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An artificial intelligence powered study of enlarged facial pore prevalence on one million Chinese from different age groups and its correlation with environmental factors

Huanjun Zhou[1] | Hang Xie[1] | Liang Wu[1] | JinYan Song[2] | Zitao Ma[2] | Danning Zeng[1] | Xiaodi Wang[1] | Su Shi[1] | Yulan Qu[1] | Yajun Luo[1] | Xia Meng[3] | Yue Niu[3] | Haidong Kan[3] | Jian Cao[1] | Nadine Pernodet[4]

[1]Estée Lauder Companies Innovation R&D (China) Co., Ltd, Shanghai, China

[2]Hangzhou C2H4 Internet Technology Co., Ltd., Hangzhou, China

[3]School of Public Health, Key Lab of Public Health Safety of the Ministry of Education and NHC Key Lab of Health Technology Assessment, Fudan University, Shanghai, China

[4]Research and Development, The Estée Lauder Companies, Melville, New York, USA

Correspondence
Jian Cao, Estée Lauder Companies Innovation R&D (China) Co., Ltd, Shanghai, China.
Email: jcao@cn.estee.com

Xia Meng, School of Public Health, Key Lab of Public Health Safety of the Ministry of Education and NHC Key Lab of Health Technology Assessment, Fudan University, Shanghai, China.
Email: mengxia@fudan.edu.cn

AI unveiled insights on one million Chinese pore

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Abstract

Background: Enlarged pores are amidst one of the top cosmetic concerns, especially among Chinese. Many small-group studies have been conducted in understanding their prevalence and beauty relevance. Nonetheless, population-level investigations are still lacking because of gaps in data collection and processing of large-scale studies. Owing to the recent technological advancement enabled by artificial intelligence, databases on the scale of millions can be processed and analyzed readily.

Materials and methods: Powered by big data capabilities, revealed a number of novel trends on pore conditions among over-a-million Chinese participants recruited via the “You Look Great Today” mobile application. A scoring model was constructed, which demonstrated high consistency with conventional grading method from dermatologists. Environmental data (weather, air pollution, light at night satellite) were applied to correlate with pore severity.

Results: Intraclass correlations between the two scoring systems were strong, with coefficients ranging from 0.79 to 0.92 for different facial areas. Statistical differences in pore severity among all four facial areas (cheek, forehead, nose, and overall) were observed, with the cheek exhibiting the most severe pore condition. Interestingly, Chinese men suffer from more severe pore condition than females. Multiple environmental factors exhibited strong correlations with cheek pore severity and were statistically fitted into linear regressions. Specifically, incremental risk with Each Low Temperature, Low Humidity, And High Solar Exposure correlate to worse cheek pore conditions. Although the Pearson correlation was low between cheek pore severity and light at night, comparison between representative cities demonstrated that in geologically similar cities, higher light at night corresponds to more severe cheek pore conditions.

Conclusion: Our study is showcasing a robust and reliable AI model in facial pore evaluation. More importantly, insights uncovered using this facile approach also bear significant cosmetic ramifications in treatment of pore enlargement.

KEYWORDS
artificial intelligence, Chinese population, environmental impact, facial pores, risk factors

1 | INTRODUCTION

Facial pores are topological openings that allow sebum (oil) and sweat to be excreted to the surface of the facial skin. Commonly found on the nose, forehead, cheeks, and chin, such skin surface structures are essential in the maintenance of healthy skin functions such as the regulation of body temperature as well as skin moisturization.[1,2] However, pilosebaceous units can occasionally become notably enlarged or clogged, causing skin problems such as acnes, blackheads, and a rough texture.[3–5] By morphological subtypes, skin pores have previously been classified into three different categories—'visible skin pores' (size of 0.1–0.6 mm), 'enlarged skin pores' (size of 0.3–0.6 mm) and 'blackhead embedded skin pores' (pores with darker skin tone).[2,6]

To deepen the understanding in terms of ageing mechanism, researchers have identified various biological hallmarks, including biomarkers on the skin over the years.[7] Variations in skin appearance can stem from both endogenous (such as genetics, hormones and age) and exogenous (such as sunlight, pollution and comedogenics) factors.[8–11]

