An AI Method to Score Celebrity Visual Potential

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Abstract

It has long been a mantra of marketing practice that, particularly in low-involvement situations, spokespeople should be physically attractive. This paper suggests there is a higher probability of gaining fame and influence (i.e., celebrity potential) than is captured by attractiveness or typicality. The authors identify 11 facial features that may predict celebrity potential by virtue of their purported relationship with charisma and resulting personality trait inferences. Using machine learning methods and a sample of 22,000 faces, the authors calculate the direction and strength of the correlation of each feature with celebrity potential. The model is 95.92% accurate in predicting whether a given face belongs to a celebrity or noncelebrity, and it allows calculating a *celebrity visual potential* (CVP) metric for any face. Two controlled experiments and two studies using photographs of faces of Instagram and LinkedIn users further validate that the model-generated CVP is consistent with human-rated CVP, showing predictive power above and beyond facial typicality and averageness. This paper challenges prior assumptions about the importance of attractiveness in spokesperson choice, offers a useful additional metric for marketers, and provides novel insights about the relative importance of various inferred personality traits for celebrity potential.

Keywords: Celebrity Visual Potential, Facial Features, Personality Traits, Deep Learning, Explainable Artificial Intelligence (XAI).

INTRODUCTION

For brands, the increasingly visual nature and democratization of influence offer both an opportunity and a challenge. On the one hand, brands have a virtually infinite supply of potential spokespeople, influencers, and bloggers from whom to draw. They may even simply generate virtual spokespeople (Hwang, Liu, and Srinivasan 2021), further increasing their choice set of various spokespeople. On the other hand, there is little beyond the time-honored suggestion that celebrities should be physically attractive or familiar (Kahle and Homer 1985; Faerber et al. 2016) to help marketers predict the likelihood that a given visually depicted influencer will have enough charisma to drive the inference of positive personality traits, and with it, to gain celebrity. Further, we know little about whether a celebrity can be predicted by the same visual traits across social media platforms, or if a corporate "celebrity" (e.g., a C-suite executive) has the potential for celebrity rooted in different features than an influencer on Instagram.

Celebrity itself is a comprehensive quality that can be judged from both (inner) personality traits and (outer) physical appearance. In this paper, we focus on the visual aspect of celebrity (Moraes et al. 2019; Verčič and Verčič 2011), as manifest in facial features, which has been studied widely (Troncoso and Luo 2023; Banker et al. 2023; Chen et al. 2023). Critically, we propose the construct of *celebrity visual potential* (CVP) as a metric that can be developed based on past theories related to charisma, facial features, and inferred personality traits, and through machine learning models and experimental validation. CVP can play a crucial role in different contexts. If a high CVP salesforce accomplishes significantly higher sales, companies can direct training and support resources more effectively to those with lower CVP, creating a more level playing field. Also, physician detailing is an expensive and important marketing activity.

Salesforce with higher CVP, potentially having more persuasion capabilities, may accelerate physicians' education and prescription of such products.

To assess the importance of CVP, we identify 11 facial features that past literature suggests may drive this metric, based on their relationship with inferred charisma, a central characteristic in celebrity. Six of these (i.e., dominance, warmth, competence, trustworthiness, generosity, and aggressiveness) are inferred personality traits[1] that may mediate the connections between facial features and celebrity potential (Gray, Ward, and Norton 2014; Keating 2002, 2011). We then develop a high-performing, generalizable, and scalable model informed by a unique dataset of 6,000 celebrity and 6,000 noncelebrity images. The model's output is the *CVP score* (CVP), or the probability that the input face is a celebrity. Notably, although the input to CVP is facial features, it is not equivalent to physical appearance or attractiveness, because CVP is also a proxy for persuasiveness. By measuring the direction and ranking the strength of the correlation between CVP and each hypothesized facial feature, we identify the stronger and the weaker drivers of CVP. To bolster our causal argument, we then report one controlled experiment and a conceptual replicate that suggest the convergence of model-generated CVP and consumers' predictions of celebrity potential. These studies also help us understand which previously identified inferred personality traits explain the effects of facial characteristics on CVP. Additionally, we show the power of our model across demographic groups and platforms. Across our data, CVP's explanatory power is above and beyond predictions that would be made based on facial attractiveness alone.

This paper contributes large-scale empirical evidence for the relationship between 11 different facial features and CVP. Although various facial attributes and personality traits have

[1] A personality trait is an internal characteristic (Cattell 1950) excluding attractiveness, though it may mediate the relationships between facial features and CVP (Berscheid and Hatfield 1978; Griffin and Langlois 2006).

been studied in marketing and economics, most studies have limited generalizability because they used small samples or human judgment to rate inferred personality traits (Gangestad et al. 2004; Penton-Voak et al. 1999). Further, prior work has usually considered only one or a small group of facial features at a time; this approach makes it difficult to estimate the overall effect of a composite face on visually imputed charisma, a key factor in celebrity (Stirrat and Perrett 2012). In addition, in some cases, facial features have been suggested to be associated with two inferred personality traits that could have countervailing effects on charisma and thus celebrity potential. For example, in one study a feature might be associated with dominance, a positive predictor of charisma (Wong, Ormiston, and Haselhuhn 2011) and in another study, with aggressiveness, a negative predictor of charisma (Carré, McCormick, and Mondloch 2009). Using machine learning to understand these relationships allows us to conduct a larger-scale analysis that is not only generalizable but also offers rich insights into the relationships between these facial features, as well as providing novel insights into the role of various personality inferences in determining CVP. Finally, we empirically demonstrate that attractiveness, while important, does not tell the whole story of CVP. Thus, we extend prior research on people's responses to others' facial characteristics, providing a more complete picture than presented in prior work (Alley and Cunningham 1991; Baker and Gilbert 1977; Griffin and Langlois 2006).

Methodologically, we join other recent studies (e.g., Zhou et al. 2021) that improve the interpretability of machine learning predictions. Deep learning distinguishes itself from parametric models, such as regression, by accommodating nonlinear, complicated variable relationships with high flexibility in an entirely data-driven way, leading to much higher prediction accuracy than regression models (Schulz et al., 2020). Yet, the "black-box" nature of deep learning makes model predictions hard to interpret. However, we employ interpretable machine learning techniques to construct a metric that allows identifying the facial features that most affect CVP, leading to clear practical and managerial implications.

Our results have significant managerial implications for marketing, media, entertainment, and business. Marketing researchers are interested in exploring key image features related to economic value (Grewal, Gupta, and Hamilton 2021; Li and Xie 2019; Zhang and Luo 2022; Zhang et al. 2021; Zhou, Lu, and Ding 2020), among which human face is a popular topic (Hartmann et al. 2021; Hu and Ma 2021; Kachur et al. 2020; Peng et al. 2022; Wang and Kosinski 2018; Zhou et al. 2021). The CVP metric may be fruitfully used in such efforts as a reference in career choice, as a control variable in randomized experiments that aim to improve persuasiveness or celebrity influence, or as a factor to examine whether human resource professionals excessively use facial features in recruiting. Further, our model may help optimize the design or enhancement of AI-generated virtual personas, such as fashion models, digital influencers, video game or movie characters, and figures in advertising campaigns. Additionally, CVP can be used as one of the indexes for screening and recruiting salesforce, a costly activity for companies such as big pharmaceuticals. However, there are also a couple of noteworthy aspects of CVP that merit careful consideration. We close with a discussion of how CVP can be further examined and applied in theoretical, practical, and policy contexts.

THEORETICAL FRAMEWORK

Celebrity and Charisma

What determines celebrity? A substantial literature would argue that when it comes to visual representation, the most important characteristic of a celebrity is their physical attractiveness. It has been shown to facilitate attitude change in communications and interactions (Baker and Gilbert 1977; Chaiken 1979; Bersheid and Walster 1974). The physical attractiveness of celebrity endorsers often has an obvious impact on product sales (Kahle and Homer 1985), since even a two-second glance at an advertisement is enough to leave a meaningful impression (Kahle, Kulka, and Klingel 1980).

