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Beauty Sells: Identifying Physical Attractiveness Effect In an Online Dating Platform

Qi Zhang
Fudan University, q_zhang16@fudan.edu.cn

Chee Wei Phang
University of Nottingham Ningbo, phangcw@gmail.com

Cheng Zhang
Fudan University, zhangche@fudan.edu.cn

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Qi Zhang
Fudan University
q_zhang16@fudan.edu.cn

Cheng Zhang
Fudan University
zhangche@fudan.edu.cn

Chee Wei Phang
University of Nottingham Ningbo China
phangcw@gmail.com

Abstract:

While online dating platforms offer new IT-enabled capabilities which do not exist in the physical world before, little is known about whether any fundamental matching rules are reshaped in the online environment. In this paper, we address the gap by studying one such factor, i.e. mate physical attractiveness, in an online dating platform. By using a unique dataset and machine-learning based algorithmic approach, the study successfully overcomes various confounding issues, selection bias and physical attractiveness measurement issues and estimates the physical attractiveness effect in online users' dating decision. Results reveal the essence of physical attractiveness in online context and the disappearing geographic boundary. The findings and methods are essential to both our understanding of the mechanisms that drive match mating online and our knowledge of how to propagate them in various fields where large scales of objective physical attractiveness and behavioral data are emerging.

***Key words*:**

Physical attractiveness; online dating, machine learning; multilevel logit model

1. Introduction

While online dating platforms offer new IT-enabled capabilities which do not exist in the physical world, such as overcoming geographic boundary of partners by lowering communication cost, deliberating appearance lookup through high-resolution digital photos, and varying levels of anonymity through web functionality, little is known about whether any fundamental matching rules are reshaped in the online environment. In this paper, we address the gap by studying the impact of mate physical attractiveness, a fundamental factor to influence human's decision in social relationship formation and economic evaluation (Mobius and Rosenblat, 2006; Eckel and Petrie, 2011), in online users' mate matching process and how geographic distance may or may not moderate the decision.

Although recent availability of massive online dating data sets has enabled studies of mate matching (Hitsch Hortaçsu and Ariely 2010a, 2010b; Rosenfeld and Thomas, 2012; Bapna et al., 2016), there are at least three challenges in identifying true physical attractiveness effect in the matching process. First is to distinguish confounding information offered by dating platforms from the physical attractiveness effect. Also because of the IT-enabled capabilities, dating platforms usually offer rich information and free browsing style to facilitate online users' decision. Users can browse mates' profile containing rich personal information like demographic background, hobbies and experience in any sequence (e.g. Bapna et al., 2016). The information and comparison process, however, are likely to result in significantly different mechanisms to influence the matching decision. For example, similar demographic background and hobbies between two peers are likely to evoke homophily effect that makes them more willing to make friends (Aarabi et al., 2002; Zhang and Zhao et al., 2011). If the platforms such as Facebook, Instagram, Youtube and HOTorNOT provide social networking functions, peer influence can also take effect in such situation. These distinctions make distinguishing true physical attractiveness effect from the confounding factors at early stages important for the success or failure of this study.

Second major challenge is the selection bias between the physical attractiveness and matching. Although dating platforms can record down users' behavior of browsing mates' photos and sending invitations, the data can hardly identify the causal effect of the physical attractiveness. A common question is whether users select mates, often by searching or browsing function provided by the platforms, with some observable or unobservable bias, such as users' different life experience of friend making or search preference of using IT functions.

Third major challenge is the lack of reliable physical attractiveness measurement that can be applied to real situation with large scale of photo dataset. One previous practice is to take advantage of the embedded rating in the platform to represent physical attractiveness (Maldeniya et al., 2017). This approach, however, suffers from projection bias flaw: one may rate another's physical attractiveness in a very biased way, according to his liking and purpose (Rhodes, 2006). A similar approach is through self-reported physical attractiveness by a three- or five-level scale (Fiore and Donath, 2005) but still cannot avoid the same defect. Another common practice is to use a great number of human raters, saying 15 raters for one photo, in a lab setting (Chen and Xiao et al., 2016; Xiao and Ding, 2014). Considering time and cost, this method is suitable for a small dataset of several hundreds of users, but cannot be extended to a larger scale, such as thousands or millions.

