

Technological Landscape of Artificial Intelligence for Ophthalmic Diagnosis: A Scoping Review and Technology Surveillance Study

Panorama tecnológico de la inteligencia artificial para el diagnóstico oftalmológico: una revisión exploratoria y un estudio de vigilancia tecnológica.


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Review article

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Abstract

Introduction: Artificial Intelligence (AI) has become a key enabler in ophthalmic diagnostics, offering advanced capabilities for disease detection, medical image analysis, and clinical decision support. Its application is especially relevant in conditions such as diabetic retinopathy and glaucoma. However, the rapid growth of scientific literature, patents, and commercial tools makes it difficult to clearly understand the current technological landscape.

Objective: To map existing technological developments in AI-based ophthalmic diagnosis through a comprehensive Scoping Review complemented by a Technology Surveillance exercise, identifying trends, maturity levels, and innovation opportunities.

Method: The study followed the Arksey and O’Malley framework and the PRISMA-ScR guidelines. Evidence was collected and analyzed from scientific databases, patent records, commercial product catalogs, and software repositories. The review also assessed the maturity of identified solutions using Technology Readiness Levels (TRLs), a 1–9 scale developed by NASA to evaluate the development stage of a technology, from basic research to operational deployment.

Results: The findings identified deep learning and convolutional neural networks (CNNs) as predominant technological trends in AI-based ophthalmic diagnosis. The results also showed a transition from theoretical algorithms to commercially validated products with regulatory endorsement, such as IDx-DR and EyeArt. Nevertheless, important gaps remain in terms of accessibility, dataset diversity, regulatory integration, and device affordability, particularly in emerging economies.

Conclusions: AI-based ophthalmic diagnostic technologies are progressing toward validated and commercially available solutions. However, persistent economic and contextual barriers limit their adoption in regions such as Latin America. The study highlights strategic opportunities for innovation, especially in the development of low-cost, portable diagnostic tools adapted to underserved and resource-limited settings.

Keywords

Artificial intelligence, Ophthalmology, Diagnostic technologies, Scoping review, Technology surveillance, Deep learning, Patents, Medical imaging.

Resumen



Introducción: La Inteligencia Artificial (IA) se ha consolidado como un elemento clave en el diagnóstico oftalmológico, al ofrecer capacidades avanzadas para la detección de enfermedades, el análisis de imágenes médicas y el apoyo a la toma de decisiones clínicas. Su aplicación es especialmente relevante en enfermedades como la retinopatía diabética y el glaucoma. Sin embargo, el rápido crecimiento de la literatura científica, las patentes y las herramientas comerciales dificulta la comprensión clara del panorama tecnológico actual.

Objetivo: Mapear los desarrollos tecnológicos existentes en el diagnóstico oftalmológico basado en IA mediante una Revisión de Alcance complementada con un ejercicio de Vigilancia Tecnológica, con el fin de identificar tendencias, niveles de madurez y oportunidades de innovación.

Método: El estudio siguió el marco metodológico de Arksey y O'Malley y las directrices PRISMA-ScR. Se recopiló y analizó evidencia proveniente de bases de datos científicas, registros de patentes, catálogos de productos comerciales y repositorios de software. Además, se evaluó la madurez de las soluciones identificadas mediante los Niveles de Madurez Tecnológica, o Technology Readiness Levels (TRL), una escala de 1 a 9 desarrollada por la NASA para medir el estado de desarrollo de una tecnología, desde la investigación básica hasta su despliegue operativo.

Resultados: Los hallazgos identificaron el aprendizaje profundo y las redes neuronales convolucionales (CNN) como las principales tendencias tecnológicas en el diagnóstico oftalmológico basado en IA. Asimismo, los resultados evidenciaron una transición desde algoritmos teóricos hacia productos comercialmente validados y con respaldo regulatorio, como IDx-DR y EyeArt. No obstante, persisten brechas importantes relacionadas con la accesibilidad, la diversidad de los conjuntos de datos, la integración regulatoria y la asequibilidad de los dispositivos, especialmente en economías emergentes.

Conclusiones: Las tecnologías de diagnóstico oftalmológico basadas en IA avanzan hacia soluciones validadas y disponibles comercialmente. Sin embargo, las barreras económicas y contextuales continúan limitando su adopción en regiones como América Latina. El estudio destaca oportunidades estratégicas de innovación, especialmente en el desarrollo de herramientas diagnósticas portátiles, de bajo costo y adaptadas a contextos con recursos limitados.

