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Learning Faces to Predict Matching Probability in an Online Matching Platform

Short Paper

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Abstract

With the increasing use of online matching platforms, predicting matching probability between users is crucial for efficient market design. Although previous studies have constructed various visual features to predict matching probability, facial features, which are important in online matching, have not been widely used. We find that deep learning-enabled facial features can significantly enhance the prediction accuracy of a user's partner preferences from the individual rating prediction analysis in an online dating market. We also build prediction models for each gender and use prior theories to explain different contributing factors of the models. Furthermore, we propose a novel method to visually interpret facial features using the generative adversarial network (GAN). Our work contributes the literature by providing a framework to develop and interpret facial features to investigate underlying mechanisms in online matching markets. Moreover, matching platforms can predict matching probability more accurately for better market design and recommender systems.

Keywords: online dating, deep learning, individual rating, CNN, GAN, matching probability

Introduction

An online matching market is a two-sided platform that allows matches between two users with common interests (Parker and Van Alstyne 2005). With the advancement of technology and the spread of non-contact trends caused by COVID-19, online transactions have been actively carried out in various fields such as dating, e-commerce, labor market, and ride-sharing.

Predicting the matching probability between users within an online matching market is an important factor directly related to the user engagement and revenue of the platform, as the performance of market design and recommender systems may vary depending on the matching probability (Jung et al. 2021, Lee et al. 2020). Especially, sophisticated matching probability predictions are needed in two-sided platforms since the preferences of both users must be considered (Pizzato et al. 2010; Jung et al. 2021; Lee et al. 2020).

One of the key features in predicting the matching probability of an online matching market is visual features. In particular, facial features play an essential role in various online matching markets, such as dating, hiring, and selling, and the importance gets bigger when tasks or products are associated with appearance. (Langlois et al. 2000; Shi et al. 2020; Jung et al. 2021). According to Peng et al. (2020), the facial attractiveness of a user's profile picture is vital for determining matching probabilities in e-commerce platforms.

This work presents a deep learning-based methodology for predicting matching probabilities of online matching markets using visual features. We predict individual ratings in an online dating market where visual features are critical among the various matching markets. We use both theory-based features and data-driven features to significantly improve prediction accuracy. We also analyze the result by each gender and explain their different preference in connection with prior theories. Furthermore, we propose a novel method to visually interpret deep learning-enabled generic facial features using StyleGAN, which were previously difficult to interpret.

Our work significantly contributes to both academic research and industry practice. Researchers can leverage our deep learning-based methodology to predict matching probabilities more accurately than conventional methods and interpret facial features to investigate underlying mechanisms in online matching markets. Our work motivates information systems (IS) researchers to accelerate synergy between big data and theory. From a practical perspective, matching probability predictions will allow practitioners to improve market design and recommender systems, which in turn will maximize matching outcomes. This will increase consumer value and maximize the platform's user engagement.

Literature Review

Visual Feature Analysis

Various IS studies have built visual features for use in matching probability predictions. Before the advent of methodologies such as machine learning (ML) and deep learning (DL), human coders manually created visual features, which may include bias and scalability issues (Li et al. 2016; Petty et al. 1983). Later, with advances in ML, many studies have utilized theory-based features that are automatically extracted from images using ML-based data mining models (Chan and Wang 2014; Rhue 2015; Zhang et al. 2021). However, these methods pose limitations that predictive errors can occur since the model used to generate features is imperfect and because the features are based on prior theories, making it difficult to analyze phenomena beyond existing theories (Yang et al. 2018).

From this point of view, attempts have recently emerged to use DL-generic features automatically extracted from images through DL models. For instance, Shin et al. (2020) demonstrated that the combination of theory-based features and DL-generic features could improve the prediction performance of social media posts' popularity. However, DL-generic features have limitations that are difficult to interpret by researchers because they are created through DL models with many deep layers. To the best of our knowledge, DL-generic facial features have not been used to predict the matching probability of an online matching market. This work fills this research gap. It improves matching probability prediction performance using theory-based visual features and DL-generic facial features and offers a visual interpretation of DL-generic features visually, which were difficult to interpret before.