To overcome these challenges that have not been well addressed in literature, we exploit a unique dataset from an online dating platform which comprehensively captures 25,389 active users' over one million mate matching information in a 13 months' period. Two special designs on the platform help scholars overcome the first two challenges greatly. First, the platform doesn't allow users to browse others' profile before the mate matching succeeds, thus it avoids confounding factors and associated alternative mechanisms greatly, focusing only on physical attractiveness and geographic information. Second, the platform does not allow users to browse photo freely. They are randomly provided four photos at one time. This design helps scholars avoid selection bias greatly as the selection process is random.

To solve the third challenge on scalability and reliability of physical attractiveness rating, we apply an algorithmic approach by using the advanced face recognition and machine learning algorithms that have been proved their success in various human-like physical attractiveness assessment practices (Yan, 2014). The algorithms help scholars to rate users' physical attractiveness reliably for a large scale of user base. Moreover, given the rich matching behaviors in the dataset, we further distinguish users' selection and response behavior during the matching process.

Our study contributes to literature in several important ways. First, upon our best knowledge, this is the first study that investigates physical attractiveness in online dating context. The results are consistent after controlling for various contextual factors like weather, timing, geographic location and experience, showing its essence in mate matching. Second, the insignificant interactive effect with geographic distance reveals that the global village phenomenon enabled by IT (Ding et al., 2010; Van Alstyne & Brynjolfsso 2005), in which barriers of geographic distance is largely overcome. Finally, the study overcomes several major challenges on causal effect of physical attractiveness, identifies its impact more accurately than in literature and extends the application to current big data age. These findings and methods are essential to both our understanding of the mechanisms that drive matching mates online and our knowledge of how to propagate them in fields like social networking, online dating, marketing, and labor economics where large scales of objective physical attractiveness and behavioral data emerge.

2. Literature Review

Our research is motivated by three streams of studies, covering physical attractiveness, matching in online dating and geographic distance. Physical attractiveness has proven its importance in various disciplinary, particularly in online context (Bakhshi et al., 2014; Kreager et al., 2014; Fiore et al., 2008). Based on this prior research, we propose the first hypothesis here that physical attractiveness has a positive effect on dating decisions. This claim is consistent with the intuition that physical attractiveness increases interpersonal attraction. Previous literature also provided preliminary support for this hypothesis. In a speed-dating study, partners' physical attractiveness was identified as the strongest predictor of attraction for both sexes (Luo, S., and Zhang, G., 2009). Similarly, research documented a preference for physical attractiveness in general (Kreager et al., 2014; Buss and Schmitt, 1993; Eastwick and Finkel, 2011). Hence, we organize our arguments into the first hypothesis:

H1: Physical attractiveness has a positive effect on dating decisions, that is, the more beautiful the opposite side is, the more likely users are to contact.

Understanding how much two individuals are alike has become virtually essential for many applications and services in online social networks (Han, Xiao, et al, 2015). One way to look at similarity in physical attractiveness is through the lens of online disinhibition, which refers to the lack of restraint one feels when communicating online in comparison to communicating in-person. Hamilton (2016) stated in his book that one area where people preferred dissimilar was attractiveness, where all people preferred others more attractive than themselves, within the limits of who they might realistically date (Kreager et al., 2014). It is high likely that online dating made it possible because of the low risk in contacting others, due to less fear of rejection (Rosenfeld & Thomas, 2012). Therefore, it is natural that people prefer those who score higher than themselves. We can derive the second hypothesis:

H2a: The difference in physical attractiveness will encourage people to interact. That is, the higher the difference the more likely users will contact.

