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Beyond Visual Acuity: Imaging Technologies, Functional Vision, and Future Clinical Workflows for Low Vision Care

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Abstract

Low vision significantly affects daily functioning and quality of life, yet clinical assessment and rehabilitation planning often remain fragmented. This narrative review examines current structural and functional assessment technologies used in low vision care, including fundus photography, optical coherence tomography, visual field testing, microperimetry, and electrophysiological testing, as well as emerging applications of artificial intelligence, tele-ophthalmology, and home-based monitoring. Particular emphasis is placed on the limitations of relying on visual acuity alone and the importance of integrating structural findings with functional vision assessment. We also discuss barriers to implementation, including technology access and data integration, and propose a unified clinical workflow connecting diagnostic assessment, functional testing, rehabilitation planning, and longitudinal monitoring. Greater integration of these components may support more personalized and patient-centered low vision care.

Categories: Ophthalmology
Keywords: artificial intelligence, low vision, low vision rehabilitation, ophthalmic imaging, tele-ophthalmology

Introduction And Background

Low vision is a growing global health concern that significantly affects functional independence, psychosocial well-being, and quality of life. Low vision is a medical condition defined by a permanent reduction in visual function that cannot be corrected through optical, medical, or surgical interventions [1]. Common causes include macular degeneration, diabetic retinopathy, and glaucoma, particularly in older adults [1,2]. Low vision significantly interferes with everyday activities, including reading, facial recognition, mobility, driving, and digital interaction [3]. Therefore, traditional clinical measures and diagnostics for this condition often fail to capture the exact degree and extent of the visual disability and lived experience of the patient. While low vision has been categorized as an irreversible condition, ophthalmic assessments have made it possible to achieve an accurate diagnosis alongside targeted intervention [4].

Over the past two decades, advances in ophthalmic imaging and functional diagnostic testing have improved the ability to detect retinal and optic nerve diseases [5]. Technologies such as optical coherence tomography (OCT), OCT angiography, perimetry, microperimetry, fundus-tracked microperimetry, and electrophysiology provide complementary structural and functional information that can better guide diagnosis and rehabilitation [6]. These technologies have completely transformed the ability to characterize and identify structural and physiological changes in the visual system [5,7,8]. The combination of modalities has shown the complex and non-linear nature of retinal structure with functional impairments and visual challenges.

More recently, artificial intelligence (AI), multimodal analytics, tele-ophthalmology, and portable home-based imaging systems have emerged as promising tools to improve detection, monitoring, and access to care [9]. Researchers have shown that when AI is implemented into technologies such as fundus photographs, OCT scans, and visual field tests, it has demonstrated high sensitivity, specificity, and accuracy for detecting various ophthalmic diseases [10-12]. Newer multimodal AI systems can improve prediction of disease severity and progression by integrating structural and functional data [5,7,13]. Simultaneously, the development of more affordable and portable imaging tools, like at-home-based and patient-operated OCT devices, has helped make eye care more accessible and continuous [6,14]. With more patient-centered models, there is potential to reduce the need for frequent clinic visits and allow changes in structure and function to be more closely followed and detected earlier.

Despite advances in ophthalmic imaging, clinical care continues to rely heavily on visual acuity as the primary measure of vision. Visual acuity alone often fails to reflect how patients function in the real world. Individuals with measured 20/20 acuity may still experience disabling contrast sensitivity loss, severe floaters, visual field restriction, impaired mobility, reading difficulty, or driving limitations. For example, patients with severe vitreous floaters may report major visual disturbance despite normal acuity, while individuals with advanced glaucoma or retinitis pigmentosa may retain central 20/20 vision despite profound peripheral field loss that limits driving and safe navigation. This disconnect highlights an important limitation in traditional ophthalmic assessment.

High-contrast best-corrected visual acuity (BCVA) remains essential for diagnosis and monitoring, but it does not capture the full range of functional impairment. In a nationally representative sample of 2,951 older US adults, contrast-sensitivity impairment was associated with recurrent falls (20.8% versus 14.7%; adjusted prevalence ratio 1.30, 95% CI 1.01-1.67) and recent falls (17.1% versus 9.9%; adjusted prevalence ratio 1.40, 95% CI 1.01-1.94), whereas distance and near acuity were not significantly associated with falls [15]. In 153 drivers with glaucoma, those reporting a motor-vehicle collision had similar visual acuity to those without a collision but had worse binocular standard automated perimetry sensitivity and contrast sensitivity; binocular perimetry discriminated collision history with an area under the curve of 0.69, compared with 0.80 for a low-contrast divided-attention driving-simulator task [16].

Macular disease also produces measurable deficits despite preserved letter acuity. Among 151 eyes with maculopathy and visual acuity of 20/30 or better, the area under the log contrast-sensitivity function was lower than in 93 control eyes (adjusted beta -0.174; $p<0.001$), with the largest losses at low and intermediate spatial frequencies [17]. In a prospective study of 100 patients with center-involving diabetic macular edema, retinal sensitivity contributed most strongly to five of ten RetCAT quality-of-life domains, whereas BCVA was the dominant predictor only for driving [18]. Together, these findings support a multidimensional assessment that combines acuity with contrast sensitivity, visual field or retinal-sensitivity mapping, task-based measures such as reading speed, and patient-reported outcomes.

Even with these technological advancements, low vision care is often fragmented due to imaging data, functional testing, and rehabilitation planning often being handled independently [19,20]. Imaging and functional data are not often properly utilized to guide decisions such as device selection, training tactics, or long-term follow-up, despite evidence demonstrating that low vision rehabilitation is most effective when therapy is tailored and involves a multidisciplinary team [21]. Furthermore, challenges, including inadequate system compatibility, a lack of standardized data, difficulties with workflow, and unequal access to technology, particularly in settings with limited resources or communities, continue to restrict the practical application of these cutting-edge solutions [22,23].