Previously, chronological age, which refers to the number of years one has lived, was shown to dominate the process of intrinsic skin aging.[12] It was reported to appreciably impact skin-related biological markers such as wrinkles, sagging, skin pH and transepidermal water loss (TEWL).[10] Additionally, Yang et al. discovered a unique trend among Chinese females, characterizing the process of ageing from 18 to 60 into four different stages—incubation period (Y18-30), ageing occurrence period (Y31-42), rapid ageing period (Y43-47) and stabilized ageing period (Y48-60).[13] The number of facial pores, among all investigated skin features, increases after the age of 29 and peaks at the age of 50.[13] Besides, pore size and density can vary by ethnicity.[14,15]

On the other hand, exogenous changes are known to lead to differentiation in skin features as well. For instance, Flament et al. showed that observable skin darkening was detected in a group of Chinese women without sun protection.[16] A parallel study among Chinese men differed slightly where the effect from sun exposure was more prominent at an older age.[17] The correlation between air pollution and pre-mature skin ageing is also well-established in the literature.[18] In addition, a change in seasonality can lead to differences in skin parameters including pore—Korean men presented more skin pores in the summer compared to in the winter.[19]

Often, Chinese tirelessly experiment with traditional remedies and modern skincare regimens, in hopes of attaining the perfect skin. Among many, skin smoothness, translucency and radiance, are highly praised and sought after, whereas features such as enlarged pores are deemed undesirable.[20] Albeit their innocuity, these skin features can be visually disappointing, especially among cosmetic enthusiasts, due to their frequent association with unwanted health attributes such as ageing.[9,21] Pore minimization, in particular, has been a long-standing obsession for Asians with the ultimate goal of a 'peeled egg-like' appearance.[13] For instance, more than 50% of Japanese women are dissatisfied with their pores and complained about them being too conspicuous.[22] Another study suggested that noticeable pores are ranked among one of the top facial problems for young women in North Asia.[23] In short, enlarged pores are causes of both aesthetic concerns and erosion to one's self-esteem.

Previously, a plethora of techniques have been devised for quantitative measurement of pores severity. Two types of methods are commonly adopted—subjective evaluation and machine-based assessment. The former, often accomplished by trained individuals such as dermatologists or professional panelists, involves visual inspection of the skin surface followed by score assignments referencing a standardized grading system.[24] The latter, on the other hand, requires imagery capture under controlled environment such as consistent lighting, followed by analysis using standardized algorithm with an output on relevant parameters such as size, shape and distributions of the pore.[25–27]

Image-based approaches are often preferentially implemented for the high image resolution, which facilitates ensuing analyses. Regrettably, the inherent limitations of such methods become apparent when the number of participants exceed what the study can accommodate. Such studies, often conducted in clinical settings, typically do not exceed 100 participants for cost reasons. With artificial intelligence (AI) capabilities, which first gained traction in the field of medicine as diagnostic tools, researchers can now use deep learning algorithms trained on large datasets of images to provide rapid detection of diseases conventionally identified via visual inspection.[28] Though still in its infancy, studies have been carried out to assess and validate the accuracy of AI-enabled analysis in dermatology to promote a wider application of this computational approach.[29,30] For instance, an epidemiological application of automatic grading systems was carried out in an attempt to address the sample size constraints—comparative studies on facial features at a population-level using automatic grading systems among different groups.[28,31]

Nowadays, selfies taken with readily available cellphones require little effort at time of data collection, improbably for previous settings studies when large number of participants are involved. In addition to the increased accessibility and accelerated turnaround time, a machine learning-aided approach can also minimize human errors and enhance study accuracy. Aside from the recent advancement of AI, this is in part enabled by the wide adoption of smartphones with high-resolution camera. In China, ownership of smartphone has reached 72% among urban residents and 63% in rural areas in 2018.[33] A high penetration rate of smartphone established the basis for the study described in this study.

Researchers involved in cosmetic studies have presently taken the opportunity to use augmented AI capabilities, investigating factors that may impact facial skin features such as skin texture, level of hydration and pigmentation.[34] However, fewer studies to date have explored the effect of environmental factors on skin features. Few have captured variations of skin features on a population level. Herein, we report an AI-powered analysis on facial pores using data from one million Chinese from different age groups, including its validation with dermatologist grading and correlational study with environmental factors such as temperature, humidity, solar irradiation, pollution level and light at night. We hope that this study will help shed light on the causation of enlarged pores as well as potential remedies on this cosmetic annoyance.

