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The beauty premium of tour guides in the customer decision-making process: An AI-based big data analysis

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ABSTRACT

This study investigates how the facial cues of tour guides in their profile pictures, and especially aesthetically pleasing facial features, play a role in the different stages of a tourist's decision-making process. Facilitated by an artificial intelligence (AI) facial recognition system, a comprehensive model is developed which incorporates the facial and service cues of 3786 tour guides. The results show that beauty scores and smiles have a positive effect on purchase decisions, while post-service ratings are only subject to service cues. The contingency effects of the beauty premium are also examined. The results indicate greater beauty premium effects for females, and for tour guides who are responsible for chauffeured, package or walking tours. This research is a pioneering study in AI-based facial analyses in the context of tourism, and offers insights into the impression management of online profiles in the customer decision-making stages.

Beauty is power; a smile is its sword. –Charles Reade

1. Introduction

Tour guides continue to be an integral part of both group tours and individual travel, gratifying tourists who long for hassle-free vacations, bringing a destination to life, and testifying to the reputation of a tourist destination (Weiler & Black, 2015; Tu, Guo, Xiao, & Yan, 2020). The advances and convenience of technology have contributed to supporting the tourism industry, which has seen a paradigm shift to online travel sales. The COVID-19 pandemic has further accelerated this digital transformation, driving tour guides to adopt virtual measures (China Association of Travel Services, 2020). Tour guides have thus had an immense presence on peer-to-peer platforms such as Ctrip (ctrip.com), Showaround (showaround.com), and Withlocals (withlocals.com). Tour guides register and receive orders online, and later book shore excursions for their clients (Banerjee & Chua, 2020). In addition to providing itineraries and service package details, tour guide profiles also include introductions to themselves, with a very visible profile picture. In the online context, this image is a means of verifying identity and a catalyst for interaction (Guttentag, 2015). The facial characteristics obtained from these profile pictures thus provide important cues that shape and form the impressions of customers and influence their decisions accordingly (Peng, Cui, Chung, & Zheng, 2020).

Studies of the facial cues of service providers have increased in volume in the tourism literature (e.g, Dallimore, Sparks, & Butcher, 2007; Li, Zhang, & Laroche, 2019; Tsai, Wang, & Tseng, 2016; Tu et al., 2020), and the role of online profiles has commanded research attention (Banerjee & Chua, 2020; Ert, Fleischer, & Magen, 2016; Fagerstrøm, Pawar, Sigurdsson, Foxall, & Yani-de-Soriano, 2017). Recent studies have set out to analyze the impact of facial cues by employing big data and machine learning techniques (e.g., Barnes & Kirshner, 2021; Li, Peng, Ma, & Zhou, 2022; Peng, Cui, et al., 2020). Although these studies are very insightful, two research gaps have been notably identified. First, big-data research has to date predominantly investigated a product-dominant context that involves physical products, while studies on service products are limited. Second, no study to date has juxtaposed purchase decisions and post-service evaluations to compare the role of facial cues in different customer decision-making stages, which is another underexplored area worthy of further investigation. This study sets out to bridge these research gaps by using massive field data obtained from online tour guide platforms, and particularly, via a case study of tour guides in China based on AI-facilitated big data analysis.

Our focal variable is one of the most prominent facial cues found in the photographs of service providers—physical attractiveness (Banerjee

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& Chua, 2020; Peng, Cui, et al., 2020). As noted in implicit personality theory (Bruner & Tagiuri, 1954; Cronbach, 1955), individuals assume inferential relationships among attributes when forming impressions about an unfamiliar person, and beauty is an attribute frequently associated with a multitude of desirable features (Eagly, Ashmore, Makhijani, & Longo, 1991; Feingold, 1992). The "what is beautiful is good" heuristic (Dion, Berscheid, & Walster, 1972) has guided individual behaviors in a variety of social settings. The current study investigates the beauty premium of tour guides on peer-to-peer platforms in two stages—purchase decision making and service evaluation. We adopt a novel dataset crawled from a tour guide selection platform operated by Ctrip.com—the largest Chinese online travel agency. Data for the tour guides include their profile pictures, service information, and customer reviews. The profile pictures are further recognized and assessed using an artificial intelligence (AI) facial recognition system by Baidu—an open-source platform that uses deep-learning algorithms. The results of the face detection generate AI-based information about the tour guides, including their beauty scores, facial expressions, face shape, and other facial cues. A comprehensive regression model is developed, building on implicit personality theory, to analyze the determinants of the service demand and ratings of the tour guides, and in particular, whether a beauty premium effect is present in the two stages; that is, whether more physically attractive tour guides receive more orders in the purchase decision stage, and are rated more highly in the service evaluation stage. The contingency effects of beauty premium are also examined through the lens of implicit personality theory, across different groups characterized by gender, age, and tour destination city, as well as the type of tour package.

The current research makes four contributions. First, the work is pioneering in its adoption of big data to analyze the determinants of decision-making in a service-dominant context. The study has new implications that differ from the mixed results in the product-dominant context. Second, the study is among the first to juxtapose purchase decisions and after-service evaluations, and shows the disparities of the premium effect in different customer decision stages. The beauty premium effect is salient in the purchase decision stage but not in the evaluation stage—a novel finding that has not been reported in previous studies. Third, the contingency effects of facial cues can inform tour guides and other service providers in the tourism sector about how to tailor their online presence for different scenarios. The contributions in this study also push the boundaries of research into implicit personality theory by elucidating the theoretical underpinnings of the beauty premium effect and its heterogeneity. Fourth, as COVID-19 continues to take its toll on tourism, the industry has seen a surge in demand for small and private tours, and online tour guide platforms. The impression management of online profiles has become a more pertinent issue amid the pandemic. The results offer managerial insights to help tourism practitioners better adapt themselves to the new normal in a post-pandemic world.

2. Literature review

2.1. Beauty premium in decision-making processes

Physical attractiveness is defined as "the degree to which one's facial image elicits favorable reactions from others" (Morrow, 1990, p. 47). The concept has been further extended from the face to general physical appearance (Ahearne, Gruen, & Jarvis, 1999). It is worth noting that the definition of beauty is constantly evolving. An example is the shift in ideal beauty standards in China from traditionally preferred characteristics to the endorsement of, and preference for, Western aesthetics. For instance, the conventionally preferred body shape for women has been one that is full-figured, but now the preference is for a slim body (Jung, 2018). Men are also subjected to the new narratives of body image, which prioritize grooming and new definitions of male beauty such as metrosexuality (Wen, 2021). While digital techniques give users a sense of empowerment, as they can manipulate their image, this technological affordance also exacerbates existing gender power relation issues, reinforcing the social norms of beauty, and heightening appearance anxiety (Peng, 2021).

It is human nature to be drawn to attractive individuals, and decisions tend to favor beautiful people. This stereotype, or beauty premium, reflects the hypothesis that beautiful is good (Dion et al., 1972). The theory of implicit personality is a line of psychological inquiry that disentangles the pervasiveness of the beauty premium in cognitive thinking (Bruner & Tagiuri, 1954; Cronbach, 1955). The theory starts from the tenet that there is general judgement bias, as evaluations are often made based on incomplete information and an overall impression. As a result, inferential relationships among individual characteristics are often taken for granted (Schneider, 1973). Physical attractiveness is one of the most prominent traits to increase positive cognition, and is associated with a multitude of desirable features, resulting in favorable outcomes for attractive individuals (Dion et al., 1972). That is, beautiful people are considered to be more knowledgeable, caring, honest, humorous, and successful, and there are expectations that they have many other positive characteristics (see Eagly et al. (1991) and Feingold (1992) for reviews of relevant studies).

Nevertheless, the beauty premium effect may well depend on the cultural context. For example, while female analysts in China reap the benefits of their physical attractiveness in job evaluations, their counterparts in the United States are affected by a beauty penalty instead (Li, Lin, Lu, & Veenstra, 2020). These differences may be due to the fact that the pursuit of beauty is particularly prevalent in Asia, as interdependent self-construal in Asian cultures compels conformity to social norms (Madan, Basu, Ng, & Ching Lim, 2018). Investigating the beauty premium effect is thus particularly pertinent in the Asian context, including China, as in the current study.

The power of physical attractiveness is also ubiquitous in a service context. The beauty premium effect has been well examined in the service marketing literature. Customers partially base their purchase decisions on the attributes of service providers, and physical attractiveness has been postulated as an important influential factor in buying decisions (Ert et al., 2016; Peng, Cui, et al., 2020). Physical attractiveness also plays a salient role during service interactions. Customers are more likely to desire social interactions with aesthetically pleasing service providers, and thus engage more with them (Fang, Zhang, & Li, 2020). Physical attractiveness can facilitate smoother service interactions, improve the persuasiveness of service providers (Tsai et al., 2016), and increase customer satisfaction and perceived service quality, as well as improving salesperson performance (Ahearne et al., 1999; Li et al., 2019; Wan & Wyer, 2015). The beauty premium effect has been identified in service settings that are both labor-intensive (Fang et al., 2020) and technical (Shtudiner & Klein, 2020), and could be more prominent for women (Shtudiner & Klein, 2020) in sales-intensive positions (Deng, Li, & Zhou, 2020), and those who sell appearance-relevant products (Peng, Cui, et al., 2020).

In a tourism context, physical attractiveness is an important trait for tour guides. A tour guide is defined as "a person, usually a professional, who guides groups (and sometimes individuals) around venues or places of interest… interpreting the cultural and natural heritage in an inspiring and entertaining manner" (Weiler & Black, 2015, p. 364). In line with marketing research, whether a tour guide is physically attractive plays an important role in pre-purchase assessments, on-site tour guide–client interactions, the subsequent evaluation of service quality and level of satisfaction, and loyalty intentions. As first impression is key, a tour guide is also expected to be neat and tidy (Huang, 2010; Huang, Weiler, & Assaker, 2015). Tourists will associate the favorable physical appearance of a tour guide with his/her knowledge and integrity (Chang, 2014). They are also more likely to gain a better understanding of the subject of travel when the tour guide is attractive, which results in more favorable evaluations of the tour guide (Tsai et al., 2016). Facial cues in particular are important in the online profiles of tour guides, as they provide salient non-verbal cues that inform the consumer about whether the individual is helpful, and encourage a positive attitude towards the tour guide (Banerjee & Chua, 2020). Investigations into the impression management of the online profiles of tour guides are largely lacking, however. There has been some research into the profile pictures of Airbnb hosts in peer-to-peer accommodation. For instance, Ert et al. (2016) conducted controlled experiments, and found that perceived trustfulness based on the host photos significantly affected prices, but that the effect of attractiveness was less salient. Using a similar approach, Jaeger, Sleegers, Evans, Stel, and van Beest (2019) achieved different results, and concluded that it was the attractiveness of Airbnb hosts rather than their trustworthiness that enabled higher prices. A recent study by Barnes and Kirshner (2021) used a deep learning model and showed that trustworthy and attractive host photos contributed to increases in Airbnb prices. Li et al. (2022) examined an open-source AI platform and suggested that moderately attractive hosts of peer-to-peer accommodations had the highest listing performance. Peng, Cui, et al. (2020) use a machine learning technique to show the effects of both a beauty premium and an ugliness premium in sales performance.