Online Dating Market

Profile pictures in online dating markets can play more important role in the user's attractiveness measurement process than those in offline dating markets (Guan et al. 2015). Facial features are essential because attractive faces make the person look more socially skillful, intelligent, and popular (Magro 1999; Eagle et al. 1991; Hamermesh 2011). Many evolutionary psychological studies have highlighted the importance of facial attractiveness in mate preferences and mate choice processes (Lang et al. 2000; Rhodes

2006). However, online dating literature mainly focused on user's non-visual features such as age and occupation, partially due to the methodological challenges (Skopek et al. 2011; Xia et al. 2014). This study uses both visual features and non-visual features to predict user preferences in online dating markets.

Deep Learning

This study utilizes a convolutional neural network (CNN) model, which shows excellent performance in visual data analysis (LeCun et al. 2015). In particular, we used FaceNet, proposed by Google, which successfully represents facial information in 512-dimensional embedding (Schroff et al. 2015). We created theory-based facial features through various pre-trained CNN models and used the FaceNet-based facial embedding generated from the user's profile picture as DL-generic features. Furthermore, we used a generative adversarial network (GAN) to visually interpret DL-generic facial features, which were previously difficult to interpret. GAN is a generative model that generates new data from latent space that contains information about data (Goodfellow et al. 2014). StyleGAN, proposed by NVIDIA, introduced a mapping network to solve the entanglement of the latent space and succeeded in generating more real-looking face images compared to the existing model (Karras et al. 2019). We visually interpret DL-generic facial features that affect individual ratings using StyleGAN.

Data and Feature Construction

The data used in this study is from one of the largest online dating platforms in South Korea, and it consists of 603,741 evaluations (individual ratings) in which 45,399 users rated each other for two months between February and March 2021. The data was collected by gathering the evaluations exchanged by all the users who have newly signed up for the platform within the period, and all data has been anonymized. There are 123,501 photos of users, about 2.72 photos per identity. In the data collection process, users look at opponents' photos and profile information together and score them with an integer between 1 and 5. This score, an individual rating given by one user to another, is the target variable predicted in this study. Although there exists some difference between individual rating and matching probability, it is widely known that the former can act as a crucial predictor for the latter (McGloin and Denes 2018; Ranzini et al. 2022). The non-visual profile information consists of 12 features, including gender, age, height, occupation, and university. A total of 20,834 users were evaluated at least once, consisting of 15,071 males and 5,866 females. A detailed description of the dataset is shown in Table 1.

Dependent Variable						
Variable	Description	Count	Mean	SD	Min	Max
Score	Individual Rating of All Users	603,741	2.66	1.34	1.00	5.00
- Male	Individual Rating of Male Users	207,159	2.08	1.08	1.00	5.00
- Female	Individual Rating of Female Users	396,582	2.96	1.37	1.00	5.00
Independent Variable						
Group	Description (Dimension)	Features				
F1	Profile Feature (162)	Gender, Age, Height, Region, Job, University, Body, Personality, Religion, Drink, Smoke, Blood Type				
F2	Profile + Theory-Based Visual Feature (253)	Profile + Image Quality, Image Sexuality, Facial Attributes, Facial Expression, Face Similarity				
F3	Profile + DL-Generic Facial Feature (1186)	Profile + 512-D Facial Embedding				

Table 1. Description of Data Used in the Prediction of Individual Rating

We divided the features into three groups to explore the effects of the features on predictive performance. F1 is a feature group created by processing each user's non-visual profile information. The processing was carried out as follows: First, occupations and universities were categorized since they were written freely without any restrictions. The occupations were classified into ten categories: high-income, artist, student, and unemployed, and the universities were also classified into ten categories, including top, national, abroad, and high school graduation.[1] All categorical features were created as dummy features, and min-max scaling was performed on continuous features such as age and height.