Accordingly, there is a clear need for a more integrated and technology-based approach to low vision care. This narrative review examines current and emerging imaging modalities, identifies workflow gaps, and proposes a clinical framework that better connects diagnosis, functional assessment, and rehabilitation planning. An integrated approach could support more efficient and individualized care for people with impaired vision, assist doctors in making more informed decisions, and establish a closer link between structural results and functional outcomes [5,19,24]. While this review focuses on patients with low vision, these limitations extend beyond this population as functional impairment may also exist beyond this population and in patients with clinically normal acuity.

Objectives

This review aims to examine the imaging and functional assessment tools that are commonly used in low vision care and discuss how they contribute to diagnosis and rehabilitation planning. Particular attention is given to technologies such as OCT, visual field testing, microperimetry, and electrophysiological testing. The review also explores how imaging findings and functional vision measures are currently used in clinical practice and highlights areas where these data are not fully incorporated into rehabilitation decision-making. In addition, emerging technologies, including AI, tele-ophthalmology, and home-based imaging systems, are discussed for their potential to improve detection, monitoring, and long-term management of low vision. Finally, the review examines barriers to implementation and proposes a clinical framework that better connects imaging, functional assessment, and rehabilitation to support more individualized patient care.

Review

Review methodology

This narrative review was conducted using literature related to low vision, ophthalmic imaging, functional testing, rehabilitation, and newer technologies used in vision care. Searches were conducted using PubMed and Google Scholar, with a primary focus on articles published between 2015 and 2026. Earlier studies were also included when they provided important background or foundational information related to low vision assessment and rehabilitation. Search terms included combinations of “low vision,” “low vision rehabilitation,” “ophthalmic imaging,” “fundus photography,” “optical coherence tomography,” “OCT,”

"OCT angiography," "visual field," "microperimetry," "electrophysiology," "artificial intelligence," "telemedicine," and "remote monitoring."

Articles were selected based on their relevance to the technologies and clinical applications discussed in this review. Studies were included if they discussed structural imaging, functional vision assessment, low vision rehabilitation, or newer technologies that could have a potential role in low vision care. Articles that were not related to ophthalmology or visual function or did not have a clear application to the topics discussed in this review were excluded. Additional articles were found by reviewing the references of relevant publications, and other relevant studies were also identified by the authors during the development of the review.

The selected literature was reviewed and organized based on the main areas discussed throughout the paper, including structural imaging, functional and physiological assessment, rehabilitation, AI, and remote monitoring technologies. The findings from these areas were then compared to better understand how structural and functional information could be used together in low vision care. Since this was a narrative review, the purpose was to provide an overview of the available technologies and their potential clinical applications rather than perform a systematic review or meta-analysis.

Background

Low Vision and Clinical Needs

Beyond reduced visual acuity, patients with low vision may experience decreased contrast sensitivity, visual field loss, poor fixation stability, and difficulty adapting to low-light environments [25,26]. For example, patients with age-related macular degeneration often develop blind spots that severely affect reading and facial recognition [8,27]. Patients diagnosed with glaucoma often still have preserved visual acuity despite peripheral visual field loss that may impair mobility [26,28]. In inherited retinal diseases such as retinitis pigmentosa, progressive "tunnel vision" causes vision to become significantly limited to a very small field [29]. These impairments often affect daily tasks such as reading, navigating new and unfamiliar places, recognizing faces, or using digital devices [30].

Clinical needs vary widely depending on disease type, pattern of vision loss, and individual lifestyle demands. Effective diagnosis, treatment planning, and rehabilitation therefore often require more than just a basic health exam. To provide more personalized care that is tailored to an individual's specific stage of low vision, comprehensive testing including a combination of structural imaging, functional testing, and an understanding of low vision's impact on daily activities is required [31]. Imaging modalities such as OCT have been able to identify retinal and optic nerve changes more accurately, while functional tests such as visual fields, contrast sensitivity testing, and microperimetry could help explain the structural changes that cause the specific vision challenges [6,11,26,27,32]. Microperimetry provides complementary information about retinal sensitivity, fixation location, and fixation stability that is associated with reading performance in macular disease. In a cohort of 120 people with visual impairment, reading speed was associated with the proportion of fixation points within 2 degrees (r-squared 0.51; $p<0.001$) and with bivariate contour ellipse area measures of fixation stability (r-squared up to 0.39; $p<0.001$) [33]. These relationships were strongest in selected patterns of central or peripheral loss and should be interpreted with visual acuity, scotoma geometry, print size, oculomotor control, cognition, and use of magnification. Microperimetry can therefore help explain reading difficulty and guide preferred-retinal-locus training, but it should not be used as a stand-alone predictor of reading speed. Other studies in glaucoma have shown that defects in the visual fields are associated with higher fall risks and a slower walking speed, while contrast sensitivity has been associated with mobility tasks such as driving performance.

Optimizing functional vision in low vision patients plays an important role in helping patients maximize their remaining visual abilities. The process of rehabilitation would include various optical and electronic assistive devices, lifestyle and environmental modifications, and training to improve practical and functional performance of the devices in combination with the environment [34]. Creating a rehabilitation program tailored to an individual and supported by a medical multidisciplinary team has been shown to help improve independence for many patients with low vision [35]. However, the first and most critical step in providing an effective rehabilitation program is obtaining an informed, accurate, and comprehensive diagnosis informed by clinical data that shows changes in the structure of the eye and its functional ability.

Current Gaps

Although there have been significant advancements in imaging technology and functional vision tests, there are still large gaps in the way that low vision care is both addressed and delivered [36]. A first major issue is the lack of integration between the different testing modalities, such as diagnostic imaging, functional tests, and rehabilitation planning [20,37]. With each patient, including their imaging and functional assessments, being reviewed individually rather than as a comprehensive whole, linking diagnostic findings to rehabilitation planning remains challenging [38,39]. The lack of connection between each of these individual components often limits the ability to translate clinical data into a personalized intervention plan

[36].