The literature thus supports the beauty premium effect in both pre-purchase appraisals and service evaluations. Although these studies are insightful, they are predominately conducted using an empirical or survey approach; the former has long been criticized for the hypothesis–reality incongruence (Falk & Heckman, 2009), while the latter has the problem of generalization due to sample size and sampling bias considerations (Li, Xu, Tang, Wang, & Li, 2018). It was not until recently that massive data analyses based on advanced techniques was been applied to address these issues (e.g., Barnes & Kirshner, 2021; Li et al., 2022; Peng, Cui, et al., 2020).

2.2. Photo-based tourism studies facilitated by machine learning and AI

Big data, AI, and machine learning have emerged as new buzzwords in business, and have commanded research attention from scholars in different areas, including tourism and hospitality (Lv, Shi, & Gursoy, 2022). Big data is defined as “massive data sets having large, more varied and complex structure with the difficulties of storing, analyzing and visualizing for further processes or results” (Sagiroglu & Sinanc, 2013, p. 42). The adoption of big data with new analytical techniques has eliminated the limitations of data obtained from conventional methods such as experiments, interviews and surveys. Big data can explain behaviors in the real world as opposed to hypothetical scenarios, and is not subject to sampling bias or limited representativeness (Li et al., 2018). Machine learning gives computers the ability to learn without hard-coded programs by learning from “experience” instead. AI techniques based on deep learning algorithms have particularly been on the rise to process massive numbers of images, which have been widely used in photo-based studies for pattern recognition and classification (Ma & Sun, 2020).

Photo-based tourism research grounded in machine learning and AI techniques has proliferated in recent years. Visual content offers multisensory experiences, and allows a substantial amount of information to be explained, which delivers rich information about the subjects in photos (Spencer, 2010). A plethora of studies have used image-based, user-generated content to gain insights into a destination. The first stream of research uses behavioral and location clues from photos to obtain a comprehensive understanding of tourist behaviors in a destination (Hasan, Abdunurova, Wang, Zheng, & Shams, 2020; Payntar, Hsiao, Covey, & Grauman, 2021; Zhang et al., 2019, 2020). The second stream sees photos as representative semiotics for a place, and focuses on destination images and the attributes projected on the photos (Arefieva, Egger, & Yu, 2021; Deng, Liu, Dai, & Li, 2019; Deng & Li, 2018; Wang, Luo, & Huang, 2020; Yu & Egger, 2021). The third school of research scrutinizes the visual contents of lodging businesses, for example, user-provided photos on hotel reviews and agency-provided cover photos (Luo, Tang, & Kim, 2021; Ma, Xiang, Du, & Fan, 2018; Ren, Vu, Li, & Law, 2021). Tourism studies have rarely used machine learning algorithms to examine photographs of faces, however, which offer a unique perspective for understanding service personnel and customer decisions.

Machine learning techniques have facilitated face detection and facial beauty prediction, and thus been adopted in different areas, for example, to investigate the effect of physical attractiveness on product sales (Peng, Cui, et al., 2020), income (Song & Baek, 2021), academic performance (Chen, Wang, & Zhao, 2019), and social interaction intentions (Gao, Wang, Chen, Dai, & Ling, 2021). Among the machine learning techniques, AI-based deep learning has been increasingly used. Unlike traditional machine learning methods built on an instruction algorithm, deep learning automatically extracts distinguishing features with brain-like logic, and significantly improves results by using large-scale data (LeCun, Bengio, & Hinton, 2015). Considerable efforts have been made to improve deep learning models, with the aim of improving their self-learning abilities, obtaining better feature representation, and ultimately improving the accuracy of machine-generated scores of facial beauty (Cao, Choi, Jung, & Duan, 2020; Iyer, Nersisson, Zhuang, Joseph Raj, & Refayee, 2021; Zhai et al., 2020). AI-based deep learning has recently been used in various disciplines to analyze the effects of facial cues. For example, Momtaz (2021) investigated how CEO emotions signal firm valuations. Park, Kim, and Hong (2019) reported on the beauty premium effect for female recipients of online crowdfunding. Ling, Li, Luo, and Pan (2020) examined the nexus between CEO attractiveness and corporate philanthropy, and found that unattractive managers tend to give more in order to compensate for feeling inferior due to their appearance.

While machine learning is an advanced technique for face detection in contemporary research, two research gaps have been found in studies of the beauty premium in sales and marketing. First, the physical attractiveness of service operators has been overwhelmingly discussed in a product-dominant context with physical products such as digital devices for sale and apartments for rent (e.g., Barnes & Kirshner, 2021; Li et al., 2022; Peng, Cui, et al., 2020), but investigations of service products remain scarce. Service products differ substantially from physical products in that they are characterized by intangibility, vague descriptions, and the strong involvement of service personnel. The sales and marketing of service products therefore largely depend on tangible surrogates for the intangible—the image of the service operators (Rushton & Carson, 1989; Wirtz, Fritze, Jaakkola, Gelbrich, & Hartley, 2021). Tour guides are an example in that they are an imperative and integral part of service product delivery, rather than merely an asset used to tout physical products (Rushton & Carson, 1989). They have intensive interactions with tourists during tours, and act as “coordinators, entertainers, information givers, pathfinders, and sources of knowledge” (Hwang & Lee, 2019, p. 1331), and are responsible for tour satisfaction.

The second research gap is that research to date has not juxtaposed customer decision-making stages to compare the different roles of physical attractiveness, but only centered on the purchasing stage (e.g., Jaeger et al., 2019; Li et al., 2022; Peng, Cui, et al., 2020). Online appraisals of customers are determined by distinct service attributes embedded in discrete decision-making stages—information available on the website before purchase, and perceived performance after service delivery (Park, Cho, & Rao, 2012, 2015). Customers resort to the physical attractiveness of the service personnel during the purchasing stage as a means of inferring product and service quality (Li et al., 2022; Peng, Cui, et al., 2020). When customers have direct personal experiences with a service provider, their post-service evaluations are based not only on the website information (including the profile information), but also on the valence of their service experiences and its incongruence with prior information (Liu, Jayawardhena, Osburg, & Babu, 2019). It is expected that the beauty premium effect is as salient here, as it is in the pre-purchase stage with tour service encounters, as a consideration in evaluations and playing a dominating role in the evaluation stage, however, this has not been examined in depth in the literature yet.

The current research intends to address the aforementioned research gaps. AI-facilitated big data is adopted to examine the facial cues of tour guides in two different decision-making stages, including the pre-purchase stage when the client chooses a tour guide, and the post-service evaluation stage to provide feedback to the service personnel. According to the rationales in previous studies, physically attractive tour guides are more likely to be selected during the purchasing stage, and will receive better evaluations in the after-service evaluation stage. We therefore propose the following hypotheses:

H1a. . Physical attractiveness is positively associated with a tour guide's number of service transactions.

H1b. . Physical attractiveness is positively associated with the review ratings given to a tour guide.

2.3. Heterogeneity of beauty premium

While the beauty advantage is seemingly a natural advantage, it is important to bear in mind that the definition and perspective of beauty may vary based on socio-cultural contexts (Broer et al., 2014), and thus also the power of beauty. The implicit personality theory posits contextual factors that condition how cues can influence individual judgement, including the relevance, availability, detection and utilization of the cues (Funder, 1995). When establishing the strength and extent of the beauty premium, the effect is first determined according to the degree to which physical attractiveness and individual perceptions are associated. For example, the attractiveness–ability belief that associates the physical attractiveness of flight attendants with their service abilities may reinforce the beauty premium effect (Li et al., 2019), while selling expertise-relevant but not appearance-relevant products reduces the effect (Peng, Cui, et al., 2020). The effect is also determined by the extent to which physical attractiveness is recognized and acknowledged. If consumers are highly involved, for example, then they are more interested and spend more time on something, and the power of physical attractiveness will have more precedence (Lee, 2022). The beauty premium effect is also affected by how beauty cues are used. For instance, similarities between customers and service providers may increase the use of beauty cues, as similarity catalyzes trust and favorable interpersonal relationships, thus encouraging customers to make more positive interpretations of physical attractiveness (Li et al., 2022).

Differences in the beauty premium may also be found among different groups, as characterized by their gender, age, and service contexts. The relevance of physical attractiveness cues to making favorable judgements is more evident for women and young professionals. The beauty norm that primes individuals to evaluate women based on their physical attractiveness is one of the reasons that women are subject to injustice, bias and social pressure more than their male counterparts (Kim & Lee, 2018; Muth & Cash, 1997; Strahan, Wilson, Cressman, & Buote, 2006). Although the notion that society values beautiful women invites criticism (Wolf, 1990), the ever-evolving and increasingly stringent beauty standards for women continually drive an intense pursuit of beauty, which in fact, only serves to emphasize the gender hierarchy (Ramati-Ziber, Shnabel, & Glick, 2020). As such, the beauty premium is found to be more prominent for females than males, and this conclusion has been validated in various regions, including China (Gu & Ji, 2019; Peng, Wang, & Ying, 2020), Israel (Shtudiner, 2019), and European countries (Patacchini, Ragusa, & Zenou, 2012). We therefore hypothesize that the beauty premium is higher for female tour guides in both the decision-making and service evaluation stages.

H2a. . Physical attractiveness has a higher impact on the number of service transactions of female tour guides.

H2b. Physical attractiveness has a higher impact on the review ratings given to female tour guides.

Age is another boundary condition that might determine the size of the beauty premium. Age may reduce the salience of physical attractiveness as experience, skills and professionalism increase with maturity (Cleveland & Lim, 2007). Studies in the literature have mainly examined the effect of the beauty premium with young populations, as physical appearance is considered more important for young professionals in the labor market (Doorley & Sierminska, 2012; Maurer-Fazio & Lei, 2015). Empirical results also show that the effect of the beauty premium on income is largely eliminated when female employees are over 50 (Anýžová & Matějů, 2018). Physical attractiveness also plays a more salient role for comparatively younger candidates in elections, compared with their older opponents (Jäckle & Metz, 2017). Based on these findings, we propose that there is a higher beauty premium among younger tour guides:

H3a. . Physical attractiveness has a higher impact on the number of service transactions of younger tour guides.

H3b. . Physical attractiveness has a higher impact on the review ratings of younger tour guides.

