Empirical data was collected from Upwork, one of the largest digital labor platforms, with over 17 million registered users worldwide. Upwork connects workers and employers in different fields worldwide, providing great opportunities in the era of economic globalization and post-pandemic. Specifically, Upwork has 12 major categories, including Accounting & Consulting, Customer Service, Data Science & Analytics, Design & Creative, Engineering & Architecture, IT & Networking, Legal, and Sales & Marketing. We collected detailed information on 53,950 workers using Python scripts, added to the platform by January 2021 (the time of data collection). Considering it is necessary to control the impact of verbal information on the results, we first removed 20,864 workers without self-description. Second, we removed 5,353 workers whose photos were too fuzzy or were not human faces. Finally, we selected 27,733 workers' information to conduct our research.

4.2. Operationalization of focal variables

In this study, we used Baidu API, a public cloud API service providing face recognition in the form of an interface, to obtain demographic cues, used deep learning method to obtain physical appearance cues, and used the library OpenCV to extract 68 face features points and calculate non-verbal behavioral cues.

4.2.1. Demographic cues. We estimated workers' demographic cues by evaluating their gender, age, and race. We used Python to connect the Baidu Face Recognition API. Specifically, we first processed each image into a base64 encoding (A method of representing binary data based on 64 printable characters) and then submitted an HTTP request to the interface to get the data returned by the interface. It is worth mentioning that Baidu Face Recognition API will also return the confidence level of recognition results, ranging from 0-1. We saved results with a confidence level greater than 0.95.

4.2.2. Physical appearance cues. We estimated workers' physical appearance cues by evaluating their glasses-wearing, make-up, and appearance. First, we built a six-layer deep convolutional neural network to identify make-up using a training dataset consisting of 2600 images of 1300 people from five independent datasets (FAM, MIFS, VMU, MIW, YMU (Alzahrani, Al-Bander, & Al-Nuaimy, 2021). Each person included two photos: one with make-up and one without make-up. Finally, the prediction model achieves 95% accuracy.

We used the ResNet-50 convolutional neural network to score the appearance of workers, and the softmax fully connected layer was removed for regression. The training dataset is from the SCUT-FBP5500 dataset, which contains four subsets of different races and genders, including 2000 Asian women (AF), 2000 Asian men (AM), 750 Caucasian women (CF), and 750 Caucasian men (CM). A total of sixty volunteers labeled all images with aesthetic scores ranging from 1 to 5. If the correlation coefficient between the two scores of a photo is less than 0.7, the third score is required, and the final score is the average of all the scores. We used RMSE to evaluate the model prediction effect. This index refers to the arithmetic square root of the squared value of the difference between the parameter's estimated value and actual value. The smaller the value of RMSE, the better the accuracy of the prediction model in describing the experimental data. Finally, the RMSE value of the model reached 0.3, indicating that the appearance prediction model achieved a good effect. Finally, we use Baidu Face Recognition API to identify glasses-wearing and figure illumination. As with identifying demographic cues, we retained identification results with a confidence level greater than 0.95.

4.2.3. Non-verbal behavioral cues. We estimated workers' non-verbal behavioral cues by evaluating the facial expression, eye openness degree, head pose angle, distance from the camera, and face number.

We used the cross-platform computer vision library OpenCV to identify 68 feature points of the face. We used these feature points' coordinates (x, y) to compute the non-verbal behavioral cues. According to the OpenCV recognition results of facial feature points, each eye is represented by six-coordinate points. According to the suggestions of Soukupová and Cech (2016), we took the length-to-width ratio of the two eyes averaged together as our eye openness value.

$$\mathrm{EAR} = \frac{\|P2 - P6\| + \|P3 - P5\|}{2\|P1 - P4\|}$$

We use the Euler Angle to measure the head pose angle. Euler angle constitutes a rotation matrix through three parameters, namely Pitch, Yaw, and Roll, which correspond to the rotation angle around the X-axis, Y-axis, and Z-axis, respectively. Specifically, we first obtain the coordinates of 68 feature points and then use the OpenCV Perspective-n-Point (PnP) pose computation algorithm to calculate these three angles.