F2 is a feature group in which theory-based visual features extracted from a user's photo using a DL model are added to F1. These theoretically motivated visual features include image quality, sexual content, facial attributes, facial expression, and pairwise users' face similarity. Image quality was estimated by the neural image assessment model proposed by Google, and the sexuality of a photo was extracted via a CNN-based pre-trained model (Talebi et al. 2018). We also used geometric facial attributes and facial expressions as theory-based facial features because both can be good predictors of one's attractiveness (Bell 1978; Mueser et al. 1984). Thirty-six geometric facial attributes such as face length, eye size, and lips thickness were extracted from a user's face (Eisenthal et al. 2006). In addition, the facial expression of each face was classified into one of seven emotions by using a CNN-based pre-trained model. The face similarity between the rate giver and taker was measured by the cosine similarity between their FaceNet facial embeddings.

F3 is a feature group in which DL-generic features, which can only be extracted by deep learning, are added to F1. Each user's face was embedded as a 512-dimensional facial vector using the FaceNet model pre-trained in the VGGFace2 dataset (Cao et al. 2018). To validate the potential of data-driven features as good predictors compared to theory-based features, we did not include theoretically motivated visual features on F3.

All features described above were extracted from giver and taker, respectively, then concatenated for each feature group. The entire process of creating each feature and using it for analysis is shown in Figure 1.

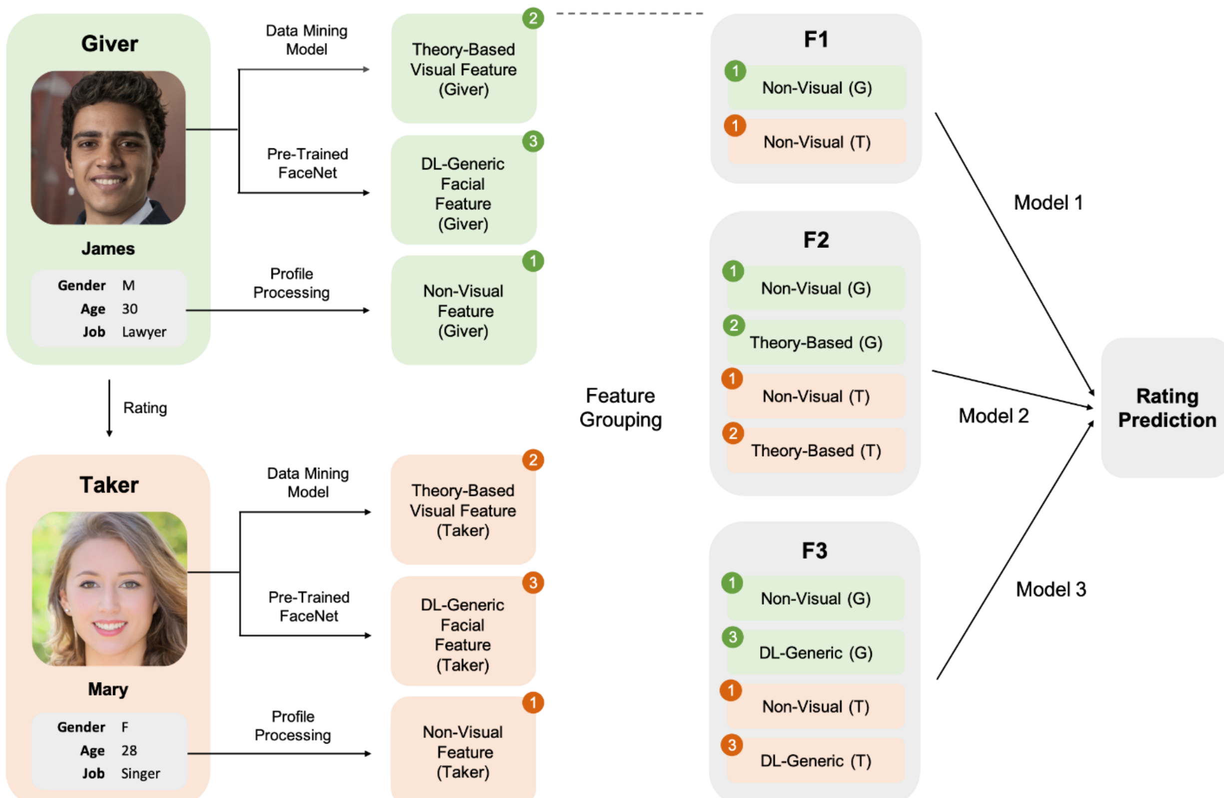


Figure 1. Schema of Feature Construction and Rating Prediction

[1] In South Korea, top universities and universities abroad are generally considered the best, followed by universities inside the capital and national universities.

