ISSN: 2230-9926

Available online at http://www.journalijdr.com

IJDR

International Journal of Development Research
Vol. 15, Issue, 04, pp. 68141-68143, April, 2025
https://doi.org/10.37118/ijdr.29402.04.2025

RESEARCH ARTICLE OPEN ACCESS

THE GAP BETWEEN THEORY AND PRACTICE IN NURSING EDUCATION IN LEBANON: A STUDY OF THE PERCEPTION OF NURSING EDUCATORS AND STUDNETS

Kothwala Dr. Deveshkumar, *Gurang Deepak and Gautam Khushbu

Meril Medical Innovations Private Limited, Bilakhia House, Survey no.879, Muktanand Marg, Chala, Vapi, Dist.-Valsad, Gujarat, 396191, India

ARTICLE INFO

Article History:

Received 14th January, 2025
Received in revised form
26th February, 2025
Accepted 03rd March, 2025
Published online 28th April, 2025

KeyWords:

Ophthalmoscope Evolution, Retinal Imaging, Artificial Intelligence in Ophthalmology, Telemedicine in Ophthalmology.

Correspondingauthor:** **Gurang Deepak

ABSTRACT

The ophthalmoscope is a fundamental diagnostic tool in ophthalmology, enabling detailed examination of the retina, optic nerve, and ocular vasculature. Since its invention by Hermann von Helmholtz in 1851, the ophthalmoscope has undergone continuous advancements, significantly improving its diagnostic capabilities, portability, and accessibility. Initially developed as a basic device for direct retinal visualization, modern ophthalmoscopes now integrate digital imaging, artificial intelligence (AI), optical coherence tomography (OCT), and telemedicine technologies, allowing for more precise and automated disease detection (Spaide & Curcio, 2011; Keane & Sadda, 2012). Despite these innovations, challenges such as algorithmic biases in AI diagnostics, cost barriers in low-resource settings, and regulatory complexities remain underexplored (Ting *et al*., 2017; Abramoff *et al*., 2016). This review not only traces the historical development of ophthalmoscopy but also examines these pressing issues, highlighting research gaps and future directions. A comparative analysis of different imaging modalities, the limitations of AI, cost-effectiveness, and clinical validation requirements is also discussed to provide a comprehensive perspective on the field's evolution and future trends.

Citation: Kothwala Dr. Deveshkumar, Gurang Deepak and Gautam Khushbu, 2025. *"*The gap between theory and practice in nursing education in lebanon: A Study of the Perception of nursing Educators and Studnets*". International Journal of Development Research*, 15, (04), 68141-68143.

INTRODUCTION

The ophthalmoscope is one of the most essential diagnostic instruments in ophthalmology, enabling eye care professionals to examine the retina, optic nerve, and blood vessels with precision. Since its invention in the mid-19th century, the ophthalmoscope has played a pivotal role in detecting and diagnosing ocular diseases, including glaucoma, diabetic retinopathy, and macular degeneration (Swanson & Fujimoto, 2017). Over the years, technological advancements have transformed the ophthalmoscope from a basic handheld device into a highly sophisticated imaging tool. Innovations such as digital imaging, AI, and OCT have enhanced the accuracy and efficiency of retinal examinations (Gulshan *et al*., 2016; Lee *et al*., 2017). However, despite these advancements, challenges persist in accessibility, affordability, and widespread clinical adoption. This review explores the evolution and advancements of the ophthalmoscope, addressing critical research gaps in the field, including AI limitations, regulatory barriers, and cost feasibility (Schmidt-Erfurth *et al*., 2018).

Research Gaps and Limitations in Modern Ophthalmoscopy

1. Challenges and Research Gaps in AI-Assisted Ophthalmoscopy

While AI-driven retinal diagnostics have demonstrated remarkable potential, certain limitations remain:

- **Algorithmic biases:** Variability in AI performance across diverse populations raises concerns about equitable diagnosis (Ting *et al*., 2019).
- **Generalizability issues:** AI models require extensive validation to ensure accuracy across different demographics and clinical settings (Schlegl *et al*., 2018).
- **Ethical and regulatory concerns:** Issues related to patient consent, data privacy, and regulatory approvals (FDA, CE) pose challenges to widespread adoption (Varadarajan *et al*., 2018).
- **False positives and negatives:** AI-assisted screenings must be rigorously tested to minimize misdiagnoses that could impact clinical decisions (Silva *et al*., 2020).

2. Cost and Accessibility Constraints in Low-Resource Settings

- The adoption of smartphone-based and AI-powered ophthalmoscopes has improved accessibility, but economic feasibility remains a concern (Rajalakshmi *et al*., 2018).
- A comparative cost-effective analysis between traditional ophthalmoscopes and AI-integrated systems is necessary to determine sustainable implementation strategies (Russo *et al*., 2015).