2 | MATERIALS AND METHODS

2.1 | Subject recruitment and data acquisition

2.1.1 | User consent

Participants recruited in the study were requested to complete the consent form before using any service provided. Users agreed to the privacy policy provided by 'You Look Great Today' (YLGT), which explicitly disclosed the purpose and method of data collection in the study, ensuring absolute transparency to participants, and the legality and compliance of the data acquisition process.

2.1.2 | Image collection

Facial images were collected from YLGT users via smartphone rear cameras. Under an audio guide, users were prompted to take selfies at an appropriate distance (20–30 cm) with a $\pm$ 5° angle. Flashlight was mandatory for enhanced photo quality. All photos uploaded were then scrutinized for presence of facial covering, non-uniformed lighting and focus loss. A standard operating procedure during the photo collection helped minimize image artifacts and facilitated the high consistency of data acquired, which ensured the accuracy and reliability of subsequent assessment.

2.1.3 | Privacy protection

The study strictly followed ethical guidelines to safeguard the rights and well-being of the participants. Relevant measures were implemented to protect user privacy, ensure data security and handle the data in accordance with applicable ethical standards, regulations and legal requirements.

Data provided by Hangzhou C2H4 Internet Technology Corporation in the study was de-sensitized via an advanced anonymization algorithm of k-means clustering to mitigate privacy concerns.[35,36] Any personally identifiable information was removed for total anonymity and non-traceability.

2.2 | Construction and validation of AI-grading system

AI-enabled assessment model was established based on methodology set up in previous studies. [37,38] Briefly, different facial areas, where pores typically locate, including the forehead, nose and cheeks, were segmented and labelled accordingly using the google face detection method.[39] Distinct pore features were extracted via advanced image filtering algorithms and processed for location information on pores. Features extracted were classified using a neural network. The classification model was trained on a dataset consisting of approximately 100 000 annotated images. Engineered with an architecture similar to LeNet-5, this network determined the presence of pore in the provided feature set. The above-trained classification neural network was evaluated on its accuracy using a separate validation dataset. Our model yielded an accuracy rate of 95.7%, a recall rate of 97.6% and a precision rate of 94.6%. The two models for location and classification were integrated and run on a new dataset for validation. By utilizing the integrated model, we computed a score, ranging from 0 to 1000, reflecting level of pore severity in the forehead, nose, cheek and overall regions, respectively. The model was further verified by correlating with standard dermatologist grading. By calculating the Intraclass Correlation Coefficient (ICC), we determined the level of agreement between the two systems, and thus assessing the reliability and practicality of using this novel AI-grading system on evaluating pore-related skin parameters.

2.3 | Source of environmental data

We considered three main categories of environmental parameters in this study, including weather, air pollution and nocturnal activity. Detailed definitions, corresponding units and primary spatial resolutions of weather-related parameters are summarized in Table 1. These parameters, including temperature (T2M), relative humidity (RH) and surface solar shortwave radiation (SSRD), were retrieved from the fifth generation of European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis database ERA5[40] Gridded annual values from EAR5 in 2020 were averaged at city level according to the Chinese administrative division.

The potential effect of air pollution on pore condition is a key area of interest. We also assigned annual mean concentrations of air pollutant in 2020 to each individual, including fine particulate matter ($PM_{2.5}$), coarse particulate matter ($PM_{2.5\text{-}10}$), inhalable particulate

TABLE 1 Definition and units of weather-related parameters used in the study.

Parameters	Abbreviation	Unit	Primary spatial resolution
Temperature at 2 m of height from the surface	T2M	Celsius, °C	0.1°×0.1°
Relative humidity	RH	%	0.25°×0.25°
Surface solar radiation downwards	SSRD	J/(m²*h)	0.1°×0.1°

TABLE 2 Age and gender breakdown of study subject.

Age group	Male	Female	Total
16~19	5763	150 668	156 431
20~29	91 041	460 000	551 041
30~39	21 398	184 476	205 874
40~49	5172	65 184	70 356
50~60	1264	15 602	16 866
Total	124 638	875 930	1 000 568

matter (PM_{10}), nitrogen dioxide (NO_2) and ozone (O_3). In this study, air pollutant data were compiled from previously trained models.[41–45] Light at night (LAN) was represented using annual average global VIIRS nighttime light data in 2020 across cities.[46,47]

2.4 | Statistical analyses

All comparison analyses were completed using the non-parametric hypothesis Kruskal-Wallis H Test with a significance level of 0.01. A max-min normalization ($x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$) that linearly transforms the original data into a range of 0 to 1, was performed for standardization among various parameters.