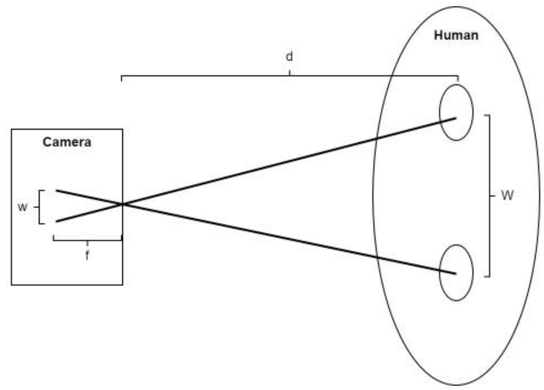

Figure 3. Calculation Principle of Distance

The distance from the camera measurement mainly uses the similar triangle principle, as shown in Figure 3, and the calculation formula of the distance from the person to the camera is as follows.

$$d = \frac{W * f}{w}$$

Where F is the camera's focal length, we set 300 here. w is the pixel value distance of the human eye imaged by the camera. W is the distance between the left eye and the right eye. The average pupil distance of men is 64mm, and women's is 62mm. In this paper, W is the median value of 63mm.

Finally, we use OpenCV's built-in Haar feature classifier that has been trained. The classifier quantifies facial features by generating a matrix of features to distinguish faces from non-faces.

4.2.4. Control variables. We included two kinds of control variables in the study. One is workers' characteristics, including the rating, task complexity, and days registered on the site. We express the task complexity according to the time it takes to complete the task. Another is verbal features, including the proportion of first-person words and the sentiment words in the description. Then, we calculated the verbal features of self-description using the NLP. The proportion of first-person words represents the proportion of personal terms (such as "I" or "My") to the total number of words in the verbal description, and the proportion of sentiment words represents the proportion of sentiment terms to the total number of words.

4.2.5. Dependent variables. Earlier studies defined employment success as employment status (whether one can get a job), However, more recent studies have more broadly assessed employment success across multiple dimensions, including the number of interviews, employment status, the number of jobs, reemployment status, and Employment quality (van Hooft, Kammeyer-Mueller, Wanberg, Kanfer, & Basbug, 2021). In this research, since the data of the other two dimensions cannot be obtained from online employment platforms, we take the employment status, number of jobs, and reemployment probability as three dimensions to measure online employment success. We collected data about employment success for each worker, including the employment decision, the number of jobs recently, and reemployment probability. The number of jobs recently is an indicator parsed from JSON data in the site's background and is not directly visible on the worker page. Because this indicator represents the jobs obtained recently and controls for periods, we do not need to consider how long workers have been on the market when analyzing this measure. In addition, given that most workers do not get any jobs, we generated a dummy variable named Employment status for the number of jobs recently. If the number of jobs exceeds 1, the Job is assigned a value of 1. Otherwise, it is assigned a value of 0. Reemployment probability is a measure provided by Upwork that represents the probability that a worker will be rehired.

5. Analytical Results

5.1. Descriptive statistics

First, we conduct a descriptive analysis. Jobs recently obtained range from 0 to 688 with a mean value 5.9. Reemployment probability ranges from 0 to 100, with a mean value of 12.4. Age ranges from 2 to 70, with a mean value of 31.5. Appearance ranges from 8.24 to 86.14, with a mean value of 44.68. Illumination ranges from 17 to 252, with a mean value of 131.25. Eye openness degree ranges from 0.027 to 1, with a mean value of 0.92. Angle yaw ranges from -69.56 to 84.95, with a mean value of -0.6. Angle pitch ranges from -26.4 to 40.22, with a mean value of 6.38. Angle roll ranges from -183.86 to 178.58, with a mean value of -2.58. Distance from the camera ranges from 1.66 to 6330, with a mean value of 33.438. Gender ranges from 0 to 1, with a mean value of 0.62, indicating that men accounted for 62%. Race consists of four categories (Black, Arabs, White, and Yellow) with a mean value of 2.06. Glasses-wearing consists of three categories (none, common, sun) with a mean value of 0.84. Make-up consists of two categories (none, make-up) with a mean value of 0.84. Facial expression consists of three categories (none, smile, laugh) with a mean value of 1.57.