However, we argue that celebrity potential extends far beyond attractiveness. Though many bases of celebrity have been proposed, psychology literature suggests celebrities across domains share the trait of charisma as a central feature (Potts 2009). Charisma is defined as "a leader's moral conviction, need for power, and ability to transfer an idealized vision to followers" (Antonakis, Fenley, and Liechti 2012; Conger and Kanungo 1987; Weber, Henderson, and Parsons 1947). Many scholars argue that charisma plays a key role in the formulation and maintenance of celebrity power, image, and status (Marshall 1997; Rojek 2001; Alexander 2010). Charisma, in turn, has been argued to be driven by a combination of personality traits, including a sense of power or dominance, trustworthiness, competence, aggressiveness, warmth, and generosity, as well as physical attractiveness (House and Howell 1992; House, Spangler, and Woycke 1991; Moraes et al. 2019; Rein et al. 2006), though predictions of attractiveness vary. Specifically, charisma is positively associated with dominance (Keating 2002); warmth, which leads to approach behaviors (Keating 2011); generosity, which is regarded as an important virtue for good leadership and social recognition (Beck 2012; Winterich, Mittal, and Aquino 2013); and competence, which elicits positive emotions (Avolio and Bass 1988; Gray, Ward, and Norton 2014). By contrast, aggressiveness decreases charisma by reducing a person's ability to arouse positive emotions in other people (Buss and Perry 1992; Costa, McCrae, and Dembroski 1989). The existing literature has diverging conclusions on the impact of physical attractiveness on charisma. For example, Riggio (1987) argues that the effect of attractiveness on charisma is small. Others believe that attractiveness influences first impressions and correlates with positive qualities (Dion, Berscheid, and Walster 1972; Griffin and Langlois 2006).

In summary, charisma is a broad concept and can be explained by combinations of traits such as success, popularity, and attractiveness, but it differs from each individual trait. For instance, success can be measured by income or company hierarchy, leading to individual identity and satisfaction (Goffman 1959; Arthur et al. 2005); however, charisma differs from success in that charisma emphasizes interpersonal influence. Popularity overlaps with celebrity potential in terms of social acceptance and the quality of being well-liked (Eder 1985); however, unlike popularity, charisma includes the ability to elicit trust and respect. Attractiveness involves external, short-term physical charm (Swami and Furnham 2008), while charisma extends to a multifaceted, long-term influence on the perceiver's mind and emotions (Chase 2016).

Facial Features and CVP

However, prior literature fails to determine how people might infer success, popularity, and attractiveness from visual stimuli, or when one inferred trait might override another in generating charisma and thus potential celebrity. Therefore, we draw from the literature in psychology, sociology, economics, and behavioral marketing and identify 11 facial features relevant to inferring these personality traits. We thus determine their relationship with charisma and, by extension, to CVP. Table 1 summarizes the possible theoretical relationships between CVP and the 11 facial features we identified, with the six personality traits as mediators.

Table 1. Theoretical Relationships Between Facial Features and CVP

Facial Feature	Do	Wa	Co	Tr	Ge	Ag	At	Theoretical
	(+)	(+)	(+)	(+)	(+)	(–)	(+)	Prediction
1. Facial width-to-height	(+)			(–)	(+)	(+)		+2, –2
2. Sexual dimorphism	(+)	(+)	(+)	(–)				+2 / +1, –1
3. Averageness							(+)	+1
4. Symmetry			(+)	(+)			(+)	+3
5. (Dark) Color	(+)					(+)		+1, –1

6. Babyfaceness	(–)	(+)		(+)		(–)		+3, –1
7. High cheekbones			(+)					+1
8. Large eyes	(–)	(+)		(+)			(+)	+3, –1
9. Thin jaw	(–)					(–)		+1, –1
10. Mouth-chin distance	(+)		(+)				(–)	+2, –1
11. Mouth-nose distance			(–)			(+)	(–)	–3

Notes. The personality traits we consider are Do: dominance, Wa: warmth, Co: competence, Tr: trustworthiness, Ge: generosity, Ag: aggressiveness, At: attractiveness; (+) and (–) denote positive and negative theoretical effects, respectively; the symbols under each personality trait in column headings are the trait's correlations with CVP, while the symbols within each row are the effects of the facial feature on the personality trait. The "Theoretical Prediction" column sums the contributions of the facial feature's effects on personality traits. For instance, in the first row, Facial width-to-height has a positive association with dominance, a negative association with trustworthiness, a positive association with generosity, and a positive association with aggressiveness. Dominance, trustworthiness, and generosity have a positive association with CVP, whereas aggressiveness has a negative association with CVP. Therefore, the overall impact of Facial width-to-height on CVP can be summarized as two positive forces (denoted as "+2"), from dominance and generosity, and two negative forces (denoted as "-2"), from trustworthiness and aggressiveness. Note that sexual dimorphism contains the effects of both masculinity and femininity; masculinity boosts dominance and competence for men, while femininity boosts warmth for women, so the overall theoretical prediction is "+2" for men and "+1" for women.

Feature 1: facial width-to-height ratio. This feature is calculated by dividing the face's width (bizygomatic) by its height (measured from the top of the eyelids to the upper lip). Previous studies have shown that the width-to-height ratio has a positive effect on inferred aggressiveness (Carré, McCormick, and Mondloch 2009), a negative effect on inferred trustworthiness (Stirrat and Perrett 2010), a positive effect on inferred generosity (in settings of cooperation and advising: Stirrat and Perrett 2012), and a positive effect on inferred dominance (in an organizational setting: Wong, Ormiston, and Haselhuhn 2011). The width-to-height ratio should contribute positively to CVP if the effects of inferred dominance and generosity outweigh the effects of inferred trustworthiness and aggressiveness.

Feature 2: sexual dimorphism. This feature captures the extent to which the face is distinguishably masculine or feminine as opposed to androgynous. For male faces, masculinity has positive effects on inferred dominance and competence (Penton-Voak et al. 1999) but may indicate less warmth and less trustworthiness (Gangestad et al. 2004; Penton-Voak et al. 1999; Perrett et al. 1998). For female faces, femininity is inferred as less trustworthy by males seeking a mate (Little et al. 2014). For both male and female faces, people associate femininity with warmth and more concern for others, and masculinity with competence and self-assertion (Gao, Mittal, and Zhang 2020; Wen et al. 2020; Zhang, Feick, and Mittal 2014). For males, if inferred dominance and competence have more influence than inferred trustworthiness, then sexual dimorphism (masculinity, not androgyny) should contribute positively to CVP. For females, if inferred warmth has more influence than inferred trustworthiness, then sexual dimorphism (femininity, not androgyny) should contribute positively to CVP.

Feature 3: averageness. Averageness is the extent to which the face's features align with the average features of all people of the same gender, race, and age. Average faces may be perceived as more attractive (Rhodes and Tremewan 1996), likely because evolutionary pressures favor characteristics close to the population mean (Langlois and Roggman 1990). If physical attractiveness has a positive correlation with CVP, we also anticipate a positive effect of averageness on CVP; however, we can only be agnostic regarding the effects of attractiveness per se or the effects of averageness above and beyond those of attractiveness.

Feature 4: symmetry. Facial symmetry is the visual similarity (in shape and color) between the left and right sides of the face. Symmetry has positive effects on inferred attractiveness (Alley and Cunningham 1991; Gangestad et al. 2004; Rhodes, Sumich, and Byatt 1999), competence (in social networking: Fink et al. 2005; Fink et al. 2006; Pound, Penton-Voak, and Brown 2007), and trustworthiness (Noor and Evans 2003). Attractiveness, inferred competence, and inferred trustworthiness are all expected to contribute positively to charisma, so we anticipate that facial symmetry will also have a positive correlation with CVP.

Feature 5: color. Color is the skin tone of the face. Darker skin is perceived as being associated with more dominance and higher status, especially for athletes and entertainers (Wade and Bielitz 2005) but also with more aggressiveness (Eberhardt et al. 2006; Livingston and Pearce 2009). Thus, we predict that darker skin should contribute positively to CVP if its positive effect via inferred dominance outweighs its negative effect via inferred aggressiveness.