Pearson correlations were assessed between facial pore condition and the environmental factors. *p*-values were computed with a significance level of 0.01 to determine if the coefficients significantly differed from zero. Linear regression analyses were then carried out to further explore the influence of relevant environmental factors on pore condition.

3 | RESULTS

3.1 | Subject demographic

Facial images of a total of 1 000 568 subjects were analysed in this study. The distribution by age and gender is summarized in Table 2. Overall gender ratio of male to female was about 1:9, while the age of participants covers Y16-Y60. All groups except the male Y50-Y60 have sample sizes over 5000. Age group Y20-Y29 represents approximately half of the entire sample pool.

TABLE 3 Intraclass correlation analysis between scores of pore severity assessed by AI-based system and dermatologist grading.

Area of assessment	Intraclass correlation coefficient	*p*
Cheek pore	0.92	<0.001***
Overall pore	0.90	<0.001***
Forehead pore	0.85	<0.001***
Nose pore	0.79	<0.001***

***represent the significance level of 0.001.

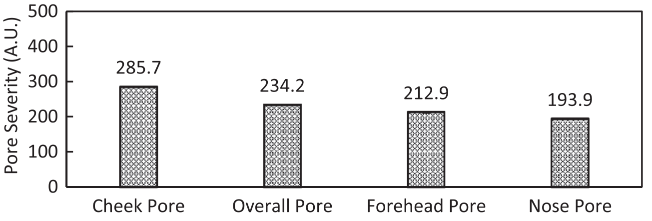

FIGURE 1 Score distribution of pore severity in different facial areas. Error bars represent standard errors (bars might be too small to be visible).

3.2 | Validation of AI-based grading system

Pore severity was scored on 70 randomly selected images by the AI-based grading system and the dermatologist grading system. ICC values between the two sets of score were then calculated on four facial areas, ranging from 0.79 to 0.92 (Table 3).

3.3 | Assessment by facial area

Scores were assigned to pores on the cheek, forehead, nose and the overall facial area. The average score of each area differs significantly from the others ($p < 0.001$). Mean score of cheek pores ranks the highest at 286, whereas that of nasal pores ranks the lowest at 194 (Figure 1).

3.4 | Assessment by gender

Pore severity was statistically higher among males than females in all four measured facial areas (Figure 2). Difference between genders was most pronounced on the nose (26%) while least on the cheek (4%).

3.5 | Assessment by age

Progression of cheek pore severity was analysed across all ages for both genders (Figure 3). Overall, small fluctuations before 20 were followed by a sudden surge at the age of 22. For males, pore severity underwent a gradual increase from age 22 and plateaued as they

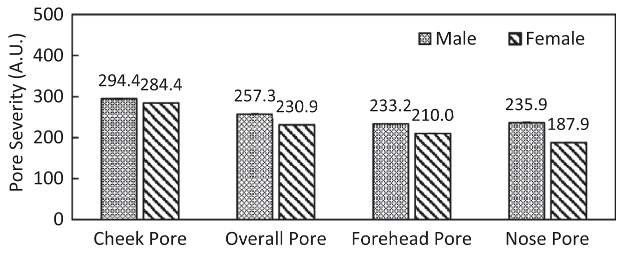

FIGURE 2 Comparison on pore severity of male and female in different facial areas. Error bars represent standard errors (bars might be too small to be visible).

entered 40s. From age 50 to 60, higher fluctuations were observed, but the general trend stayed flat. In contrast, pore condition increased among females up to 26 years old, then improved slightly from age 27 and stabilized around 30. After a flat period in their 30s, another notable surge was observed from age 40 to 44. Afterwards, a steady small increase in pore severity could be noted until age 57, followed by a slight worsening till age 60.

3.6 | Assessment by geography

Additionally, a province-level analysis was performed on cheek pore severity and summarized in Figure 4 (Hong Kong, Macao and Taiwan not included due to insufficient data). The best pore conditions were seen among populations from Chongqing, Hunan, Guangxi and Jiangxi. Meanwhile, Tibet, Inner Mongolia and Qinghai exhibited the most severe pore conditions.