Interestingly, the similarity in physical attractiveness also found some support from literature in online dating (Todd and Penke et al., 2007), in line with the similarity principle of interpersonal attraction. For instance, people found it more likely to form long standing relationships with those who were equally matched in social attributes, like physical attractiveness, and several offline studies also supported this evidence of similar facial attractiveness (Berkowitz, Leonard, 1974; Little, Burt and Perrett, 2006). Therefore, we propose the following hypothesis:

H2b: The difference in physical attractiveness will discourage people to interact. That is, the higher the difference the less likely users will contact.

Conventional wisdom from offline experience indicates that geographic distance is likely to estrange people's relationships. In online context, this remains a sensible argument as geographical distance could hinder effective communication, which increases the costs and hazards associated with later offline activities. From the information communication perspective, for one thing, geographical distance raises the cost of mate searching. As geographic distance barriers, and difference in physical attractiveness increases, combining several separate pieces of perceptions and knowledge is more and more difficult. The complementarities between physical attractiveness similarity and geographical proximity help dyad partners achieve prudent decisions. As a consequence, large geographic distance reduces the incentive of initiating and responding, which may negatively moderate the impact of physical attractiveness. For another, geography-brought attributes, such as regional tradition or core values, world outlook, may determine how people communicate with one another. Consequently, we argue that geographic difference has negative moderating effects due to increasing communication cost.

H3a: The geographical distance negatively moderates the relationship between physical attractiveness and contact propensity. That is, with the geographic distance increasing, the physical attractiveness effect will decrease.

However, the global presence of the Internet diminishes the need for spatial proximity and it is universally accepted that online environments reduces search costs in a variety of markets (Bakos 1997). One stream of work held that explosive growth in computer-mediated and networked communications could shrink distances and facilitate information exchange among people of various backgrounds (Bakos 1997; Forman and Goldfarb et al., 2018; Van Alstyne

& Brynjolfsso 2005). It follows that physical attractiveness effect will not be zoomed out through geographic distance. Thus we argue that geographic distance shows no moderating effects on the relationship between physical attractiveness and initiation or responding.

H3b: There does not exist the moderating effect of geographical distance. That is, the physical attractiveness effect will remain unchanged with and without the geographic distance as a moderator variable.

3. Methodology

3.1 Research Context

We first give a brief overview of how online dating platform works and explain how we collect our dataset. Users who first join the dating platform MMD are required to provide limited information such as nickname, avatar, sex and birthdate. After registering, however, users are not allowed to browse others' profile before the mate matching succeeds and the only information the platform provides for matching is photo and city location. Typically, whenever a user starts a matching process by pressing the matching button, the platform randomly selects four frosted photos processed as mosaic appearance. By clicking on one of them, the user can see the photo becoming transparent with city information available on the photo, while the rest three photos disappear simultaneously. Upon reviewing the photo, user has to make a Yes-or-No decision for invitation. From the perspective of recipient, users also need to make a decision for responding. Our data contain a detailed, second-by-second account of all these user activities. In particular, we know if, when and how a user browses another user, views his or her photo(s), sends an invitation or responds to another user.

The platform features two characteristics ideal for our research question: First, only after the mate matching can users browse others' profile, which precludes confounding factors and associated alternative mechanisms, like detailed profiles information concerning income, religion, education and so on. Rather, it helps scholars focus only on physical attractiveness and geographic information Second, as the platform assigns photos randomly, scholars can well avoid selection bias.

Our full sample contains information on the attributes and online activities of 25,389 active users of the online dating service. The users are located in all around China, and we observe their activities over a 13-month period from August 2014 to September 2015. The definitions for variables and descriptive statistic is shown in Table 2 in APPENDIX.

3.2 Identifying Physical Attractiveness

To construct attractiveness rating for these available photos, we take advantage of face recognition algorithms to get facial features and then assess attractiveness automatically with machine learning algorithms. Currently, the prevalent mature face recognition algorithms include those supported by Tencent (Youtu), Microsoft (Azure) and IBM (Alchemy). Although the three have proved their success in various human-like physical attractiveness assessment practices, it remains doubt whether they could register high accuracy in our sample. So we first designed a pilot study for algorithm selection, covering 475 photos randomly selected from the dataset. By comparing the returned results with human judgments, and considering distinct features provided by each, we chose the optimal performer as Microsoft Azure.

