• Review Article •

Artificial intelligence in assessment and diagnosis of binocular vision dysfunction and related ocular motor disorders: a narrative review

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Abstract

● Binocular vision dysfunction (BVD) encompasses a range of conditions affecting ocular alignment, vergence, accommodation, and sensory fusion, yet conventional assessment methods remain limited by subjectivity, examiner variability and poor reproducibility. Artificial intelligence (AI), including machine learning (ML) and deep learning (DL), has emerged as a promising adjunct in the objective assessment and diagnosis of BVD. This narrative review synthesizes current evidence on AI applications across eye tracking and oculomotor analysis, automated ocular alignment detection, vergence and accommodative measurement, stereoacuity assessment, and diagnosis of convergence insufficiency, strabismus, amblyopia, and nystagmus. AI-driven tools demonstrate strong diagnostic performance, with several systems achieving sensitivity and specificity exceeding 90%. Smartphone-based and wearable platforms further extend BVD care to remote and resource-limited settings. However, limitations including small training datasets, lack of external validation, inconsistent diagnostic criteria, and limited model interpretability must be addressed before routine clinical integration. AI currently functions best as a decision-support tool rather than a replacement for expert clinical assessment.

● **KEYWORDS:** artificial intelligence; binocular vision dysfunction; convergence insufficiency; eye tracking; strabismus

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INTRODUCTION

Vision is a fundamental sensory function that provides input for the performance of fine motor skills, which are important in human interaction, learning, and daily life activities[1]. Among its components, binocular vision is essential for maintaining a single image, and to perceive and interact with the dynamic three-dimensional world[1-2]. Binocular vision dysfunction (BVD), as used in this review, refers specifically to non-strabismic disorders of vergence, accommodation, and fusion including convergence insufficiency (CI), divergence insufficiency, convergence and divergence excess, basic heterophoria, and fusional vergence dysfunction that affect a person's binocular coordination and visual comfort despite normal or near normal ocular alignment[3-5]. This distinguishes BVD from strabismus, which involves a manifest, measurable ocular deviation, and from amblyopia and nystagmus, which involve primary deficits in visual acuity or fixation rather than binocular coordination. Despite these distinctions, BVDs are frequently under-recognized or misdiagnosed, particularly in pediatric and neuro-optometric populations[6-7].

The impact of BVD extends beyond visual symptoms, affecting daily activities such as reaching and grasping, reading, screen use, and mobility, and reducing overall quality of life[8-9]. The binocular vision anomalies are commonly associated with the refractive errors, strabismus, amblyopia, heterophoria, and other neurological conditions, which can complicate diagnosis[10-12]. Conventional clinical tests for BVD including the cover test, maddox rod, near point of convergence (NPC), and prism fusion ranges are well established and remain the clinical standard, supported by decades of normative and diagnostic valid data[13]. However, these tests depend on examiner technique and patient response, which can introduce variability, particularly in children and patients with communication or cooperation difficulties[13-14]. A further and arguably more fundamental challenge is that many non-strabismic BVD subtypes lack universally accepted diagnostic criteria; different studies apply different threshold values for NPC, fusional vergence, and symptom scores, which limits comparability across the literature this review draws upon[10,15].

With the evolution of new digital technologies, current eye care incorporates automated and computer assisted tools, including virtual reality (VR) based testing systems[16], eye tracking technologies[17], and digital visual function assessment platforms[14]. In this context, artificial intelligence (AI) including machine learning (ML) and computer vision, has emerged as a promising tool for objective and reproducible analysis of the data[18-20]. AI refers to the ability of a computerized system to mimic human thinking and perform tasks that normally require human intelligence[19-21]. ML is the branch of AI that enables computer to learn patterns automatically from data and improve their performance over time[19-20]. Deep learning (DL), a further subset of ML, uses layered neural networks to recognize complex patterns within large amounts of data[18-19]. AI systems are capable of combining multiple clinical inputs including patient history, ocular motility, vergence, accommodation, and other data to identify diagnostic patterns that may be difficult to detect through conventional clinical methods[18,22].

AI has gained an interest in optometry and ophthalmology due to its potential to improve diagnosis and management of various eye conditions. While early research largely focused on posterior segment diseases[22-23] such as diabetic retinopathy, glaucoma, and age-related macular degeneration but now it has expanded to anterior segment disorders[19-20], refractive error assessment[18,24], and pediatric conditions including amblyopia, strabismus, and binocular vision disorders[25-27]. Because these conditions share overlapping diagnostic methods, comorbidities, and clinical pathways with non-strabismic BVD, this review also discusses relevant AI applications in strabismus, amblyopia, and nystagmus where they directly inform or parallel BVD related diagnostic approaches, while keeping non-strabismic BVD as the central focus.

While AI applications in strabismus and amblyopia screening have been reviewed previously, no comprehensive review has yet specifically examined the role of AI in the assessment and diagnosis of BVD[18-19,22-23]. Therefore, the goal of this review is to summarize current evidence on AI-based assessment and diagnosis of BVD, to critically examine the limitations of conventional clinical approaches in this context, and to identify priorities for future development of AI tools in binocular vision care.

Binocular Vision Dysfunction

Introduction and classification BVD is a condition in which visual system is unable to maintain proper ocular alignment and coordination, making it difficult to maintain single and comfortable vision during every day visual tasks[1,28-29]. Unlike strabismus, BVD often involves subtle or small angle deviations that may not be easily detected during routine clinical examination[6,28].