3.7 | Correlational analyses

Pearson correlation analyses were run on cheek pore severity score and environmental factors, including NO_2, O_3, PM10, PM2.5-10, PM2.5, T2M, RH, SSRD and LAN (Figure 5). Due to the variation in sample size, only cities with over 1000 subjects were included. Correlations with coefficient > 0.5 or <- 0.5 were found between the score and T2M/RH/SSRD, of which the correlations were negative for T2M/RH and positive for SSRD. No significant correlation was detected between any pollutants and cheek pore severity. Similarly, no statistical significance was observed on correlation between LAN and the cheek pore severity.

Linear regressions were subsequently conducted on RH/ SSRD and cheek pore severity. Analysis with T2M was not included because of its strong correlation with RH. Results showed that each 1% decrease in RH is associated with a 0.6% increase in cheek pore score with a R-square of 0.38 (Figure 6A); On the contrary, each 1% increase in SSRD is associated with a 0.48% increase in cheek pore score with a *R*-square of 0.36 (Figure 6B). Furthermore, we noted that given a similar level of SSRD, pores are more severe for cities with lower RH (Figure 6C). Comparably, at similar level of RH, pores are more severe for cities with higher SSRD (Figure 6D).

Zooming in the possible impact of LAN on facial pore severity, different city pairs (under similar level of RH and SSRD) were picked and analysed. Surprisingly, dramatic differences were observed under three pairs of cities (representing North, East and South, separately) (Table 4.). In pair A northern cities, with similar SSRD/RH, Beijing with higher LAN value comparing to Baoding showed much higher overall pores. Similarly, pair B eastern cities (Shanghai vs. Suzhou), pair C southern cities (Shenzhen vs. Zhanjiang) are in line with the trend. Thus, this result indicates the potential impact of longer exposure to light at night with possibly shorter sleep time correlated with facial pore severity.

4 | DISCUSSION

4.1 | Method reliability

Previous studies have verified the reliability of the standardized image capture procedure on the measurement of facial erythema, dark circle and most recently acne.[37,48,49] Results from this study further corroborated with the reported findings and showcased the high consistency of the image collection method. Moreover, model devised in this study reached an accuracy of 91.5% and demonstrated higher correlation (coefficient around 0.9) compared to literature reported ones (coefficient of 0.63),[50] making it a trustworthy tool in such population-level research of skin biomarkers.

4.2 | Assessment on pore severity

4.2.1 | By facial area

Using an AI-based grading system, pore severity was ranked, from highest to lowest, as follow: cheek, overall, forehead and nose (Figure 1). The trend coincided with the ranking of intraclass correlation coefficients between the two scoring systems (Table 3). It is likely that the AI detection becomes more sensitive and yields scores closer to dermatologist grading as the number of pores or pore sizes increases. Cheek, the area with the worst pore condition evaluated by the AI system, is often where pores are first noticed visually. In addition, cheek area is often selected for before-and-after comparison of pore severity in clinical assessment of cosmetic treatments.

4.2.2 | By gender

Statistical differences were observed in all four measured facial areas between male and female (Figure 2). This finding, consistent with previous reported,[20] indicates that more attentive care on pores is needed among males. Interestingly, the gendered difference appeared to be the most pronounced on the nose where pores are the least severe while least pronounced on the cheek where pores are in their worse condition. Nevertheless, more studies are to be carried out for further clarifications.