After algorithm selection, and following Hitsch Hortaçsu and Ariely (2010a), we recruited 1121 subjects (576 female and 545 male) to conduct physical attractiveness rating for 800 photos (400 male and 400 female). Each subject was asked to rate 20 photos on a scale of 1 to 10, and each photo was shown 28-40 times among them. In worry of bias due to boredom or fatigue, we randomized the ordering of photos. Demographic information of the subjects was also collected, showing the perceptions of physical attractiveness is representative of the whole country.

Then, we recast the problem of predicting physical attractiveness into a classification problem: discerning "beautiful" faces from "normal" faces. The main classifiers used were decision trees, neural network, and logistic regression method. Research (such as Hill, 2002) found that standards for attractiveness show gendered patterns, thus we identified physical attractiveness in male and female group, respectively. After trial and error, the "beautiful" class in male samples comprised the photos with ratings larger than five, and larger than six in female. The model fitness for male under logistic regression algorithm was good, accuracy rate attaining 81.4%. For female samples, the decision tree algorithm had higher efficiency, with an accuracy rate of 80.7%. After that, we tried to learn and analyze the mapping from facial images to their attractiveness scores, as determined by human raters.

3.3 Model Setup and Estimation

Since a user can upload multiple photos, it is apparent to find two levels in our analysis: photo-level and user-level. It would be more appropriate to construct a multi-level logit model rather than logit model to describe users' behavioral patterns. To examine validity, a two-level empty model is established and shows that random intercept error is much larger than the error, validating the significance of characteristics in the user-level. Furthermore, AIC and BC criteria both confirm this practice.

We first develop a multilevel logit model to analyze a user's initiating decision, accounting for individual heterogeneity. As Kreager (2014) pointed out, gendered patterns of online dating were diverse in both relationship initiation and termination. Thus, we incorporate gender and age into model. Because experience, geographic location and some other covariates also affect users' dating behaviors, we then include all these factors. In Table 1, we present the results with stepwise models. Controls comprise gender, age, physical locations such as the whether the user is in Western or Eastern China. Behavior pattern variables like number of requests initiated, days between request and post and APP use time are also included. We then consider physical attractiveness of self in the mating decision. Lastly, we investigate the effect of looks rating difference.

In the same vein, we again analyze the recipients' responding process with multilevel logit model. Results with stepwise strategy are presented in Table 3, in APPENDIX. Model (1) shows the regression with only control variables, model (2) with the looks rating of the recipients, model (3) includes self-rating, while model (4) concerns the difference in looks rating.

Based on city location information, we further calculate the distance between the initiator and the recipient, trying to find whether geography distance moderates the online dating decision. Results are displayed in column (5) and (6), representing stepwise regressions for moderating effects. In column (5), we consider the moderating effects on difference in looks rating, and that on users' looks ratings in column (6).

3.4 Robustness Check

We conclude our analyses with a set of robustness checks. To rule out alternative explanations, we examined factors that could potentially contribute to the observed results. First, we examine the length of comment, a signal for one's sincerity since users responding actively could be due to users receiving an initial really "sincere" message. Second, we explore the timing and match propensity to test whether physical attractiveness effect would be impacted due to users' temporal rhythms in behavior. Third, we explicitly investigate the role of weather, which has been identified to affect people's social behaviors. Consequently, there is no significant relation in each above cases controlling for all other factors. This result is in keeping with our general analysis and rules out the potential explanations.

3.5 Results

We start our analysis by exploring the opposite's looks rating, in the initiating and responding processes. Table 1 reports our findings for initiating process, Table 3 demonstrates results for responding process. Compared with the initiating process, recipients show preference for those locate in Central China, which requires future study due to lack of detailed information. Meanwhile, although in initiation older users are more likely to target younger users, in responding process recipients exhibit strong tendency to reply to the older initiators. We find it clear that longer use time will result in greater possibility of responding. Other behavioral factors like number of requests received and number of requests sent do not show significant influence.