Empirical Analysis

With the aforementioned feature groups (F1, F2, and F3), we built prediction models with Decision Tree Regression (DTR), Ridge Regression (RR), Random Forest Regression (RFR), XGBoost Regression (XGBR), and DL-based Feed Forward Neural Network (FFNN) model. We used Pearson Correlation (PC), Mean Absolute Error (MAE), and RMSE (Root Mean Squared Error) as evaluation metrics for the task.

As shown in Table 2, the performance of all models substantially improved when using F2 and F3 compared to F1. Especially in the FFNN model, the increment due to visual and facial features is over 50%. It suggests that visual and facial features are essential in judging matching probability in an online dating market. In particular, the models' performance in F3 is similar to or even better than in F2. It shows that DL-generic features extracted from faces without prior theories can represent information that theory-based features contain. In addition, we can see that the performance of the DL-based FFNN model is significantly higher than that of other ML models, even within the same set of features. Therefore, these results suggest that our proposed DL-based methodology can positively contribute to both feature extraction and model learning.

Model	PC			MAE			RMSE		
	F1	F2	F3	F1	F2	F3	F1	F2	F3
DTR	0.3300	0.3366	0.3329	1.0471	1.0458	1.0553	1.2717	1.2694	1.2757
RR	0.3522	0.3609	0.3833	1.0411	1.0395	1.0359	1.2587	1.2557	1.2490
RFR	0.4317	0.4664	0.5073	0.9909	0.9544	0.9620	1.2132	1.1911	1.1681
XGBR	0.4198	0.4216	0.4753	1.0061	1.0086	0.9760	1.2207	1.2256	1.1897
FFNN	**0.5664**	**0.8984**	**0.8922**	**0.7538**	**0.2218**	**0.2510**	**1.1636**	**0.5968**	**0.6139**

Table 2. Performance Comparisons for Different Feature Sets Across Different Models
FFNN model was trained for 100 epochs. All metrics were evaluated with 5-fold cross-validation.

Feature Analysis

Feature Importance

To examine the role of the newly proposed DL-based facial feature in the attractiveness prediction process, we used the Shapley value method on the FFNN model (Lundberg and Lee 2017). Here we analyzed the evaluations of each gender group separately since the preferences of men and women in the online dating market appear quite different (Abramova et al. 2016). Table 3 shows the five most important features on each side for predicting individual ratings in each of F1, F2, and F3 features for the evaluation of each gender. A (+) sign next to a feature name means that the feature has a positive effect on the predictive score as the value of that feature increases, and a (-) sign means the opposite. We did not add any signs if the effect is complex.

Gender	Side	Non-Visual Feature	Theory-Based Visual Feature	DL-Generic Facial Feature
Male → Female	Giver (M)	religion_none	face_similarity (-)	face_318
		personality_humorous	face_neutral	face_399
		region_Seoul (-)	face_happy	face_33
		personality_kind	image_quality	face_197
		personality_optimistic	face_width	face_202
	Taker (F)	body_chubby (-)	face_width (-)	face_245 (-)
		region_Seoul (+)	lips_length (+)	face_125 (+)
		region_Gyeonggi (+)	face_similarity (-)	face_314 (-)
		personality_calm (-)	face_neutral	face_160 (-)
		age (-)	face_happy (+)	face_378 (+)
Female → Male	Giver (F)	region_Seoul (-)	face_similarity (+)	face_455
		personality_emotional	face_neutral	face_329
		personality_vivid	face_happy	face_245
		religion_none	face_sad	face_87
		personality_kind	image_sexuality	face_464
	Taker (M)	height (+)	lips_length (+)	face_318 (-)
		region_Seoul (+)	face_width (+)	face_245 (-)
		body_slim (+)	face_similarity (+)	face_33 (-)
		job_student (-)	eyes_gap (-)	face_498 (-)
		religion_none	nose_width (-)	face_467 (+)

Table 3. Top 5 Important Features of Users on Each Side Divided by Gender
The importance of features was evaluated on FFNN model with SHAP.
The effect of each feature on the rating is described by +/- sign.