BVDs can be classified based on the nature of the underlying anomaly, severity, and etiology. Based on functional characteristics, BVD may include convergence related disorders such as CI and convergence excess, divergence related anomalies include divergence insufficiency and basic esophoria or exophoria[30-31]. The vertical and cyclo-deviations including vertical heterophoria and cyclophoria also contribute to the binocular instability[28,31]. Sensory fusion disturbances and accommodative-vergence interactions further disrupt binocular vision[10,32]. These dysfunctions may be further classified as compensated or decompensated based on the ability to maintain fusion[33]. Compensated deviations remain asymptomatic as long as adequate fusional reserves are maintained, while decompensated cases are characterized by symptomatic breakdown of binocular control[33]. BVD may arise as a primary condition or may be secondary to factors such as head trauma, neurological disease, surgery, or extended accommodative strain[10-11,29].

BVD can impair visual function and reduce quality of life in children, adults, and older individuals[8,34-35]. It is more commonly observed among individuals engaged in prolonged near work and digital screen use. A hospital based study conducted in Nepal reported a prevalence of 39.39% of non strabismic binocular vision anomalies among symptomatic adults[36]. The symptoms of BVD are commonly confused with those of dyslexia, attention disorders, or anxiety, delaying its diagnosis and appropriate management[6,28,35]. When identified early, BVD responds well to treatment, with prism correction, vision therapy, and appropriate refractive management that shows significant symptomatic and functional improvement[37-39]. This highlights the importance of early detection and accurate measurement of binocular vision anomalies.

Limitations of conventional assessment Several conventional binocular vision assessment tools, including the Maddox rod, Von graefe method, prism fusion ranges, rely on patient's subjective responses, such as perceived diplopia, blur, or recovery[10,13]. The test results may vary between examiners and across repeated measurements, especially in children, patients with neurodevelopmental disorders, or those who have difficulty understanding or communicating their visual experiences[13,40]. Standard binocular vision tests are typically performed once under ideal clinical conditions that may not represent the dynamic visual demands of everyday life, including variable lighting, prolonged near work, and fatigue-related changes in binocular vision[10,13,15]. Many of these tests also rely on gross end points that lack the sensitivity required for early detection.

Evaluating binocular vision comprehensively involves a series of tests performed under varying distances and conditions, with accuracy highly dependent on clinician's expertise[10,13].

This makes comprehensive binocular vision assessment difficult to perform in busy clinical setting or in areas where specialist eye care professionals are not readily available[18,22]. Binocular vision assessment involves collecting data from multiple sources, including patient history, symptoms, refractive status, vergence amplitudes, and ocular motility findings[10,31]. However, these data are typically recorded and analyzed separately rather than being analyzed together as a whole, which may limit the overall diagnostic picture[18,22].

Emerging technologies such as VR-based vision testing and AI-based diagnostic tools offer more objective and reproducible measurements, addressing several limitations of conventional binocular vision assessment[13,22,41]. These tools offer objective quantification of binocular function with reduced subjectivity, and allow repeated monitoring over time, thereby addressing several key limitations of traditional clinical methods[13,16,42]. Some tests lack objective accuracy and some conventional tests cannot capture the visual demands of everyday life. AI-based tools may therefore offer a more reliable and comprehensive alternative for binocular vision assessment.

Literature search strategy A literature search was performed in PubMed and Google Scholar for studies published between 2015 and 2026. The time window was selected to capture the period during which AI and DL applications in ophthalmic and optometric diagnostics expanded substantially, while still including foundational studies relevant to conventional binocular vision assessment. Search terms included combinations of "AI", "binocular BVD", "eye tracking, vergence", "convergence insufficiency", "strabismus", "amblyopia" and "tele-optometry", combined using Boolean operators (AND/OR).

Original research articles, review articles, validation studies, reviews, and Meta-analyses describing AI-based or computer-assisted approaches to binocular vision assessment or diagnosis were considered for inclusion. Studies were prioritized for inclusion if they reported a clinical or diagnostic application directly relevant to ocular alignment, vergence, accommodation, stereoacuity, or related oculomotor function. Studies addressing AI applications in strabismus, amblyopia, and nystagmus were also included where they shared overlapping diagnostic methodology with non-strabismic BVD or were frequently co-discussed in the optometric literature, given the close clinical relationship between these conditions. Studies using eye movement or oculomotor classification in non-ophthalmic contexts (*e.g.* dyslexia or general neurological screening) were included only where their methodology was directly applicable to binocular vision assessment, and their relevance to BVD is discussed critically rather than treated as direct diagnostic evidence.

As this is a narrative rather than a systematic review, formal quality appraisal and risk of bias assessment were not performed; however, study design, sample size, and validation status are described where relevant throughout the review to allow the reader to judge the strength of the underlying evidence. The included studies vary considerably in design, ranging from large validation cohorts to small proof of concept investigations, and this heterogeneity is acknowledged rather than treated as uniformly comparable evidence. As this is a narrative review based entirely on previously published literature, it does not involve new data collection from human participants, and no original ethics committee or institutional review board approval was required for this study.

AI in Assessment of Binocular Vision and Related Disorders

Eye tracking and oculomotor analysis The integration of AI with eye tracking technology has improved the objective assessment of oculomotor function by enabling precise, automated measurement of saccades, smooth pursuits, fixations, and vergence that are difficult to measure using traditional clinical examination[43-44].