Feature 6: babyfaceness. Babyfaceness is the extent to which the face's features resemble a typical baby's features rather than a typical adult's. The defining characteristics are large eyes, a small nose, a high forehead, and a small chin. Babyfaceness has positive correlations with honesty and warmth (Gorn, Jiang, and Johar 2008) and negative correlations with inferred power, dominance, and aggressiveness (Livingston and Pearce 2009). Babyfaceness should have a positive correlation with CVP if its positive effects through warmth, trustworthiness, and aggressiveness outweigh its negative effects through dominance.

Feature 7: thin jaw. Jaw width is calculated as the distance between the two edges of the jaw. A broader jaw has positive correlations with inferred dominance and strength (Cunningham, Barbee, and Pike 1990) as well as aggressiveness (Třebický et al. 2013). A thin jaw should correlate negatively with CVP if its positive effect on inferred dominance outweighs its negative effect on inferred aggressiveness.

Feature 8: large eyes. Eye size is a relative measure of the size of the eye against the whole face. Large eyes are perceived as more attractive (specifically, the perception that one is "charming"; Alley and Cunningham 1991) and heighten inferences of warmth, trust, and submissiveness (the opposite of inferred dominance; Montepare and Zebrowitz 1998). If the effects of large eyes on warmth and trust, and on attractiveness outweigh the effects on dominance, then large eyes should correlate positively with CVP.

Feature 9: high cheekbones. The cheekbones, particularly the malar bones, support facial structure; a person has "high cheekbones" if their malar bones are located closer to the eyes. In males, high cheekbones have positive effects on inferred competence and dominance (in social networking: Cunningham, Barbee, and Pike 1990). Females with low cheekbones are perceived as being less competent (in reproductivity and social networking: Cunningham 1986) than those with high cheekbones. Thus, we predict a positive correlation between cheekbone height and CVP.

Feature 10: mouth-nose distance. This is the vertical distance between the nose tip and the upper lip. Researchers have found that attractive faces usually have a shorter mouth-nose distance (Perrett, May, and Yoshikawa 1994) and that a longer mouth-nose distance may predict sarcasm (Tay 2014), which is a passive, verbal form of aggressiveness (Pickering, Thompson, and Filik 2018; Szymaniak and Kałowski 2020). Additionally, people with a shorter mouth-nose distance are perceived as being more focused and flawless, so they likely are perceived to be more competent (Dunn 2018). The effects of the mouth-nose distance on attractiveness, aggressiveness, and competence suggest a negative effect on CVP.

Feature 11: mouth-chin distance. This is the vertical distance between the bottom edge of the lower lip and the base of the chin. Although a shorter mouth-chin distance looks more attractive, a longer distance predicts higher inferred competence in financial affairs (Alley and Cunningham 1991; Perrett, May, and Yoshikawa 1994). Also, Sinko et al. (2018) showed that people with a shorter mouth-chin distance are perceived as being less dominant and more submissive. If the effects of the mouth-chin distance on inferred competence and dominance outweigh its effect on attractiveness, then mouth-chin distance should correlate positively with CVP.

While these literature streams support separate predictions for each of these facial characteristics considered in isolation, in reality, faces represent composites of differences in each. If we wish to understand which features affect charisma, and which inferred personality traits in turn drive visual aspects of celebrity potential, we need to build a model that can assess multiple features at the same time. We next describe the model that we use to do this. First, we present our data construction process. Second, we detail our findings about the facial features that appear to be most robustly associated with a given face's likelihood of celebrity as captured in the CVP score.

CVP MODEL DEVELOPMENT

Data Construction

We used three datasets for celebrities and six datasets for noncelebrities. All are benchmark datasets in computer vision and face recognition research, and they contain photos of people who vary in pose, age, gender, and race. The noncelebrity face datasets contain photos from social media, the Chicago Research Laboratory (Ma, Correll, and Wittenbrink 2015), and the internet. The celebrity face datasets contain photos from daily life, movies, and other scenarios. Most faces are labeled with the subject's identity, date of birth, date of the photo, and a rich set of attributes such as facial landmark locations, attractiveness, lip size, nose size, and hair color (Liu et al. 2015). The datasets include celebrities from a wide range of industries, such as entertainment (actors and influencers), sports, politics, and business (Liu et al. 2015), though individual photographs are not labeled with the celebrity's occupation. To explore whether CVP varies by industry, we compared the average CVP of 1,000 images of actors from the IMDb dataset and 1,000 images of people with various other occupations that we obtained from the other datasets combined. We found no significant difference ($t(1998) = 1.48$, $p = .14$), suggesting there is no obvious systematic bias arising from the occupations of celebrities.

Next, we randomly sampled 22,000 face images (11,000 each of celebrities and noncelebrities), drawing a balanced sample of images from each original dataset (details are in Web Appendix A). Then, after shuffling the dataset, we selected 12,000 images for training (80%) and validation (20%), and reserved 10,000 images for testing. We used a subset instead of the full sample for computational efficiency. However, we ensured accuracy by incrementally expanding our training set size until the model achieved satisfactory performance on the validation set and testing set (95.92% accuracy); beyond that point, we found a diminishing return on accuracy with more than about 12,000 images, as shown in Figure 1. The testing accuracy on 20,000 images is indeed higher (98.30%), but the improvement is marginal given the magnitude of the increase in computation costs. Given this trade-off, we set the cutoff at the "elbow" of 12,000 (see Kaplan et al. 2020 for a discussion of diminishing returns on model performance).

Figure 1. Diminishing Returns on Model Performance with Increasing Data Size

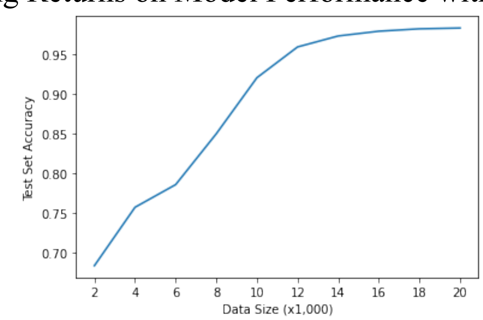


Table 2 presents the demographic composition of the datasets, with subjects categorized by celebrity status.[2] In Web Appendix A, we provide detailed descriptions of the datasets.

Table 2. Demographic Composition of Subjects in Datasets

Datasets	Gender		Age			
	Female	Male	< 20	20 – 40	40 – 60	> 60
Celebrity	29.43%	70.57%	.02%	82.28%	17.63%	.07%
Noncelebrity	28.62%	71.38%	.33%	93.56%	6.11%	.00%

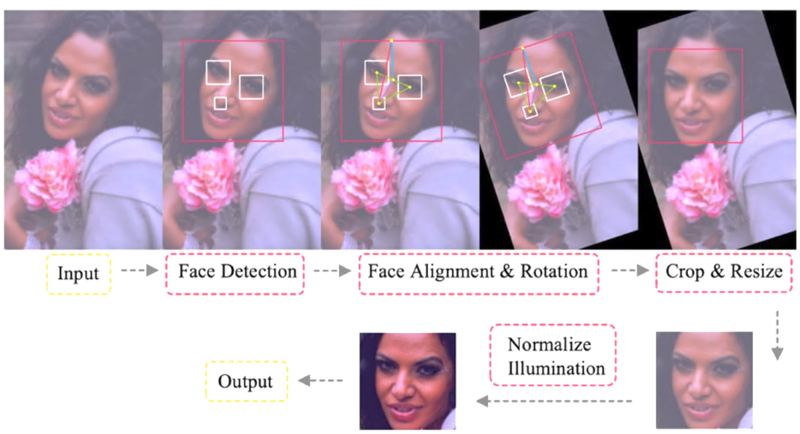
[2] The age, gender, and race of each face image was predicted using *Deepface*, which is based on the VGG-Face framework (Serengil and Ozpinar 2020).