Palabras clave

Inteligencia artificial; Oftalmología; Tecnologías de diagnóstico; Scoping Review; Vigilancia tecnológica; Deep Learning; Patentes; Imagenología médica.

INTRODUCTION

Ophthalmic diseases, such as diabetic retinopathy (DR), glaucoma, and age-related macular degeneration, are the leading global causes of preventable visual impairment and blindness. Early detection of these conditions is critical to improving clinical outcomes and patients' quality of life; however, access to specialized diagnostic equipment and expert personnel remains a significant barrier in many regions, especially in Latin America. Faced with this challenge, advances in artificial intelligence (AI) and computer vision have transformed the sector, enabling automated screening, segmentation, and classification of diseases using deep learning architectures.

In recent years, the visual health ecosystem has experienced rapid expansion, not only in the production of scientific literature, but also in the development of portable imaging devices, integrated AI systems, and the growth of patent registrations. However, despite this technological proliferation, most current reviews tend to focus exclusively on scientific articles, leaving out vital components such as the status of patents, the availability of specialized software, public datasets, and actual commercial market trends. This fragmentation of information makes it difficult for researchers and clinicians to understand the comprehensive technological landscape and the maturity of existing solutions. Unlike those approaches, this study explicitly extends its scope beyond peer-reviewed articles to include patent records, commercial product catalogs, and software repositories, thereby connecting scientific evidence, technological development, and regulatory/market availability within a unified framework.

Finally, this study conducts a Scoping Review enriched with a Technology Surveillance methodology. This combined approach allows for multidimensional mapping of AI technologies applied to ophthalmic imaging, identification of the main players in patent development, and evaluation of currently available clinical decision support tools (CAD and CDSS systems). The study is based on the methodological framework of Arksey & O'Malley and the PRISMA-ScR guidelines. Importantly, the review is not limited to scientific articles: it integrates evidence from scientific databases (Scopus, PubMed, IEEE Xplore, Web of Science, arXiv), patent repositories (WIPO, Google Patents, Espacenet, USPTO), commercial device catalogs, and software repositories (GitHub, Kaggle, Papers with Code), covering the full spectrum from research evidence to technological development and market/regulatory availability. Through this review, we seek not only to consolidate the state of the art, but also to identify critical gaps in accessibility and affordability, outlining strategic opportunities for innovation in low-cost devices adapted to emerging economies.

CONTRIBUTIONS

This study distinguishes itself through its multidimensional and integrative approach, which goes beyond traditional scientific literature reviews to offer a comprehensive overview of the technological ecosystem in visual health. Unlike previous studies that focus exclusively on deep learning algorithms and academic publications, this work links scientific

evidence with patent development, commercial device availability, public dataset maturity, and specialized software tools. The main contributions are:

- A. Quantitative mapping of the technological landscape: analysis of 144 scientific articles, 67 patents, and 34 commercial devices, documenting the transition of ophthalmic AI from theoretical algorithms to validated commercial products (such as IDx-DR and EyeArt), with evaluation of their technical and regulatory maturity level.
- B. Multi-source scope beyond peer-reviewed literature: unlike conventional scoping reviews, this study explicitly integrates evidence from scientific databases, patent repositories, commercial product catalogs, and software repositories, thereby connecting scientific evidence, technological development, and regulatory/market availability within a unified framework.
- C. Identification of representativeness gaps: Latin American populations are underrepresented in global training datasets, which limits the external validity of AI diagnostic models for the region. Similarly, the lack of affordability of high-end devices in developing economies constitutes a critical barrier to adoption.
- D. Strategic proposals for innovation: the study identifies clear pathways for future development, including multimodal diagnostic systems (Fundus + OCT-A), the implementation of explainable AI (XAI - systems designed to make AI decision-making transparent and interpretable to clinicians) to increase clinical confidence, and the use of edge computing (local on-device processing that does not require cloud connectivity) in low-cost portable devices adapted to contexts such as Latin America.

RELATED WORKS

The field of artificial intelligence (AI)-assisted ophthalmic diagnosis has evolved rapidly, moving from experimental segmentation models to complex clinical decision support systems (CDSS). This section reviews the previous literature and current technological developments, contrasting the multidimensional approach of this study with traditional reviews.