Then, we performed a Pearson's correlation analysis, and all the correlation coefficients were less than 0.3. Also, we calculated the VIF, and all VIF values are less than 5. This result indicates that there is no multicollinearity issue.

5.2. Data analysis and results

We used logistic regression and ordinary least squares (OLS) to test the influence of visual cues on employment success, including employment status (Model 1), the number of jobs recently (Model 2), and reemployment probability (Model 3), as depicted in Table 1 below.

Table 1. Analytical Results of Visual Cues on Constituent Dimensions of Employment Success

Variable	Model 1	Model 2	Model 3
	Employment Status	**Number of Jobs**	**Reemployment Probability**
Control variables			
Days registered	1.000006*** [1.000, 1.000]	-	0.0009808*** [0.001, 0.001]
Rating	1.180*** [1.161, 1.201]	1.120*** [1.023, 1.218]	7.281*** [6.976, 7.587]
Ratio of first-person words	40.218† [0.699, 2313.929]	46.385*** [25.744, 67.026]	150.316*** [86.678, 213.954]
Ration of sentiment words	0.202*** [0.127, 0.321]	-3.353** [-5.845, -0.861]	-19.746*** [-27.432, -12.061]
Task Complexity	1.042 *** [1.033, 1.051]	-0.039*** [-0.060, -0.019]	-0.179*** [-0.243, -0.115]
Demographic cues			
Gender (male=1; female=0)	1.070* [1.005, 1.140]	0.532** [0.195, 0.869]	4.876*** [3.835, 5.916]
Age	1.008** [1.003, 1.013]	0.044** [0.017, 0.071]	0.167*** [0.083, 0.251]
Arab	1.503*** [1.264, 1.787]	1.589*** [0.745, 2.434]	7.299*** [4.693, 9.904]
Caucasian	0.969 n.s. [0.872, 1.077]	-0.387 n.s. [-0.949, 0.176]	4.639*** [2.906, 6.373]
Asian	1.122† [1.000, 1.259]	-0.589† [-1.201, 0.022]	-1.646† [-3.530, 0.238]

Physical appearance cues			
Glasses-wearing: common	1.026 n.s. [0.950, 1.108]	0.341† [-0.062, 0.743]	1.409* [0.168, 2.649]
Glasses-wearing: sun	0.558* [0.330, 0.942]	-1.078 n.s. [-4.115, 1.959]	6.587 n.s. [-2.775, 15.949]
Make-up	0.959 n.s. [0.908, 1.013]	-0.030 n.s. [-0.319, 0.259]	-0.147 n.s. [-1.037, 0.744]
Appearance	0.9996 n.s. [0.997, 1.002]	0.014* [0.000, 0.028]	0.088*** [0.046, 0.129]
Image quality cues			
Illumination	0.998*** [0.998, 0.999]	-0.005* [-0.010, 0.000]	-0.017* [-0.031, -0.003]
Non-verbal behavioral cues			
Facial expression: laugh	1.138 n.s. [0.879, 1.472]	-0.733 n.s. [-2.093, 0.627]	1.412 n.s. [-2.780, 5.603]
Facial expression: smile	1.060† [0.999, 1.125]	0.403* [0.090, 0.715]	0.529 n.s. [-0.436, 1.494]
Eye openness degree	0.912 n.s. [0.745, 1.115]	-1.066* [-2.085, -0.047]	-2.848† [-5.990, 0.293]
Angle yaw	0.998* [0.996, 1.000]	-0.003 n.s. [-0.014, 0.009]	-0.024 n.s. [-0.058, 0.011]
Angle pitch	0.992*** [0.988, 0.996]	-0.017 n.s. [-0.038, 0.004]	-0.070* [-0.134, -0.006]
Angle roll	1.0004 n.s. [0.998, 1.003]	-0.004 n.s. [-0.018, 0.010]	0.021 n.s. [-0.023, 0.064]
Distance from the camera	1.001* [1.000, 1.003]	0.0004 n.s. [-0.003, 0.004]	0.005 n.s. [-0.005, 0.015]
Cons	1.551* [1.101, 2.185]	1.007 n.s. [-0.743,2.757]	-27.698*** [-33.124, -22.272]
F-test	837.41***	33.89***	401.42***
R^2	0.0264	0.025	0.2417