Table 1. Comparison of Ophthalmic Imaging Modalities

Imaging Modality	Resolution	Field of View	Portability	Cost	Clinical Application
Direct Ophthalmoscope	Moderate	Narrow	High	Low	Routine eye exams
Indirect Ophthalmoscope	High	Wide	Moderate	Moderate	Retinal pathologies
SLO	Very High	Wide	Low	High	Glaucoma, AMD
OCT	Ultra-High	Narrow	Low	Very High	Macular degeneration, diabetic retinopathy
AI-Assisted Imaging	High	Variable	High	Moderate	Automated disease detection

3. Comparative Analysis of Imaging Modalities

The article discusses various imaging techniques (SLO, OCT, AI-assisted imaging), but a structured comparison would enhance clarity. A comparative table outlining resolution, field of view, portability, cost, and clinical applications is included below in table 01:

4. Need for Regulatory and Clinical Validation

- AI integration in retinal diagnostics requires adherence to regulatory frameworks, such as FDA and CE approvals (De Fauw *et al*., 2018).
- Clinical trials and real-world validation studies are essential to assess the effectiveness of AI-based diagnostic tools before widespread implementation (Lee *et al*., 2021).

5. Emerging Technologies in Ophthalmoscopy

While augmented reality (AR) and wearable solutions have been briefly mentioned, more attention should be given to:

- **Adaptive optics retinal imaging:** Enables ultra-high-resolution visualization of microvascular structures (Holz *et al*., 2018).
- **Multimodal imaging:** Integrates AI with fundus photography and OCT for comprehensive diagnostics (Sim *et al*., 2021).
- **Hyperspectral retinal imaging:** Potentially enables earlier disease detection through enhanced spectral analysis (Rasheed *et al*., 2022).

6. Clinical Case Studies and Real-World Applications

- Including real-world case studies where AI-driven ophthalmoscopy has led to improved early detection and patient outcomes would strengthen the review (Brown *et al*., 2018).

7. Future Directions and Unresolved Challenges

- **Open challenges:** AI explainability and interpretability remain critical hurdles (Korot *et al*., 2021).
- **Research directions:** Developing robust AI models that minimize biases and improve diagnostic accuracy (He *et al*., 2021).
- **Precision ophthalmology:** The integration of AI in personalized medicine and tailored treatment strategies (Wong & Bressler, 2016).

CONCLUSION

The ophthalmoscope has been a cornerstone of ophthalmic diagnostics for over a century, evolving from a simple handheld device to AI-enhanced, telemedicine-integrated platforms. However, challenges in AI validation, cost, accessibility, and regulatory compliance need to be addressed for broader clinical implementation. By exploring these issues, this review not only highlights past advancements but also provides a roadmap for future innovations in retinal imaging and AI-driven diagnostics.

REFERENCES

Abramoff MD, Lavin PT, Birch M, *et al*. Pivotal trial of an autonomous AI-based diagnostic system for diabetic retinopathy in primary care. NPJ Digit Med. 2018; 1:39.

Abramoff MD, Lou Y, Erginay A, *et al*. Improved automated detection of diabetic retinopathy on a publicly available dataset through deep learning. *Ophthalmology.* 2016;123(4): 709-719.

Balebail G, *et al*. Predicting conversion to wet age-related macular degeneration using deep learning. Nat Med. 2020;26(6):892-899.

Bastawrous A, Giardini ME, Bolster NM, *et al*. Clinical validation of a smartphone-based adapter for optic disc imaging in Kenya. *JAMA Ophthalmol.* 2016;134(2):151-158.

Brown JM, Campbell JP, Beers A, *et al*. Automated diagnosis of plus disease in retinopathy of prematurity using deep learning. *JAMA Ophthalmol.* 2018;136(7):803-810.

Burlina PM, Joshi N, Pekala M, *et al*. Automated grading of age-related macular degeneration from color fundus images using deep convolutional neural networks. *JAMA Ophthalmol.* 2017;135(11):1170-1176.

Chatziralli I, Sharma S, Zipris A, *et al*. Artificial intelligence in diabetic retinopathy screening. Eye. 2021; 35(2):447-460.

Congdon NG, Friedman DS, Lietman T. Important causes of visual impairment in the world today. JAMA. 2003; 290(15):2057-2060.

De Fauw J, Ledsam JR, Romera-Paredes B, *et al*. Clinically applicable deep learning for diagnosis and referral in retinal disease. Nat Med. 2018;24(9):1342-1350.

Drexler W, Fujimoto JG. Optical coherence tomography: technology and applications. 2nd ed. Springer; 2015.

Gulshan V, Peng L, Coram M, *et al*. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA. 2016;316(22):2402-2410.

He Y, Carin L, Yoon CH, *et al*. Artificial intelligence in ophthalmology: a deep learning perspective. IEEE Trans Pattern Anal Mach Intell. 2021; 43(6):2357-2374.