A. Methodological Frameworks and Evolution of Scope

Scoping reviews in digital health have been consolidated under the Arksey and O'Malley (2005) framework [1], which defines the stages for mapping evidence in emerging areas. Authors such as Levac et al. (2010) [2] have extended this framework to emphasize qualitative synthesis and transparent reporting through the PRISMA-ScR guidelines. While conventional reviews tend to be limited to scientific literature, this study integrates Technology Surveillance [20] as a critical dimension to capture the ecosystem of patents and commercial products, overcoming the fragmentation of information identified in previous works.

B. Advances in Algorithms: From CNN to Multimodal Models

Academic research has demonstrated outstanding effectiveness in the use of Convolutional Neural Networks (CNN), such as ResNet and DenseNet [7][8], and more recently in Vision Transformers [9], for the classification of diabetic retinopathy (DR) and glaucoma. In the case of DR, 84% of the patents identified focus on fundus images, although only 53% explicitly document the use of deep learning, leaving a significant margin for heuristic or proprietary algorithms.

In contrast, for glaucoma, there has been a shift in the commercial literature from the use of a single modality to multimodal approaches that integrate fundus, Optical Coherence Tomography (OCT), and visual fields. This trend responds to the clinical need to combine the structural damage observed in OCT with functional information, something that reviews focused solely on image algorithms tend to omit.

C. Overview of Datasets and Geographic Bias

The maturity of AI models depends on massive repositories such as EyePACS, MESSIDOR, and APTOS for DR, and RIM-ONE or ORIGA for glaucoma [10][11]. However, recent research published in forums such as Lancet Digital Health warns of an overrepresentation of populations from Asia, Europe, and the United States. This study coincides with this literature by identifying a critical gap in the representation of Latin American populations, which limits the external validity of algorithms developed globally for specific regional contexts [12]. In addition, there is a clear asymmetry: massive datasets tend to have "coarse" labels (only disease grade), while small datasets have millimeter-precise expert segmentations, as in the case of DRIVE.

D. Transition to the Market and Regulatory Environment

Unlike academic work that prioritizes accuracy, technical and surveillance literature highlights the importance of operational autonomy and regulatory endorsement. Currently, the market is divided into three archetypes: integrated OEMs (such as Zeiss or Topcon), independent AI/CDSS (such as EyeArt or Pegasus AI), and clinical risk calculators [13]. A key finding of this review compared to previous studies is the identification of commercial opacity: while 47% of patents detail their architecture (e.g., ResNet-34), more than 50% of commercial products are generically described as

‘proprietary AI’ [14], reflecting a transition from academic transparency to competitive confidentiality as products obtain FDA or CE mark certifications.

E. Telemedicine and Low-Cost Devices

The rise of tele-ophthalmology has been driven by networks such as EyePACS and Joslin Vision Network, which have operated for decades with human reading. However, recent literature highlights the emergence of hybrid models that use edge AI in portable devices (such as Remidio or Optomed), enabling offline diagnoses in less than a minute [15][16]. This review contributes by highlighting that, despite these advances, there remains a gap between the development of high-end algorithms and the affordability of devices for emerging economies.

MATERIAL AND METHODS

A. Research Process Phases

The study was structured in seven consecutive phases to ensure comprehensive data collection and analysis:

1. Planning and scope definition: Establishment of initial research questions and search criteria.
2. Information collection: Comprehensive search of scientific databases, patent repositories, and commercial catalogs.
3. Data analysis and processing: Application of statistical and qualitative techniques to interpret the collected data.
4. Evaluation of findings: Comparison of the advantages, disadvantages, and clinical applicability of the technologies identified.
5. Development of strategic recommendations: Development of an action plan based on the gaps and opportunities identified.
6. Preparation and presentation of the final report: Consolidation of results and technology maps.
7. Monitoring and advice: Continuous review and adjustment of the strategy based on institutional feedback.
8. Information Sources and Search Strategy

To ensure comprehensive coverage of all dimensions of the technological landscape (scientific evidence, patent development, and market/regulatory availability) the following sources were consulted. This multi-source approach explicitly extends the review beyond peer-reviewed literature to capture the full innovation pipeline, from laboratory research to commercial deployment:

- Scientific literature: Scopus, Web of Science, PubMed, IEEE Xplore, and arXiv.
- Patents: WIPO (Patentscope), Google Patents, Espacenet, and USPTO.
- Datasets and Software: GitHub, Kaggle, and Papers with Code.
- Commercial technologies: Manufacturer catalogs (e.g., Zeiss, Topcon, Optomed), technical data sheets, and regulatory databases (FDA, CE Marking).