First, we analyzed the influence of visual cues on the employment decision. We found that demographic cues had a significant impact on the employment decision. Specifically, men have a 7.03 percent higher chance of getting a job than women. Each unit increase in age increases the probability of getting a job by a factor of 1.008. Race has a significant effect on employment decisions. Second, we found that appearance cues also significantly impacted the results. Workers wearing sunglasses are 55.8 percent less likely to get at least one job than those who do not wear glasses. We unexpectedly found that better lighting significantly negatively affected job offers. Odds ratio results show that for every unit increase in light intensity, the probability of the worker getting a job decreases to 0.99 times the original one. Finally, we found that non-verbal behavioral cues multifacetedly impact employment success. Compared with those with no expression, smiling workers increased their chances of getting a job by 6.02%. The degree of eye closure had no significant effect on the results, but the head pose angle and distance from the camera played an important role. When the angle yaw and angle pitch increase by one unit, the probability of getting a job opportunity decreases to 0.99 times the original one. Distance from the camera has a positive influence on employment decisions. The probability of the workers getting a job opportunity increases to 1.0014 times for each unit increase in the distance.

Second, we analyzed the influence of visual cues on the number of jobs. We found that demographic cues have a significant impact on employment success. Specifically, the number of jobs by men is 0.53 units higher than that of women and is statistically significant. Age and race have a significant positive effect on the number of jobs. In terms of physical appearance cues, workers who wore common glasses received 0.34 units more jobs than those who did not wear glasses. In addition, appearance has a significant positive effect on the number of jobs, while illumination has a significant negative effect. In terms of non-verbal behavioral cues, workers who smiled received 0.4 units more work than those without facial expressions. The degree of eye closure significantly negatively affects the number of jobs. The head pose angle and distance from the camera had no significant effect on the number of jobs.

Third, we analyzed the effect of visual cues on the reemployment probability. Men are 4.88 units more likely to be reemployed than women, which is statistically significant at the 0.1% level. Age has a significant positive effect on the reemployment probability. Race has a significant effect on reemployment probability. Workers who wore glasses were 1.41 units more likely to be reemployed than those who did not. The appearance positively affects the reemployment probability, while illumination has a negative effect on the reemployment probability. The degree of eye closure and angle pitch has a negative effect on reemployment probability.

Although not all the cues that make up these four categories significantly affect employment success, our results confirm all 12 hypotheses. In total, we found that the performance of visual cues differs for three dimensions of employment success. Demographic cues were even more significant in reemployment probability. Physical appearance cues had little effect on employment success, and make-up had no significant effect on all three dimensions of employment success. Glasses-wearing and appearance still significantly affected the number of jobs and the reemployment probability. Our newly added image quality cues significantly impacted all three dimensions of employment success. The influence of non-verbal behavioral cues on employment success is complex. Specifically, smiling appeared to be a safe choice, and this cue significantly influenced employment status and the number of jobs. The degree of eye openness significantly affected the number of jobs and the reemployment probability. Moreover, head pose angle significantly impact employment decisions. Furthermore, distance from the camera only significantly affected employment decisions.

6. Discussion

The findings of our study revealed several positive and negative effects of visual cues on employment decisions. Men were found to fare better than women in relation to all three dimensions of employment success, which is consistent with the results of Chan and Wang (2014). However, contrary to existing studies that only consider age and gender (Carlsson & Eriksson, 2019), "age anxiety" is less evident in the digital labor market under a holistic framework, and older workers seem to perform better on employment success than younger workers. We speculate that employers might be particularly concerned about worker reliability due to information asymmetry in online contexts. Older workers are praised for their commitment to the task, as well as their enthusiastic personality and reliability(Van Selm & Van Den Heijkant, 2021).In terms of physical appearance cues, wearing sunglasses has a negative impact on job acquisition, while wearing common glasses has a significant positive impact on the number of jobs and the reemployment probability, which is consistent with the study of Wei and Stillwell (2017) that glasses-wearing increase people's perception of intelligence. Appearance has a significant positive effect on the number of jobs and the reemployment probability, which confirms the research of Lee (2012). Illumination (image quality cues) significantly negatively affected all three dimensions of employment success. A possible explanation is that higher illumination may reduce the perception of authenticity by employers. Moreover, in the online employment system with asymmetric information, the perceived authenticity of workers may play an important role.