Another challenge for low vision is the lack of use of advanced functional testing technology like microperimetry and detailed contrast-sensitive testing within the progressive low vision care plan. Both technologies can provide valuable information regarding retinal sensitivity and preferred retinal loci; however, they often get excluded from care plans due to time constraints, cost, and the clinical standardization of these tests [8,26]. Clinicians often continue to rely heavily on visual acuity despite its limited ability to predict real-world visual performance. Measures such as contrast sensitivity and visual field testing frequently correlate more strongly with mobility, fall risk, reading ability, and driving safety [24]. This creates an issue, as deficits in visual acuity are poorly correlated with deficits in real-world task performance, whereas contrast sensitivity and visual field measures have been shown to better predict mobility, fall risk, and driving ability [40,41].

Disparities in access to comprehensive low vision care and diagnosis exist at multiple different levels, specifically geography, socioeconomic status, and the structure of an individual's corresponding healthcare systems [23,42,43]. Studies have shown that many individuals with moderate to severe levels of low vision never received a proper rehabilitation plan, partially due to having never been referred even when functional needs were clearly present [44]. Challenges of provider availability, limited insurance for imaging and testing, and logistical challenges of transportation and mobility to receiving care have contributed to more polarized gaps [44]. Devices like micro perimeters, OCT angiography systems, and eye-tracking platforms are extremely costly and require specialized training by a professional, making them harder to use as a primary resource for both diagnosis and care [45]. This results in patients in community clinics receiving general diagnostics with structural information without a specific and detailed functional explanation behind their low vision [46]. Data have shown that low vision rehabilitation services are disproportionately used by patients who have better access to multidisciplinary healthcare services in comparison to underserved populations [21,44]. The lack of function information then translates into a less personalized care plan. The implementation of telemedicine calls in the healthcare field throughout COVID-19 has helped address some of these gaps but not consistently [47]. Even with the accessibility promise of tele-med, some patients may not have the right tools for it or know how to use it. Further advancements in technology risk making the inequalities even greater than they currently are if systems that connect imaging, functional data, and rehabilitation don't become scalable and accessible [48,49].

Equity requires a delivery model that places basic assessment closer to the patient while preserving specialist oversight. Trained technicians or optometrists can obtain visual acuity, Pelli-Robson contrast sensitivity, fundus photographs, selected OCT scans, and a brief patient-reported outcome measure in primary-care or community settings. Images and test results can then be reviewed asynchronously by ophthalmology or low-vision specialists using predefined image-quality thresholds and escalation criteria. In a cluster-randomized trial in Kenya, a smartphone-supported community eye-health pathway increased attendance for confirmed eye problems from 522 to 1,429 per 10,000 population, a rate difference of 906 per 10,000 (95% CI 689-1,124; p<0.0001) [50]. Task sharing should include competency assessment, periodic supervision, accessible patient instructions, and a direct route for urgent in-person examination.

Referral alone is insufficient. Low-vision services should be co-located with ophthalmology or embedded in community health centers when possible, with patient navigation for scheduling, transportation, language access, and device acquisition. In an EHR-based implementation study, on-site low-vision service was associated with twice the odds of service use after referral (adjusted odds ratio 2.06, 95% CI 1.18-3.61), and utilization among eligible patients increased from 6.1% before the decision-support intervention to 13.8% during implementation [51]. EHR prompts should therefore connect directly to scheduling and record functional goals, test results, device recommendations, and follow-up status rather than merely flagging eligibility.

While access and multidisciplinary communication are two of the largest gaps in the diagnosis and treatment of low vision, there are other gaps and challenges such as a limited integration of information between imaging division and the EHR (electronic health records), inconsistent clinical and data standards, and workflow difficulties that make it difficult to attain interdisciplinary communication [22].

Current structural imaging and functional assessment modalities for low vision

The type of imaging technology being used plays an important role in the diagnostic and management of low vision by helping clinicians identify structural damage within the eye and understand how the structural damage is related to the functional vision loss. Currently, there are many different imaging tools used in clinical practice for diagnosis [52]. Each different type of device provides different information that can help contribute to the low vision patient evaluation and rehabilitation planning [34].

Structural Imaging Modalities

Fundus photography: Fundus photography is an imaging modality that uses a specialized retinal camera to

obtain colored 2D images of the back of the eye, including the retina, optic disc, and blood vessels [12,53-55]. It can allow clinicians to visualize features like macular degeneration, hemorrhages, glaucoma, retinal scars, etc. For patients with low vision, fundus photography is a valuable tool that can help document how the disease has progressed over time in comparison to the baseline record of the disease [56]. While fundus photography is a valuable exam for an overall understanding of the retinal structure, it does not provide enough depth resolution of microstructural changes [55,56]. Therefore, it is typically used in combination with other eye exams rather than alone.

Optical coherence tomography: OCT is another ophthalmic imaging technique that uses “low-coherence interferometry with near-infrared light” to create cross-sectional images of the retina with high resolution [57-59]. OCT exams show a very detailed visual of the retina including layer thinning or thickening, macular atrophy, and retinal nerve fiber loss. This is because OCT technology uses the echo delay of light within the retina to reconstruct tissue structure at a tiny resolution [58]. For patients with low vision, OCT images can help identify structural abnormalities in specific retinal layers and correlate these findings with functional visual deficits. For example, OCT can explain and show how damage to the photoreceptors is often associated with central vision loss, whereas glaucoma is described by nerve fiber layer thinning and peripheral vision loss [11,28]. OCT has therefore been a very useful tool for helping clinicians understand the extent of the structural damage and support rehabilitation plans.

Optical coherence tomography angiography (OCT-A): OCT-A simply builds on OCT technology but has an additional component that shows blood flow within the retina and choroid [60,61]. These kinds of tests can help reveal any areas of reduced blood flow or abnormal vessel growth [60,62]. For low vision patients, OCT-A becomes useful when understanding why one's visual field worsens when there are few structural changes. In vascular diseases, where there is limited and reduced blood flow supply, functional vision loss does not always come with structural malformations [63]. Many times, the retinal layers may even appear stable. OCT-A therefore provides additional information into how retinal and choroidal vascular health can also affect visual structure.