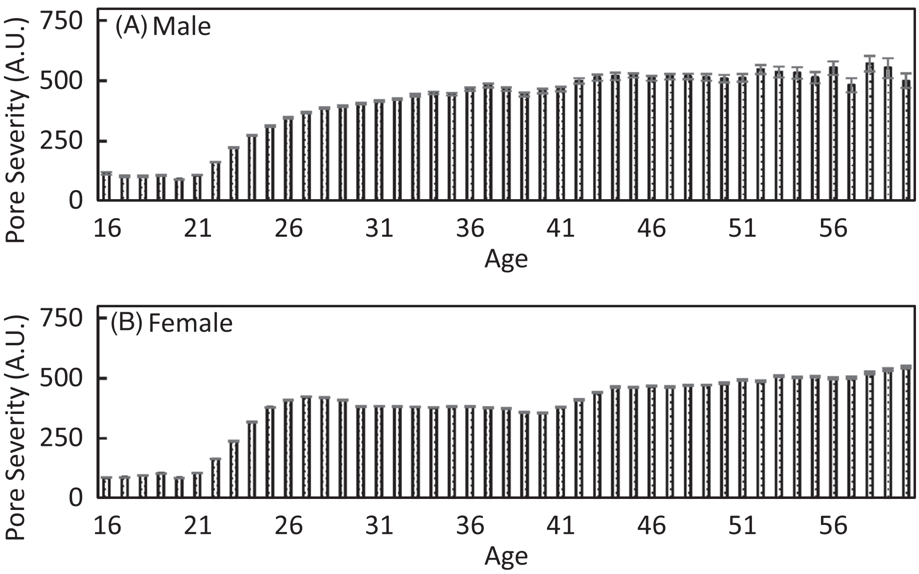

FIGURE 3 Score distribution of cheek pore severity by age for (A) male and (B) female.

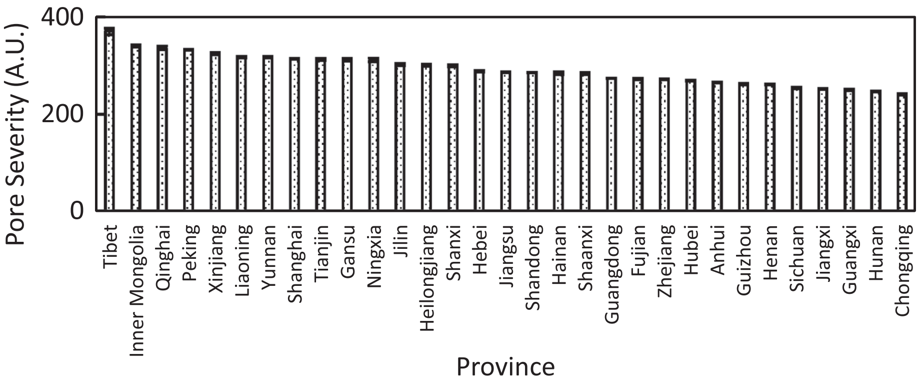

FIGURE 4 Score distribution of cheek pore severity by province.

4.2.3 | By age

In general, pores worsen steadily with age in both genders, with a rapid climb at age 20+. This is possibly attributed to the role transition from college to workforce, which is often accompanied by an elevation of psychological/emotional stress due to changes of locations and increase of workloads. However, different from male, female facial pore appears a spike during age 22–27. The underlying cause could be drastic hormonal change associated with pregnancies.[51,52] To authors' knowledge, this phenomenon has not been reported before. It indicated that during this period when pore severity rapidly intensifies, special cosmetic care might be especially relevant to female.

4.2.4 | By geography

By province, Tibet, Inner Mongolia, Qinghai ranked the top three cities with the most severe cheek pore possibly due to high solar exposure at high altitude and high dairy/GI food intake (Figure 4).[53] Meanwhile, populations from Guangxi, Hunan and Chongqing exhibited the mildest cheek pore condition thanks to the low level of solar exposure and high humidity (Figure 4). Given literature description that population from southwestern China (specifically, Sichuan and Chongqing) generally have lighter skin tone (Fitzpatrick II/III), this also is consistent with the alignment we see between lighter skin tone and smaller pores.[54]

4.3 | Correlation analysis with environmental parameters

4.3.1 | Pearson correlation and linear regression analysis

Despite the many correlations reported in the literature between various skin biomarkers and environmental factors, in-depth studies between pores and the environment are still scarce. Among the weather-related parameters studied, we noticed a strong positive correlation (coefficient = 0.717) between T2M and RH (Figure 5).