Among non-visual features, personality and region features were found to be important. Interestingly, when the users in Seoul give a rating, they tend to give a lower score, whereas Seoulites receive a higher score. It is consistent across men and women. A similar trend is observed in the areas around Seoul (Gyeonggi), which is interpreted as a characteristic of users living in the capital area. Besides, female users receive good evaluations when they are young and their body is not chubby, whereas male users get higher scores when they are tall. These results are consistent with previous studies on male and female preferences in the mate choice process. (Fan et al. 2004; Foo et al. 2017; Alterovitz and Mendelsohn 2011; Pierce et al. 1996).

In theory-based visual features, face similarity between giver and taker is selected as one of the critical features. When male users give a rating to female users, the more similar their faces to themselves, the lower the score. On the contrary, female users give a higher score to male users with similar faces. Since previous studies on homophily in mating preference mostly used non-visual features, this study is meaningful since it is the first to observe the effect of facial homophily extracted from real users' faces. Other than that, female users tend to receive better ratings as their faces are slimmer and have happier expressions. Male users get higher scores as their face widths increase and their mouths get larger.

Visual Interpretation

DL-based features have shown to be effective in improving prediction accuracy (Shin et al. 2020). However, a critical issue with DL-based features is that researchers cannot easily interpret them. Hence research on interpretable AI that makes complex DL models into a form that humans can understand is being actively researched (Doran et al. 2017). Compared to other ML models or statistical methodologies, interpretable DL models have the advantage of higher prediction performance and causal inference.

As shown in Table 2, DL-generic features significantly improve the predictive model's performance. Table 3 shows that there are a few face embedding features (e.g., face_245, face_318, face_125) that are important across different models. However, since they are not created based on any prior theory, it is impossible to understand what information each feature contains. Therefore, we propose a framework using StyleGAN to visually explore specific facial attributes corresponding to the DL-generic facial features. Specifically, we change each dimension of the facial embedding to generate new faces using StyleGAN and visually compare the difference between the generated faces and the original ones. Table 4 shows some illustrative examples of faces generated by increasing or decreasing the value of each DL-generic feature selected as important and the facial attributes inferred from them.

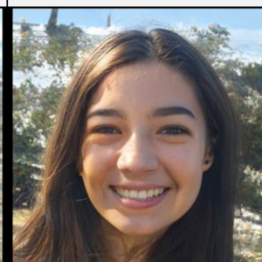
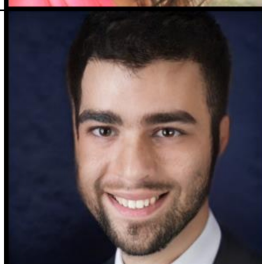
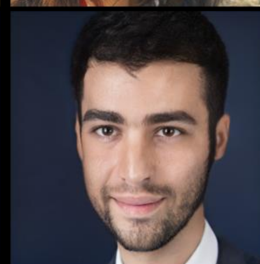
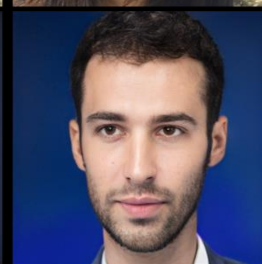
Feature	**Generated Faces**			**Facial Attribute**
	Decrease	**Original**	**Increase**	
face_245				Facial Age
face_318				Smile
face_125				Glasses

Table 4. Visual Interpretation of DL-generic Facial Features from Generated Faces

For example, *face_318* feature shows high importance only in male users. As the feature decreases, the generated face has a smiling face, and as it increases, it becomes a neutral face. From this, it can be inferred that the feature contains smile information. This result is also consistent with the study showing that smiling increases men's attractiveness more than women's (Golle et al. 2014). Since the impact of *face_318* feature in male takers is negative, we can interpret that as the feature value decreases, the taker's face gets more smiles, consequently rating increases.

In addition, we can see that DL-generic facial features express facial attributes such as facial age (*face_245*) and glasses (*face_125*). It means that facial embeddings can even represent information that theory-based features do not contain, leading to more accurate predictions. If researchers use this methodology in fields where existing theories are not established, they will be able to derive new theories from data more effectively.