AI-based video eye tracking systems, including devices such as Pupil Core, can objectively detect and classify gaze deviations and oculomotor abnormalities, replacing the subjective and examiner dependent methods used in conventional clinical practice[43-45]. Valliapean *et al*[46] showed that smartphone cameras can track eye movements with accuracy similar to expensive laboratory systems, making it feasible for use in community and remote settings. Lotze *et al*[47] developed a low cost robotic eye movement stimulator called the EyeRobot, which can replicate abnormal eye movements, and was used to assess the performance of the Pupil Core eye tracker under simulated oculomotor conditions.

ML algorithms have proven effective at classifying eye movement disorders from oculomotor data, though most of this evidence remains at the proof-of-concept stage. Using features such as saccadic latency, velocity, and fixation duration, Mao *et al*[48] showed that random forest and decision tree algorithms effectively classified different oculomotor disease patterns in a relatively small dataset without external validation. El Hmimdi and Kapoula[49-50] recently demonstrated that ML models trained on saccade and vergence eye movement parameters were able to distinguish between children with dyslexia, attention deficit, and learning disorders, indicating that comparable approaches may be applicable to BVD classification, though the studies themselves were not conducted in BVD populations and their diagnostic relevance to BVD remains inferential rather than direct. Zhao *et al*[51] developed a wearable AI eye tracking system for intermittent strabismus screening. Using random forest algorithm, the system achieved 97.1% accuracy in 70

participants under diverse conditions without the need for specialist clinicians. VR-based eye tracking platforms have also shown clinical utility for the optometric assessment. Sipatchin *et al*[16] confirmed that the HTC Vive Pro Eye, a VR-based headset to be a clinical usable tool for eye movement analysis in ophthalmology. Pijpaert *et al*[52] conducted a validation study confirming that stereoscopic eye tracking technology can accurately and precisely measure both gaze and vergence parameters.

The clinical value of AI-based eye tracking is particularly useful in pediatric practice, where short attention spans, uncooperative behavior, and difficult communication make standard oculomotor tests unreliable and time consuming[53-54]. Such AI-based tools are especially beneficial in children with global developmental delay and neurodevelopmental conditions, where standard clinical assessment is often inaccurate or incomplete due to communication and cooperation difficulties[53,55]. These advances in objective oculomotor assessment naturally lead to the application of AI in automated ocular alignment detection which is discussed in the following section.

Automated ocular alignment and cover test Several AI-driven tools have been developed to automate ocular alignment detection and quantification from photographic, video-based, cloud processed inputs, and other digital inputs. It should be noted that several of these systems function primarily as automated image analysis or computer vision tools rather than true diagnostic AI, with DL applied mainly to feature extraction and measurement rather than independent clinical decision making.

One of the most clinically significant applications of DL in ocular alignment assessment is its use with the Hirschberg test, quick clinical screening tool for detecting ocular misalignment in clinical practice[56-57]. Karaaslan *et al*[56] developed an automated Hirschberg test using DL and image processing to measure corneal reflections and pupil centers from facial photographs achieving 90%–91% accuracy across 88 strabismic patients; this sample size, while reasonable for a proof of concept study, has not yet been validated in an independent or multi-center cohort. Yarkheir *et al*[58] trained a Convolutional Neural Network (CNN) on over 4000 facial images, which successfully detected and classified strabismus type and deviation angle with high accuracy in binary and multiclass classification. Garg *et al*[59] developed StrabNet-CQ, a DL framework that integrates YOLOv8 and ResNet architectures for classification and quantification of strabismus. The system automatically computed horizontal and vertical indices and angular deviation from standard photographs[59].

Wu *et al*[60] developed and validated a DL algorithm for automatic precision cropping of eye regions in strabismus photographs improving workflow efficiency in busy clinics by reducing reliance on manual preprocessing. Rodriguez *et al*[61] developed a low-cost embedded tool for visual misalignment screening that works without internet connectivity or specialized equipment, making it suitable for resource limited clinical environments.

For tele-optometry applications, He *et al*[62] developed the Eyeturn Cloud web application, which uses AI to analyze smartphone captured cover test images through iris segmentation and corneal reflection analysis. The system achieved R^2=0.95 correlation with prism cover test measurements and a repeatability of 1.53 prism diopters in 79 participants, confirming that reliable strabismus measurement is possible using only a smartphone and AI[62]. Supporting this clinical validity of image-based alignment tools in children, Yehezkel *et al*[63] demonstrated that automated photo-based strabismus measurement showed a mean difference of -2.9 prism diopters, with a haf-width of the 95% limits of agreement of ±11.4 prism diopters compared with manual prism alternate cover testing, in a single-center validation study.

For more comprehensive binocular alignment assessment, Yu *et al*[64] demonstrated that VR-based system could map incomitant deviations across multiple planes of gaze more effectively than the conventional Hess Screen test.

Vergence, accommodation, fusional reserve Measuring vergence, accommodation, and fusional reserves objectively remains one of the most difficult aspects of binocular vision assessment. AI-based tools can now objectively and automatically measure vergence and accommodative function in real time, improving both the diagnosis of BVD and monitoring the treatment process. It is important to note that clinical diagnosis of convergence insufficiency and accommodative dysfunction relies on the integration of multiple findings including NPC, fusional vergence ranges, accommodative facility, and symptom burden rather than any single measurement in isolation; the AI tools discussed below largely automate individual components of this assessment rather than replicate the full diagnostic process.