The search strategy employed a tiered combination of control terms and keywords tailored to each database, organized into seven critical categories:

- Category 1: Image-based diagnosis of retinopathy using deep learning.
- Category 2: Diagnosis of retinopathy based on clinical data using machine learning.
- Category 3: Diagnosis of glaucoma based on clinical data using deep learning.
- Categories 4-5: CAD and CDSS systems applied to ophthalmology and glaucoma.
- Category 6: Telemedicine systems in ophthalmology.
- Category 7: Hardware technologies or mobile devices for diagnosis support.

B. Inclusion and Exclusion Criteria

Rigorous criteria were defined for the selection of material in order to maintain the technical focus of the study:

Inclusion Criteria:

- Sources published or registered between 2010 and 2024, covering the period of significant growth in deep learning applied to medical imaging. For commercial products and regulatory approvals, sources up to the date of data collection (2024) were considered regardless of original publication year.
- AI technologies specifically applied to ophthalmic diagnosis.
- Patents related to image algorithms, sensors, or devices.

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- Public datasets and technically accessible software tools.
- Validated commercial diagnostic equipment.
- Documentation in English and Spanish language.

Exclusion Criteria:

- Clinical studies without an AI or diagnostic technology component.
- Duplicate, inaccessible, or non-technical/unverified documents.
- Data Extraction and Synthesis of Results

The information was extracted using structured data matrices to normalize heterogeneous variables. The variables extracted included:

- Type of AI model and architecture (e.g., CNN, Vision Transformers).
- Image modality (Fundus, OCT, OCT-A, Multimodal).
- Technology readiness level (TRLs) and regulatory status (FDA/CE) [19].
- Dataset characteristics (geographic representation, size, and annotation type).

The synthesis was performed through an analysis of technological correlations and the creation of technology maps (heat maps and histograms) to visualize emerging trends and innovation gaps.

In accordance with the PRISMA-ScR guidelines [3], Figure 1 presents the flow diagram illustrating the identification, screening, eligibility, and inclusion process applied to all source types consulted in this study, namely scientific articles, patents, and commercial products. It is important to note that, unlike conventional scoping reviews limited to peer-reviewed literature, the present study extends its screening process to patent records and commercial product catalogs, in order to capture the full innovation pipeline from research evidence to market and regulatory availability.

The search across all databases and repositories yielded a total of 699 records (articles: 412, patents: 198, commercial products: 89). After removing 108 duplicates, 591 sources were screened by title and abstract, of which 341 were excluded for not meeting the inclusion criteria defined in Section 4.3. Full-text assessment was subsequently conducted for 250 sources; following this evaluation, 93 were further excluded due to inaccessibility, lack of technical content, or duplication of evidence. This process resulted in the final inclusion of 144 scientific articles, 67 patents, and 34 commercial products, which constituted the evidence base for data extraction and synthesis.