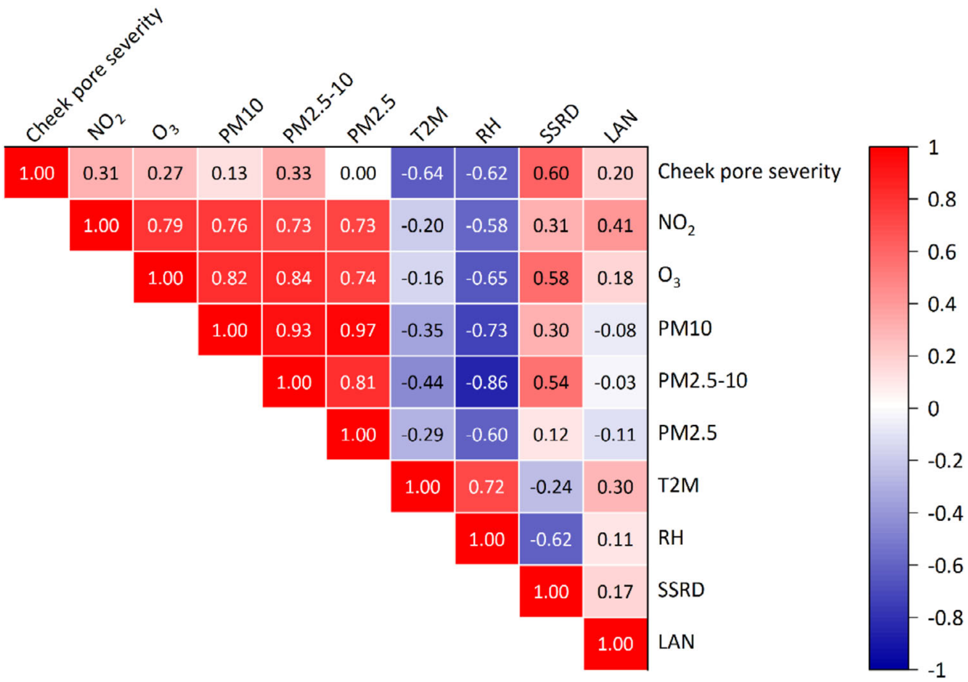

FIGURE 5 Pearson correlation analysis between cheek pore score and environmental factors.

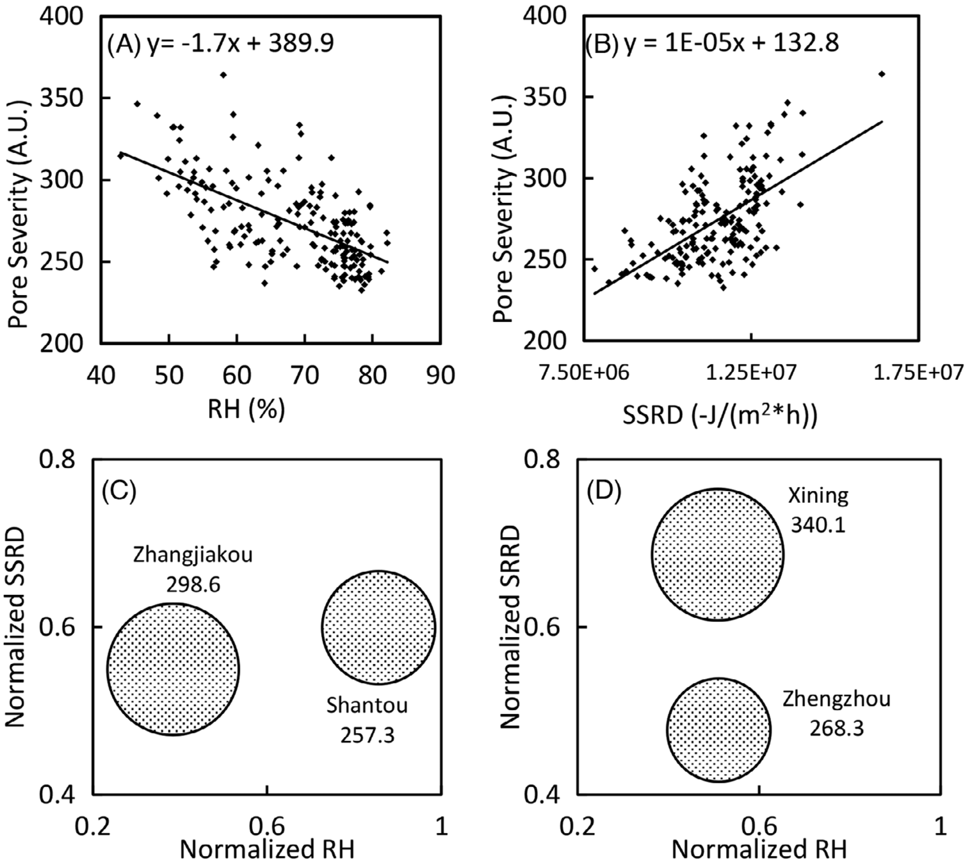

FIGURE 6 Linear regression analysis of cheek pore severity score and (A) RH; (B) SSRD; and cheek pore severity (bubble width represents severity score) of cities with (C) similar level of SSRD but different levels of RH. (D) Similar level of RH but different levels of SSRD.