As for non-verbal behavioral cues, it is worth mentioning that the degree of eye openness has a negative effect on employment success. A standard eye openness degree is sufficient, but a greater eye openness degree or enlarging the eyes through photo editing can be counterproductive. This beautifying photo effect may create a sense of inauthenticity, leading to fewer job opportunities in the online employment market focusing on reliability and authenticity. However, the head pose angle significantly negatively impacts employment decisions, performance rating, and the reemployment probability. Because it is a static image, any angle deviation will make the employer unable to perceive eye contact in the photo (Van der Land et al., 2016), leading to worse employment results. This result also indicates that static images are consistent with offline communication, significantly impacting the communication between employers and workers (Kapidzic & Herring, 2015). Our research found that distance from the camera positively affects employment decisions, contrary to the negative effects of camera distance on social attractiveness found in Kapidzic and Herring's study (2015). The possible reason is that the greater the distance from the camera, the more professional.

6.1. Implications for theory and practice

Our study has three theoretical implications. First, this is among pioneering studies of utilizing the classification model of non-verbal cues in an online employment context. Our research enriches the literature on visual cues. It also provides a more complete and systematic understanding of the role of portraits in the digital labor market. Second, we investigate the differences in the role of four types of visual cues in three contexts, providing more specific constraints for studying the influence of visual cues on online employment success.

Meanwhile, this study contributes to the literature on online decision-making with more refined dimensions. Specifically, we add image quality cues to the non-verbal cues classification model and innovatively introduce the new cues of distance from the camera and head pose angle. We enrich the relevant research on non-verbal cue classification and provide suggestions for building a more comprehensive model of non-verbal cues. Finally, our research provides a theoretical basis for research on image manipulation in the online employment market. The analysis results suggest that excessive facial retouching or lack of realistic image can be counterproductive. Evidence suggests that professionalism and reliability are essential in online employment markets.

Regarding implications for practice, first, our findings provide guidance on how workers can manipulate their portraits for better performance on employment success. Specifically, employees should control the degree of illumination, keep a smile, increase the photography distance from the camera, avoid the deviation of angle yaw and angle pitch, and avoid wearing sunglasses to improve employment status. It effectively increases the number of jobs by wearing common glasses and controlling the level of light and the degree of eye openness. Controlling the degree of illumination and eye openness and avoiding angle pitch deviation can increase the reemployment probability. Second, our results provide some references for platform managers of digital labor markets. Through these research results, the platform can provide accurate guidance for profile picture shooting to gig workers to help workers improve their performance on employment success and increase the retention rate of the platform. Besides, the impact of demographic cues on employment success can provide clues for the platform to mitigate employment discrimination. For example, the platform can reduce the impact of employment discrimination by increasing push intensity or rating weight. Finally, our study provides a reference for automated processing of online visual cues. We utilized a highly automated approach to recognizing the visual cues, which allows for processing a huge number of cases.

6.2. Limitations and future research

This study has some limitations which shed light on future research. First, the impact of visual cues conveyed by worker portraits on employment success may be related to the job category. For example, a worker wearing glasses may be considered very suitable for programming tasks but less suitable for creative design tasks. Future research may consider the moderating effect of job type on the relationship between the two. Second, it would be interesting if future work could include dressing (formal or casual wear) in the non-verbal classification cue model. Deep learning algorithms could be employed to identify the dressing characteristics of workers for further analysis. Third, the interaction between different types of visual cues could be scrutinized by future research. Specifically, more insights would be generated if future studies examine how controllable visual cues mediate the impact of uncontrollable visual cues on employment decisions. Moreover, a large dataset could be collected by future research to investigate the effect of the number of faces on employment success.

7. References

Alzahrani, T., Al-Bander, B., & Al-Nuaimy, W. (2021). Deep Learning Models for Automatic Makeup Detection. *AI*, *2*(4), 497–511.

Barbosa, E. (2022). Upwork Reports Third Quarter 2022 Financial Results. Retrieved November 7, 2022, from https://investors.upwork.com/news-releases/news-release-details/upwork-reports-third-quarter-2022-financial-results

Carlsson, M., & Eriksson, S. (2019). Age discrimination in hiring decisions: Evidence from a field experiment in the labor market. *Labour Economics*, *59*, 173–183.