The size of the beauty premium may also be conditioned by the service context. As the relevance and detection of the cues are situational factors that influence the effect of the beauty premium (Funder, 1995), a service context that emphasizes service factors other than the service provider themselves, may reduce the effect. Physical attractiveness may therefore be less prioritized in a service context where there are other appealing elements to a destination—the scenery, attractions, and other tourism offerings. These may distract customers, so that the physical appearance of the tour guide is relatively peripheral and less important. It is therefore proposed that the beauty premium is reduced in a service context where the destination has more offerings:

H4a. . Physical attractiveness has less impact on the number of service transactions when the service context offers more attractive destination elements.

H4b. . Physical attractiveness has less impact on review ratings when the service context offers more attractive destination elements.

3. Methodology

3.1. Data

The data used in this research study was obtained from two sources: the Ctrip tour guide platform and AI facial recognition technology offered by Baidu, a Chinese multinational technology company.

3.1.1. Tour guide dataset from ctrip

The tour guide data used in this study was obtained from Ctrip—the largest online travel agency in China. Ctrip launched its first peer-to-peer online tour guide platform in August 2016 in order to virtually connect local tour guides and tourists. The platform allows tour guides to register and receive online orders through the Ctrip mobile app.

Fig. 1 is an example of the tour guides listed on the Ctrip tour guide platform. Their profile information is open and transparent, signifying to potential customers that these tour guides are experienced and professional. Customers are able to compare the options based on this information, and make a decision. The profile information of each tour guide includes the following:

Profile picture: shows the frontal face of the tour guide.

Service cues: information about the services provided, including studio information, when the tour guide joined the platform, starting price of service packages, number of service personnel who would be assisting the tour guide, type of tour vehicles used, whether rewards are given for product reviews, and the accessories and resources provided, such as selfie sticks, child car seats, and rain gear.

Tourist reviews: review ratings, the number of positive, neutral and

Fig. 1. Examples of tour guide profiles on Ctrip platform.

negative reviews, the textual contents of the reviews, and the type of tour taken by the tourists (for example, chauffeured, line, walking, or featured experience tour).

Number of service transactions: the total number of service orders completed by the tour guide.

A web crawling code written in Python was used to collect information from the tour guide entries from the Ctrip app in February 2021. All the tour guide profiles listed under "guide appointment" were downloaded, including profile pictures, service cues, tourist reviews, and information on service transactions. The dataset included all 5589 listings for Ctrip tour guides between August 2016 and February 2021.

3.1.2. AI-facilitated scores of facial cues from baidu

The main objective of this research is to analyze the effect of the facial cues of tour guides, and in particular their physical attractiveness, on the purchase decisions/service evaluations made by tourists. Information from the profile pictures of the tour guides was therefore further extracted using AI developed on deep learning algorithms. This method has been widely adopted in marketing research to facilitate big data analyses, including image processing (Ma & Sun, 2020). We used the Baidu AI open platform to detect and evaluate facial cues from the profile pictures of the tour guides. The platform is a comprehensive open-source AI platform powered by Baidu, which is the largest search engine in China; the platform provides an array of AI products/services to the public and businesses, for example, automatic speech recognition, image recognition technology, natural language processing, virtual reality service, and facial detection and attributes analysis.

This study uses the AI facial recognition system by Baidu (https://ai.baidu.com/tech/face/detect) to collect information on facial cues. This face recognition method has proven to be a world leading technique that outperforms other similar models in terms of verification accuracy (Chaudhuri, 2020; Chen, Geng, Zou, Xu, & Tan, 2020; Yang, Zhao, Wang, & Lv, 2020). As the largest search engine in China, Baidu is also expected to have advantages in the model training of data from Chinese professionals, with one of the largest rating sets for training (Gu, 2020). Facial cues and scores generated by Baidu AI have been used in studies in a Chinese context (Gu, 2020; Ren, Sun, Jing, Cui, & Shi, 2019). Built on deep-learning algorithms and the massive data training of 200 million images from two million people, Baidu face recognition can currently recognize the faces of different genders, races, and ages. The system can quickly detect the position of the face frame, identify up to 150 key points of the face, and generate information on a variety of attributes, including gender, age, physical attractiveness, expression, emotion, face shape, and whether eyeglasses or face masks are worn. See Fig. 2 for an example of face recognition using the Baidu AI facial recognition system.

Note: A virtual portrait was generated by the authors via www.artbreeder.com.

We coded a Python program to instruct the Baidu AI system and attributes analysis application programming interface (API) to conduct facial recognition. The profile pictures of all the tour guides obtained from Ctrip were detected and evaluated. Information about their facial cues (gender, age, physical attractiveness, expression, emotion, and face shape, and whether eyeglasses or a face mask is worn) was extracted to an Excel file. The physical attractiveness scores ranged from 0 to 100, in which higher values imply more favorable evaluations of facial beauty.

Some of the profile pictures could not be recognized or detected by the system due to flaws in the image, for example, the low resolution of retakes or distorted images. A total of 4815 profile pictures were identified by the system. Due to the high correlation between expression (smile or no smile) and emotion (happy or unhappy), only the former were retained in the analyses.

In the final step, we removed tour guides with incomplete information or missing ratings and retrieved a dataset of 3786 tour guides for analysis. Males (N = 2480) outnumbered females (N = 1306) among the 3786 tour guides. The age range of the sample was 20–55 years old.

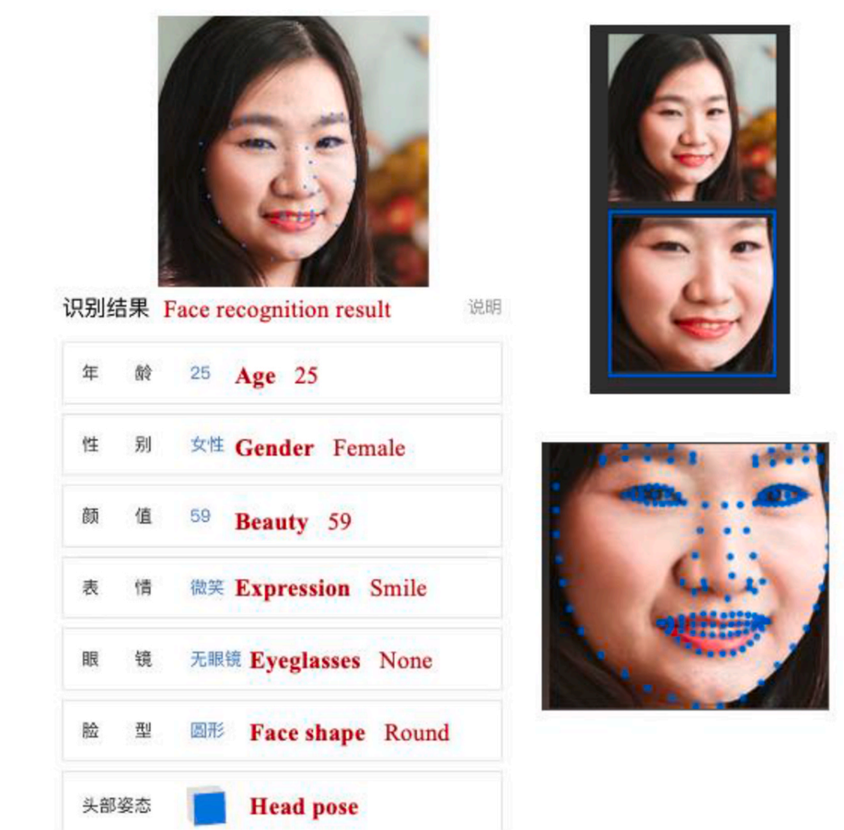

Fig. 2. An example of face recognition by AI facial recognition system on Baidu.

According to previous studies in the literature that used an age threshold of 40 years old to delineate younger and middle-aged tour guides (Luoh & Tsaur, 2014; Quiroga, 1990), the sample was categorized into younger (20–39 years old, N = 2005) and middle-aged (40–55 years old, N = 1781) groups. On average, each tour guide received 272.72 reviews (374.33 and 219.15 reviews for female and male guides, and 280.21 and 255.03 for younger and middle-aged guides, respectively).

3.2. Models

This study aims to analyze the beauty premium effect on the purchase decisions and service evaluations of tourists. Purchase decision is measured through *Transaction* (the number of service transactions, i.e., the number of service orders that a tour guide has received and completed); and service evaluation is measured through *Rating* (the rating score that a tour guide has received). The following models were established to include the effect of facial and service cues, and tourist reviews:

$$Transaction = f(FACE,\ SERVICE, DESTINATION) \quad (1)$$

$$Rating = f(FACE,\ SERVICE, DESTINATION) \quad (2)$$

In the models, *Transaction* and *Rating* are dependent variables which represent the number of service orders completed by each tour guide and their overall review score, respectively. *FACE, SERVICE* and *REVIEW* are a set of determinant categories that represent facial cues, service cues, and tourist reviews, respectively. Each category includes multiple variables. *DESTINATION* is a variable that controls the popularity of the destination offered by a tour guide. The ordinary least square (OLS) regression models are therefore defined as follows:

$$\begin{aligned} Transaction\ or\ Rating &= \beta_0 + \beta_1 Beauty + \beta_2 Smile + \beta_3 Age + \beta_4 Glass \\ &+ \beta_5 Oval\_shape + \beta_6 Round\_shape + \beta_7 Square\_shape + \beta_8 Gender \\ &+ \beta_9 Studio + \beta_{10} Entry\_time + \beta_{11} Price + \beta_{12} Personnel + \beta_{13} Large\_car \\ &+ \beta_{14} Mid\_car + \beta_{15} Small\_car + \beta_{16} Review\_reward + \beta_{17} Selfie\_stick \\ &+ \beta_{18} Child\_seat + \beta_{19} Rain\_gear + \beta_{20} Popular\_cities + \varepsilon \quad (3) \end{aligned}$$

where ε is the error term.

Definitions of the variables are provided in Table 1.

Table 1
Definition of variables.

Variable	Definition
Transaction	Number of service transactions for each tour guide.
Rating	Overall review score from tourists rated on a scale from 1 to 5, with 5 as the highest rating.
FACE	
Beauty	Rated on a scale from 1 to 100 for each profile picture, with 100 as the highest rating.
Smile	Dummy variable equal to 1 if the tour guide is smiling in his/her profile picture; 0 otherwise.
Age	Age of the tour guide in photo.
Glasses	Dummy variable = 1 if the tour guide wears glasses in his/her photo; 0 otherwise.
Oval_shape	Dummy variable = 1 if the face shape of the tour guide is oval in his/her profile picture; 0 otherwise.
Round_shape	Dummy variable = 1 if the face shape of the tour guide is round in his/her profile picture; 0 otherwise.
Square_shape	Dummy variable = 1 if the face shape of the tour guide is square in his/her profile picture; 0 otherwise.
Gender	Dummy variable = 1 if the tour guide is female; 0 otherwise.
SERVICE	
Studio	Dummy variable = 1 if the tour guide has a studio; 0 otherwise.
Entry_time	Years of the tour guide on Ctrip app
Price	Base price (CNY) of the service provided by the tour guide.
Personnel	Number of service personnel who work for the tour guide.
Large_car	Dummy variable = 1 if the tour guide offers large tour vehicles to tourists; 0 otherwise.
Mid_car	Dummy variable = 1 if the tour guide offers mid-size tour vehicles to tourists; 0 otherwise.
Small_car	Dummy variable = 1 if the tour guide offers small tour vehicles to tourists; 0 otherwise.
Review_reward	Dummy variable = 1 if the tour guide offers review rewards to tourists; 0 otherwise.
Selfie_stick	Dummy variable = 1 if the tour guide offers selfie sticks to tourists; 0 otherwise.
Child_seat	Dummy variable = 1 if the tour guide offers child seats to tourists; 0 otherwise.
Rain_gear	Dummy variable = 1 if the tour guide offers rain gear to tourists; 0 otherwise.
DESTINATION	
Popular_cities	Dummy variable = 1 if the destination is among the Top 20 popular cities; 0 otherwise. Data collected from 2019 to 2020 Top China Travel Destinations Ranking by Ctrip.