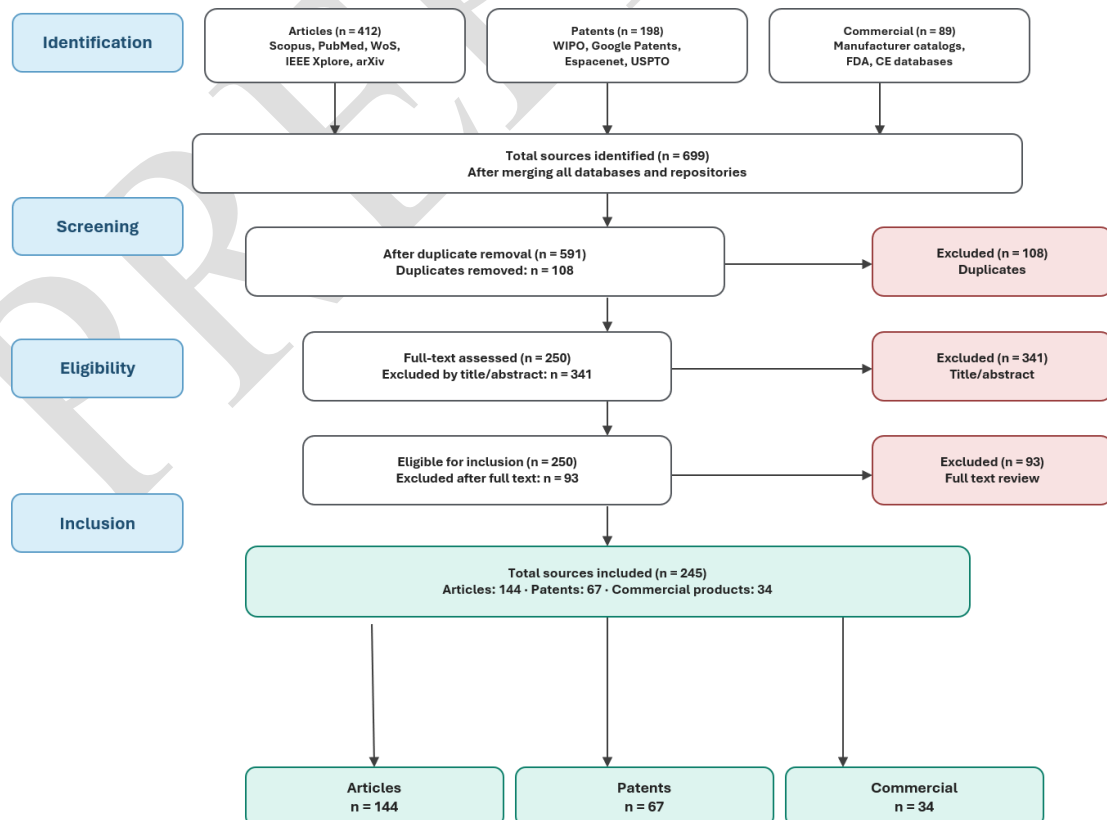


Figure 1. PRISMA-ScR flow diagram, source selection and screening process.

E. Availability of Materials and Ethical Considerations

In compliance with open science policies, all protocols, data matrices, and bibliographic annexes used in this study are available for public consultation. Information management is governed by Law 1581 of 2012 on data protection in Colombia, guaranteeing the anonymization of any sensitive data and respect for the intellectual property of the sources consulted. Approval from an ethics committee was not required for experimentation, as the study was based exclusively on secondary evidence and publicly available data.

RESULTS

A. Diagnosis of diabetic retinopathy (DR), Patent Analysis

Nineteen patent families (2010–2022) related to the diagnosis of DR using artificial intelligence were identified. The use of fundus images ($\leq 84\%$) predominated, with a minority presence of OCT and combined approaches. Although all patents declare the use of AI, only $\leq 53\%$ specify deep learning techniques, evidencing a progressive increase in technical transparency from 2020 onwards (Table 1, Figure 2).

TABLE 1. SUMMARY OF PATENTS ON DIABETIC RETINOPATHY.

Variable	Distribution	Key reading
Imaging modality	Fundus (majority), OCT (minority), combined	Fundus dominates population screening
Machine Learning technique	CNN/DL > Classical ML > Not Specified	Greater specificity post-2020
Severity grading	Partial	Approach still binary in many proposals
Telemedicine	Limited integration	Value not always explicit

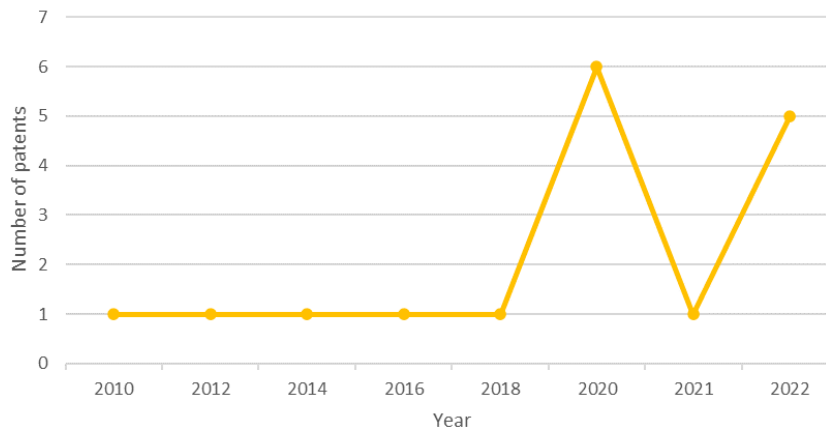


Figure 2. Temporal trend in patent applications for diabetic retinopathy (accelerated growth after 2018, consolidation in 2020).