Datasets	Race					
	Asian	Black	Indian	Latino / Hispanic	Middle Eastern	White
Celebrity	9.14%	7.27%	1.16%	9.36%	8.01%	65.06%
Noncelebrity	17.74%	5.98%	1.32%	11.55%	7.09%	56.33%

Data Preprocessing

We followed a five-step process to preprocess the images to address variations in size, face-background ratio, direction, and illumination (Figure 2). First, we detected the human face in the image. Second, we digitally aligned and straightened the face image (Kazemi and Sullivan 2014; Kovenko 2019) to reduce noise from variations in position and direction. Third, we cropped the image of each face to standardize the face-background ratio. Fourth, we resized the images to $224 \times 224 \times 3$ pixels, the required input size for the pretrained ResNet-50 model. Last, we normalized illumination (Zhang et al. 2007) to address systematic differences between datasets.

Figure 2. Face Image Preprocessing Steps



Notes. In preprocessing, we (1) detected the human face, nose, and eyes in the image; (2) rotated the image around the nose to straighten the face; (3) cropped the face from the image; (4) resized the image to $224 \times 224 \times 3$ pixels; and (5) normalized illumination. Details of each preprocessing step and more examples are in Appendix B.

Model Development

We next developed our central construct, CVP, from the image data described in the previous subsection. To do so, we used a supervised deep learning model, shown in Figure 3 and described in detail in Web Appendix B. The input of the model is an image, and the output is the probability that the image is of a celebrity (i.e., CVP).

We employed ResNet-50 (He et al. 2016) as the backbone structure of the model; ResNet-50 is a computer vision deep learning architecture that was initially trained on more than a million images from the ImageNet database. We chose ResNet-50 for several advantageous features, including fast optimization and accuracy gain with model depth (i.e., number of layers). Since ResNet-50 was pretrained for facial recognition, as a related but distinct task, we adapted ResNet-50 to our analysis by adding two layers. One layer is a customized dense layer with 50 nodes, where one node is one neuron in a neural network model. We added this layer for model interpretation. The other layer is a sigmoid layer[3] that predicts CVP. We added the sigmoid layer to transform neuron values from real numbers to the range of 0 to 1, because CVP is defined as a probability. We further converted the continuously distributed CVP into a binary classification (i.e., celebrity or noncelebrity) using the threshold of .5, because our data are balanced across categories (Collell, Prelec, and Patil 2018).

We also took several steps to optimize the model's performance. First, we selected the variant of the ResNet-50 model with the highest out-of-sample prediction accuracy and a stable optimization curve, or lower variation in convergence. Second, we experimented with five optimizers:[4] AdaGrad (Dean et al. 2012), SGD (Bottou 1998), AdaDelta (Zeiler 2012), Adam (Kingma and Ba 2015), and RMSprop. We achieved the highest accuracy and most stable optimization with the AdaGrad optimizer combined with preprocessing, as we explain in Web Appendix B.

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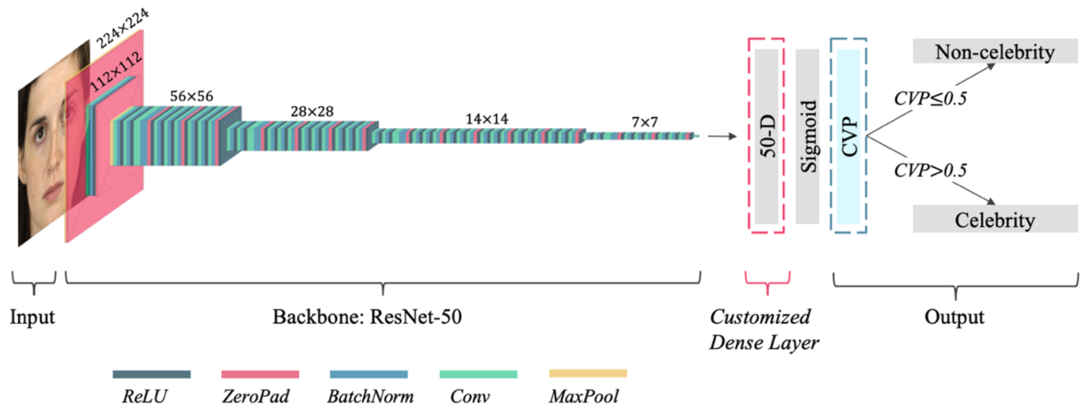
[3] In the context of artificial neural networks, the term "sigmoid function" is an alias for the logistic function, which is calculated as $s(x) = 1/(1+e^{-x})$.

[4] An optimizer is an algorithm that reduces loss and improves accuracy by modifying the attributes of the neural network, such as weights and learning rate.

Figure 3. Architecture of the Classification Model Based on ResNet-50

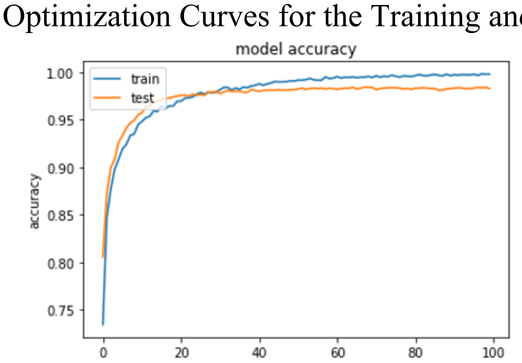


Notes. The structure of our classification model. The input is an image of 224 × 224 × 3 pixels. The backbone structure is ResNet-50, and the colors denote the layer types (see Web Appendix B). We added a customized dense layer with 50 nodes before the final sigmoid layer: the probability that the subject in the image is a celebrity (i.e., CVP). The 3D backbone was plotted using the Python package *visualkeras*.

Results

We used 12,000 images for training to calculate the model parameters, and reserved 10,000 for a holdout test set to assess the model's prediction accuracy. Based on results from the hyperparameter tuning stage (Web Appendix B), we achieved an accuracy of 95.92% on the test set. Figure 4 shows the improvement in accuracy on both the training and test sets during optimization. We also conducted a fivefold cross-validation to train five new models to make sure that our model has the optimal performance. A tenfold cross-validation on the optimized model demonstrates that our model has robust performance on different testing subsets (see details in Web Appendix B, pages 18-19).

Figure 4. Optimization Curves for the Training and Test Sets



Notes. The figure shows the optimization curves from the model with the best performance on the test set. We recorded the accuracy at each epoch. The blue line denotes the training accuracy, and the orange line denotes the accuracy on the hold-out set. The optimization curve became stable after epoch 40.

Table 3 presents summary statistics of CVP for each of the nine datasets (three celebrity datasets and six noncelebrity datasets) we used for training and testing.

Table 3. Summary Statistics on CVP for Different Datasets

Dataset	Type	Mean CVP	Max CVP	Min CVP
CelebA	Celebrity	.887	1.000	.002
IMDb-WIKI	Celebrity	1.000	1.000	.824
LFW	Celebrity	.993	1.000	.016
FEC	Noncelebrity	.214	1.000	.000
CFD	Noncelebrity	.001	.069	.000
GENKI-4K	Noncelebrity	.000	.003	.000
MTFL	Noncelebrity	.000	.002	.000
Selfie	Noncelebrity	.009	.983	.000
FFHQ	Noncelebrity	.003	.269	.000

Notes. Given the extraordinarily large size of each dataset, we calculated these summary statistics based only on the 22,000 images in our training and test sets. Dataset names are abbreviated; details are in Web Appendix A.

We benchmarked our model against two baseline models, support vector machine (SVM), and logistic regression. We tried two alternative inputs, including pixel-level vector and 11 facial features. For both types of input data, our model significantly outperforms both benchmarks on various performance metrics including prediction accuracy, recall, precision, and F1-score on the test set (details in Web Appendix B).

ASSOCIATION BETWEEN FACIAL FEATURES AND CVP

In this section we test the relationships between CVP and the 11 facial features discussed in the theoretical framework. First, we discuss the direction of the correlation between each facial feature and CVP, and then the contribution ranking of the facial features to CVP.