Note: All of the variables (except popular_cities) are collected from Ctrip app.

4. Results

4.1. Summary statistics

Table 2 provides the summary statistics of the variables, and Table 3 provides the correlations between them. As shown in the latter, the physical attractiveness score for all facial cues is highly and positively correlated with the number of service transactions. The time that a tour guide has been registered with the platform, whether they have a studio, and their number of reviews are all highly correlated with the number of service transactions. Adding these control variables can therefore better ensure an unbiased estimation of the results when analyzing the effect of the profile pictures of the tour guides on the number of service transactions. There is also a highly negative correlation between age and physical attractiveness; physical attractiveness might therefore be more closely associated with younger tour guides. Furthermore, there is a highly positive correlation between smiling expressions and happy faces, thus implying that photos with smiling tour guides might be more readily associated with emotional happiness.

Table 2
Summary statistics of the variables.

Variable name	Obs	Mean	Std. Dev.	Min	Max
Transactions	3786	416.662	872.154	1	11,628
Rating	3786	4.854	0.060	1	5
FACE					
Beauty	3786	46.183	13.977	12.38	85.42
Smile	3786	0.432	0.495	0	1
Age	3786	31.079	7.729	20	55
Glasses	3786	0.110	0.313	0	1
Oval_shape	3786	0.233	0.423	0	1
Round_shape	3786	0.236	0.424	0	1
Square_shape	3786	0.365	0.482	0	1
Gender	3786	0.345	0.476	0	1
SERVICE					
Studio	3786	0.318	0.466	0	1
Entry_time	3786	2.771	1.353	0	5
Price	3786	727.475	1365.51	1	29,000
Personnel	3786	1.779	3.285	0	21
Large_car	3786	0.006	0.076	0	1
Mid_car	3786	0.209	0.407	0	1
Small_car	3786	0.942	0.233	0	1
Review_reward	3786	0.063	0.243	0	1
Selfie_stick	3786	0.104	0.306	0	1
Child_seat	3786	0.119	0.324	0	1
Rain_gear	3786	0.261	0.439	0	1
DESTINATION					
Popular_cities	3786	0.247	0.431	0	1

4.2. Beauty premium effect in purchase decisions and service evaluations

Based on the theoretical underpinnings and empirical evidence in Section 2, we study the factors that may affect the purchase decisions of tourists (measured by the number of service transactions) as well as their

Table 3
Correlations among variables of interest.

	Transac-tions	Rating	Beauty	Smile	Age	Glasses	Oval	Round	Square	Gender
Transactions	1									
Rating	0.184***	1								
Beauty	0.216***	0.057***	1							
Smile	0.152***	0.035*	0.169***	1						
Age	−0.161***	−0.030*	−0.588***	−0.237***	1					
Glasses	0.050***	0.043**	0.070***	0.042**	0.019	1				
Oval_shape	0.070***	0.005	0.402***	0.251***	−0.278***	0.039**	1			
Round_shape	0.106***	0.016	0.067***	0.299***	−0.102***	0.106***	0.311***	1		
Square_shape	0.165***	0.045**	0.344***	0.228***	0.365***	0.207***	0.433***	0.402***	1	
Gender	0.098***	0.052***	0.402***	0.228***	−0.451***	0.157***	0.275***	0.184***	0.479***	1
Studio	0.490***	0.181***	0.133***	0.113***	0.088***	0.040**	0.007	0.072***	0.131***	0.018
Entry_time	0.345***	0.248***	0.078***	0.097***	0.019	0.002	0.008	0.000	0.045***	0.074***
Price	−0.031*	−0.003	−0.049***	−0.044**	−0.104***	−0.023	−0.039**	−0.018	−0.043**	0.077***
Personnel	0.560***	0.143***	0.213***	0.105***	0.110***	0.047***	0.075***	0.016	0.128***	0.072***
Large_car	0.034*	0.020	0.043**	0.028*	0.007	0.018	0.024	0.044**	0.058***	0.005
Mid_car	0.063***	0.001	0.019	0.001	0.018	0.019	0.055***	0.092***	0.002	0.034*
Small_car	0.067***	0.055***	0.001	0.033*	0.096***	0.074***	0.060***	0.015	0.068***	0.180***
Review_ reward	0.053***	0.044**	0.045**	0.043**	0.060***	0.033*	0.029*	0.037**	0.056***	0.073***
Selfie_stick	0.055***	0.056***	0.036*	0.024	0.005	0.050***	0.016	0.046***	0.046***	0.104***
Child_seat	0.099***	0.024	0.013	0.058***	0.004	0.014	0.027*	0.008	0.057***	0.035**
Rain_gear	0.029*	0.045**	0.019	0.036**	0.013	0.043**	0.025	0.075***	0.060***	0.072***
Popular_ cities	0.004	0.009	0.014	0.022	0.077***	0.008	0.003	0.026*	0.025	0.054***

Notes: $*p < 0.05$; $**p < 0.01$; $***p < 0.01$.

service evaluations (measured by the review rating). The regression results are presented in Table 4, where Columns (1)–(3) show the determinants of the number of service transactions, and Columns (4)–(6) are the results of the review rating scores.

When Column (3) controls other factors, including the service cues and reviews of tour guides, and their tour destinations, the number of service transactions will increase by 1.7% for each increase in their physical attractiveness score. In other words, a one standard deviation increase (13.977 as in Table 2) in physical attractiveness will increase service demand by 23.8%. The result in Column (6) shows that physical attractiveness has no significant effect on the rating. That is to say, physical attractiveness plays a salient role when a tourist is choosing a tour guide, however, the beauty premium effect diminishes during post-service evaluation.

It is also worth noting that other facial cues also play different roles in the two stages of the decision-making process. When tourists are choosing tour guides online, a smiling face will positively influence purchase decisions. A round or an oval face shape is also preferred. Tourists also tend to choose relatively younger female tour guides. Most facial cues do not affect a guide's post-service evaluation, however, except that female tour guides tend to receive higher ratings than their male counterparts. Unlike purchase decisions, service evaluations are predominantly determined by the service and review cues of the tour guides.

As the impact of COVID-19 may be a confounding factor, the regression analyses were conducted with data from before and during the outbreak of the pandemic. The review scores are categorized into two sets of data based on the point when cases of COVID-19 were first reported by health officials in Wuhan, China; that is, before and after December 31, 2019 (Patel & Jernigan, 2020). The results are robust, which shows that the beauty premium effect is not significant in the evaluation of the service of both samples before and amid the outbreak of COVID-19.

4.3. Heterogeneous effects of the beauty premium

The heterogeneous effects of the beauty premium are examined here with tour guides characterized by their gender and age group, as well as two factors that reflect the service context with different destination-related attractiveness—type of city and type of tour.

Gender. Table 5 shows the results by gender. In general, the beauty premium effect in the purchase decision stage is significant for both male and female tour guides, and more salient for females. Each unit increase in the physical attractiveness score leads to a 1.4% (Column 1) and 2.2% increase (Column 2) in the number of service transactions for males and females, respectively. The test for the equality of coefficients (Paternoster, Brame, Mazerolle, & Piquero, 1998) implies that the beauty premium effect is significantly stronger among female tour guides ($Z = -2.219$, $p < 0.05$). It is also interesting that other facial cues such as smile, age, whether eyeglasses are worn and face shape also matter for male tour guides, while physical attractiveness and a round face shape are the only significant determinants for females during the selection process. In addition, physical attractiveness does not affect the service evaluations for either group.

Age. Table 6 shows the results by age, in which the younger group includes tour guides between 20 and 39 years old, and the middle-aged group is between 40 and 55 years old. The results show that in the purchase decision stage, the beauty premium effect is more salient for younger tour guides. Each unit increase in physical attractiveness score leads to a 2.1% (Column 1) and 1.7% increase (Column 2) in the number of service transactions for the younger and middle-aged groups, respectively. The test for the equality of coefficients, however, does not show a significant difference between the two age groups ($Z = 0.632$, $p > 0.05$). In addition, physical attractiveness does not affect the service evaluations for either group.

Type of city. Table 7 shows the results by type of city; whether a tour guide is based in one of the top 20 most popular cities. The results show that in the purchase decision stage, the beauty premium effect is slightly lower for popular cities. Each increase in physical attractiveness score leads to a 1.6% (Column 2) and 1.8% increase (Column 1) in the number of service transactions for popular and other cities, respectively. This difference is not significant, as implied by the test for the equality of coefficients ($Z = 0.555$, $p > 0.05$). Besides this, physical attractiveness does not affect the service evaluations for either group.

Type of tour. Finally, we are also interested in the beauty premium effect on different tourist groups characterized by the type of tour. The information on the type of tour is included in the tourist review section. Four types are discussed, including chauffeured, package (with pre-arranged itineraries), walking, and featured experience (escorted) tours. The results (Table 8) show that in the purchase decision stage, the

Studio	Entry_ time	Price	Personnel	Large_car	Mid_car	Small_ car	Review_reward	Selfie_ stick	Child_ seat	Rain_ gear	Popular_ cities
1											
0.379***	1										
0.034*	0.035**	1									
0.788***	0.362***	0.048***									
0.060***	0.062***	0.011	0.048***	1							
0.107***	0.021	0.053***	0.121***	0.003	1						
0.123***	0.005	0.121***	0.106***	0.004	0.113***	1					
0.083***	0.075***	0.022	0.066***	0.017	0.000	0.010	1				
0.050***	0.051***	0.011	0.046***	0.019	0.024	0.030*	0.099***	1			
0.143***	0.036**	0.032*	0.102***	0.032*	0.098***	0.078***	0.010	0.082***	1		
0.014	0.073***	0.006	0.079***	0.029*	0.015	0.106***	0.124***	0.207***	0.147***	1	
0.002	0.007	0.065***	0.001	0.004	0.079***	0.066***	0.023	0.006	0.051***	0.018	1

Table 4
Determinants of purchase decision and service evaluation of tourists.