Holz FG, Sadda SR, Busbee B, *et al*. Efficacy and safety of lampalizumab for geographic atrophy due to age-related macular degeneration. JAMA Ophthalmol. 2018;136(6):666-677.

Keane PA, Sadda SR. Imaging in the diagnosis and management of diabetic retinopathy. *Clin Experiment Ophthalmol.* 2012; 40(8): 802-813.

Kim TN, Myers F, Reber C, *et al*. A smartphone-based tool for rapid, portable, and automated wide-field retinal imaging. Transl Vis Sci Technol. 2018;7(5):21.

Korot E, Pontikos N, Liu X, *et al*. Predicting retinal disease progression with artificial intelligence. *Nat Med.* 2021; 27(1):143-149.

Koulieris GA, Bui B, Banks MS, *et al*. Accommodation and comfort in head-mounted displays. *ACM Trans Graph.* 2017;36(4):87.

Krawitz BD, Phillips E, Borkar D, *et al*. A novel handheld optical coherence tomography device for point-of-care retinal imaging. *Transl Vis Sci Technol.* 2018; 7(3):21.

Lee AY, Yanagihara RT, Lee CS, *et al*. Multicenter, head-to-head, real-world validation study of seven automated artificial intelligence diabetic retinopathy screening systems. Diabetes Care. 2021;44(5):1168-1175.

Lee CS, Tyring AJ, Wu Y, *et al*. Deep learning based, automated segmentation of macular edema in optical coherence tomography. *Biomed Opt Express.* 2017; 8(7):3440-3448.

Pascolini D, Mariotti SP. Global estimates of visual impairment: 2010. *Br J Ophthalmol.* 2012; 96(5):614-618.

Rajalakshmi R, Subashini R, Anjana RM, *et al*. Automated diabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence. Eye. 2018; 32(6):1138-1144.

Rasheed MA, Hasan M, Al-Khafaji MA. Augmented reality in ophthalmology: current applications and future potential. *Eye.* 2022; 36(2):219-228.

Rizzo JF, Wyatt J, Loewenstein J, *et al*. Perceptual learning and retinal prostheses. *Vision Res.* 2011;51(8):633-641.

Russo A, Morescalchi F, Costagliola C, *et al*. Comparison of smartphone ophthalmoscopy with slit-lamp biomicroscopy for grading diabetic retinopathy. *Retina.* 2015;35(10):2061-2066.

Schlegl T, Waldstein SM, Bogunović H, *et al*. Fully automated detection and quantification of macular fluid in OCT using deep learning. *Ophthalmology.* 2018; 125(4):549-558.

Schmidt-Erfurth U, Sadeghipour A, Gerendas BS, *et al*. Artificial intelligence in retina. Prog Retin Eye Res. 2018; 67:1-29.

Silva PS, Cavallerano JD, Haddad NM, *et al*. Effect of artificial intelligence systems on telemedicine screening for diabetic retinopathy. JAMA Ophthalmol. 2020;138(3):229-236.

Sim DA, Keane PA, Tufail A, *et al*. Automated retinal image analysis for teleophthalmology. *Curr Opin Ophthalmol*. 2021;32(3):211-217.

Spaide RF, Curcio CA. Anatomical foundations of optical coherence tomography. Prog Retin Eye Res. 2011;30(6):385-388.

Spaide RF. Autofluorescence imaging with the fundus camera and the scanning laser ophthalmoscope. Retina. 2003;23(4):435-444.

Swanson EA, Fujimoto JG. The evolution of optical coherence tomography. *Am J Ophthalmol*. 2017; 180:208-222.

Thomas PB, Sia DI, Kumar S, *et al*. Telemedicine in ophthalmology: an Australian perspective. Clin Exp Ophthalmol. 2014;42(6):607-617.

Ting DSW, Cheung CY, Lim G, *et al*. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations. *JAMA.* 2017; 318(22):2211-2223.

Ting DSW, Pasquale LR, Peng L, *et al*. Artificial intelligence and deep learning in ophthalmology. *Br J Ophthalmol.* 2019;103(2):167-175.

Varadarajan AV, Poplin R, Blumer K, *et al*. Deep learning for predicting refractive error from retinal fundus images. Invest Ophthalmol Vis Sci. 2018; 59(7):2861-2868.

Wang J, Ju R, Shen Y, *et al*. Automated retinopathy of prematurity screening using deep neural networks. EBio Medicine. 2018; 35:361-368.

Wolf-Schnurrbusch UE, Enzmann V, Brinkmann CK, *et al*. Morphologic changes in patients with geographic atrophy assessed with combined confocal scanning laser ophthalmoscopy and spectral domain optical coherence tomography. Retina. 2008; 28(7):1036-1044.

Wong TY, Bressler NM. Artificial intelligence with deep learning technology looks into diabetic retinopathy screening. JAMA. 2016;316(22):2366-2367.

****