Direction of the Correlation Between Each Facial Feature and CVP

To test the relationships in Table 1, we created a contrasting dataset for each facial feature. That is, we selected or manipulated images to create two groups of images (Group 1 and Group 2) that varied in the focal feature. We then calculated the average CVP of the two groups using our deep learning model. For instance, for the facial width-to-height ratio, we digitally stretched the face in the image horizontally to create wider faces (Group 1) and vertically to create longer faces (group 2); the two groups had approximately the same facial features except for the width-to-height ratio. A higher average CVP in Group 1 (resp., Group 2) would indicate that at the population level, wider (resp., narrower) faces are associated with higher (resp., lower) CVP, implying a positive (resp., negative) correlation between the width-to-height ratio and CVP. We repeated this approach for all 11 facial features. The selection and manipulation processes and examples of contrasting images are provided in Web Appendix C, Table W2.

The group means and statistics appear in Table 4. CVP correlates positively and significantly with high cheekbones, (dark) color, large eyes, sexual dimorphism, and symmetry. CVP correlates negatively and significantly with facial width-to-height ratio and babyfaceness. However, there is no significant correlation between CVP and thin jaw, mouth-nose distance, mouth-chin distance, or averageness. Although CVP is predicted as a nonlinear function by the deep learning model of facial features, a dominant linear component may still exist in complex and nonlinear relationships. If it exists, such a dominant linear component will be reflected in the population-level data.

Table 4. Direction of Correlation Between Each Facial Feature and CVP

Facial Feature	Correlation	Group 1	Group 2	t-Stat	*p*-Value
Facial width-to-height ratio	Negative	.953	.964	2.557	.01
High cheekbones	Positive	.014	.002	-63.039	.00
(Dark) Color	Positive	.006	.002	-36.803	.00
Thin jaw	Negative	.002	.009	1.544	.13
Mouth-nose distance	Negative	.002	.002	.240	.81
Large eyes	Positive	.005	.003	-2.387	.02
Sexual dimorphism	Positive	.633	.298	-19.187	.00
Mouth-chin distance	Positive	.002	.002	-1.578	.12
Babyfaceness	Negative	.001	.005	1.788	.08
Symmetry	Positive	.007	.001	-14.572	.00
Averageness	Negative	.897	.906	.959	.34

Notes. The table shows the direction of the correlation between each facial feature and CVP. The columns labelled "Group 1" and "Group 2" provide the mean CVP for the sets of selected or manipulated images explained in Web

Appendix C. The "t-Stat" column compares the CVP distributions between Group 1 and Group 2 with a two-tailed test of the population mean with unknown variance. The "*p*-Value" column denotes the *p*-value for the corresponding t-statistics.

Ranking the Contributions of the Facial Features to CVP

To understand the relative importance of each facial feature to CVP, we leveraged SHAP (Lundberg and Lee 2017), a state-of-the-art explainable AI method. We went through a two-step process and used the customized dense layer with 50 nodes, as previously described.

In the first step, we used SHAP to calculate the contribution of each of the 50 nodes to CVP, namely $\mathrm{NODESHAP}$. We assumed that the input node value from the second-to-last layer to the final sigmoid layer was the set of players, and the output was the payoff. We built a new XGBoost tree model (Chen and Guestrin 2016) and implemented the Tree SHAP algorithm. We chose Tree SHAP over Deep SHAP because the former is much faster in computation, computes the exact instead of approximated Shapley values, and allows for better visualization of the feature contribution (Lundberg et al. 2020). For additional details, see Web Appendix D.

In the second step, we calculated the contribution of each facial feature to CVP, denoted by FeatureSHAP. We derived FeatureSHAP based on the weighted NODESHAP, where the weights are the ranking of the node's relevance to the focal feature.

At the image level, the formula for $\mathrm{FeatureSHAP}_i^{(p)}$ for feature i of individual p is

$$(1) \qquad \mathrm{FeatureSHAP}_i^{(p)} = \sum_{j=1}^{50}\{(51 - j) \times \mathrm{NODESHAP}_{n_{ijp}}\},$$

where i denotes the i^{th} facial feature (= 1, 2, …,11); n_{ijp} (= 1, 2, …, 50) denotes the j^{th} (= 1, 2, …, 50) active[5] node (i.e., the j^{th} most relevant node to CVP) that captures the i^{th} feature for individual p; and $\mathrm{NODESHAP}_{n_{ijp}}$ denotes the SHAP value for node n_{ijp} for individual p. For

[5] In neural networks, whether a node is active is determined by its activation value—the higher the activation value, the more active the node is. This value is the output from a scalar-to-scalar activation function, which propagates the output of one layer's nodes to the next layer (Montesinos López, Montesinos López, and Crossa 2022).

individual p, the weights (51– j) indicate that the most relevant node n_{i1p} (e.g., node 15) for feature i receives the highest weight, 50, whereas the least relevant node n_{i50p} (e.g., node 32) for feature i receives the lowest weight, 1.

At the population level, the FeatureSHAP for feature i is termed $\mathrm{FeatureSHAP}_i^{(\mathrm{mean})}$:

(2) $$\mathrm{FeatureSHAP}_i^{(\mathrm{mean})} = \frac{1}{|P|} \sum_{p \in P} \sum_{j=1}^{50} \{(51 - j) \times \mathrm{NODESHAP}_{n_{ijp}}\},$$

where P denotes the total population (i.e., all faces to be considered in the dataset), and |P| denotes the size of the total population (i.e., the total number of faces).

To determine the relevance of each node for each of the 11 facial features, we then used the following procedure. For each feature, we entered the contrasting groups of images (see Web Appendix C for details) and calculated the activation value of each node in the 50-D layer. Then, for each node, we calculated the Wasserstein distance[6] between the activation values for the contrasting groups (e.g., wider faces vs. longer faces). If a node captures the variation in this focal feature, then the node has a larger difference in activation values between the contrasting groups of images. Therefore, nodes with larger Wasserstein distances most strongly capture the predictive power of the focal feature (e.g., the facial width-to-height ratio) on the predicted CVP.

In Table 5, we rank the facial features (column 2) based on their FeatureSHAP values (column 3). Note that we focus on the predictive power of each facial feature here, not the level of significance in the correlation between each facial feature and CVP. We found that facial width-to-height ratio is the strongest predictor of CVP, followed by sexual dimorphism and averageness. This is because past literature has proved that significant variables are not always good predictors (Lo et al. 2015).

Table 5. Feature Importance Ranking Based on FeatureSHAP

[6] The Wasserstein distance is a distance function defined between probability distributions. For a definition, see Petitjean (2002) and Arjovsky, Chintala, and Bottou (2017).

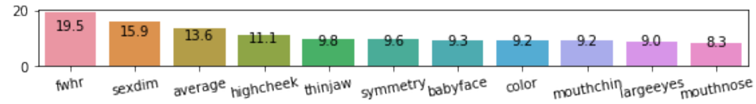
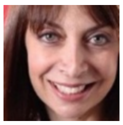
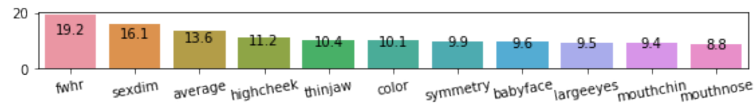
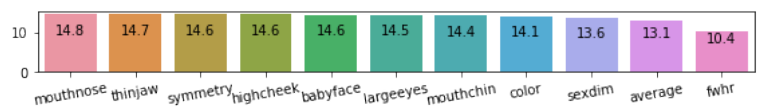
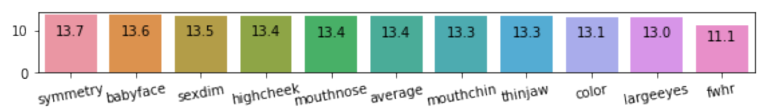
Facial Features	Ranking	FeatureSHAP$^{(mean)}$
Facial width-to-height ratio	1	13.093
Sexual dimorphism	2	11.993
Averageness	3	10.408
High cheekbones	4	8.894
Color	5	8.494
Thin jaw	6	8.141
Mouth-chin distance	7	7.882
Large eyes	8	7.720
Symmetry	9	7.697
Mouth-nose distance	10	7.660
Babyfaceness	11	7.520

Significance levels: *p < .1, **p < .05, ***p < .01.