	(1) Transaction	(2) Transaction	(3) Transaction	(4) Rating	(5) Rating	(6) Rating
FACE						
Beauty	**0.038*** **	**0.038*** **	**0.017*** **	**0.001**	**0.002**	**0.001**
	(0.003)	**(0.004)**	**(0.002)**	**(0.001)**	**(0.001)**	**(0.001)**
Smile		0.569***	0.065**		0.026	0.004
		(0.073)	(0.023)		(0.017)	(0.007)
Age		−0.004	−0.012***		−0.002	−0.001
		(0.005)	(0.003)		(0.001)	(0.001)
Glasses		0.036	0.026		0.011	0.009
		(0.104)	(0.061)		(0.016)	(0.015)
Oval_shape		0.108	0.408***		0.055	0.063
		(0.239)	(0.107)		(0.029)	(0.037)
Round_shape		0.498*	0.454***		0.085	0.078
		(0.255)	(0.129)		(0.047)	(0.046)
Square_shape		0.111	0.370**		0.059	0.074
		(0.228)	(0.125)		(0.032)	(0.038)
Gender			0.080***			0.026***
			(0.019)			(0.008)
SERVICE						
Studio			1.613***			0.086***
			(0.081)			(0.013)
Entry_time			0.754***			0.053***
			(0.020)			(0.009)
Ln(Price)			−0.090***			−0.004
			(0.026)			(0.004)
Personnel			0.076***			0.003**
			(0.010)			(0.001)
Large_car			0.715***			0.039
			(0.165)			(0.033)
Mid_car			0.206***			0.013
			(0.056)			(0.009)
Small_car			0.287*			0.025
			(0.116)			(0.021)
Review_reward			0.015*			0.002
			(0.007)			(0.002)
Selfie_stick			0.213**			0.027*
			(0.066)			(0.013)
Child_seat			0.155*			0.017
			(0.072)			(0.010)
Rain_gear			0.154**			0.020**
			(0.059)			(0.007)

(continued on next page)

Table 4 (*continued*)

	(1) Transaction	(2) Transaction	(3) Transaction	(4) Rating	(5) Rating	(6) Rating
DESTINATION						
Popular_cities			0.595***			0.008
			(0.141)			(0.009)
Constant	3.710***	2.880***	2.056***	5.076***	5.241***	5.372***
	(0.156)	(0.359)	(0.259)	(0.018)	(0.053)	(0.084)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3786	3786	3786	3786	3786	3786

Notes: $*p < 0.05$; $**p < 0.01$; and $***p < 0.001$. Clustered standard errors (city-level) are in parentheses.

beauty premium effect is more salient for tourists who opt for chauffeured, package or walking tours, where each increase in the physical attractiveness score leads to a 1.6% (Column 1), 1.5% (Column 2) and 0.9% (Column 3) increase in the number of service transactions, respectively. In comparison, the increase is only 0.2% (Column 4) for featured experience tours. Z-tests of differences show that the beauty premium effect is significantly weaker for featured experience tours compared with chauffeured tours ($Z = 4.427, p < 0.001$), package tours ($Z = 3.153, p < 0.001$), and walking tours ($Z = 2.214, p < 0.05$). Physical attractiveness again does not affect the service evaluations for any group.

5. Conclusion and discussion

This study used AI-facilitated big data to investigate the effect of various facial cues of tour guides, in particular physical attractiveness, on two different decision-making stages of customers. The main results (Table 4) imply that the physical appearance of tour guides is a key factor determining the purchase decisions of tourists; however, tourists do not directly reciprocate with higher service evaluations as a beauty premium on physically attractive tour guides. The beauty premium effect in purchase decisions is also higher for tour guides who are female (Table 5), young (Table 6), and working in a popular tourist destination (Table 7). This effect is also subject to the type of tour taken by the tourists (Table 8). The findings highlight the differences between customers in different stages of decision-making, and have implications for service providers in the tourism sector as regards adapting their online

Table 5
Determinants of purchase decision and service evaluation of tourists by gender of tour guide.

	(1) Transaction Male	(2) Transaction Female	(3) Rating Male	(4) Rating Female
FACE				
Beauty	**0.014*****	**0.022*****	**0.001**	**0.001**
	(0.002)	**(0.003)**	**(0.001)**	**(0.001)**
Smile	0.069**	0.011	0.001	0.012
	(0.021)	(0.104)	(0.003)	(0.007)
Age	−0.016***	−0.003	−0.001	−0.001
	(0.004)	(0.009)	(0.001)	(0.001)
Glasses	0.228***	−0.001	0.011	−0.072
	(0.066)	(0.170)	(0.010)	(0.037)
Oval_shape	0.601**	0.173	0.017	0.031
	(0.209)	(0.166)	(0.014)	(0.025)
Round_shape	0.539*	0.424*	0.012	0.039
	(0.219)	(0.170)	(0.014)	(0.021)
Square_shape	0.573**	−0.186	0.004	−0.008
	(0.210)	(0.253)	(0.014)	(0.009)
SERVICE	Yes	Yes	Yes	Yes
DESTINATION	Yes	Yes	Yes	Yes
Constant	0.735*	1.218**	4.998***	5.145***
	(0.368)	(0.396)	(0.026)	(0.029)
City fixed effect	Yes	Yes	Yes	Yes
Obs.	2480	1306	2480	1306

Notes: $*p < 0.05$; $**p < 0.01$; and $***p < 0.001$. Clustered standard errors (city-level) are in parentheses.

Table 6
Determinants of purchase decision and service evaluation of tourists by age group of tour guide.

	(1) Transaction Younger	(2) Transaction Middle-aged	(3) Rating Younger	(4) Rating Middle-aged
FACE				
Beauty	**0.021*****	**0.017*****	**0.001**	**0.001**
	(0.006)	**(0.002)**	**(0.001)**	**(0.001)**
Smile	0.042**	0.033	0.004	0.002
	(0.013)	(0.052)	(0.004)	(0.003)
Glasses	0.449***	0.172**	0.035	0.016
	(0.137)	(0.069)	(0.018)	(0.011)
Oval_shape	0.991***	0.488***	0.156	0.033
	(0.243)	(0.108)	(0.081)	(0.026)
Round_shape	0.934***	0.633***	0.099	0.033
	(0.239)	(0.129)	(0.062)	(0.025)
Square_shape	0.724***	0.413***	0.116	0.038
	(0.194)	(0.128)	(0.073)	(0.027)
Gender	0.393*	0.230**	0.052***	0.011***
	(0.187)	(0.079)	(0.009)	(0.003)
SERVICE	Yes	Yes	Yes	Yes
DESTINATION	Yes	Yes	Yes	Yes
Constant	0.966	1.167***	4.944***	5.002***
	(0.500)	(0.221)	(0.038)	(0.016)
City fixed effect	Yes	Yes	Yes	Yes
Obs.	2005	1781	2005	1781

Notes: $*p < 0.05$; $**p < 0.01$; and $***p < 0.001$. Clustered standard errors (city-level) are in parentheses.

Table 7
Determinants of purchase decision and service evaluation of tourists by type of city.

	(1) Transaction Other cities	(2) Transaction Popular cities	(3) Rating Other cities	(4) Rating Popular cities
FACE				
Beauty	**0.018*****	**0.016*****	**0.001**	**0.001**
	(0.002)	**(0.003)**	**(0.001)**	**(0.001)**
Smile	0.023***	0.108**	0.001	0.004
	(0.056)	(0.032)	(0.003)	(0.004)
Age	−0.012**	−0.016***	−0.001	−0.00
	(0.004)	(0.005)	(0.000)	(0.000)
Glasses	0.178**	0.251*	0.027	0.006
	(0.068)	(0.125)	(0.014)	(0.009)
Oval_shape	0.443***	0.153	0.020	0.012
	(0.123)	(0.211)	(0.011)	(0.012)
Round_shape	0.558***	0.243	0.024	0.017
	(0.149)	(0.242)	(0.013)	(0.011)
Square_shape	0.471**	0.036	0.027	0.016
	(0.147)	(0.241)	(0.015)	(0.012)
Gender	0.270**	0.118	0.014***	0.009
	(0.089)	(0.176)	(0.003)	(0.005)
SERVICE	Yes	Yes	Yes	Yes
Constant	1.495***	1.408***	5.013***	4.996***
	(0.280)	(0.418)	(0.023)	(0.025)
City fixed effect	Yes	Yes	Yes	Yes
Obs.	2851	935	2851	935

Notes: $*p < 0.05$; $**p < 0.01$; and $***p < 0.001$. Clustered standard errors (city-level) are in parentheses.

Table 8
Determinants of purchase decision and service evaluation of tourists by type of tour.

	(1) Transaction Chauffeured	(2) Transaction Package	(3) Transaction Walking	(4) Transaction Featured experience	(5) Rating Chauffeured	(6) Rating Package	(7) Rating Walking	(8) Rating Featured experience
FACE								
Beauty	**0.016*** **	**0.015*** **	**0.009** **	**0.002* **	**0.001**	**0.001**	**0.001**	**0.001**
	(0.003)	**(0.004)**	**(0.003)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Smile	0.056**	0.032	0.103	0.090	0.001	0.013**	0.018***	0.005
	(0.022)	(0.092)	(0.101)	(0.126)	(0.003)	(0.005)	(0.003)	(0.005)
Age	−0.011**	−0.005	−0.018*	−0.012	−0.001	−0.001	−0.002*	−0.003**
	(0.004)	(0.008)	(0.009)	(0.007)	(0.001)	(0.001)	(0.000)	(0.001)
Glasses	0.205***	0.399***	0.089	0.093	0.004	0.019	0.013	0.023
	(0.070)	(0.116)	(0.133)	(0.138)	(0.007)	(0.011)	(0.007)	(0.016)
Oval_shape	0.296***	0.513***	0.609***	0.289	0.021	0.021	0.031	0.017
	(0.096)	(0.155)	(0.185)	(0.226)	(0.012)	(0.012)	(0.019)	(0.014)
Round_shape	0.295*	0.381	0.613**	0.469*	0.028	0.006	0.044	0.001
	(0.116)	(0.215)	(0.211)	(0.238)	(0.019)	(0.013)	(0.028)	(0.016)
Square_shape	0.272*	0.584**	0.559**	0.247	0.020	0.024	0.034	0.035
	(0.109)	(0.190)	(0.211)	(0.253)	(0.011)	(0.014)	(0.021)	(0.024)
Gender	0.003**	0.084	0.127	0.101	0.014**	0.013	0.007	0.008
	(0.001)	(0.101)	(0.148)	(0.122)	(0.005)	(0.008)	(0.006)	(0.006)
SERVICE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DESTINATION	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.345***	2.138***	2.056***	2.967***	5.114***	5.011***	5.193***	5.119***
	(0.372)	(0.477)	(0.586)	(0.619)	(0.032)	(0.034)	(0.029)	(0.041)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3309	1560	1803	1339	3309	1560	1803	1339

Notes: *$p < 0.05$; **$p < 0.01$; and ***$p < 0.001$. Clustered standard errors (city-level) are in parentheses.

presence to different scenarios.