As displayed in column (2), during the two processes, people are all seeking to date with the beautiful ones. We therefore find evidence in support of Hypothesis 1 that looks rating of the opposite side has a positive effect on friend-making decisions, regardless of the initiating or responding processes. Our findings are consistent with numerous studies, based on both stated and revealed preferences, that document a preference for physical attractiveness in general (Buss and Schmitt 1993, Eastwick and Finkel 2011). Results also reveal some behavioral patterns. For example, regional difference negatively affects the initiating decision, indicating that users prefer to initiate an invitation to people in the same place.

Further, we examine the efficacy of the looks rating difference in initiating a request and at the response of the potential mate. In the initiating process, we find a significantly positive impact of looks rating difference: people favor those more beautiful than themselves and the larger the difference, the stronger the propensity to socialize. This finding may be credited to the anonymity environment of internet, due to low risk in contacting others and less fear of being rejected. However, in the responding process the relationship disappears. Note that two mechanisms may both play a part and effects are neutralized. This result emphasizes the existence and importance of looks rating difference.

Moreover, we find that geographic distance does not moderate the relationship between looks rating difference and propensity to initiate or respond, revealing the disappearing geographic boundary in online context and lending support to Hypothesis 3b. In particular, owing to the Internet connection, effect of geographic distance is dampened, thereby letting users concentrate more on other traits, like physical attractiveness.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Controls	yes	yes	yes	yes	yes	yes
Initiator’s Looks Rating			-0.234			-0.191
			(0.191)			(0.198)
Recipient’s Looks Rating		0.258**	0.258**			0.266**
		(0.131)	(0.131)			(0.133)
Difference in Looks Rating				0.250**	0.246**	
				(0.108)	(0.110)	
Difference in Looks Rating ×Geographic Distance					-0.007	
					(0.045)	
Initiator’s Looks Rating × Geographic Distance						0.043
						(0.053)
Recipient’s Looks Rating × Geographic Distance						0.016
						(0.040)
N	8,799	8,799	8,799	8,799	8,799	8,799
Log likelihood		-3628.357	-3627.611	-3627.616	-3627.604	-3627.206
Prob > chi2		0.000	0.000	0.000	0.000	0.000

Table 1 - Regressions for Initiating Process

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4. Discussions

Our work is motivated by the fact that today’s IT-enabled online dating and matching platforms introduce new capabilities and features, while the causal impact of physical attractiveness is hard to analyze meaningfully in most dating platforms. As we demonstrate, IT-enabled capabilities such as shrinking geographic distance, selecting and responding potential mates, all affect user behaviors and outcomes in several ways that are not always easy to anticipate. In our analysis, we particularly concentrate on two factors: physical attractiveness and geographic distance. The certain online platform setting provides us with an environment where various confounding issues, selection bias and physical attractiveness measurement issues are absent.

Here we further explore the physical attractiveness similarity issues from another perspective: “to what extent the face is the same as mine”. Though at first glance it seems plausible to substitute difference in physical attractiveness for similarity (Fiore and Donath, 2005b; Stirrat and Perrett, 2010), to further dig into the similarity topic, we rely on Youtu and Azure algorithms for similarity measurement. Youtu declares to “calculate the similarity of two faces and facial features”, while Azure announces to be able to “check the possibility of two faces belonging to the same person”. Then, we modify model (4) to replace physical attractiveness value difference with similarity indicators. To our surprise, results for regression under the two algorithms contradict with each other. The coefficient of Youtu indicator is positive but not significant, whereas the coefficient in Azure context is negative and significant. It is evident that the perception of similarity behind the algorithm leads to the contradictory, and only after we collect similarity from human-ratings can we find out the true result. This is left as a further work to deliberate.

Our study contributes to several important streams of IS research. First, this study adds to recent discussions on matching rules in online dating context. The results are robust after controlling for various contextual factors like weather, timing, geographic location and experience. Second, we unravel the interactive effect of geographic distance, adding evidence to a small world caused by internet connection. Finally, this study also extends prior research on physical attractiveness and online dating in several ways. It overcomes a number of major challenges on causal effect of physical attractiveness, identifies its impact more accurately than in literature and extends the application to current big data age.