Functional Vision and Physiological Assessment

Structural imaging provides important information about retinal anatomy, but structural findings alone may not fully explain a patient's functional vision loss. Functional and physiological assessments provide complementary information by measuring visual performance or physiological responses within the visual system.

Visual field testing: Visual field testing is often used to simply measure how well a person can see across their field of vision [26,64]. This test uses automated perimetry, which presents different light stimuli at different locations while the patient keeps their eyes fixated in front of them [65]. The different lights flash and then create a map with areas that have reduced or missing vision [65,66]. This form of test is especially important for patients with conditions like glaucoma, retinal degeneration, and even neurological disorders, as visual field loss significantly affects safety, mobility, and independence [29]. Low vision rehabilitation and care often includes and refers to visual field tests to help quantify the functional limitations that influence a patient's daily life. The test, however, is very dependent on the patient’s cooperativity, which can sometimes limit its findings [65,66].

Microperimetry: Another technology used for low vision care is microperimetry, which uses fundus images and real-time eye tracking to project light stimuli onto specific areas of the retina while keeping the eye fixated [8,27]. Microperimetry works to connect retinal structure precisely with functional vision and helps evaluate fixation stability. Microperimetry also helps clinicians measure how sensitive the retina is at different points and determines the patient's preferred retinal loci (PRLs) [8,32]. Clinicians often value microperimetry for patients with low vision because it shows which parts of the retina are still functioning and usable in visual tasks [27,67]. It can help guide different aspects of the rehabilitation plan such as PRL training, reading strategies, and assistance placement [25,68]. By combining structure and function directly, microperimetry helps create a more personalized rehabilitation process [27].

Microperimetry should not, however, be presented as a universal replacement for standard automated perimetry. In a prospective glaucoma study including 60 glaucoma eyes and 45 control eyes, macular sensitivity measured with microperimetry and standard automated perimetry showed similar structure-function relationships with ganglion cell-inner plexiform layer thickness on OCT [69]. Test-retest reliability also varies according to the outcome being analyzed. In 50 patients with macular disease tested twice with the Nidek MP1, the coefficient of repeatability was 1.81 dB for mean retinal sensitivity, compared with an average of 5.56 dB for pointwise sensitivity across individual loci [70]. This greater pointwise variability means that small changes at a single retinal location should be interpreted cautiously, and longitudinal follow-up should ideally use the same device, stimulus grid, and testing strategy.

Clinically, microperimetry is most useful when precise central structure-function mapping is likely to change management, such as defining a central scotoma, assessing fixation stability, identifying a preferred retinal locus (PRL), or following localized macular function alongside OCT. These findings may also inform

eccentric-viewing or preferred-retinal-locus training when appropriate. Important limitations include longer testing time, specialized equipment, learning and fatigue effects, and incomplete comparability between devices and protocols. Microperimetry should therefore be used selectively as a complementary functional test when its spatial information is expected to improve interpretation or rehabilitation planning rather than as a routine requirement for every patient with low vision.

Electrophysiological testing: Electrophysiological tests use electrodes to measure the electrical responses of retinal cells (ERG) or how the visual cortex responds to light stimuli [71]. These tests help assess photoreceptor activity, inner retinal function, and signal transmission through the visual pathways [72]. They are particularly helpful when structural imaging does not clearly explain a patient's visual loss [72]. While not yet a routine part of low vision diagnosis and care, they can provide valuable functional information that complements visual field data (Table *1*).

Modality	Structural Information	Functional Relevance	Limitations	Clinical Utility
Fundus Photography	Provides 2D images of the retina, optic disc, and retinal blood vessels.	Allows structural findings to be considered alongside changes in visual function.	Limited depth resolution and ability to identify microstructural changes.	Documents retinal appearance and disease progression over time; useful as a baseline record.
OCT	Provides high-resolution cross-sectional images of retinal layers, including retinal thinning, thickening, macular atrophy, and nerve fiber loss.	Helps relate damage in specific retinal layers to functional deficits, such as photoreceptor damage with central vision loss.	Primarily evaluates retinal structure and does not directly measure visual function.	Identifies and monitors structural abnormalities and supports low-vision evaluation and rehabilitation planning.
OCT-A	Visualizes retinal and choroidal vasculature and areas of reduced blood flow or abnormal vessel growth.	May help explain functional vision loss when structural retinal changes are limited or appear stable.	Provides vascular information rather than a direct measure of visual function.	Adds information about retinal and choroidal vascular health, particularly in vascular disease.
Microperimetry	Uses fundus imaging to identify specific retinal locations during testing.	Directly measures retinal sensitivity, fixation stability, and preferred retinal loci (PRLs).	Requires patient participation and stable fixation/eye tracking for testing.	Connects retinal structure with function and can guide PRL training, reading strategies, and individualized rehabilitation.
Electrophysiological Testing	Provides limited direct structural information.	Measures electrical responses of retinal cells or visual cortical responses to light stimuli.	Not routinely used as part of low vision diagnostic and rehabilitation care.	Helps assess photoreceptor, inner retinal, and visual pathway function when structural imaging does not clearly explain visual loss.

TABLE 1: Comparison of Structural Imaging and Functional Assessment Modalities Used in Low Vision

This table was designed using data from [8,11,12,25,27,28,32,53-68,71,72]

OCT: Optical coherence tomography; OCT-A: Optical coherence tomography angiography

Within a low-vision workflow, electrophysiology should therefore be considered a condition-specific investigation rather than a routine baseline test. ERG and/or visual evoked potentials are most valuable when there is unexplained visual loss, suspected inherited retinal dysfunction, suspected rod-cone dysfunction, possible optic-nerve or post-retinal disease, or a substantial mismatch between the patient's measured function and the structural appearance of the eye. Framing electrophysiology in this way clarifies that its purpose is to localize or characterize otherwise unexplained dysfunction rather than to replace standard imaging or functional testing.