Individual heterogeneity. Previously, we have estimated the relationship between facial features and CVP at the population level, but individuals are heterogeneous in the contribution of each facial feature to CVP. For example, a thin jaw could be the most critical factor for one face and could have only a marginal influence on the CVP of another face.

Table 6 presents examples from these datasets, where the contribution of each feature to CVP is plotted but does not indicate the direction of these relationships. Combining this table with Table 4, which presents the correlation between CVP and facial features at the population level, we derive interpretations such as the following: If Table 6 shows that an individual with a high CVP has Feature X (where X represents one of the 11 features) ranked highly, and Table 4 indicates a positive correlation of Feature X with CVP at the population level, we infer that this individual's high CVP is partly due to a high value of Feature X. For example, in the first two rows of Table 6, facial width-to-height ratio and sexual dimorphism are ranked highly. According to Table 4, facial width-to-height ratio correlates negatively with CVP, while sexual dimorphism correlates positively with CVP. Thus, individuals in these rows exhibit high CVP, attributed to their low facial width-to-height ratio and high sexual dimorphism. The CVP of the female in the last row is also driven down by her relatively small eyes; and the CVP of the male in the third row is driven down by his high degree of averageness.

Table 6. Four Examples of CVP Values

Image	CVP	FeatureSHAP$^{(p)}$
	.80	
	.81	
	.19	
	.22	

Notes. Variable FeatureSHAP$^{(p)}$ is calculated at the individual level and thus the ranking for each individual is different from the FeatureSHAP$^{(mean)}$ ranking. Here "fwhr" means facial width-to-height ratio, "sexdim" means sexual dimorphism, "highcheek" refers to high cheekbones, "mouthchin" denotes mouth-chin distance, and "mouthnose" denotes mouth-nose distance.

Comparison Between Empirical and Theoretical Correlations

We used the literature and our empirical evidence to derive the likely relationships between facial features and CVP. A symbolic summary is in Table 7. Some of our empirical results are consistent with the theoretical predictions, while others contradict them. For instance, our results show that symmetry is positively associated with CVP, and mouth-nose distance is negatively associated with CVP, reinforcing theoretical predictions. However, we find that averageness is negatively associated with CVP, in contrast with the theoretical prediction. Detailed explanations are presented in Web Appendix E.

Table 7. Symbolic Summary of the Theoretical and Empirical Comparison

Facial Feature	Theoretical	Empirical
1. Facial width-to-height	+2, –2	(–)
2. Sexual dimorphism	+2 / +1, –1	(+)
3. Averageness	+1	(–)
4. Symmetry	+3	(+)
5. (Dark) Color	+1, –1	(+)
6. Babyfaceness	+3, –1	(–)
7. High cheekbones	+1	(+)
8. Large eyes	+3, –1	(+)
9. Thin jaw	+1, –1	(–)
10. Mouth-chin distance	+2, –1	(+)
11. Mouth-nose distance	–3	(–)

Notes. The "Theoretical Prediction" column sums the contributions of the facial feature's effects on the personality traits (e.g., "+2, –1" means that two personality traits make positive connections between the facial feature and CVP, while one trait makes a negative connection). Note that sexual dimorphism contains the effects of both masculinity and femininity; masculinity boosts dominance and competence for men, while femininity boosts warmth for women, so the overall theoretical prediction is "+2" for men and "+1" for women (see Section *THEORETICAL FRAMEWORK,* Feature 2, for details). We include in the "Empirical Result" column from Table 4 to facilitate comparison.

INTERNAL VALIDITY: EXPERIMENTS 1 AND 2

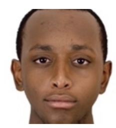
In order to validate the causal relationships suggested in the development of the CVP measure, we next report one controlled experiment and, briefly, results from a replicate. We used them to test whether systematic variations in model-predicted CVP as presented in morphed faces result in corresponding variations in the human judgment of CVP. We also measured participants' personality trait inferences and attractiveness perceptions, which we tested as simultaneous mediators in our model. These tests allow us to better understand whether CVP metrics may provide explanatory power that moves beyond the aforementioned ambiguous predictions associated with attractiveness. We describe Experiment 1 in detail and refer briefly to Experiment 2, which was a conceptual replication with a slightly different dependent measure. For the full details of Experiment 2, see Web Appendix F.

Experimental Design and Procedure

Participants. We recruited 1,153 US-based participants (43.06% male, 74.88% White) from Prolific.com. We excluded invalid, unfinished, or low-quality responses (see Web Appendix F for selection criteria), leaving 1,065 responses for analysis.

Stimuli. We used face-morphing (Venkatesh et al. 2021) to transform each of a set of faces (Black female, Black male, White male, White female) so their CVP values equaled 0, .2, .4, .6, and .8, yielding a total of 20 images (Table 8). The detailed procedure on face morphing is in Web Appendix H.

Table 8. Examples of Face Morphing to Achieve a Certain CVP Threshold

Face No.	**Original Face**	**CVP Threshold**	**Morphed Face**	**CVP Threshold**
1 Black Female		0		.6
2 Black Male		0		.6
3 White Female		0		.6
4 White Male		0		.6

Notes. The second column of the table shows the four original faces, whose CVP values are 0. The fourth column shows the modified faces after face-morphing transformations to the CVP levels of .6. Other examples of morphed faces with CVP values of .2, .4, and .8, are provided in Web Appendix F.

Procedure. Each participant was randomly assigned one morphed image from each of the four race-gender categories. For each of the four assigned faces, participants answered three questions about CVP as well as about measures of inferred personality traits. To measure CVP, we asked participants the following questions about each morphed image they were presented with: (1) How likely do you think that this person could become a celebrity? (2) If this person were on your favorite social media site, how likely is it that you would subscribe to their content or follow them? (3) This person is active on social media. Relative to other people, how many followers or subscribers do you think they have?

We used a 9-point Likert scale for responses, with higher numbers indicating a higher likelihood of having more followers. Participants also indicated their perceptions of the seven traits (i.e., dominance, warmth, trustworthiness, aggressiveness, competence, generosity, attractiveness) for each face on a 9-point Likert scale, with higher values indicating stronger inferred levels of each trait. Finally, participants provided demographic information about themselves including age, gender, race, state, political ideology,[7] social media usage, and financial scarcity.

Model

Using the observed variable OLS and logistic regression path analysis modeling tool, PROCESS Model 4 (5,000 bootstrapped samples; Hayes 2013), we explored the simultaneous parallel mediation effect of seven mediators—six personality traits (i.e., dominance, warmth, trustworthiness, aggressiveness, competence, generosity) and attractiveness—on the relationship in terms of how model-predicted CVP predicts human-rated CVP. We also controlled for the gender and race of the targeted face, as well as participants' gender, race, age, political ideology, social media usage, finance scarcity, and residence state.

Results

We combined participants' responses to the three CVP questions (Cronbach's alpha = .75) into a single index of human-rated CVP. The correlation between model-predicted CVP and human-rated CVP is .51 (p = .02). Figure 5, which shows the relationship between human-rated CVP

[7] The political ideology measure comprises 10 questions from a standard Pew Research Center survey, where option 0 indicates a conservative position and option 1 indicates a liberal position. The sum of the scores indicates the strength of the person's liberal position. See https://www.pewresearch.org/politics/2014/06/12/appendix-a-the-ideological-consistency-scale/.

and model-predicted CVP, demonstrates a positive and significant linear relationship (slope = .6699, *p* = .02) between the two. The figure shows model-free evidence that model-predicted CVP correlates positively with human-rated CVP. The y-axis represents the average human-rated CVP of each targeted face (about 210 ratings per face). The x-axis represents model-predicted CVP at five different levels. Each dot on the plot represents the average human-rated CVP for each of the 20 targeted faces. The blue line is the linear trend we obtained by fitting a regression model on these points with the formula Average Human-Rated CVP ~ Model-Predicted CVP.