Ozhan *et al*[65] developed a prototype device that uses Purkinje reflections and a neural network to measure accommodation and vergence in real time. The system achieved accuracy better than 0.22 D using subject specific data and 0.40 D across subjects, superior to conventional methods and especially useful in children where subjective testing is often unreliable[65]. Gao *et al*[66] combined a consumer grade infrared eye tracker with dichoptic display to automatically and objectively measure fusional reserves without patient verbal responses. In 29 adults, the system correlated strongly with conventional subjective measures, with differences of only 0.3–2 prism diopters, supporting its use in both clinical and

home monitoring settings[66], though this sample size is modest and pediatric or clinical population validation has not yet been reported. Using dual rotational Risley prisms and eye tracking, Su *et al*[17] created an automated method for objective and repeatable evaluation of binocular alignment and vergence. Rovira-Gay *et al*[13] further confirmed that objective fusional vergence amplitudes measured with haploscopic setup and infrared eye tracking are in close agreement with conventional subjective prism vergence tests.

Khatib *et al*[42] developed MobileS, an AI smartphone application that measures NPC and vergence facility through front camera tracking. The system correlated significantly with conventional ruler based NPC measurement and showed notable diagnostic accuracy for CI[42]. A subsequent study by the same group showed that AI-derived graphical NPC outputs improved ophthalmologists CI detection accuracy from 78% to 94%, supporting their role as effective clinical decision support tools rather than autonomous diagnostic system[67]. Stuermer *et al*[22] further demonstrated that an AI-based virtual assistant trained on over 1125 optometric examinations could classify vergence disorders and propose BVD subclassification with performance exceeding 98.1% in primary care settings. While this is a large training dataset relative to others in this field, performance in settings outside the original primary care context has not yet been established.

These contactless AI tools achieve accommodation precision, repeatability fusional reserve, providing objective alternatives to conventional vergence and accommodative tests in both clinical and remote settings[42,65-66]. However, as with eye tracking and alignment tools discussed earlier, most systems here automate specific measurements rather than replicate the full multi-component diagnostic process that conditions such as CI and accommodative dysfunction require.

Stereoacuity assessment Stereoacuity assessment is a critical component of binocular vision evaluation, providing a sensitive measure of the integrity of cortical binocular processing. Conventional stereotests such as Titmus Fly, TNO, and Randot are widely used clinically but they are limited by monocular cues, variable illumination, patient guessing, and poor cooperation in children. In addition, conventional stereotests exhibit high test retest variability exceeding two octaves, limiting their reliability in pediatric and neurodevelopmental populations[68-69]. Recent advances in AI, eye tracking technology, and VR have enabled the development of objective, cue minimized stereoacuity assessment systems. These systems are capable of providing more accurate disparity threshold measurements. It should be noted that several of these systems rely primarily on eye tracking and image-based measurement rather than AI-based diagnostic classification, with ML applied mainly to disparity estimation or pattern detection rather than independent clinical interpretation.

Yu *et al*[68] developed an AI face tracking autostereoscopic tablet, Lume Pad2, to stimulate parts of the Stereo Fly and TNO stereotests in children and adults. The system achieved high inter session reliability with kappa values greater than 0.80 and showed good agreement with conventional stereotests confirmed by Bland-Altman analysis[68]. As a validation study against existing clinical tests rather than a diagnostic accuracy study, its performance reflects measurement agreement rather than diagnostic sensitivity or specificity, and the study population's cooperation level and visual function range were not detailed, leaving open the possibility of spectrum bias favouring more cooperative or less impaired participants. Complementing this, Liu *et al*[69] validated a new eye tracking based stereotest against conventional methods, showing significant correlation with conventional stereotests. A glasses free display with eye tracking further demonstrated strong repeatability and good agreement with polaroid and titmus stereotests[70]. The ASTEROID tablet stereotest developed by Vancleef *et al*[71] and Read *et al*[72] demonstrated reliable stereo threshold measurement using dynamic random dot stereograms and adaptive Bayesian algorithms, and has been evaluated across a wider age range than most other tools in this section, which strengthens its evidence base relative to single-cohort studies discussed elsewhere.

VR technologies are increasingly being integrated into stereoacuity evaluation. In post COVID patients, Mehringer *et al*[41] measured stereopsis performance by combining VR, random dot stimuli, and a random forest classifier, achieving 71% classification accuracy for stereopsis deficits and demonstrating significant correlation between stereoacuity and vergence function. This is a genuine diagnostic classification task rather than a measurement agreement study, but the moderate accuracy and single-cohort design mean the findings should be regarded as preliminary rather than clinically established. Yu *et al*[64] also showed that a VR-based system performed better than the conventional Hess screen test in mapping incomitant deviations, a comparative rather than diagnostic accuracy findings. Cao *et al*[73] evaluated a novel glasses-free distance stereotest using eye tracking, demonstrating high sensitivity, validity, and reliability while effectively masking monocular cues. Across this section as a whole, the evidence is dominated by evidence validation studies rather than diagnostic accuracy studies in defined clinical populations, which is an important distinction when interpreting the clinical readiness of these tools.