Future/emerging imaging and technological frameworks

New technologies are constantly evolving and are now starting to change how low vision can be detected, monitored, and managed. With improvements in AI, telemedicine, and portable imaging devices, eye care

has shifted to become more continuous, data-driven, and patient-centered. The development of these future technologies can help close existing gaps within diagnostics, monitoring, and rehabilitation, especially for patients who have limited access to healthcare.

Artificial Intelligence in Ophthalmology

As AI systems progress, they are being used in medicine and ophthalmology more and more to analyze imaging and functional data [73]. AI systems that are based on machine and deep learning are now trained to manage and analyze large data sets of different kinds of vision technologies such as fundus photographs, OCT scans, and visual field tests [73-75].

Artificial intelligence has demonstrated strong performance for selected ophthalmic screening tasks, but these results should be presented with the specific disease and testing context rather than described broadly as "high accuracy." In a prospective multicenter study of 893 patients with diabetes, the EyeArt autonomous system evaluated diabetic retinopathy severity from fundus photographs. Using the undilated protocol, the system detected more-than-mild diabetic retinopathy with 95.5% sensitivity (95% CI, 92.4%-98.5%) and 85.0% specificity (95% CI, 82.6%-87.4%). For vision-threatening diabetic retinopathy, sensitivity was 95.1% (95% CI, 90.1%-100%) and specificity was 89.0% (95% CI, 87.0%-91.1%). The proportion of eyes that could be graded increased from 87.4% without dilation to 97.4% with a dilate-if-needed protocol [10]. These findings support AI for a defined retinal-screening task, but they do not establish equivalent performance for low-vision rehabilitation decisions.

Performance also depends on the imaging modality and how a model is validated. A 2024 systematic review and meta-analysis of 53 studies evaluating AI for detection of diabetic macular edema found a pooled area under the receiver operating characteristic curve of 0.964 for fundus-photograph models, with 92.6% sensitivity and 91.1% specificity. OCT-based models had a pooled area under the curve of 0.985, with 95.9% sensitivity and 97.9% specificity [76]. The same review reported better performance with internal than external validation, while models trained on multiple datasets performed better during external validation. These findings highlight the importance of evaluating algorithms across new devices, institutions, and populations rather than assuming that performance in a development dataset will generalize directly to clinical practice.

For low vision in particular, the use of AI has the potential to help clinicians go above and beyond in the diagnostics and care decision-making process. AI models can integrate structural imaging and functional data, allowing them to improve prediction of disease severity and progression [77,78]. These systems can serve as support tools for physicians making decisions on large amounts of data in a more efficient manner. However, several limitations should be considered before AI systems can be widely integrated into ophthalmic and low vision care. AI performance depends heavily on the quality and diversity of the datasets used for training, which can introduce bias and affect how well models perform across different patient populations, imaging devices, and clinical settings [20,38,47]. For this reason, external validation across diverse populations and multiple clinical centers, as well as prospective testing and continued monitoring after implementation, are important before these systems are broadly used in clinical practice [20,38]. AI systems have already been evaluated for autonomous detection of diabetic retinopathy, demonstrating the growing clinical and regulatory role of AI in ophthalmology [10]. However, AI applications specifically designed for low vision assessment and rehabilitation remain much less established. In addition, patient privacy, data security, and integration with existing electronic health record and imaging systems remain important challenges for clinical implementation [19,20,38]. Further validation and careful integration are therefore needed as these technologies continue to develop.

Tele-Ophthalmology and Remote Monitoring

One major advance in the field of medicine has been the use of telehealth as a form of communication. Tele-ophthalmology involves delivering eye care to patients remotely by obtaining data through different mediums (community clinics, primary care centers, or at home) and having it reviewed by specialists elsewhere [47,79]. The option of tele-ophthalmology has greatly improved access to care for patients who aren't able to travel to certain clinics, live in remote areas, or even simply require frequent monitoring [47].

Tele-ophthalmology has become a valuable tool for low vision patients, as remote monitoring tools may help detect structural or functional vision changes earlier than waiting for routine visits [80]. Platforms that can assess visual function, changes in symptoms, and visual performance continuously can help provide information in between appointments. Having such tools accessible may eventually reduce delays in identifying how the condition progresses and allow for adjustments to be made to the care plan much earlier [81,82].

Evidence for telerehabilitation in low vision is developing but remains more limited than the evidence supporting tele-ophthalmology for disease screening. A 2023 Cochrane review found only one completed controlled trial that indirectly met its eligibility criteria, involving 57 participants, and rated the certainty of evidence for all evaluated outcomes as very low because of risk of bias, missing data, and imprecision [83].

The review therefore did not support broad conclusions about equivalence between remote and conventional low-vision rehabilitation. This distinction is important because evidence that retinal images can be acquired remotely and graded by a specialist does not by itself demonstrate that every component of rehabilitation can be delivered effectively at a distance.

More recent randomized evidence provides stronger support for remote device training. In a multicenter trial, 61 adults with visual impairment were randomized after receiving new portable electronic, handheld, or stand optical magnifiers; 47 completed the study. From one to four months, after magnifier training, reading ability improved by 0.44 logits in the telerehabilitation group (95% CI, 0.08-0.80; P=0.018) and by 0.43 logits in the in-office group (95% CI, 0.15-0.71; P=0.003), with no significant difference between groups across follow-up (P=0.73) [84]. These findings support telerehabilitation as an alternative delivery method for magnifier training and related follow-up in appropriately selected patients, while avoiding the stronger claim that all low-vision services can be replaced by remote care.

A practical model is therefore hybrid rather than exclusively remote. History review, rehabilitation goal review, selected patient-reported outcomes, device-use coaching, and follow-up of previously prescribed magnification may be appropriate for telehealth when the patient can access and use the required technology. In contrast, examinations that depend on direct ocular assessment or specialized instrumentation, including precise refraction, slit-lamp or dilated examination, microperimetry, electrophysiology, or evaluation of acute and unexplained visual change, generally require in-person care. Remote pathways should also include clear escalation criteria when testing is unreliable or when symptoms and available measurements do not agree. This approach uses tele-ophthalmology to extend access without treating it as a substitute for examinations that cannot be reproduced adequately outside the clinic.