B. Technological correlations in diabetic retinopathy patents

Consistent associations were observed between fundus and CNN, and between grading capacity and telemedicine-oriented solutions, suggesting that clinical scalability drives the inclusion of severity classification (Table 2).

TABLE 2. KEY CORRELATIONS IN DIABETIC RETINOPATHY PATENTS.

Correlation	Evidence	Interpretation
Fundus + CNN	High	Availability of public datasets
Fundus + Grading	High	Direct transition from ETDRS
CNN + Binary Detection	Frequent	Replication of screening objectives
Telemedicine + Grading	Moderate	Added value for triage

C. Commercial technologies in diabetic retinopathy

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Fifteen commercial solutions were analyzed, mainly image-based ($\leq 87\%$). Fully autonomous technologies concentrated grading capacity, and software algorithms showed greater market maturity compared to dedicated devices (Table 3, Figure 3 and 4).

TABLE 3. OPERATIONAL VARIABLES OF COMMERCIAL TECHNOLOGIES IN DIABETIC RETINOPATHY.

Dimension	Categories
Modality	Images / Data / Both
Autonomy	Yes / Partial / No
Grading	Yes / No
Market status	Commercial / Pilot
Technology type	Software / Platform / Device

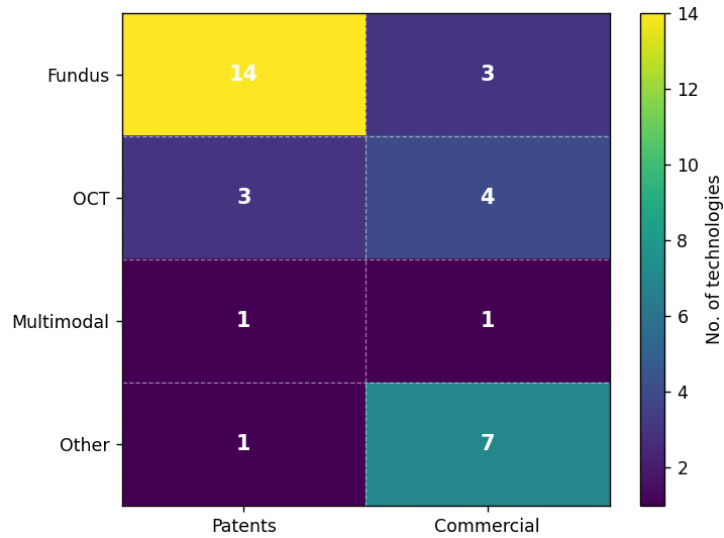


Figure 3. Distribution of imaging modalities by development stage (patent vs commercial).

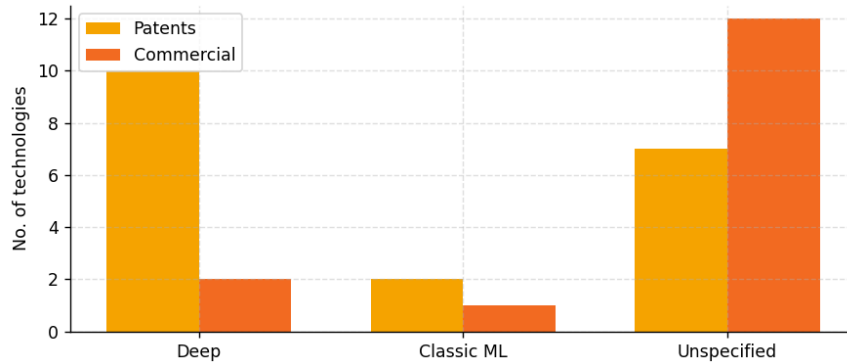


Figure 4. Algorithms declared in diabetic retinopathy: gap between academic transparency and commercial opacity.

D. Diabetic retinopathy based on clinical data (without images)

Data-only solutions are geared toward population risk prediction and, to a lesser extent, adapted severity classification. Logistic regression models, decision trees, random forests, and boosting are simpler to implement but have less diagnostic power than image-based approaches (Table 4).