Accommodative convergence/accommodation The accommodative convergence/accommodation (AC/A) ratio is a fundamental parameter in binocular vision assessment,

Table 1 Summary of AI and technology-assisted binocular vision assessment

Study	BVD parameter	AI methods	Study design and sample size (*n*)	Key outcomes
Kędras and Sobecki[43]	Eye tracking/oculomotor	AI integrated eye tracking survey	AI tracking survey	Identified AI integration gaps in oculomotor assessment
Valliappan *et al*[46]	Eye tracking	CNN smartphone gaze tracking	Smartphone gaze tracking validation; *n*≥100	Accuracy comparable to lab grade trackers
Lotze *et al*[47]	Eye tracking, fixation	Robotic simulator, Pupil Core	Robotic eye movement simulator validation (simulator based no primary human)	Reliable tracker performance under simulated nystagmus and eccentric fixation
Zhao *et al*[51]	Vergence, alignment	Wearable AI eye tracking	Wearable eye tracker diagnostic validation; *n*=70 participants	97.1% accuracy for intermittent vergence disorder detection
Pijpaert *et al*[52]	Vergence, stereoscopic tracking	Stereoscopic eye tracking	Stereoscopic eye tracking validation; *n*=8 participants	Validated gaze and vergence accuracy in binocular conditions
He *et al*[62]	Ocular alignment, cover test	Iris segmentation and corneal reflection AI	Smartphone cover test *vs* prism validation; *n*=79 participants	R^2=0.95 with prism cover test, 1.53 PD repeatability
Yehezkel *et al*[63]	Strabismus, alignment	Automated photo based measurement	Automated photo based strabismus measurement validation study; *n*=69 children	Mean difference of -2.9 PD compared with conventional prism alternate cover testing
Yu *et al*[64]	Incomitant deviation	VR and AI gaze mapping	VR-based deviation mapping compared with Hess screen; *n*=66 patients	Enabled deviation mapping across multiple gaze positions
Ozhan *et al*[65]	Vergence, accommodation, AC/A	Neural network, Purkinje reflections	Purkinje-based vergence/ accommodation prototype; *n*=11 young adults	Real time simultaneous objective vergence and accommodation measurement
Gao *et al*[66]	Fusional reserves	Dichoptic AI system	Objective fusional reserve validation; *n*=29 adults	Automated objective fusional reserve measurement
Khatib *et al*[42]	NPC, vergence facility	MobileS AI smartphone app	Mobile NPC/vergence facility validation; *n*=86 subjects	Significant correlation with ruler NPC
Liu *et al*[70]	Stereoacuity	AI and VR random dot stereotest	VR random dot stereotest validation; *n*=74 adults	Strong repeatability, agreement with Titmus and polaroid stereotests
Cao *et al*[73]	Stereoacuity	Eye tracking glass free stereotest	Glasses-free eye tracking stereotest validation; *n*=185 participants	High sensitivity and validity; effective monocular cue masking
Mehringer *et al*[41]	Stereopsis, vergence	VR and random forest classifier	VR stereopsis RF classifier study; *n*=35 patients	71% accuracy for stereopsis deficit, correlation with vergence function
Su *et al*[17]	Phoria, vergence ranges	Dual rotational Risley prism automation	Automated Risley prism phoria/ vergence validation; *n*=39 participants	Automated objective phoria and vergence range measurement

AI: Artificial intelligence; DL: Deep learning; NPC: Near point of convergence; PD: Prism diopter; RF: Random forest; AC/A: Accommodative convergence/accommodation ratio; VR: Virtual reality; BVD: Binocular vision dysfunction; CNN: Convolutional Neural Network.

reflecting the relationship between vergence response and accommodative stimulus. The gradient and heterophoria methods of AC/A measurement are limited by examiner dependence, accommodative lag, and vergence adaptation[10]. Objective measurement approaches therefore offer a more reliable clinical alternative, though it should be noted that none of the systems described below were designed or validated specifically as AC/A measurement tools: rather, AC/A values are derived secondarily from vergence and accommodation data collected for other primary purposes.

Ozhan *et al*[65] used purkinje reflections and a neural network to measure accommodation and vergence simultaneously in real time, enabling automated response AC/A ratio derivation without subjective patient input. Similarly, the infrared eye tracking developed by Rovira-Gay *et al*[13] and the dichoptic fusional reserve system reported by Gao *et al*[66] capture concurrent vergence and accommodative data, which can be used to derive AC/A ratios objectively, although neither study reports or validates an AC/A output directly. Such objective systems may support more objective assessment of vergence and accommodation, particularly when subjective responses are difficult to obtain, such as in children and patients with co-existing binocular vision anomalies[10,13].

Table 1 summarizes the main AI-based methods used for the assessment of binocular vision, including BVD parameters, AI methods and key outcomes of the study.

AI in Diagnosis of Binocular BVD and Related Disorders

Convergence insufficiency and vergence disorders AI systems have advanced beyond quantification to enable diagnostic classification of CI and vergence disorders using established clinical criteria including NPC greater than 6 cm, positive fusional vergence below 15 prism diopters, and a Convergence Insufficiency Symptom Survey (CISS) score of 16 or higher. It is worth emphasizing, consistent with the broader limitation discussed earlier, that CI is a multi-criterion diagnosis, and the AI tools discussed below largely classify individual components of this criteria set rather than replicate the full clinical diagnostic process. Moon *et al*[74] performed receiver operating curve (ROC) analysis of conventional clinical signs for CI screenings in young adults, demonstrating

high discriminative ability for NPC, Sheard's criterion, and Percival's criterion with area under the curve (AUC) values of up to 0.920. This study used conventional statistical methods rather than AI, but established a diagnostic baseline that subsequent AI-based work has built upon.