Portable and Home-Based Imaging Technologies

Technological advancements have also led to the development of portable and at-home imaging devices that can be used outside of a typical eye clinic [82,85,86]. Some of these devices include fundus cameras, smartphone-based retinal imaging systems, and patient-operated OCT devices. With the technologies being accessible from at home, continuous imaging and more frequent monitoring of disease progression become possible.

Having access to at-home imaging could help patients with low vision track structural changes in the eye over shorter periods of time without requiring frequent visits to the ophthalmologist [6,82]. This becomes especially helpful for patients who have limited mobility or for patients living in remote locations. Portable devices could also become a large support for underserved communities where there is limited access to imaging technology and equipment [87,88].

Challenges and Future Directions

Although many technologies have emerged with potential benefits, several challenges still prevent their full integration into low vision care [20,89]. A major challenge is a lack of communication between the different testing systems, electronic health records, and imaging devices, making it difficult to integrate information from multiple diagnostic modalities into a unified clinical assessment [19]. Other barriers that have an impact are cost and access to such technologies [20,89,90]. Certain tools may not be available in all clinics and may require clinicians to receive additional training on how to use and interpret these technologies effectively [86]. As AI becomes more involved in inpatient care, the concern of ethical considerations and security is becoming a growing challenge [91]. Future directions for care of low vision patients will be dependent on future abilities to create systems and frameworks that are able to connect imaging, functional tests, and rehabilitation all in one place [92]. Future goals should look at creating integrated workflows that focus on continuous monitoring, personalized treatments, and improved functional outcomes, rather than creating one individual device for each component [93].

Proposed clinical workflow framework

Currently, care plans for low vision often separate the imaging processes, functional testing, and rehabilitation, making it more difficult to develop informed clinical decisions. Using the technologies discussed, a more integrated approach that uses different devices within the same diagnostic and testing could help connect structural and functional findings with a unified assessment pathway. This would be beneficial in creating rehabilitation plans that are tailored to each individual patient. The framework proposed below outlines a step-by-step approach to how low vision can be managed in a way that combines the three components of imaging, functional tests, and continuous monitoring through easily accessible devices (Figure *1*).

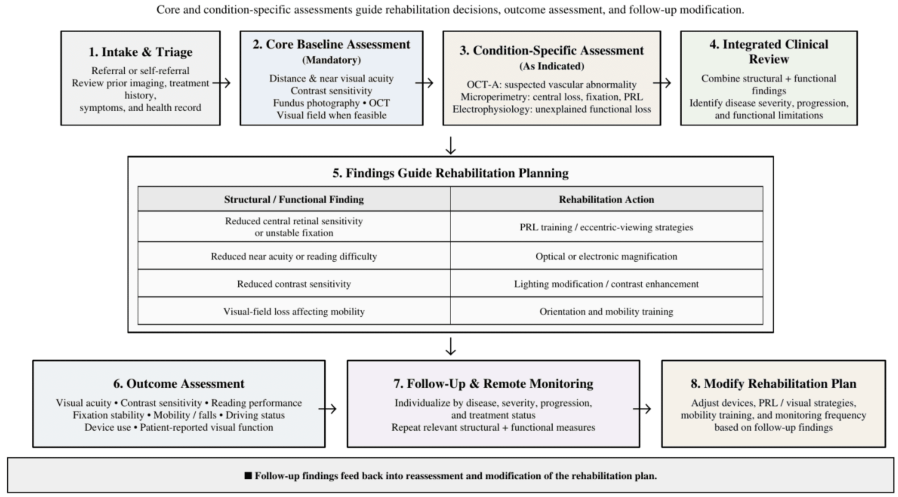


FIGURE 1: Proposed Integrated Clinical Workflow for Low Vision

Proposed integrated clinical workflow for low vision assessment, rehabilitation, and follow-up. Core baseline assessments are combined with condition-specific structural and functional testing. Findings from these assessments guide individualized rehabilitation strategies, including preferred retinal locus training, magnification and electronic devices, contrast and lighting modification, and mobility interventions. Functional outcomes are reassessed during follow-up, with findings used to modify the rehabilitation plan and determine the need for additional testing or monitoring [19,24,47,79].

Intake & Triage

Low vision diagnostic first begins when a patient is either referred or self-referred for abnormalities in their vision. Patients often get referred from retina, glaucoma, cornea, neuro-ophthalmology, or simply just outside providers. Prior to the visit, clinicians should review previous clinical data, imaging, treatment history, and the patient's EHR [6,81]. Future AI-based tools could eventually help identify patients who are at a higher risk of developing low vision or those experiencing rapid changes simply through their health data [28,94,95]. An early review of the patient's medical history could help determine how urgent the progression of the disease is and which tests are best to review during the in-person visit [95].

Baseline Structural Imaging

The next process of documenting the structural changes and causes of vision loss in a patient involves a standard imaging protocol which includes tests like color fundus photography, OCT scans with and without angiography, as well as vision field imaging. These technologies may help classify pathology, including macular disease, glaucoma, retinal vascular disease, or optic neuropathy [59,87]. Creating a structural baseline to track disease progression and relate it to anatomical changes and findings is essential [82]. These assessments eventually help form a bridge between the structural and functional changes of the eye [29].

Within this framework, there are some tests that should be included as part of the baseline assessment for most patients. These include distance and near visual acuity, contrast sensitivity, fundus photography, and OCT. Visual field testing should also be used when possible. Other tests can be added depending on the patient's disease and visual needs. For example, OCT-A can be used when vascular abnormalities are suspected, while microperimetry can be useful for patients with central vision loss to measure retinal sensitivity, fixation stability, and preferred retinal loci [25,27,32]. Electrophysiological testing can also be considered when the structural findings do not fully explain the patient's vision loss [71,72].