5.1. Theoretical implications

The beauty premium of tour guides in different customer decision processes. This research is novel as it adopts AI-facilitated big data analysis to investigate the beauty premium in a service-dominant context. The work also provides new empirical evidence on the role of physical attractiveness in different customer decision-making stages. The results show that the power of beauty is inherent when tourists compare tour guides online and need to make a purchase decision. It is worth noting that previous studies involving physical products have had mixed results, which support the beauty premium effect (Ert et al., 2016), both a beauty premium and a beauty penalty (Li et al., 2022), both beauty and ugliness premiums (Peng, Cui, et al., 2020), or no beauty premium but an ugliness penalty (Jaeger et al., 2019). The findings imply that physical attractiveness may have a volatile effect in a product-dominant context when interactions with service personnel are dispensable—the effect of beauty can be further conditioned by product features (Peng, Cui, et al., 2020) and regional disparities (Jaeger et al., 2019), yielding mixed results in the literature, but the impact is decisive in a service-dominant context when those interactions are necessary. The beauty premium effect is salient in the purchasing stage, and the result is robust to different sub-groups characterized by demographics and service contexts. Through the lens of implicit personality theory (Funder, 1995), the relevance and detection of the cues of service operators are strengthened in a service-dominant context, therefore reinforcing the beauty premium effect.

Physical attractiveness has little impact when it comes to service evaluation, however, for either the overall dataset or the tour guides in the different sub-groups. The results imply that the evaluation of tour guide service, after all, mainly depends on the quality of the service encounters, seniority of the tour guide, and the accessories and resources provided, such as a studio, number of service personnel, selfie stick, child car seat, or rain gear. This is in line with discussions on the dynamics of pre- and post-purchase evaluations of online consumptions, such that distinct attributes count in different decision-making stages (Liu et al., 2019; Park et al., 2012, 2015). From the perspective of implicit personality theory, the relevance and detection of attractiveness cues are eroded by actual service experiences (Funder, 1995), therefore diminishing the beauty premium effect in the service evaluation stage.

These findings differ from those in previous studies that have associated physical attractiveness with more favorable service evaluations through an experimental or survey approach (e.g., Li et al., 2019; Li, Liu, Chen, & Huan, 2021; Wu, Liang, & Gursoy, 2021). This difference in findings reinforces the value of analyses that use massive data from real service transactions. A number of issues are noted for experimental or survey designs. First, the respondents may be influenced by previous exposure to certain questions, and connections identified between scales which might be the result of an "order effect", for example, due to the close sequencing of research items (Wilcox & Wlezien, 1993). Having both physical attractiveness and service evaluations in the same study may therefore increase their association, and the perception of one may cue the response to the other. This subconscious association in experimental/survey settings is not an issue in the current research. Second, the results of related experimental studies have inspired lively debates over the problem of realism (Falk & Heckman, 2009). It is common practice in experimental research on physical attractiveness to present hypothetical scenarios and photos of service providers to a group of respondents (who may not be "real" service providers and customers). Such controlled manipulations in an experimental setting often invite skepticism about the representation of reality. Third, experimental/survey research work is subject to the methodological caveat of a small sample size and limited generalization of the findings, although this study offers robust results obtained from massive data of a large volume of diverse information (Li et al., 2018).

Other facial cues in decision-making process. This study has contributed to the related literature by considering the role of other facial cues in customer decision-making processes. In addition to physical attractiveness, the AI-facilitated analyses have elucidated the effects of other facial cues identified from the profile pictures, such as facial expression, face shape, whether eyeglasses are worn, perceived age, and gender. In particular, smiling young female tour guides with an oval shaped face have an advantage in the purchase decision stage. The findings corroborate with previous studies that testify to the power of positive facial expressions in the decision-making process of customers (Banerjee & Chua, 2020; Fagerstrøm et al., 2017). A happy service provider conveys an accommodating and congenial personality, and thus exudes a personable and trustworthy disposition—the reason that smiles prompt great service experiences.

This research has also enriched studies of facial cues by extending the discussion to other nuanced information identified from a profile photo—accessories and face shape. Interestingly, wearing eyeglasses is advantageous for male tour guides. Empirical evidence shows that individuals, in particular male professionals, photographed with eyeglasses are perceived to be more intelligent, dependable and honest (Fetscherin, Tantleff-Dunn, & Klumb, 2020; Guéguen, 2015; Thornton, 1943). Males are also considered to be less threatening (Elman, 1977) and more conscientious (Guéguen & Martin, 2017) when they wear eyeglasses. All of the above projected personalities could invite a more favorable tour guide evaluation and thus increase purchase intentions. The effect of eyeglasses is not significant for female tour guides, however, which might be attributed to the sociocultural effect that prioritizes the appearance of women but overlooks their intelligence and competencies (Luo, Jackson, Niu, & Chen, 2020). An oval or a round face is found to be more favorable, which demonstrates the contemporary Chinese preference for a round or oval face shape "with a smoothly tapered jaw angle" as an ideal feature (Samizadeh & Wu, 2020, p. 1173). It is worth noting, however, that such a beauty ideal may be evolving due to media influence, for example, from the traditional preference for round faces to the endorsement of more elongated faces with a pointy chin (Jung, 2018).

Heterogeneous effects of beauty premium. Another contribution of this study is in its investigation of the heterogeneous effects of beauty premium among different groups. This has enriched the research on the situational conditions of the beauty premium by elucidating the theoretical foundations and substantiating the empirical findings. The investigation also furthers current understanding of implicit personality theory. The beauty effect is found to be more salient for females. While the number of service transactions of male tour guides is also affected by age, accessories and face shape, physical attractiveness is the only salient facial cue for female tour guides. Although conflicting discourses are found in the literature and there are debates on whether the beauty premium differs between gender groups (Eagly et al., 1991), it is still widely believed that physical attractiveness is more central to females (Bar-Tal & Saxe, 1976; Rodin, Silberstein, & Striegel-Moore, 1985). This is particularly true in Asia due to the tendency to conform to social norms of beauty (Madan et al., 2018). Such a gender bias has been empirically demonstrated in the labor market in China. The effect of the beauty premium is higher for female candidates than male candidates in the hiring process (Maurer-Fazio & Lei, 2015). Females with an aesthetically pleasing appearance also earn more, compared to males who are handsome (Gu & Ji, 2019; Peng, Wang, & Ying, 2020).

The result also implies heterogeneous effects of beauty premium in different service contexts. Specifically, physical attractiveness has fewer benefits for tour guides in featured experience tours that place more emphasis on the en route scenery and unique destination attractions. In comparison, chauffeured, package or walking tours are characterized by more interaction with tour guides, and therefore see a stronger beauty premium effect. This disparity should motivate researchers to explore the effect of physical attractiveness in different situational contexts.

While age slightly reduces the beauty premium, which could be attributed to a shift in focus to the increased professionalism, experience, practical skills and know-how of service providers when they mature (Cleveland & Lim, 2007), the heterogeneous effect is not significant. Previous research also implies an interplay between gender and age (Anýžová & Matějů, 2018), which may confound expectations and offer future research avenues.

5.2. Managerial implications

This study also has practical implications for tour guides and online platforms. As COVID-19 continues to take a toll on tourism, increased safety concerns have created an upsurge in demand for small and private tours and online tour guide platforms (China Association of Travel Services, 2020). The impression management of online profiles is therefore a more pertinent issue for tour guides in the pandemic. The results offer managerial insights to help tour guides to better adapt themselves to the new normal in a post-pandemic world by adapting their online presence. Online tour guide platforms can also benefit from the findings of this research through its in-depth investigation of the factors that influence the decisions of tourists.

There are a few important implications from our discussion that may help tour guides in China to better present themselves. While it is true that any effort may have a limited effect in diminishing the power of beauty, these suggestions offer some ways for tour guides to manage their online profiles and images in a more favorable and professional way, and to acquire more business opportunities. As photogenicity evokes positive customer responses, it is recommended that tour guides take professional photos for their online profile. A skilled photographer can capture better images, which is particularly important for females and tour guides who provide chauffeured, package or walking tour services. A happy expression with a smile is also preferred. Male tour guides might don a pair of eyeglasses. A recent study concludes that wearing round-shaped eyeglasses increases perceived warmth, while square-shaped eyeglasses are associated with competence (Okamura & Ura, 2019). Different eyeglass options may help male tour guides to shape their image. Adequate makeup (e.g., highlighting and contouring) can also help to create a favorable face shape that is in line with the preference of the targeted customers, which in general is an oval or a round face. Men with a square face shape might be perceived as attractive, and female tour guides can try to create a round-shaped face by using cosmetics. These guidelines can be used as a reference for travel agencies if they wish to tailor the online presence of their tour guides. For example, consider the case of two young tour guides: Tour Guide A, a male tour guide mainly responsible for featured experience tours, and Tour Guide B, a female tour guide mainly responsible for chauffeured tours. A physically attractive online presence is in general more important for Tour Guide B. She would find it worthwhile to seek the services of a professional make-up artist and photographer to enhance the attractiveness of her profile. Makeup skills such as shading and hair styling to soften the angles of the face can better contour a round face shape to give the impression that she is kind and caring. A pair of eyeglasses, a sincere smile, and a simple contoured oval face would all greatly benefit the image of Tour Guide A.

It is also noted that the beauty premium effect has little impact at the service evaluation stage. For a higher customer rating, tour guides should equip themselves with accessories and resources, such as selfie sticks, child car seats, and rain gear. A studio and more service personnel would also contribute to a better perceived tour experience, and subsequently increase ratings. After all, beauty is powerful, but not in all circumstances. Service professionals should also understand that appropriate methods of beautification improve attractiveness, while excessive beautification invites mistrust. In the end, superb customer service is still a competitive advantage that sustains word-of-mouth business and long-term career advancement.

5.3. Limitations and future research

As with many studies, this study has several limitations which can be used to provide directions for future research. First, these results are based on respondents in China and may not apply to other cultural contexts that have different social desirability and beauty standards. Future research could validate the results in different countries. Second, there are also other factors beyond beauty that may affect the decision-making process of tourists. Future studies might also further explore information from unstructured online data, for example, the sentiment, context richness and length of a tour guide's self-introduction may influence purchase decisions. The results show that service experiences rather than physical attractiveness could be the main influences on post-service ratings. Textual messages in customer reviews may help to provide a better understanding of customer–tour guide interactions, as well as the synergy between physical attractiveness and service cues. The demographics and travel characteristics of tourists may also be factors that help to examine the heterogeneous effects of the beauty premium among different customer segments. Third, the physical attractiveness scores were derived from an AI facial recognition system on Baidu. The results could be cross-validated by using other deep-learning methods, which we intend to examine as a future study. Fourth, a longitudinal dataset with the same pool of users could further our understanding of this dynamic decision-making process. Future studies might wish to adopt a controlled experiment design that incorporates choice modelling to simulate the process, and compare the results with those obtained from the current study. A breakdown of data obtained before and after the pandemic could also help to further understand the changes, for example, whether the beauty premium effect is higher with the increasing demand for small private tours after the outbreak of COVID-19, which we leave for future endeavors.