Conclusion

This study presents a deep learning-based framework to predict the matching probability of the online matching platform using visual features. Using unique data from the online dating market, where the importance of visual features is critical, we predict individual ratings by generating various visual features from users' profile photos. We found the prediction accuracy significantly improves when using theory-based features and DL-generic features, and explain important features in connection with prior theories. In addition, we propose a novel method to visually interpret DL-generic facial features using StyleGAN.

Although the paper is based on a large dataset and sophisticated DL methods, it has several limitations. First, our results did not capture attractiveness perception and user behavior from various countries and cultures since the data is limited to South Korea. The StyleGAN-based feature analysis method proposed in this study may have bias and scalability issues as the researcher needs to check the facial attributes manually by looking at the difference in the generated faces. We will validate the facial attributes using an online crowdsourcing platform like Amazon Mechanical Turk. Moreover, we found that several facial attributes change simultaneously in some photos even though only one variable in facial embedding is changed during StyleGAN analysis. This may be due to the entanglement of the attributes in the latent space, and we will further examine this issue in our future research.

We are expanding this research in to ensure the generalizability of the proposed DL-based methodology. Specifically, we are applying the framework to a different online matching context: online labor markets where profile pictures can play an important role. In addition to the DL-based visual features, we plan to utilize DL-based textual features (e.g., BERT) to capture the unique characteristics of the labor market. If the results of these two distinct datasets (online dating and online labor markets) can be successfully integrated, we think our research will make a significant methodological contribution to the IS literature by providing a DL-based grounded theory method, which can be used to discover new theories from unstructured visual data.

References

Abramova, O., Baumann, A., Krasnova, H., & Buxmann, P. (2016). Gender differences in online dating: what do we know so far? a systematic literature review. In *Proceedings of 2016 49th Hawaii International Conference on System Sciences* (pp. 3858–3867).

Alterovitz, S. S. R., & Mendelsohn, G. A. (2011). Partner preferences across the life span: Online dating by older adults.

Bell, P. A. (1978). Affective state, attraction, and affiliation: Misery loves happy company, too. *Personality and Social Psychology Bulletin*, 4(4), 616–619.

Cao, Q., Shen, L., Xie, W., Parkhi, O. M., & Zisserman, A. (2018, May). Vggface2: A dataset for recognising faces across pose and age. In *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)* (pp. 67-74). IEEE.

Chan, J., & Wang, J. (2014). Hiring biases in online labor markets: The case of gender stereotyping.

Doran, D., Schulz, S., & Besold, T. R. (2017). What does explainable AI really mean? A new conceptualization of perspectives. *arXiv preprint arXiv:1710.00794*.

Eisenthal, Y., Dror, G., & Ruppin, E. (2006). Facial attractiveness: Beauty and the machine. Neural Computation, 18(1), 119–142.

Fan, J., Liu, F., Wu, J., & Dai, W. (2004). Visual perception of female physical attractiveness. In *Proceedings of the Royal Society of London. Series B: Biological Sciences*, 271(1537), 347–352.

Golle, J., Mast, F. W., & Lobmaier, J. S. (2014). Something to smile about: The interrelationship between attractiveness and emotional expression. *Cognition & Emotion*, 28(2), 298–310.

Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., . . . Bengio, Y. (2014). Generative adversarial networks. *arXiv preprint arXiv:1406.2661*.

Guan, S.-S. A., Subrahmanyam, K., Linares, K., & Cheng, R. (2015). Beauty in the eye of the beholder? attractiveness in a virtual world. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, 9(2).

Hamermesh, D. S., & Hamermesh, D. S. (2011). Beauty pays. Princeton University Press.

Jung, J., Lim, H., Lee, D., & Kim, C. (2021). The secret to finding a match: A field experiment on choice capacity design in a online dating platform. *Information Systems Research, forthcoming*.

Karras, T., Laine, S., & Aila, T. (2019). A style-based generator architecture for generative adversarial networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 4401–4410).

Lang, P. J., Davis, M., & Öhman, A. (2000). Fear and anxiety: animal models and human cognitive psychophysiology. *Journal of Affective Disorders*, 61(3), 137–159.