Smartphone-based AI has brought CI diagnosis closer to point of care and tele optometry settings. As described in section 4.3, Khatib *et al*[42] demonstrated 92% sensitivity and 89% specificity for CI diagnosis using smart phone based NPC measurement. In a follow up study, the same group showed that providing ophthalmologists with AI-generated graphical outputs of NPC measurements improved their accuracy in estimating NPC compared with video-based interpretation[67], supporting AI as a decision-support tool rather than an autonomous diagnostic system.

ML classifiers have demonstrated strong ability to sub-classify CI and vergence related disorders, though with varying degrees of external validation. Stuermer *et al*[22] demonstrated that a random forest AI-based virtual assistant trained on over 1125 optometric examinations achieved performance exceeding 99.7% for BVD classification and 98.1% for ocular-disorder subclassification in primary care settings. This is among the larger training datasets in this review, although external validation is independent clinical settings is still needed. Yang *et al*[27] reported pooled sensitivity and specificity of 0.94 across 24 AI-based strabismus screening studies, confirming strong diagnostic performance across diverse AI models and input modalities. Zhao *et al*[51] further demonstrated 97.1% accuracy in detecting intermittent vergence disorders using a wearable AI eye tracking system, without specialist involvement as described in section 4.1, though in a sample of 70 participants that has not yet been replicated in an independent cohort.

Neurophysiological biomarkers represent a novel and emerging frontier in AI-based CI diagnosis, though this evidence remains preliminary. Lu *et al*[75] demonstrated that EEG-based ML could objectively classify non-strabismic BVD with 76.67% accuracy and an AUC of 0.87. Thus, this provides preliminary proof of concept for neurophysiological AI biomarkers in vergence disorder diagnosis. Complementing this, Alvarez *et al*[76] used functional magnetic resonance imaging (MRI) to investigate the neurological basis of symptomatic CI, identifying significant differences in convergence peak velocity and functional imaging activity within key oculomotor brain regions between CI and binocularly normal participants achieving 90% classification accuracy[76]. Both neuroimaging approaches are resource intensive and unlikely to be clinically scalable in the near term, but they offer mechanistic insight that purely behavioural or image-based AI tools cannot provide.

AI-driven alignment assessment tools also contribute to CI diagnosis through their link between ocular misalignment and vergence failure. He *et al*[62] and Yehezkel *et al*[63] demonstrated that photographic alignment tools can support the assessment of ocular misalignment, as described in section 4.2. Supporting these findings, Hartness *et al*[57] concluded through Meta-analysis that automated strabismus and vergence assessment technologies provide highly consistent diagnostic performance. Advancing this field further, Yang *et al*[77] introduced the wearable Eyelectronics system, a skin-like AI-enabled platform capable of integrated assessment of ocular alignment, vergence behavior, and oculomotor dynamics within a single contactless diagnostic workflow. As a recently introduced platform, its clinical performance data remain limited to initial feasibility reporting.

Accommodative dysfunction Conventional accommodative assessment methods, including push-up amplitude testing and subjective blur-end point evaluation, are limited by patient response variability, examiner dependence and poor reproducibility, especially in the pediatric populations and in patients with the coexisting binocular vision anomalies[10,78-79]. As with convergence insufficiency, accommodative dysfunction is a clinical diagnosis based on the integration of amplitude, facility, and lag findings together with symptoms, rather than any single accommodative parameter measured in isolation. This distinction is important when interpreting the AI tools discussed below, most of which target individual accommodative measurements rather than the full diagnostic picture.

Ozhan *et al*[65] developed an ML-based dynamic accommodation measurement system using Purkinje reflections that enables accurate real time accommodative tracking with reduced reliance on subjective responses, though this remains a measurement precision tool rather than a diagnostic classifier for accommodative dysfunction itself. Similarly, Kanclerz *et al*[78] reported that newer closer field autorefractors provide more objective and reproducible measurements of accommodative amplitude than traditional subjective techniques in a comparative validation study. Reproducibility gains here reflect instrumentation and automated measurement rather than AI-based diagnostic reasoning.

Beyond objective measurement, AI is increasingly being integrated into diagnostic decision support systems in optometry. Reviews by Du *et al*[80] and Krishnan *et al*[18] discuss the growing role of AI in screening, classification, and treatment planning for accommodative and binocular vision disorders by integrating accommodative metrics, symptom profiles, and vergence findings though as narrative and perspective reviews rather than primary studies, they describe an anticipated direction for the field more than an established clinical evidence base. Because accommodative dysfunction may coexist with the convergence insufficiency

and other vergence anomalies, AI-based multimodal diagnostic frameworks may help differentiate isolated accommodative disorders from other BVDs[10,79]. However, no study identified in this review has yet validated such a multimodal differentiation directly, and this remains a conceptual rather than demonstrated capability. Smartphone-based and portable AI systems may support the future development of tele optometry and remote binocular vision assessment[42,80].

Strabismus Although strabismus is a distinct clinical entity from non-strabismic BVD, it is discussed briefly here because AI methodologies for ocular alignment detection and classification are frequently shared between the two, and several tools described in earlier sections were originally validated in strabismic populations. AI-driven tools have demonstrated strong performance in automated strabismus detection and ocular alignment quantification from photographs, corneal light reflection images, and cloud processed inputs, with DL enabling subtype classification and deviation angle estimation alongside binary detection[59,81].

Yang *et al*[27] and Hartness *et al*[57] confirmed that AI-based models can match specialist level performance in identifying diverse strabismus subtypes under varying examination conditions.