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Author contributions

Fiona X. Yang: Conceptualization; Methodology, Formal analysis, Writing – original draft, Writing – review & editing. Ying Li: Formal analysis, Data curation, Writing – review & editing. Xiaotong Li: Conceptualization, Data curation, Methodology, Formal analysis. Jia Yuan: Conceptualization, Methodology, Formal analysis, Writing – review & editing

Impact statement

Our study shows the impact of digitized visual cues of service personnel in two different stages of the decision-making process of tourists—at the time of purchase and after-service evaluation. With a more comprehensive understanding of beauty premium and the role of other facial/service cues, tour guides can adapt their online presence for different scenarios. As COVID-19 continues to take a toll on tourism, the upsurge in demand for small private tours and online tour guide platforms has become the subject of increasing safety concerns. The results provide managerial insights for tour guides to better adapt themselves to the new normal in a post-pandemic world. Online tour guide platforms can also benefit from this research through an in-depth investigation of the influential factors of tourist decisions.

Declarations of interest

None.

References

Ahearne, M., Gruen, T. W., & Jarvis, C. B. (1999). If looks could sell: Moderation and mediation of the attractiveness effect on salesperson performance. *International Journal of Research in Marketing, 16*(4), 269–284.
Anýžová, P., & Matějů, P. (2018). Beauty still matters: The role of attractiveness in labour market outcomes. *International Sociology, 33*(3), 269–291.
Arefieva, V., Egger, R., & Yu, J. (2021). A machine learning approach to cluster destination image on Instagram. *Tourism Management, 85*, 104318.
Banerjee, S., & Chua, A. Y. (2020). How alluring is the online profile of tour guides? *Annals of Tourism Research, 81*, 102887.
Bar-Tal, D., & Saxe, L. (1976). Physical attractiveness and its relationship to sex-role stereotyping. *Sex Roles, 2*(2), 123–133.
Barnes, S. J., & Kirshner, S. N. (2021). Understanding the impact of host facial characteristics on Airbnb pricing: Integrating facial image analytics into tourism research. *Tourism Management, 83*, 104235.
Broer, P. N., Juran, S., Liu, Y.-J., Weichman, K., Tanna, N., Walker, M. E., … Persing, J. A. (2014). The impact of geographic, ethnic, and demographic dynamics on the perception of beauty. *Journal of Craniofacial Surgery, 25*(2), e157–e161.
Bruner, J. S., & Tagiuri, R. (1954). The perception of people.(Vol. 2). In G. Lindzey (Ed.), *Handbook of social psychology* (Vol. 2, pp. 634–654). Cambridge: Addison Wesley.
Cao, K., Choi, K.-n., Jung, H., & Duan, L. (2020). Deep learning for facial beauty prediction. *Information, 11*(8), 391.
Chang, K.-C. (2014). Examining the effect of tour guide performance, tourist trust, tourist satisfaction, and flow experience on tourists' shopping behavior. *Asia Pacific Journal of Tourism Research, 19*(2), 219–247.
Chaudhuri, A. (2020). Deep learning models for face recognition: A comparative analysis. In R. Jiang, C. T. Li, D. Crookes, W. Meng, & C. Rosenberger (Eds.), *Deep biometrics* (pp. 99–140). Cham: Springer.
Chen, P., Geng, X., Zou, M., Xu, Q., & Tan, D. (2020). Development and optimization of check-in system based on face recognition technology. *IOP Conference Series: Materials Science and Engineering, 782*, Article 052022.
Chen, Q., Wang, X., & Zhao, Q. (2019). Appearance discrimination in Grading?– evidence from migrant schools in China. *Economics Letters, 181*, 116–119.
China Association of Travel Services. (2020). *The survival status and career development needs of tour guides in the pandemic*. http://www.cats.org.cn/index.php?m=content&c=index&a=show&catid=6&id=43.
Cleveland, J. N., & Lim, A. S. (2007). Employee age and performance in organizations. In K. S. Shultz, & G. A. Adams (Eds.), *Age and work in the 21st century*. London: Lawrence Erlbaum Associates, Publishers.
Cronbach, L. J. (1955). Processes affecting scores on" understanding of others" and" assumed similarity. *Psychological Bulletin, 52*(3), 177–193.
Dallimore, K. S., Sparks, B. A., & Butcher, K. (2007). The influence of angry customer outbursts on service providers' facial displays and affective states. *Journal of Service Research, 10*(1), 78–92.
Deng, N., & Li, X. R. (2018). Feeling a destination through the "right" photos: A machine learning model for DMOs' photo selection. *Tourism Management, 65*, 267–278.
Deng, N., Liu, J., Dai, Y., & Li, H. (2019). Different cultures, different photos: A comparison of Shanghai's pictorial destination image between east and west. *Tourism Management Perspectives, 30*, 182–192.
Deng, W., Li, D., & Zhou, D. (2020). Beauty and job accessibility: New evidence from a field experiment. *Journal of Population Economics, 33*(4), 1303–1341.
Dion, K., Berscheid, E., & Walster, E. (1972). What is beautiful is good. *Journal of Personality and Social Psychology, 24*(3), 285–290.
Doorley, K., & Sierminska, E. (2012). *Myth or fact? The beauty premium across the wage distribution*. IZA Discussion Papers. No. 6674. Retrieved from https://ssrn.com/abstract=2101941.
Eagly, A. H., Ashmore, R. D., Makhijani, M. G., & Longo, L. C. (1991). What is beautiful is good, but: A meta-analytic review of research on the physical attractiveness stereotype. *Psychological Bulletin, 110*(1), 109–128.
Elman, D. (1977). Physical characteristics and the perception of masculine traits. *The Journal of Social Psychology, 103*(1), 157–158.
Ert, E., Fleischer, A., & Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism Management, 55*, 62–73.
Fagerstrøm, A., Pawar, S., Sigurdsson, V., Foxall, G. R., & Yani-de-Soriano, M. (2017). That personal profile image might jeopardize your rental opportunity! on the relative impact of the seller's facial expressions upon buying behavior on Airbnb. *Computers in Human Behavior, 72*, 123–131.
Falk, A., & Heckman, J. J. (2009). Lab experiments are a major source of knowledge in the social sciences. *Science, 326*(5952), 535–538.
Fang, S., Zhang, C., & Li, Y. (2020). Physical attractiveness of service employees and customer engagement in tourism industry. *Annals of Tourism Research, 80*, 102756.
Feingold, A. (1992). Good-looking people are not what we think. *Psychological Bulletin, 111*(2), 304–342.
Fetscherin, M., Tantleff-Dunn, S., & Klumb, A. (2020). Effects of facial features and styling elements on perceptions of competence, warmth, and hireability of male professionals. *The Journal of Social Psychology, 160*(3), 332–345.
Funder, D. C. (1995). On the accuracy of personality judgment: A realistic approach. *Psychological Review, 102*(4), 652–670.
Gao, P., Wang, X., Chen, H., Dai, W., & Ling, H. (2021). What is beautiful is not always good: Influence of machine learning-derived photo attractiveness on intention to initiate social interactions in mobile dating applications. *Connection Science, 33*(2), 321–340.
Gu, P. (2020). The effects of social bias against female analysts on markets. *Journal of Corporate Finance, 64*, 101681.
Guéguen, N. (2015). Effect of wearing eyeglasses on judgment of socioprofessional group membership. *Social Behavior and Personality: An International Journal, 43*(4), 661–665.
Guéguen, N., & Martin, A. (2017). Effect of interviewer's eyeglasses on compliance with a face-to-face survey request and perception of the interviewer. *Field Methods, 29*(3), 194–204.
Gu, T., & Ji, Y. (2019). Beauty premium in China's labor market: Is discrimination the main reason? *China Economic Review, 57*, 101335.
Guttentag, D. (2015). Airbnb: Disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism, 18*(12), 1192–1217.
Hasan, M. R., Abdunurova, A., Wang, W., Zheng, J., & Shams, S. R. (2020). *Using deep learning to investigate digital behavior in culinary tourism*. Journal of Place Management and development.
Huang, S. (2010). A revised importance–Performance analysis of tour guide performance in China. *Tourism Analysis, 15*(2), 227–241.
Huang, S., Weiler, B., & Assaker, G. (2015). Effects of interpretive guiding outcomes on tourist satisfaction and behavioral intention. *Journal of Travel Research, 54*(3), 344–358.
Hwang, J., & Lee, J. (2019). Relationships among senior tourists' perceptions of tour guides' professional competencies, rapport, satisfaction with the guide service, tour satisfaction, and word of mouth. *Journal of Travel Research, 58*(8), 1331–1346.