TABLE 4 Score of cheek pore severity for represented cities.

Pair	City	SSRD	RH	LAN	Pore severity score (A.U.)
A	Beijing	0.510	0.331	0.24	332.3
	Baoding	0.525	0.385	0.06	278.7
B	Suzhou	0.346	0.764	0.49	292.4
	Shanghai	0.361	0.796	0.75	313.6
C	Shenzhen	0.555	0.875	1.00	292.9
	Zhanjiang	0.565	0.865	0.06	257.2

Consequently, only RH was selected for further analyses. Low temperature and humidity are known to intensify skin issues such as weakened barrier, increasing skin roughness and even dermatitis, especially during seasonal transitions.[55–57] Similarly, this study revealed strong negative correlations between T2M/RH and cheek pore severity (Figure 6A). Under similar level of sun exposure, pore severity is lower in Shantou, a more humid city, than Zhangjiakou (Figure 6C). Conversely, a strong positive correlation was observed between SSRD and cheek pore severity (Figure 6B), consistent with findings reported by Flament et al. where an older age is perceived on Chinese women when no sun protection is used.[58] Under similar level of humidity, cheek pores are more severe in Xining, a city with more sun exposure, than Xining (Figure 6D). In summary, these findings suggest the importance of skin hydration and sun protection against cheek pore enlargement.

Observable correlation between ageing biomarkers and pollution, a by-product of rapid industrialization and urbanization, have been described.[59] Nevertheless, all correlations between pollution-related parameters and cheek pore severity were low to moderate (coefficients ranging from 0.002 to 0.33). These findings, though differ from previous insights, could be attributed to the recent enormous effort dedicated to pollution reduction in China. Further studies comparing geologically similar cities with different levels of pollution may generate additional insights.

4.3.2 | Indications from outlier analysis on LAN

Satellite images captured at night represent a proxy of nocturnal activities including electricity consumption, and subsequently population-level activities.[60] Although the Pearson correlation between cheek pore severity and LAN was weak (Figure 5), we noticed that after segmenting the cities by level of LAN, cheek pore condition in geologically similar cities displayed striking variance at different levels of LAN. For example, populations in cities with higher LAN such as Beijing, Shanghai and Shenzhen have more severe cheek pores than their respective neighbours—Baoding, Suzhou and Zhenjiang (Table 4). Residents in the former cities typically endure longer days and short night sleep with possible higher level of stress compared to those living in latter areas. Studies have demonstrated that lack of sleep, exposure to light at night, stress and skin conditions are closely correlated.[61] It Is possible that an increase in stress-related hormones such as cortisol and adrenaline, which could elevate oil secretion in skin glands, results in pore clogging and acne breakouts. Higher LAN is possibly associated with later bedtime and sleep deprivation as well. It is well-established that excessive night light exposure, disrupted circadian rhythms and sleep deprivation can lead to suboptimal skin conditions.[62–65] Therefore, a healthier circadian rhythm might be beneficial in alleviating pore enlargement. Further studies on the relationship between sleep and facial pores could elucidate more explanations.

5 | CONCLUSION

To summarize, we report a rigorous AI-based algorithm that efficiently enables big data photo-analytics in the context of skin feature evaluation. This model yielded findings on pore prevalence among a million Chinese. In addition to validation of previously described trends, such as males generally display worse pore conditions than females and inhabitants residing in areas with lower temperature, lower humidity and higher sun exposure suffer from more severe pore conditions, this work has also revealed novel understanding between pore and non-geological factors. We identified an unexpected exacerbation of cheek pore condition among Chinese females in their 20s, possibly attributable to hormonal changes experiencing pregnancies. Level of LAN, an estimate of nocturnal activities and a potential indicator of lack of sleep and stress level, is also a contributing factor to the variance of pore condition among geologically comparable areas. We hope that the methodology devised in this study will inspire the development of more tools and aid the progression of future cosmetic treatment.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ORCID

Jian Cao https://orcid.org/0009-0003-8201-9898

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