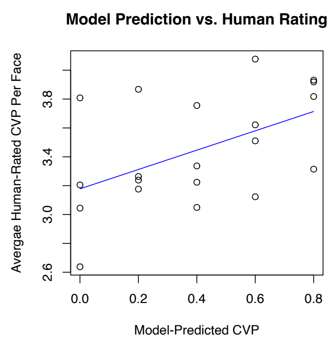


Figure 5. Scatterplot of Human-Rated CVP versus Model-Rated CVP

The results from Experiment 1 are shown in Table 9. The direct effect of model-predicted CVP on human-rated CVP is .05 (F(17, 4218) = 236.00, p < .001), and the total mediation effect of the 7 mediators is .09. After accounting for the effect of attractiveness, we find significant indirect effects of model-predicted CVP through inferred dominance, warmth and competence and marginally significant mediation effects through inferred trustworthiness. Meanwhile we do not observe a significant mediation effect through inferred generosity or aggressiveness. Results are robust to the exclusion of covariates (Web Appendix F).

Table 9. Direct and Indirect Effect Analysis in Experiment 1 with Covariates

Variables	Effect	SE (Bootstrapped)	*p*-Value	95% CI (Bootstrapped)
		Direct Effect		

Model-Predicted CVP	.047	.008	.000	[.031, .063]
Indirect Effects				
Total	.086	.008	.000	[.071, .101]
Dominance	.014	.003	.000	[.008, .019]
Warmth	.011	.002	.000	[.007, .016]
Trustworthiness	.002	.001	.023	[.000, .004]
Aggressiveness	-.000	.001	.420	[-.002, .002]
Competence	.006	.001	.000	[.003, .009]
Generosity	.002	.001	.023	[-.000, .004]
Attractiveness	.052	.005	.000	[.043, .062]

Notes. The dependent variable is human-rated CVP. Covariates on demographic information of targeted faces and participants are included but not displayed. The p-values in column 3 are approximated based on Wald t-tests by dividing the estimate by the bootstrap standard error to arrive at a t-statistic (see practice in Abbua and Gopalakrishna 2021), but they are not accurate if the sampling distribution of the statistic is not symmetric. Thus, some papers only report bootstrapped CIs (e.g., Grewal, Hmurovic, Lamberton, & Reczek 2019). Furthermore, for concerns that faces of CVP = 0.8 seems to have makeup which might be a confounding factor, we conduct the analysis using faces with CVP < 0.8 and still find that the direct effect of model-predicted CVP on human-rated CVP is .04 ($p < .001$). Note that we did not "add" make up to faces, but rather it was part of the morphing process to change CVP of the same face. The detailed step-by-step tutorial on face morphing is in Web Appendix H. The selection of faces is random from the datasets and any attempt to select them on any specific dimension will not be appropriate. The detailed result is in Web Appendix G.

In Experiment 2, we used the same stimuli but showed the four faces side by side. Moreover, for the questions on CVP and personality traits, participants ranked the four faces instead of rating them individually. The results, in Web Appendix F, are consistent with those of Experiment 1.

As an alternative way of validation, we report average human-rated and model-predicted CVPs of faces ranked at 1, 2, 3, and 4 (Table 10). The average model-predicted CVP bears the same ranking order, showing that human judgment and model prediction are the same at the population level; the average human-rated CVP from Experiment 1 bears the same ranking order, suggesting consistency between the two experiments.

Table 10. Average Human-Rated CVP and Model-Predicted CVP of Faces Ranked at 1, 2, 3, and 4 in the Lab Experiment

Human-Ranked CVP	**Average Model-Predicted CVP**	**Average Human-Rated CVP**
1	0.4846	3.7268
2	0.4340	3.5182
3	0.3712	3.3178
4	0.3116	3.2250

EXTERNAL VALIDITY: OBSERVATIONAL STUDIES 1 AND 2

While Experiments 1 and 2 suggest that general celebrity potential might be inferred from photographs, the nature of celebrity across domains may differ. For example, whereas greater Instagram "celebrity" would translate into higher post engagement (Tal and Gordon 2015), greater LinkedIn "celebrity" would be reflected in the likelihood of holding a C-suite position (Agle et al. 2006). Therefore, we undertook validation analyses on two external datasets that contained face photographs and outcomes that can be taken to represent domain-specific celebrities. We predicted that users with higher CVP would experience outcomes more consistent with domain-specific celebrities than those with lower CVP, even after we controlled for other contextual factors and measures of attractiveness.

Selfies of Instagram Influencers

To mitigate concerns that top-tier influencers may possess more resources for capturing higher-quality photographs compared to influencers with significantly fewer followers, we conducted data collection on the top 500 Instagram influencers of 2024. Within this cohort, only 230 influencers posted either a selfie or a photograph showing a clearly identifiable frontal face within our data collection period. Given that each of these influencers had more than one million users, disparities in image quality should not be a substantive concern for the validity of our study. We extracted and preprocessed the face photographs as described in our initial machine-learning study. Then we used our deep learning model to predict the CVP of each face. We estimated the following model, where Follower # Change of a given influencer was tracked around one week after the time of posting the focal image, with a three-day gap (Cheng and Zhang 2024):

(3) $$\text{Follower \# Change} = \text{Intercept} + \alpha_1 \times \text{Gender} + \alpha_2 \times \text{Age} + \alpha_3 \times \text{CVP}$$

$$+\alpha_4 \times \text{Controls\_Contextual} + \alpha_5 \times \text{Facial\_Beauty} + \alpha_6 \times \text{Like \#} + \varepsilon.$$

We used the age-gender classification model proposed by Levi and Hassncer (2015) to measure Age (continuous number) and Gender (male = 1, female = 0). Here Controls_Contextual captured contextual data that might have correlated with the change in the number of followers: image visual features (Zhang et al. 2021), including brightness, colorfulness, and symmetry, scored by the pyaesthetic package in Python;[8] the text description's length and richness (type-token ratio proposed by Chotlos 1944); and the text's sentiment, predicted using the compound score by VADER Sentiment Intensity Analyzer (Hutto and Gilbert 2014). We included physical attractiveness, measured by the ResNet-50 framework trained on the SCUT-FBP5500 dataset (Liang et al. 2018), to tease out the impact of attractiveness from the impact of CVP on Follower #. Additionally, we included the logarithm of like count (Like #) as a control variable. We estimated the full regression model as well as the models after feature selection through Step AIC (Hocking 1976). Table 11 presents the estimation results of the full regression model and the models after feature selection through Step AIC.[9]

Table 11. Regression Results for the Instagram Dataset: Full Model and Step AIC Model

	Model (1)		Model (2)		Model (3)	
Variables	Full	Step AIC	Full	Step AIC	Full	Step AIC
CVP	120974.79 *	108678.10 .	113351.25 .	108678.10 .	9.00E+04	8.07E+04
	[60076.46]	[58987.41]	[59939.54]	[58987.41]	[55765.17]	[55062.47]
Attractiveness	-1.30E+04				-5.34E+03	
	[9588.71]				[9142.35]	
Gender (Female)	-2.98E+03		-3.47E+03		-9.90E+03	
	[16632.93]		[16664.09]		[16120.86]	
Age	-4.75E+03	-5.16E+03	-4.35E+03	-5.16E+03	-3.16E+03	

[8] *Pyaesthetic* provides estimates of visual features concerning the aesthetic of a still image (https://github.com/Gabrock94/pyaesthetics).

[9] AIC refers to the Akaike information criterion; see Hocking (1976).