Chan, J., & Wang, J. (2014). Hiring biases in online labor markets: The case of gender stereotyping. In *35th International Conference on Information Systems "Building a Better World Through Information Systems", ICIS 2014*. Retrieved from https://experts.umn.edu/en/publications/hiring-biases-in-online-labor-markets-the-case-of-gender-stereoty-2

Chen, L., Zhao, R., Leong, C. W., Lehman, B., Feng, G., & Hoque, M. (2018). Automated video interview judgment on a large-sized corpus collected online. In *2017 7th International Conference on Affective Computing and Intelligent Interaction, ACII 2017* (Vol. 2018-Janua, pp. 504–509).

Cowell, A. J., & Stanney, K. M. (2005). Manipulation of non-verbal interaction style and demographic embodiment to increase anthropomorphic computer character credibility. *International Journal of Human Computer Studies*, *62*(2), 281–306.

De Meuse, K. P. (1987). A review of the effects of non-verbal cues on the performance appraisal process. *Journal of Occupational Psychology*, *60*(3), 207–226.

Etheridge, B., Tang, L., & Wang, Y. (2020). Worker Productivity during Lockdown and Working from Home: Evidence from Self-Reports. *Covid Economics*, (52), 118–151. Retrieved from https://www.econstor.eu/handle/10419/248579

Hannák, A., Mislove, A., Wagner, C., Strohmaier, M., Garcia, D., & Wilson, C. (2017). Bias in Online freelance marketplaces: Evidence from TaskRabbit and Fiverr. In *Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW* (pp. 1914–1933). Association for Computing Machinery.

Hemamou, L., Felhi, G., Martin, J. C., & Clavel, C. (2019). Slices of Attention in Asynchronous Video Job Interviews. In *2019 8th International Conference on Affective Computing and Intelligent Interaction, ACII 2019* (pp. 526–551).

Kapidzic, S., & Herring, S. C. (2015). Race, gender, and self-presentation in teen profile photographs. *New Media and Society*, *17*(6), 958–976.

Kim, J. E., Ju, H. W., & Johnson, K. K. P. (2009). Sales associate's appearance: Links to consumers' emotions,