Langlois, J. H., Kalakanis, L., Rubenstein, A. J., Larson, A., Hallam, M., & Smoot, M. (2000). Maxims or myths of beauty? a meta-analytic and theoretical review. *Psychological Bulletin*, 126(3), 390.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.

Lee, G. M., He, S., Lee, J., Whinston, A. B. (2020). Matching mobile applications for cross-promotion. *Information Systems Research*, 31(3), 865-891.

Li, M., Wei, K.-K., Tayi, G. K., & Tan, C.-H. (2016). The moderating role of information load on online product presentation. *Information & Management*, 53(4), 467–480.

Li, N. P., & Kenrick, D. T. (2006). Sex similarities and differences in preferences for short-term mates: What, whether, and why. *Journal of Personality and Social Psychology*, 90(3), 468.

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In *Proceedings of Advances in Neural Information Processing Systems*, 30.

Magro, A. M. (1999). Evolutionary-derived anatomical characteristics and universal attractiveness. *Perceptual and Motor Skills*, 88(1), 147–166.

McGloin, R., & Denes, A. (2018). Too hot to trust: Examining the relationship between attractiveness, trustworthiness, and desire to date in online dating. *New Media & Society*, 20(3), 919-936.

Mueser, K. T., Grau, B. W., Sussman, S., & Rosen, A. J. (1984). You're only as pretty as you feel: facial expression as a determinant of physical attractiveness. *Journal of Personality and Social Psychology*, 46(2), 469.

Ong, D., & Wang, J. (2015). Income attraction: An online dating field experiment. *Journal of Economic Behavior & Organization*, 111, 13–22.

Parker, G. G., & Van Alstyne, M. W. (2005). Two-sided network effects: A theory of information product design. *Management Science*, 51(10), 1494–1504.

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.

Petty, R. E., Cacioppo, J. T., & Schumann, D. (1983). Central and peripheral routes to advertising effectiveness: The moderating role of involvement. *Journal of Consumer Research*, 10(2), 135–146.

Pierce, C. A. (1996). Body height and romantic attraction: A meta-analytic test of the male-taller norm. *Social Behavior and Personality: An International Journal*, 24(2), 143–149.

Pizzato, L., Rej, T., Chung, T., Koprinska, I., & Kay, J. (2010). Recon: a reciprocal recommender for online dating. In *Proceedings of the fourth ACM Conference on Recommender Systems* (pp. 207–214).

Ranzini, G., Rosenbaum, J. E., & Tybur, J. M. (2022). Assortative (online) dating: Insights into partner choice from an experimental dating app. *Computers in Human Behavior*, 127, 107039.

Rhodes, G. (2006). The evolutionary psychology of facial beauty. *Annu. Rev. Psychol.*, 57, 199–226.

Rhue, L. (2015). Who gets started on kickstarter? Demographic variations in fundraising success.

Schroff, F., Kalenichenko, D., & Philbin, J. (2015). Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 815–823).

Shi, L., & Viswanathan, S. (2020). Optional verification and signaling in online matching markets: Evidence from a randomized field experiment. *Available at SSRN 3572818*.

Shin, D., He, S., Lee, G. M., Whinston, A. B., Cetintas, S., & Lee, K. C. (2020). Enhancing social media analysis with visual data analytics: A deep learning approach. *MIS Quarterly*, 44(4), 1459-1492.

Skopek, J., Schulz, F., & Blossfeld, H.-P. (2011). Who contacts whom? Educational homophily in online mate selection. *European Sociological Review*, 27(2), 180–195.

Xia, P., Jiang, H., Wang, X., Chen, C., & Liu, B. (2014). Predicting user replying behavior on a large online dating site. In *Proceedings of the International AAAI Conference on Web and Social Media*.

Yang, M., Adomavicius, G., Burtch, G., & Ren, Y. (2018). Mind the gap: Accounting for measurement error and misclassification in variables generated via data mining. *Information Systems Research*, 29(1), 4–24.

Zhang, S., Lee, D., Singh, P. V., & Srinivasan, K. (2021). What makes a good image? Airbnb demand analytics leveraging interpretable image features. *Management Science*, 68(8): 5644-5666.