	[3808.30]	[3634.18]	[3804.71]	[3634.18]	[3558.28]	
Context Brightness	-7.21E+04		-6.13E+04			
	[69084.49]		[68774.04]			
Context Colorfulness	-592.80 .	-544.87 .	-556.03 .	-544.87 .		
	[323.48]	[317.44]	[323.03]	[317.44]		
Context Symmetry	1334.26 *	1347.26 *	1259.54 .	1347.26 *		
	[651.63]	[632.94]	[650.67]	[632.94]		
Description Length	-1.53E+01		-1.32E+01			
	[52.49]		[52.57]			
Description Richness	-5.22E+03		-1.63E+03			
	[25462.97]		[25378.73]			
Description Sentiment	3.73E+03		4.71E+0 3			
	[21814.51]		[21848.52]			
Like #	13109.71 *	13872.08 **	13339.72 *	13872.08 **		
	[5380.20]	[5097.27]	[5388.89]	[5097.27]		
R-Squared	9.46E-02	8.22E-02	8.62E-02	8.22E-02	1.61E-02	9.30E-03

Notes. The table presents the regression results of the full model and Step AIC model for the external Instagram dataset with and without contextual controls and variable Attractiveness. Standard errors are in brackets. Variables are standardized. Significance levels: **p* < .1, ***p* < .05, ****p* < .01.

CVP has a positive and significant coefficient in all cases, indicating that higher CVP predicts a higher increase in the number of followers, even after we controlled for variable Attractiveness and various features of post content (variable Controls_Contextual).

However, our results may be affected by selection bias, because people who choose to become influencers may generally have higher CVP than the average population. To verify whether selection bias is a concern for our study, we randomly selected 1,000 photographs from one of the noncelebrity datasets (the Selfie Dataset, not included in the training set) and calculated the average CVP. Additionally, we randomly selected 2,105 Instagram photographs posted between 2016 and 2020 by about 500 influencers with more than one million followers each. These noncelebrities had an average CVP of .11, while the 2,105 influencers averaged .71, confirming selection bias exists. We also investigated the relationship between variables CVP and Attractiveness in this Instagram dataset of 2,105 selfies and found a relatively low correlation of .17 ($p < .001$). This finding demonstrates that CVP and attractiveness are essentially different; specifically, CVP adds extra explanatory power above and beyond attractiveness. Another caveat is that there might exist other factors that influence the number of followers. For example, networking with brands would be absorbed by the idiosyncratic error term.

LinkedIn Profile Data

We also validated our CVP model on LinkedIn profile images of C-level executives ("C-suite") as compared to non-C-suite employees. We selected 30 Fortune 500 companies (e.g., Amazon, Apple, Walmart) and collected the profile images of 5 C-suite and 5 non-C-suite employees for each company. Then we used a similar analysis process as for the Instagram influencers. We found that the mean CVP of the C-suite employees (.85) is significantly higher than the mean CVP of the non-C-suite employees (.20, $p < .001$ in a lower-tail test of the population mean).

DISCUSSION

Our research represents the first empirical attempt to characterize the relationships between CVP and facial features. We built a deep learning model that predicts a person's CVP based on a photograph of their face, and the model achieved high accuracy on the hold-out test sample. To offer theoretical and practical implications, we used facial analytics on a large dataset to determine the direction and strength of the correlation between each of the 11 facial features we considered and CVP. We also derived a CVP formula (Equations 1 and 2) that uses SHAP to rank features by contribution to CVP. Furthermore, we experimentally showed that model-predicted CVP aligned closely with the human judgment of CVP in lab experiments. This alignment reveals the role of inferences related to different personality traits in explaining the relationship between facial features and CVP. Finally, we found that model-predicted CVP is predictive of desirable outcomes in the contexts of media and entertainment (Instagram) and business (LinkedIn).

Theoretically, our research relates closely to the literature on charisma. We consolidate prior theories on the correlations between facial features and charisma with personality traits as mediators. Our results support some of the relationships identified in prior work (e.g., CVP is hurt by a higher facial width-to-height ratio) and contradict others (e.g., the correlation between averageness and CVP is theoretically positive but empirically not significant in our data). Notably, we also found that while some proposed personality traits do explain the relationship between facial features and CVP, others seem to play a weaker mediational role. Specifically, it is more complex inferences, such as those related to generosity and aggressiveness, that fail to show robust mediation when considered in concert with other simpler but likely highly correlated inferences, such as warmth and dominance. Moreover, we empirically showed that CVP goes far beyond attractiveness. This finding calls for a qualification of widespread assumptions that emphasize the key role played by physical attractiveness to celebrity reported in previous studies.

Methodologically, while black box deep learning models are hard to interpret, we deploy the FeatureSHAP metric to provide interpretable features that lead to higher CVP. Although simpler methods, such as regression, also provide interpretable results, they are less flexible in capturing nonlinear relationships (some relationships cannot be easily captured by a simple functional form) and have much poorer prediction performance. In comparison, our deep learning model is purely data-driven and can capture very complicated forms of relationship with much higher prediction accuracy on the hold-out test sample.

MANAGERIAL IMPLICATIONS

Prior to outlining various potential managerial uses of the celebrity visual potential (CVP), it is imperative to stress that developments in machine learning raise ethical issues and concerns. Analogous to following the ethical guidelines on online data acquisition, organizations must exercise due diligence in obtaining explicit consent from individuals for the collection, disclosure, and intended utilization of facial data. Any managerial relevance discussion presupposes full compliance with such requirements.

A couple of noteworthy aspects of CVP merit careful consideration. First, in the external validation, while the impact of CVP is positive and significant, it explains only modest variance. Therefore, firms would benefit from using CVP as one of several factors, many of which are focused on skills or tangible characteristics. Second, the CVP score should theoretically generalize to professions where persuasiveness is an important job characteristic. This is likely the reason we were able to validate it for online professionals and managers. The CVP score is also a fairly widely generalizable characteristic, as persuasion is helpful in many roles. However, we note that occupations where persuasiveness is not critical to job performance may not relate well to the CVP measure as designed. We indicate managerial insights that CVP offers in domains where visual factor is crucial.

First, CVP can be leveraged by employees in their career choices. Better knowledge of one's celebrity potential may help individuals decide whether to pursue a specific career. Second, CVP can be used as a control variable in field experiments or randomized controlled trials (RCTs) to improve persuasiveness or celebrity influence. This is analogous to the incorporation of genetic information in RCTs with objectives centered on enhancing academic outcomes (Lee et al. 2018). Given the predictive power of CVP on various outcomes, such use can generate nontrivial gains in statistical power for the RCT (Rietveld et al. 2013). Third, CVP can help design faces of AI-generated characters—such as figures in advertisements (Dave 2023), fashion models (Iovine 2023), or educators (Pataranutaporn et al. 2022)—making them more persuasive in interactions with potential customers in digital settings. Fourth, CVP can be used to assess if a company's human resource professionals excessively use facial features in their selection of salesforce. Selecting candidates based on a high CVP score is unlikely to reinforce existing biases based on demographic factors, as we find no relationship between CVP and race, gender, religion, or other typical bias factors. Rather, if we observe a positive link between CVP and sales success, opting for candidates with a high CVP may help HR staff focus on candidates with the highest likelihood of being strong performers.[10] However, we emphasize that CVP is only one of the many factors that affect employee performance and should never be used as the sole criterion in screening candidates.

The limitations of our work provide opportunities for future research. First, our study measures CVP as a static metric, while variations in the associations between facial features and CVP may exist over time. Second, several facial features have theoretical correlations with more than one personality trait and subsequently exert composite effects (i.e., with both positive and negative components) on CVP. While our empirical results provide clarity regarding the overall effect, the precise nature of the trade-offs between personality traits warrants further exploration. Third, utilizing the CVP metric comes with data privacy concerns, as with the use of consumer data. Thus, it may be necessary for the firm to ensure proper disclosure and obtain consent from consumers for the collection of data required to estimate CVP. Laws and regulations vary across countries, and adherence to these regulations is crucial for the successful implementation of

[10] The prediction accuracy of our model on the testing set (10,000 images) across different race, gender, and age groups is very high and does not vary significantly across different demographic groups.

CVP. Finally, the importance of CVP varies based on occupation, but our dataset lacks this information. Additional research including this occupation information would extend the applicability of our work.

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