store image, and purchases. *Journal of Retailing and Consumer Services*, *16*(5), 407–413.
Kim, J., & Park, J. (2017). Does Facial Expression Matter Even Online? An Empirical Analysis of Facial Expression of Emotion and Crowdfunding Success. In *ICIS 2017: Transforming Society with Digital Innovation*. Retrieved from https://scholar.archive.org/work/qbkwrdvpmbahzdpgqpd26f4nui/access/wayback/https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1375&context=icis2017
Kress, G., & van Leeuwen, T. (2020). *Reading images: The grammar of visual design*. *New York: Routledge*. Routledge.
Kuttal, S. K., Chen, X., Wang, Z., Balali, S., & Sarma, A. (2021). Visual Resume: Exploring developers' online contributions for hiring. *Information and Software Technology*, *138*.
Lee, O.-H. (2012). The Effect of Nonverbal Communication on Trust, Switching Barrier and Repurchase Intention. *Journal of the Korean Society for Clothing Industry*, *14*(5), 803–810.
Leung, W., Zhang, Z., Jibuti, D., Zhao, J., Klein, M., Pierce, C., … Zhu, H. (2020). Race, Gender and Beauty: The Effect of Information Provision on Online Hiring Biases. In *Conference on Human Factors in Computing Systems - Proceedings* (pp. 1–11). Association for Computing Machinery.
Li, L., Mo, Y., & Zhou, G. (2022). Platform economy and China's labor market: structural transformation and policy challenges. *China Economic Journal*, *15*(2), 139–152.
Li, Yaoqi, Zhang, C., & Laroche, M. (2019). Is beauty a premium? A study of the physical attractiveness effect in service encounters. *Journal of Retailing and Consumer Services*, *50*, 215–225.
Li, Yuanqing, Xiao, N., & Wu, S. (2021). The devil is in the details: The effect of nonverbal cues on crowdfunding success. *Information and Management*, *58*(8), 1–18.
Liew, T. W., & Tan, S. M. (2021). Social cues and implications for designing expert and competent artificial agents: A systematic review. *Telematics and Informatics*.
Martín-Raugh, M. P., Leong, C. W., Roohr, K. C., & Chen, X. (2023). Perceived conscientiousness and openness to experience mediate the relationship between vocal and visual features and hiring decision in the interview. *Computers in Human Behavior Reports*, *10*, 100272.
Park, J. S., Bae, J. H., & Cho, K. S. (2014). The Effect of Non-verbal Communication using Cinemagraph in Mobile Electronic Commerce of Agrifood on Visual Attention and Purchase Intention. *Agribusiness and Information Management*, *6*(2), 24–31.
Peng, L., Cui, G., Chung, Y., & Zheng, W. (2020). The Faces of Success: Beauty and Ugliness Premiums in e-Commerce Platforms. *Journal of Marketing*, *84*(4), 67–85.
Pitcher, G. (2000, November 19). Reading images. *VINE*. Routledge.
Segal, E. (2021). U.S. Freelance Workforce Continues To Grow, With No Signs Of Easing: New Report. Retrieved November 7, 2022, from https://www.forbes.com/sites/edwardsegal/2021/12/08/us-freelance-workforce-continues-to-grow-with-no-signs-of-easing-new-report/?sh=6b4b89b44f91
Soukupová, T., & Cech, J. (2016). Eye Blink Detection Using Facial Landmarks. In *21st computer vision winter workshop* (pp. 1–8). Retrieved from https://scholar.google.com/ftp://cmp.felk.cvut.cz/pub/cmp/articles/cech/Soukupova-TR-2016-05.pdf
Thompson, L. F., Braddy, P. W., & Wuensch, K. L. (2008). E-recruitment and the benefits of organizational web appeal. *Computers in Human Behavior*, *24*(5), 2384–2398.
Tortoriello, T. R., Blatt, S. J., & DeWine, S. (1978). *Communication in the organization: An applied approach.* McGraw-Hill Book Comp. Retrieved from https://scholar.google.com/scholar?hl=zh-CN&as_sdt=0%2C5&q=Communication+in+the+organization%3A+An+applied+approach&btnG=
Troncoso, I., & Luo, L. (2020). Look the Part? The Role of Profile Pictures in Online Labor Markets. *SSRN Electronic Journal*.
Uhlmann, E. L., & Silberzahn, R. (2014). Conformity under uncertainty: Reliance on gender stereotypes in online hiring decisions. *Behavioral and Brain Sciences*.
Van der Land, S. F., Willemsen, L. M., & Wilton, B. G. E. (2016). Professional personal branding: Using a "think-aloud" protocol to investigate how recruiters judge LinkedIN profile pictures. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 9751, pp. 118–128). Springer Verlag.
van Hooft, E. A., Kammeyer-Mueller, J. D., Wanberg, C. R., Kanfer, R., & Basbug, G. (2021). Job search and employment success: A quantitative review and future research agenda. *Journal of Applied Psychology*, *106*(5), 674–713. Retrieved from https://psycnet.apa.org/record/2020-50171-001
Van Selm, M., & Van Den Heijkant, L. (2021). In Search of the Older Worker: Framing Job Requirements in Recruitment Advertisements. *Work, Aging and Retirement*, *7*(4), 288–302.
Walker, R. E., & Raghunathan, R. (2004). Nonverbal Cues-based First Impressions: What Can Static Images of Salespeople Tell Us\rAbout Their Success at Selling? *Advances in Consumer Research*, *31*(1), 198–214. Retrieved from https://www.acrwebsite.org/volumes/8884/volumes/v31/NA-31
Wei, X., & Stillwell, D. (2017). How smart does your profile image look? Estimating intelligence from social network profile images. In *WSDM 2017 - Proceedings of the 10th ACM International Conference on Web Search and Data Mining* (pp. 33–40). Association for Computing Machinery, Inc.
Yang, F. X., Li, Y., Li, X., & Yuan, J. (2022). The beauty premium of tour guides in the customer decision-making process: An AI-based big data analysis. *Tourism Management*, *93*.