In pediatric populations where conventional examination is often unreliable, AI-based wearable and smartphone tools enable scalable, specialist independent strabismus screening, supporting early amblyopia prevention[27,57]. This relatively mature evidence base for strabismus stands in contrast to the comparative earlier stage evidence for non-strabismic BVD discussed throughout this review, and is included here primarily for methodological comparison rather than as core BVD evidence.

Amblyopia Amblyopia is included briefly for similar reasons, it shares overlapping risk factors and screening pathways with BVD, particularly given its association with strabismus and anisometropia, and several AI tools combine amblyopia and BVD risk assessment within the same diagnostic pipeline[22]. AI-based screening tools using facial photographs, fixation eye movement data, and stereo-based outputs have shown sensitivity for amblyopia risk detection exceeding conventional stereotests in early validation studies[26,82-83], including mobile phone based systems suitable for underserved settings[25]. As with the strabismus evidence above, this body of work is presented as contextual support for AI's broader feasibility in pediatric oculomotor screening rather than as direct evidence for non-strabismic BVD diagnosis, which remains the central focus of this review.

Nystagmus AI-based eye tracking systems have enabled objective and automated detection and classification of nystagmus, addressing the limitations of conventional specialist dependent assessment.

Lotze *et al*[47] confirmed that the Pupil Core eye tracker performs reliably under simulated nystagmus and fixation instability conditions using the EyeRobot. Wagle *et al*[84] developed aEYE, a DL system trained on infrared video oculography (VOG) recordings to classify video sequences as normal or containing nystagmus. The system performed consistently across varying video resolutions and sampling rates, supporting its potential as a portable, specialist independent screening tool applicable to telemedicine settings. Cho *et al*[85] reported real time nystagmus tracking using a lightweight segmentation based DL model, with r=0.99 and F1 scores above 0.95 for both horizontal and vertical components. Beyond detection, Kong *et al*[86] applied DL combined with optical flow to classify benign paroxysmal positional vertigo (BPPV)-associated nystagmus patterns, including torsional nystagmus, achieving 94.91% accuracy and an F1 score of 93.70%. Such performance is clinically significant, as distinguishing peripheral from central nystagmus directly guides referral and management decisions in optometric practice. Like strabismus and amblyopia, nystagmus is included here for methodological relevance rather than diagnostic overlap with BVD.

Tele-optometry and clinical decision support Tele-optometry, supported by AI-driven platforms, extends binocular vision care by enabling remote screening, standardized triage, and clinical decision support. Rather than replacing face to face examination, AI supported tele optometry functions as a triage and extension model that identifies patients requiring in person evaluation, prioritizes high risk cases, and supports ongoing monitoring and follow up.

Stuermer *et al*[22] found that an AI virtual assistant can reliably classify BVD and related vergence or accommodative disorders and can calculate amblyopia risk with high accuracy, while significantly decreasing unnecessary referrals in primary care. This finding is particularly significant for primary care optometrists working in high volume or resource limited environments. Further, Wang *et al*[19] suggested that integrating AI into optometric practice may standardize binocular vision (BV) assessment findings and improve diagnostic consistency across clinicians.

Smartphone and cloud based AI tools enable remote BV assessment beyond specialist settings. He *et al*[62] found that the EyeturnCloud smartphone application could reliably quantify strabismus without the need for a specialist examiner. Khatib *et al*[42] demonstrated that the MobileS platform could measure NPC and identify CI, showing its potential for remote vergence assessment in community settings.

Du *et al*[80] found that AI decision support tools could integrate multiple clinical inputs and generate consistent

Table 2 Summary of AI systems for binocular vision dysfunction diagnosis

Study	BVD category	AI method	Study design and sample size (*n*)	Key outcome
Moon *et al*[74]	CI	ROC analysis of clinical signs	CI ROC analysis; *n*=184 participants	AUC of 0.920 for NPC, 0.912 for Sheard's criterion, and 0.717 for percival's criterion
Khatib *et al*[42]	CI	MobileS smartphone AI	Smartphone CI diagnostic accuracy; *n*=86 subjects	92% sensitivity, 89% specificity for CI diagnosis
Stuermer *et al*[22]	Vergence disorders, BVD	Random forest virtual assistant	RF BVD/vergence classifier (retrospective); *n*=1125 exams	99.7% BVD classification, 98.1% vergence sub classification accuracy
Yang *et al*[27]	Strabismus, Vergence	Meta-analysis of AI models	Meta-analysis of AI strabismus models; *n*=24 studies	Pooled sensitivity and specificity of 0.94 across 24 studies
Lu *et al*[75]	Non-strabismic BVD	EEG-based machine learning	EEG ML CI Classification; *n*=30 participants	76.67% accuracy, AUC 0.87 for neurophysiological CI classification
Alvarez *et al*[76]	CI	fMRI and AI classification	fMRI-based CI *vs* control classification; *n*=100 participants	Identified functional connectivity differences in brain regions associated with oculomotor control in CI
Garg *et al*[59]	Strabismus	StrabNet-CQ deep learning	DL photograph strabismus classification/quantification; *n*=600 eye images	Simultaneous classification and deviation quantification from photographs
Wu *et al*[81]	Strabismus	Multimodal AI	Multimodel AI in strabismus review	Enhanced accuracy in screening, classification, and surgical prediction
Csizek *et al*[26]	Amblyopia	AI perceptron model	AI amblyopia screening *vs* stereo tests; *n*=423 children	AUC 0.908, 96% sensitivity, outperformed four classic stereovision tests
Murali *et al*[82]	Amblyopia risk factors	Deep learning (facial photographs)	DL facial photo amblyopia risk study; *n*=54 young adults	79.6% accuracy, 88.2% sensitivity using facial photographs only
Shu *et al*[25]	Amblyopia (in paediatric population)	Mobile AI screening	Mobile AI paediatric amblyopia screening; *n*=1419 images from 476 patients	80% accuracy for paediatric amblyopia detection
Wagle *et al*[84]	Nystagmus	aEYE deep learning	aEYE DL nystagmus detection; *n*=435 videos	Consistent nystagmus detection across variable resolution and sampling rates
Cho *et al*[85]	Nystagmus	Lightweight DL segmentation model	Lightweight DL nystagmus tracking validation; *n*=1568 patients, 82289 images	r=0.99, F>0.95 for real time horizontal and vertical nystagmus tracking
Kong *et al*[86]	Nystagmus patterns in BPPV	DL and optical flow classification	DL BPPV nystagmus pattern classification	94.91% accuracy, F1 93.70% for BPPV nystagmus pattern classification
He *et al*[62]	Tele-optometry, strabismus	EyeturnCloud AI smartphone	Tele-strabismus quantification; *n*=79 participants	Strabismus quantification in remote area
Du *et al*[80]	Tele-optometry, BVD DSS	AI decision support integration	AI based BVD decision support review	Consistent BVD recommendations, reduced clinician dependence
Krishnan *et al*[18]	Tele-optometry, workflow	AI tele-optometry integration	Tele-optometry AI workflow review	50%–70% reduction in follow up assessment time