Functional Assessment

Following structural evaluation, functional testing should determine how anatomical abnormalities translate into usable vision loss. Standard functional tests often include distance and near visual acuity, contrast sensitivity, or low-luminance visual acuity [24,77]. More specifically, microperimetry can help map a patient's central retinal sensitivity and identify preferred retinal loci [25,27]. Together, structural and functional tests can help translate physical damage in the eye to day-to-day limitations that impact the patient's daily life.

Patient-reported outcomes: Patient-reported outcome measures capture activity limitations and participation restrictions that may not be evident from imaging or high-contrast acuity. The 25-item National Eye Institute Visual Function Questionnaire (NEI-VFQ-25) provides a widely used profile of vision-

related quality of life and supports comparison across ocular diseases [96]. The Activities of Daily Vision Scale (ADVS) adds task-focused information, including near and distance activities, glare disability, and driving [97]. Rasch-scaled instruments such as the Impact of Vision Impairment questionnaire can improve measurement of visual functioning and emotional well-being, while computerized adaptive administration can reduce respondent burden [98]. Disease-specific adaptive tools such as RetCAT can measure domains relevant to retinal disease, including activity limitation, lighting, mobility, symptoms, emotional effects, and driving.

These measures should be collected at baseline before rehabilitation goals are finalized, repeated after device training or another major intervention, and reassessed when the patient reports functional change. A practical workflow uses one core instrument consistently over time and adds a domain-specific measure when the treatment target is reading, mobility, or driving. Results should be reviewed beside contrast sensitivity, visual field or microperimetry, fixation stability, reading speed, and the patient's stated goals. A discordant pattern, such as stable BCVA with worsening lighting or mobility scores, should prompt targeted testing, environmental assessment, device review, or orientation-and-mobility referral rather than dismissal of the reported difficulty. In AMD, multimodal functional measures, including contrast sensitivity and low-luminance acuity, have shown significant associations with vision-related quality of life [99]. In diabetic macular edema, retinal sensitivity explained more variance than BCVA in several RetCAT and NEI-VFQ-25 domains [18].

Contrast sensitivity, low-luminance vision, and glare: Contrast sensitivity should be measured under standardized refractive correction, working distance, and luminance. The Pelli-Robson chart is a practical first-line test of letter contrast and can be completed quickly in most clinics. Its 0.15-logCS steps are repeatable to approximately one step; a change of 0.30 logCS is more likely to exceed test-retest variability [100]. A single impairment threshold should not be applied across all ages and devices. For context, one recent nationally representative study defined impairment as binocular contrast sensitivity below 1.37 logCS, but this cutoff was specific to that test protocol and cohort and should be interpreted against the chosen test's normative data [15].

When a full contrast-sensitivity function is clinically relevant, the CSV-1000 samples several spatial frequencies and can be paired with a glare source, while computerized quantitative contrast-sensitivity function testing estimates the area under the log contrast-sensitivity function and contrast acuity over a broader frequency range. In a retina-clinic cohort, quantitative contrast-sensitivity function metrics showed intraclass correlation coefficients above 0.90 for all metrics except 1 cycle per degree, and the area-under-the-curve measure had an intraclass correlation coefficient of 0.971 [101]. These tests may detect deficits in eyes with macular disease even when visual acuity is 20/30 or better [17]. Device availability, normative database, test duration, and the need for longitudinal comparability should guide selection.

Low-luminance visual acuity can be measured with a standardized neutral-density filter, and the low-luminance deficit is calculated as the difference between photopic and low-luminance logMAR acuity. In geographic atrophy with baseline acuity of 20/50 or better, a worse baseline low-luminance deficit was associated with a 2.88-fold risk of losing at least three lines over two years (95% CI 1.13-7.35) [102]. However, a later study of 140 participants with bilateral large drusen found that low-luminance deficit did not improve individual prediction beyond color-fundus grading; microperimetry was associated with progression at the population level but also added little to the imaging model [103]. Low-luminance and glare results should therefore supplement, not replace, structural imaging and symptom assessment. Rehabilitation decisions should follow the pattern of loss. Reduced low-frequency contrast or difficulty in dim illumination supports a home-lighting assessment, higher-contrast edges and labels, fall-risk screening, and orientation-and-mobility referral. Reduced high-frequency contrast and reading performance support increased angular magnification, electronic enlargement, improved task lighting, and reading training. Glare-related loss supports individualized control of light source position, window coverings, visors or hats, and selective filters tested during the patient's actual tasks. These recommendations should be verified with a task-based outcome, such as reading speed or an observed mobility task, and a patient-reported goal rather than inferred from the contrast result alone.

Integrated Clinical Review

Following data collection, clinicians can review both results together as a whole rather than each separately [71]. Using AI and multimodal visualization tools, clinicians can receive help in combining OCT, fundus images, visual field data, and even microperimetry results [94]. AI tools, in the future, could even help estimate the severity of the disease, predict functional effects, and help create a rehabilitation care plan. Having an in-depth and integrated review will support more personalized and informed clinical decisions for the patient.

Low Vision Rehabilitation Planning

When creating a rehabilitation plan for patients with low vision, a team that includes ophthalmologists, optometrists, low vision therapists, and even occupational therapists should be involved [24,104]. Images

alongside functional data can help explain why the patients are experiencing the symptoms they are having and can help guide the next steps and interventions [104]. Some common interventions include magnification devices, lighting changes, electronic aids, mobility training, and visual training strategies [34,45]. Having a baseline functional measure for each of these is important in setting patients' goals. Each progression, whether forwards or backwards, is also extremely important to track as the care plan and/or disease progresses to see how daily activities progress.

The results of these tests can also help determine which type of rehabilitation would be most beneficial for the patient. For example, patients with reduced central retinal sensitivity or unstable fixation may benefit from PRL training or eccentric viewing strategies [25,27,32]. Patients who have difficulty with near vision or reading may benefit from optical or electronic magnification, while patients with reduced contrast sensitivity may benefit from changes in lighting or contrast [24,34,45]. Visual field loss that affects mobility may also indicate a need for orientation and mobility training. This allows the rehabilitation plan to be based more directly on the functional problems identified during testing.