It also carries practical implications. Applications and websites could learn from the results and rearrange the referral system, in order to retain more users. For example they can update their matching or recommendation algorithms with more attention to physical attractiveness and age, gender or use time. Moreover, the physical attractiveness rating algorithms can be applied to real context and help refine potential dater referral system.

5. Conclusions

While online dating platforms offer new IT-enabled capabilities which do not exist in the physical world before, little is known about whether any fundamental matching rules are reshaped in the online environment. In this paper, we address the gap by studying one such factor, i.e. mate physical attractiveness, in an online dating platform. By using a unique dataset and machine-learning based algorithmic approach, the study successfully overcomes various confounding issues, selection bias and physical attractiveness measurement issues and estimates the physical attractiveness effect in online users’ dating decision. Results reveal the essence of physical attractiveness in online context and the disappearing geographic boundary. The findings and methods are essential to both our understanding of the mechanisms that drive match mating online and our knowledge of how to propagate them in various fields where large scales of objective physical attractiveness and behavioral data are emerging.

Social networking platforms are leveraging physical attractiveness and preference pattern to strengthen the recommendation mechanism. Yet, little reliable causal evidence exists in the literature, especially with clean data generated in a specified social environment. When we break down the interaction into initiating and responding, we find diverse behavior patterns. Our results suggest that initial contact decision is influenced by the number of requests initiated, days between request date and the date photo was posted, user's gender, age as well as location difference. Moreover, people tend to neglect their own physical attractiveness and feel no cost to contact the most beautiful ones. Apart from the physical attractiveness of initiator, factors that have impact during the responding process are initiator's age, location and recipient's gender, use time. Regarding physical attractiveness difference, due to the intertwining two forces, it does not play a part in the responding process. When it comes to the geographic distance, we verify the disappearing boundaries of geography, owing to the IT-enabled capabilities to reduce communication costs.

No study is free from limitation. First, the study focuses on the online dating behavior, however does not compare with the offline process. Further research could extend to offline context, advancing our knowledge about the permeation of online physical attractiveness-lead behaviors. Second, the study does not test more potential interactive effect of IT-enabled functionality and physical attractiveness in mate matching. To further explore IT value, future research may incorporate more IT-related factors in the model.

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APPENDIX

VARIABLES	Mean	SD	Min	Max
User's Looks Rating	0.149	0.260	0.000	1.000
User's Age	23.740	3.554	10.170	45.250
User's Gender	0.471	0.499	0.000	1.000
User in East China	0.652	0.476	0.000	1.000
User in Central China	0.244	0.429	0.000	1.000
User in West China	0.104	0.305	0.000	1.000
Number of Requests Initiated	67.609	192.064	1.000	1,237.000
Ratio of Initiator's Requests Being Replied	0.035	0.123	0.000	1.000
Days Between Request and Post	33.861	52.457	0.000	339.000
APP Use Time	0.632	0.218	0.000	1.080
Geographic Distance	0.632	0.218	0.000	1.080

Table 2 – Descriptive Statistics for Variable

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
controls	yes	yes	yes	yes	yes	yes
Initiator's Looks Rating		0.889*	0.889*			
		(0.482)	(0.482)			
Recipient's Looks Rating			-0.067			
			(0.598)			
Difference in Looks Rating				0.570		
				(0.399)		
Difference in Looks Rating ×Geographic Distance					0.088	
					(0.104)	
Initiator's Looks Rating × Geographic Distance						-0.017
						(0.096)
Recipient's Looks Rating × Geographic Distance						-0.197
						(0.135)
N	2,175	2,175	2,175	2,175	2,175	2,175
Log likelihood	-295.967	-294.423	-294.417	-294.962	-295.614	-294.780
Prob > chi2	0.0009	0.0005	0.0008	0.0009	0.0011	0.0012

Table 3 - Regressions for Responding Process