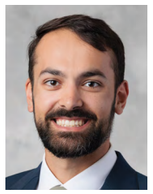
Developments in retinal pigmentation measurement and the hopes of an equitable future

WITH NIMA GHADIRI, ABRAHAM OLVERA-BARRIOS AND ANAND RAJESH

Our AI & Oculomics co-editor, Nima Ghadiri, sat down with Abraham Olvera-Barrios from Moorfields and Anand Rajesh from the University of Washington to discuss their recent international study into retinal pigmentation and its wider clinical, technological and academic applications.

Abraham Olvera-Barrios,
Moorfields Clinical Research Fellow, Moorfields Eye Hospital, London, UK.



Anand Rajesh,
Ophthalmology Resident, University of Washington, USA.

Can you summarise the key findings of your research in simple terms?

We developed a tool that objectively measures retina pigmentation directly from eye images without relying on subjective categories such as ethnicity or race [1]. This score, called the retinal pigment score (RPS), reveals that people of different ethnicities can have similar retinal pigmentation, and that ethnic categories alone do not explain retinal pigmentation. This is of relevance because rather than focusing on ethnic differences, the RPS allows us to objectively describe and assess the diversity of the population included in studies or in datasets with biological validity. The RPS challenges how we describe data for AI model development and assessment by providing a measure which supports fairer and more equitable tools in ophthalmology.

What are the limitations of using ethnicity as a factor in current AI models for eye health?

Ethnicity is a historical, social construct, not a biological measure, yet it is often used in ophthalmology and medicine to explain differences in health outcomes. This is problematic because it risks embedding existing ingrained health inequalities into clinical tools, leading to biased models that underperform in already underserved populations.

How does the RPS address these limitations and potentially improve healthcare outcomes?

The RPS gives an objective, continuous measurement of retinal pigmentation, something we can see and quantify directly from images from the back of the eye. It decouples biology from ethnicity, helping us design equitable, safe AI models with adequate representation of people from all characteristics.

Can you briefly explain how the RPS was developed and validated?

We used machine learning to analyse data from two large population studies (from over 500,000 people in the UK, namely the UK Biobank and the EPIC-Norfolk Study) and validated our findings in independent diverse datasets from Tanzania, Australia and China. Our method automatically analysed over 70,000 retinal images – first identifying the optic nerve head, retinal vasculature, and removing these structures from the analysis to focus on the background pigmentation of the eye. Second, the background retinal pigmentation is transformed into an interpretable colour space – using the CIELAB colour space, also referred to as L*a*b*, as defined by the International Commission on Illumination – to focus on the chromaticity vectors (a, b). Third, the chromaticity vectors are extracted and transformed by principal component analysis to create the RPS. Our code is production-ready and can be found in our github repository [2]. We then conducted discovery genetic analyses (UK Biobank population) evidencing a link between RPS with genetic markers known to influence skin, hair, and eye colour (which were validated in the EPIC-Norfolk study).

What challenges did you face when developing and validating the RPS, and how did you overcome them?

A main challenge was ensuring diverse representation and validating the RPS across populations. We addressed this in two main ways. Firstly, by rigorous description of imaging datasets and population characteristics. Secondly, by using two large population studies and testing the RPS on retinal images from Tanzania, Australia and China, while standardising processing to ensure consistent results across settings.

How does the RPS integrate with existing AI algorithms in ophthalmology?

The RPS can be used to describe image diversity in AI datasets and assess how well algorithms perform across the pigmentation spectrum. This helps ensure AI models are robust and fair, by reducing the risk of inadequate representation of eyes with different degrees of pigmentation which could result by relying on ethnicity categories.

What are the potential applications of the RPS beyond diabetic retinopathy?

This represents a game changer for ophthalmology and retina. The RPS can describe retinal phenotypic variation of retinal pigmentation with biological validity. This will open research avenues for the discovery of associations with clinical conditions including, but not limited to, age-related macular degeneration, uveitis, glaucoma, ocular oncology, and in wider fields, such as dermatology, cardiology and neurology, where medical forecasting from retinal images is used. Additionally, the RPS can ensure enough people and eye diversity are included for model development, and for model validation, improving fairness in AI tools.

How do you envision the RPS being used in clinical practice and research?

Clinically, the RPS can help ophthalmologists better assess image pigmentation objectively and adding information about the risk of that person for developing ocular conditions. In research, it allows scientists to study retinal biology independent of ethnicity / race and to ensure AI tools work across diverse populations. It is a step toward personalised and fair medicine.

What are the next steps in your research, and what are your long-term goals for the RPS?

We are working to standardise the RPS across different imaging devices and disease settings, and to integrate it into research and at the clinical point of care as a routine descriptor. Our long-term vision is that RPS becomes a benchmark for equity in imaging-based AI.

What is the significance of making the RPS algorithm publicly available?

Transparency builds trust. By sharing our code, we empower others to apply, test, and improve the RPS. It shows our commitment to equity and reproducibility in medical AI and an open invitation to collaborate.

Thank you both so much for your time, and I am keen to see how this develops.

References

1. Rajesh AE, Olvera-Barrios A, Warwick AN, et al. Machine learning derived retinal pigment score from ophthalmic imaging shows ethnicity is not biology. *Nat Commun* 2025;**16**:60.
2. https://github.com/uw-biomedical-ml/retinal-pigmentation-score

[Link last accessed June 2025]

Declaration of competing interests: None declared.

Eye News | August/September 2025 | VOL 32 NO 2 | www.eyenews.uk.com