TABLE 4. CORRELATION OF VARIABLES IN DATA-BASED DIAGNOSIS OF DIABETIC RETINOPATHY.

Technology	Key variables	Algorithm
ISDR Risk-Engine	Age, HbA1c	Logistic
Score DR-Pro	BP, BMI	Random Forest
HER-CDSS	Multivariable	Ensemble

E. Diagnosis of glaucoma, Image-based

Thirty-seven patents and 14 commercial products were identified. Fundus and OCT predominate in patents, while multimodality (fundus + OCT ± visual field) is emerging in the market, in line with the clinical need to assess structural and functional damage (Table , Figure 5).

TABLE 5. COMPARISON OF PATENTS AND PRODUCTS IN GLAUCOMA IMAGING.

Indicator	Patents	Commercial	
Use of DL	Majority	Majority	
Severity grading	≈ 67%	≈ 72%	
Declared autonomy	N/A	≈ 56%	
Regulatory endorsement	N/A	≈ 50%	

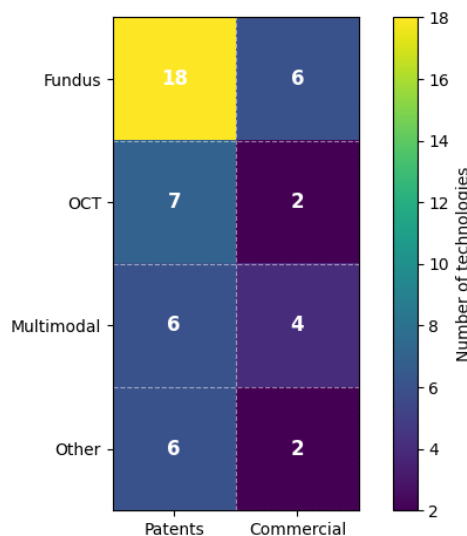


Figure 5. Heat map of imaging modality vs stage of development in glaucoma.

F. Glaucoma based on clinical data

Data-only solutions are scarce and focus on risk stratification (e.g., genetic or clinical scores). Detailed grading is associated with continuous phenotypic variables (IOP, C/D, PSD), while genetic models are limited to susceptibility (Table 6).

TABLE 6. DATA-DRIVEN GLAUCOMA TECHNOLOGIES.

Data type	Algorithm	Clinical use
Genetic (PRS)	GWAS + PRS	Risk
Clinical	Logistic regression	Risk + severity

G. Glaucoma commercial ecosystem

Solutions are grouped into integrated OEMs, standalone AI/CDSS, and clinical calculators, with differentiated regulatory pathways (Table 7).

TABLE 7. TECHNOLOGICAL ARCHETYPES IN GLAUCOMA.

Archetype	Modality	Grading	Status
Integrated OEM	Proprietary images	Yes	CE/FDA
Independent AI	Standard images	Yes	Emerging
Calculators	Tabular data	Yes (risk)	Not regulated

H. Telemedicine in ophthalmology

Twenty-one platforms were identified, with a strong focus on diabetic retinopathy. Image-based solutions and networks with human grading are the ones that consistently grade severity (Table 8, Figure 6).

TABLE 8. CORRELATIONS IN TELE-OPHTHALMOLOGY.

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Variable	Finding	Implication
Modality	Images > data	Enables grading
Regulation	Validated screening AI	Greater adoption
Focus disease	Predominant diabetic retinopathy	Financial viability

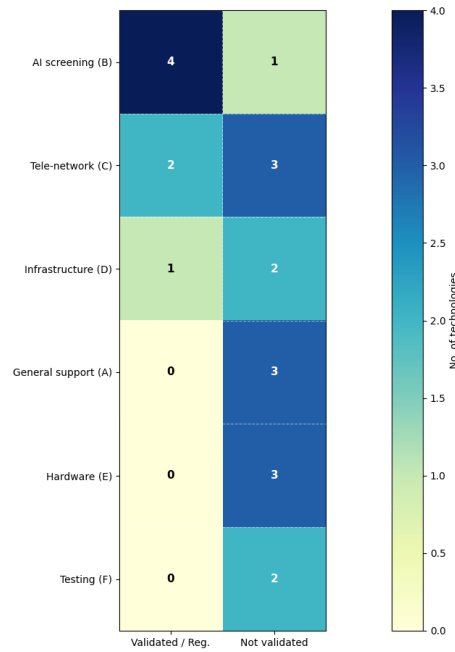


Figure 6. Telemedicine technologies with and without clinical validation.