Iyer, T. J., Nersisson, R., Zhuang, Z., Joseph Raj, A. N., & Refayee, I. (2021). Machine learning-based facial beauty prediction and analysis of frontal facial images using facial landmarks and traditional image descriptors. *Computational Intelligence and Neuroscience, 2021*, 4423407.
Jäckle, S., & Metz, T. (2017). Beauty contest revisited: The effects of perceived attractiveness, competence, and likability on the electoral success of German MPs. *Politics & Policy, 45*(4), 495–534.
Jaeger, B., Sleegers, W. W., Evans, A. M., Stel, M., & van Beest, I. (2019). The effects of facial attractiveness and trustworthiness in online peer-to-peer markets. *Journal of Economic Psychology, 75*, 102125.
Jung, J. (2018). Young women's perceptions of traditional and contemporary female beauty ideals in China. *Family and Consumer Sciences Research Journal, 47*(1), 56–72.
Kim, S., & Lee, Y. (2018). Why do women want to be beautiful? A qualitative study proposing a new "human beauty values" concept. *PLoS One, 13*(8), Article e0201347.
LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.
Lee, E.-J. (2022). Do tech products have a beauty premium? The effect of visual aesthetics of wearables on willingness-to-pay premium and the role of product category involvement. *Journal of Retailing and Consumer Services, 65*, 102872.
Li, C., Lin, A.-P., Lu, H., & Veenstra, K. (2020). Gender and beauty in the financial analyst profession: Evidence from the United States and China. *Review of Accounting Studies, 25*, 1230–1262.
Li, Y., Liu, B., Chen, P., & Huan, T.-C. (2021). Tourism service providers' physical attractiveness and customers' service quality evaluation: Is warmth or competence more important? *Tourism Review, 76*(6), 1260–1278.
Ling, L., Li, X., Luo, D., & Pan, X. (2020). Looking good by doing good: CEO attractiveness and corporate philanthropy. *SSRN working paper* https://ssrn.com/abstract=3743688.
Li, Y., Peng, L., Ma, S., & Zhou, X. (2022). Beauty premium or beauty penalty in sharing accommodation situations based on lay theories. *International Journal of Contemporary Hospitality Management, 34*(3), 929–950.
Liu, H., Jayawardhena, C., Osburg, V.-S., & Babu, M. M. (2019). Do online reviews still matter post-purchase? *Internet Research, 30*(1), 25–33.
Li, J., Xu, L., Tang, L., Wang, S., & Li, L. (2018). Big data in tourism research: A literature review. *Tourism Management, 68*, 301–323.
Li, Y., Zhang, C., & Laroche, M. (2019). Is beauty a premium? A study of the physical attractiveness effect in service encounters. *Journal of Retailing and Consumer Services, 50*, 215–225.
Luoh, H.-F., & Tsaur, S.-H. (2014). The effects of age stereotypes on tour leader roles. *Journal of Travel Research, 53*(1), 111–123.
Luo, Y.-j., Jackson, T., Niu, G.-f., & Chen, H. (2020). Effects of gender and appearance comparisons on associations between media-based appearance pressure and disordered eating: Testing a moderated mediation model. *Sex Roles, 82*(5), 293–305.
Luo, Y., Tang, L. R., & Kim, E. (2021). A picture is worth a thousand words: The role of a cover photograph on a travel agency's online identity. *International Journal of Hospitality Management, 94*, 102801.
Lv, H., Shi, S., & Gursoy, D. (2022). A look back and a leap forward: A review and synthesis of big data and artificial intelligence literature in hospitality and tourism. *Journal of Hospitality Marketing & Management, 31*(2), 145–175.
Madan, S., Basu, S., Ng, S., & Ching Lim, E. A. (2018). Impact of culture on the pursuit of beauty: Evidence from five countries. *Journal of International Marketing, 26*(4), 54–68.
Ma, L., & Sun, B. (2020). Machine learning and AI in marketing–Connecting computing power to human insights. *International Journal of Research in Marketing, 37*(3), 481–504.
Maurer-Fazio, M., & Lei, L. (2015). As rare as a panda": How facial attractiveness, gender, and occupation affect interview callbacks at Chinese firms. *International Journal of Manpower, 36*(1), 68–85.
Ma, Y., Xiang, Z., Du, Q., & Fan, W. (2018). Effects of user-provided photos on hotel review helpfulness: An analytical approach with deep leaning. *International Journal of Hospitality Management, 71*, 120–131.
Momtaz, P. P. (2021). CEO emotions and firm valuation in initial coin offerings: An artificial emotional intelligence approach. *Strategic Management Journal, 42*(3), 558–578.
Morrow, P. C. (1990). Physical attractiveness and selection decision making. *Journal of Management, 16*(1), 45–60.
Muth, J. L., & Cash, T. F. (1997). Body-image attitudes: What difference does gender make? 1. *Journal of Applied Social Psychology, 27*(16), 1438–1452.
Okamura, Y., & Ura, M. (2019). I Am physically and personality-wise warmer when wearing round eyeglasses: Shape priming influences personality judgments and estimated temperature. *Psychological Thought, 12*(2), 176–184.
Park, I., Cho, J., & Rao, H. R. (2012). The effect of pre-and post-service performance on consumer evaluation of online retailers. *Decision Support Systems, 52*(2), 415–426.
Park, I., Cho, J., & Rao, H. R. (2015). The dynamics of pre-and post-purchase service and consumer evaluation of online retailers: A comparative analysis of dissonance and disconfirmation models. *Decision Sciences, 46*(6), 1109–1140.
Park, J., Kim, K., & Hong, Y.-Y. (2019). Beauty, gender, and online charitable giving. *SSRN working paper* https://ssrn.com/abstract=3405823.
Patacchini, E., Ragusa, G., & Zenou, Y. (2012). *Unexplored dimensions of discrimination in Europe: Religion, homosexuality and physical appearance*. London: National Centre for Social Research.
Patel, A., & Jernigan, D. B. (2020). Initial public health response and interim clinical guidance for the 2019 novel coronavirus outbreak—United States, December 31, 2019–February 4, 2020. *Morbidity and Mortality Weekly Report, 69*(5), 140–146.
Paternoster, R., Brame, R., Mazerolle, P., & Piquero, A. (1998). Using the correct statistical test for the equality of regression coefficients. *Criminology, 36*(4), 859–866.
Payntar, N. D., Hsiao, W.-L., Covey, R. A., & Grauman, K. (2021). Learning patterns of tourist movement and photography from geotagged photos at archaeological heritage sites in Cuzco, Peru. *Tourism Management, 82*, 104165.
Peng, A. Y. (2021). A techno-feminist analysis of beauty-application development in China's high-tech industry. *Journal of Gender Studies, 30*(5), 596–608.
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.
Peng, L., Wang, X., & Ying, S. (2020). The heterogeneity of beauty premium in China: Evidence from CFPS. *Economic Modelling, 90*, 386–396.
Quiroga, I. (1990). Characteristics of package tours in Europe. *Annals of Tourism Research, 17*(2), 185–207.
Ramati-Ziber, L., Shnabel, N., & Glick, P. (2020). The beauty myth: Prescriptive beauty norms for women reflect hierarchy-enhancing motivations leading to discriminatory employment practices. *Journal of Personality and Social Psychology, 119*(2), 317–343.
Ren, Y., Sun, Y., Jing, X., Cui, Z., & Shi, Z. (2019). Adaptive makeup transfer via bat algorithm. *Mathematics, 7*(3), 273.
Ren, M., Vu, H. Q., Li, G., & Law, R. (2021). Large-scale comparative analyses of hotel photo content posted by managers and customers to review platforms based on deep learning: Implications for hospitality marketers. *Journal of Hospitality Marketing & Management, 30*(1), 96–119.
Rodin, J., Silberstein, L., & Striegel-Moore, R. (1985). Women and weight: A normative discontent. In T. B. Sonderegger, & R. A. Dienstbier (Eds.), *Nebraska symposium on motivation* (Vol. 33, pp. 267–307). Lincoln: University of Nebraska Press.
Rushton, A., & Carson, D. J. (1989). Services–marketing with a difference? *Marketing Intelligence & Planning, 7*(5/6), 12–17.
Sagiroglu, S., & Sinanc, D. (2013). Big data: A review. In *Proceedings of the international conference on collaboration technologies and systems (CTS)* (pp. 42–47).
Samizadeh, S., & Wu, W. (2020). Ideals of facial beauty amongst the Chinese population: Results from a large national survey. *Aesthetic Plastic Surgery, 44*(4), 1173–1183.
Schneider, D. J. (1973). Implicit personality theory: A review. *Psychological Bulletin, 79*(5), 294–309.
Shtudiner, Z. (2019). The impact of attractiveness on retail managers' decisions: Labor market discrimination when hiring salespeople. *Modern Economy, 10*(11), 2253–2263.
Shtudiner, Z., & Klein, G. (2020). Gender, attractiveness, and judgment of impropriety: The case of accountants. *European Journal of Political Economy, 64*, 101916.
Song, S., & Baek, S. (2021). Body shape matters: Evidence from machine learning on body shape-income relationship. *PLoS One, 16*(7), Article e0254785.
Spencer, S. (2010). *Visual research methods in the social sciences: Awakening visions*. London: Routledge.
Strahan, E. J., Wilson, A. E., Cressman, K. E., & Buote, V. M. (2006). Comparing to perfection: How cultural norms for appearance affect social comparisons and self-image. *Body Image, 3*(3), 211–227.
Thornton, G. R. (1943). The effect upon judgments of personality traits of varying a single factor in a photograph. *The Journal of Social Psychology, 18*(1), 127–148.
Tsai, C.-Y., Wang, M.-T., & Tseng, H.-T. (2016). The impact of tour guides' physical attractiveness, sense of humor, and seniority on guide attention and efficiency. *Journal of Travel & Tourism Marketing, 33*(6), 824–836.
Tu, H., Guo, W., Xiao, X., & Yan, M. (2020). The relationship between tour guide humor and tourists' behavior intention: A cross-level analysis. *Journal of Travel Research, 59*(8), 1478–1492.
Wang, R., Luo, J., & Huang, S. S. (2020). Developing an artificial intelligence framework for online destination image photos identification. *Journal of Destination Marketing & Management, 18*, 100512.
Wan, L. C., & Wyer, J. R. S. (2015). Consumer reactions to attractive service providers: Approach or avoid? *Journal of Consumer Research, 42*(4), 578–595.
Weiler, B., & Black, R. (2015). The changing face of the tour guide: One-way communicator to choreographer to co-creator of the tourist experience. *Tourism Recreation Research, 40*(3), 364–378.
Wen, H. (2021). Gentle yet manly: Xiao xian rou, male cosmetic surgery and neoliberal consumer culture in China. *Asian Studies Review, 45*(2), 253–271.
Wilcox, N., & Wlezien, C. (1993). The contamination of responses to survey items: Economic perceptions and political judgments. *Political Analysis, 5*, 181–213.
Wirtz, J., Fritze, M. P., Jaakkola, E., Gelbrich, K., & Hartley, N. (2021). Service products and productization. *Journal of Business Research, 137*, 411–421.
Wolf, N. (1990). *The beauty myth: How images of beauty are used against women*. New York, NY: Morrow.
Wu, G., Liang, L., & Gursoy, D. (2021). Effects of the new COVID-19 normal on customer satisfaction: Can facemasks level off the playing field between average-looking and

attractive-looking employees? *International Journal of Hospitality Management, 97*, 102996.
Yang, T., Zhao, X., Wang, X., & Lv, H. (2020). Evaluating facial recognition web services with adversarial and synthetic samples. *Neurocomputing, 406*, 378–385.
Yu, J., & Egger, R. (2021). Color and engagement in touristic Instagram pictures: A machine learning approach. *Annals of Tourism Research*, 103204.
Zhai, Y., Huang, Y., Xu, Y., Gan, J., Cao, H., Deng, W., … Scotti, F. (2020). Asian female facial beauty prediction using deep neural networks via transfer learning and multi-channel feature fusion. *IEEE Access, 8*, 56892–56907.
Zhang, K., Chen, Y., & Li, C. (2019). Discovering the tourists' behaviors and perceptions in a tourism destination by analyzing photos' visual content with a computer deep learning model: The case of Beijing. *Tourism Management, 75*, 595–608.
Zhang, K., Chen, D., & Li, C. (2020). How are tourists different?-Reading geo-tagged photos through a deep learning model. *Journal of Quality Assurance in Hospitality & Tourism, 21*(2), 234–243.

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