Follow-Up & Remote Monitoring

Another important component of low vision monitoring is maintaining follow-up visits and checks depending on the disease type, severity, and progression. The timing of follow-up should depend on the underlying disease, how severe the vision loss is, how quickly it is progressing, and the patient's rehabilitation needs. Patients with active or rapidly changing disease may need more frequent monitoring, while patients with stable vision loss may have longer periods between assessments. For rehabilitation outcomes, follow-up assessment has been performed 6 to 9 months after low vision rehabilitation to determine whether meaningful changes in visual ability have occurred [21]. During follow-up, the structural and functional tests that were important in creating the original rehabilitation plan can also be repeated when needed.

Future technologies also make it possible for some disease-specific monitoring to occur more frequently at home. For example, studies of patients with neovascular age-related macular degeneration have evaluated patient-operated home OCT with daily self-imaging to monitor retinal changes between office visits [82]. Other at-home vision testing and telehealth approaches may also allow patients and clinicians to review changes remotely [81,82,85-88]. This could help shift monitoring toward a more continuous process rather than relying only on occasional office visits.

It is also important to measure whether the rehabilitation plan is actually improving the patient's daily function. Outcomes can include visual acuity, contrast sensitivity, reading performance, mobility, use of low vision devices, and patient-reported visual function and quality of life [21,30,34]. Clinically meaningful changes can also be evaluated when validated measures are available. For example, the Activity Inventory has been used to evaluate meaningful changes in overall visual ability as well as reading, mobility, visual motor function, and visual information processing following low vision rehabilitation [21]. These follow-up results can then be used to change devices, rehabilitation strategies, or the frequency of monitoring as the patient's needs change.

Discussion

This review shows that improving low vision care is not only about creating better technology, but about using available tools in a more connected and practical way. Imaging methods such as OCT, OCT-A, fundus photography, microperimetry, and electrophysiological testing have significantly improved the ability to detect structural and functional deficits in the visual system. However, these tests are often performed and interpreted separately, limiting their usefulness in rehabilitation planning. There is often a gap between what the tests show and what the patient is experiencing in daily life.

The biggest issue highlighted is the continued reliance on visual acuity, as it doesn't always reflect how well a patient functions. A patient may read the 20/20 line while still struggling with contrast sensitivity, glare, peripheral field loss, reading endurance, mobility, or driving. Therefore, relying on acuity alone can underestimate the true burden of visual impairment. Functional testing such as visual fields, contrast sensitivity, and microperimetry may provide a more complete understanding of how vision loss affects independence and quality of life.

Clinical effectiveness supports investment in these pathways. In the 126-participant Veterans Affairs Low Vision Intervention Trial, outpatient rehabilitation produced larger gains than a waiting-list control in reading ability (between-group change 2.43 logits, 95% CI 2.07-2.77), mobility (0.84 logit, 95% CI 0.58-1.10), and overall visual function (1.63 logits, 95% CI 1.40-1.86; all $p<0.001$) [105]. In LOVIT II, adding therapist-led device training, eccentric-viewing instruction, homework, and environmental modification improved overall visual ability by 0.27 logit (95% CI 0.06-0.49; $p=0.01$) and maximum reading speed by 21 words per minute (95% CI 6.4-35.5; $p=0.005$) compared with devices alone [106]. Policy options include reimbursement for remote specialist interpretation and patient navigation, coverage of devices and occupational or orientation-and-mobility training, and bundled payments that link evaluation, device fitting, training, and

outcome reassessment. These payment approaches remain implementation recommendations and should be evaluated for access, patient-reported benefit, and total cost in the local health system.

AI has changed the way of classification of disease in various specialties including radiology and pulmonary [107], neurology [108-110], ophthalmology [111-113], audiology [114,115], orthopedics [116], gastroenterology [117]. There are specific use cases the researchers have developed for interventions like autism [118] and stuttering [119]. The researchers have also developed certain frameworks in the core areas of ophthalmology, which include ocular perfusion [120], general ophthalmology [121-123], and posterior capsule opacification [124]. The researchers have also significantly contributed to dermatology [125]. The researchers have developed methods for security that can be implemented for framework access [126]. There are researchers who have developed security methods for cloud frameworks that assist third-party developed applications to securely work on healthcare data that is collected from any IOT device [127-129].

As these technologies continue to become more involved in low vision care, there are also ethical and practical challenges to consider. AI systems depend on the data they are trained on, which can create bias when certain populations are not represented well [20,38]. Privacy and security are also important since these systems may require access to large amounts of patient imaging and health data [38]. Another challenge is that newer imaging devices, AI systems, and reliable internet access may not be equally available in lower resource settings, which could increase existing differences in access to eye care [42,47]. Lower-cost and portable technologies could help make some of these tools more accessible [47,88]. There also needs to be more training for clinicians on how to use these systems, understand their limitations, and use the results along with their own clinical judgment [20,38].

Conclusions

Low vision care requires more than the assessment of visual acuity alone. Current imaging technologies, including fundus photography, OCT, OCT-A, visual field testing, microperimetry, and electrophysiological testing, provide valuable information about the structural and functional effects of visual impairment. However, imaging findings, functional assessments, and rehabilitation planning are often used independently, which can limit their ability to fully guide patient management.

This review highlights the need for a more integrated approach to low vision care that combines diagnostic imaging, functional vision assessment, and rehabilitation within a unified clinical workflow. Emerging technologies may help improve access to care and support more personalized management, but challenges related to implementation and accessibility remain. Greater integration of these tools may improve clinical decision-making, better align rehabilitation strategies with patient needs, and ultimately enhance functional outcomes and quality of life for individuals living with low vision. Future low vision care should therefore prioritize integrated, accessible, and personalized models that translate advances in imaging and functional assessment into meaningful improvements in patients' daily lives.

Additional Information

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All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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