I. Mobile hardware and datasets

Nineteen portable devices were analyzed, predominantly low-cost smartphone adapters. Only a minority integrate embedded AI, although almost all connect to cloud platforms (Table 9).

TABLE 9. MOBILE HARDWARE CHARACTERISTICS.

Dimension	Trend
Architecture	Dedicated cameras > adapters
Cost	Mostly low-cost
Native AI	Scarce
Telemedicine	Almost universal

Analysis of ophthalmic datasets showed a clear dominance of fundus for diabetic retinopathy, while glaucoma and AMD require integration with OCT (Figure 7).

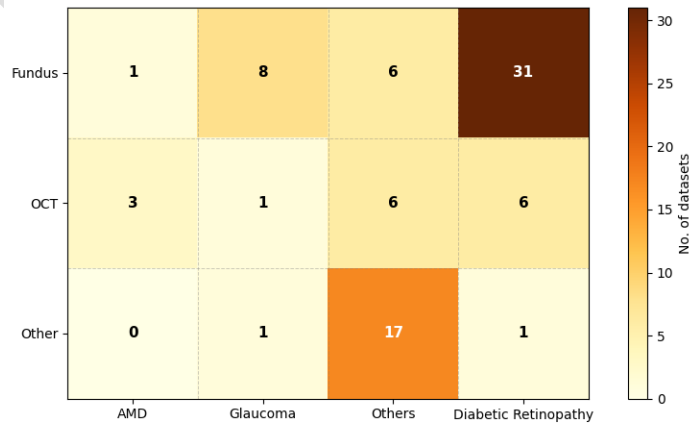


Figure 7. Image modality vs disease in ophthalmic repositories.

CONCLUSIONS

This study provides a comprehensive and multidimensional overview of the technological ecosystem of artificial intelligence (AI) applied to ophthalmic diagnosis, integrating scientific evidence, patent records, and commercial market reality for the first time. The findings confirm that the field has moved beyond the stage of purely algorithmic experimentation to enter a phase of commercial maturation and regulatory validation, evidenced by the existence of 34 medical devices and multiple solutions with FDA approval and CE marking, such as IDx-DR and EyeArt [4][5][6]. However, this transition is not uniform and reveals critical asymmetries that must be addressed to achieve equitable global impact.

One of the main conclusions is the existence of an accessibility and affordability gap that disproportionately affects emerging economies. Despite advances in the accuracy of deep learning models, most high-end commercial technologies remain expensive and rely on complex infrastructure, limiting their adoption in low-resource contexts such as Latin America. However, a strategic opportunity has been identified in the development of low-cost portable devices with native AI ("edge computing"), which allow for offline diagnostics and reduce dependence on broadband connectivity in rural areas.

In terms of data and representativeness, the study highlights a worrying homogeneity in public datasets, which are biased towards populations in Asia, Europe, and the United States. For researchers and developers in our region, the creation of specifically Latin American ophthalmic image repositories arises not only as an ethical necessity to reduce algorithmic biases, but also as an opportunity for innovation to improve the clinical validity of local diagnostic tools. Likewise, the future of the discipline depends on the transition to multimodal systems that integrate fundus with OCT-A and the implementation of explainable AI (XAI) to increase clinical confidence [17][18], essential factors for ensuring patient safety.

Finally, this work demonstrates that the methodological integration of scoping reviews and technology watch constitutes a replicable and robust framework for mapping emerging medical technologies. The implications of this study suggest that the success of AI in visual health will depend not only on the power of algorithms, but also on the ability to integrate these tools into hybrid telemedicine models that combine the efficiency of AI with expert supervision, adapting to local regulatory and economic realities.

AUTHOR CONTRIBUTION

Andrés Lowis Torregroza: Conceptualization, Investigation, Writing—original draft, Writing—review and editing.

Eugenia Arrieta Rodríguez: Methodology, Formal analysis, Writing—review and editing.

Kevin Velásquez Gutiérrez: Data curation, Visualization, Writing—review and editing.

María Claudia Bonfante: Supervision, Project administration, Writing—review and editing.

The authors reviewed the results and approved the final version of the article.

CONFLICT OF INTERESTS

The authors declare that they have no interests or financial relationships that could have influenced this work.

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