AI: Artificial intelligence; AUC: Area under curve; BPPV: Benign paroxysmal positional vertigo; CI: Convergence insufficiency; CISS: Convergence Insufficiency Symptom Survey; DL: Deep learning; EEG: Electroencephalography; fMRI: Functional magnetic resonance imaging; ML: Machine learning; NPC: Near point of convergence; ROC: Receiver operating characteristic; VOG: Video oculography; RF: Random forest; BVD: Binocular vision dysfunction; DSS: Decision support system.

recommendations for BV disorders, reducing dependence on clinician judgement. Krishnan *et al*[18] further noted that AI integration into tele-optometry workflows can reduce assessment time by 50%–70%, particularly for follow up monitoring where repeated specialist visits are impractical.

These systems are particularly valuable in primary care, rural eye health programs, and school based vision screening initiatives. Supporting early detection of CI, strabismus, amblyopia, and accommodative dysfunction and preventing long term visual and functional sequelae through timely referral and intervention.

Table 2 provides a summary of AI applications in the diagnosis of BVD.

Advantages, Limitations, and Challenges AI offers several practical benefits in the assessment and diagnosis of binocular BVD, though these benefits should be interpreted against a still-early and largely unvalidated evidence base. Its notable strength is the ability to process large and complex clinical datasets objectively, potentially reducing the examiner variability present in the conventional BV tests[13,18,22]. AI systems can also combine multiple inputs including eye movements, alignment, stereoacuity, and symptoms into a single diagnostic framework[18,22,42]. In BVD, where no single clinical test is adequate for diagnosis on its own, this multimodal capability is especially helpful[10,13].

Smartphone-based, cloud-based, and wearable AI tools extend binocular vision care beyond the clinic to primary care and remote settings, enabling screening, triage, and monitoring without specialist involvement[42,62,80]. These platforms may reduce unnecessary referrals and improve early detection of CI,

strabismus, amblyopia, and accommodative dysfunction[22,54]. In pediatric and neurodevelopmental populations, where conventional testing is often unreliable due to cooperation and communication difficulties, AI-driven objective systems may offer a useful alternative[53,55]. These potential benefits remain largely demonstrated in controlled or single center studies, however, and should not yet be read as evidence of routine clinical effectiveness.

Despite these advantages, there are several important limitations. Most current AI systems are trained on small, single center datasets with limited demographic diversity, restricting generalizability to broader clinical populations[18-20]. Many models perform well under research conditions but lack external validation in routine clinical settings, a prerequisite for safe adoption[23,87]. Critically, this gap between research performance and routine practice is not a minor caution but a central reason why none of the tools discussed in this review can currently be considered ready for unsupervised clinical use. Performance may further depend on high quality images, stable fixation, or standardized recording conditions that are difficult to achieve in young children or patients with neurodevelopmental difficulties[13,53]. In BVD care, where subtle clinical distinctions carry diagnostic weight, a technically accurate model remains of limited value if its outputs are not interpretable to the clinician[18,22]. Many advanced models function as black boxes, offering predictions without transparent reasoning, which may reduce clinician trust and limit use in high stakes decisions involving referral or therapeutic planning[87-88].

A major and arguably underappreciated structural challenge is the absence of standardization across devices, testing protocols, and diagnostic definitions. Different studies employ different reference standards and outcome measures, making cross study comparisons difficult and slowing clinical translation[10,18,27]. This problem is compounded in BVD specifically, where diagnostic labels overlap and conventional criteria are not uniformly defined[10,31]. This is not simply a data quality issue because AI models learn from existing diagnostic labels, models trained on inconsistently defined or applied diagnostic criteria risk reproducing rather than resolving the diagnostic variability that motivated their development in the first place. Addressing this will require consensus-based, standardized diagnostic definitions before AI models can be meaningfully compared or validated across studies.

Beyond standardization, regulatory approval pathways, data privacy, medico-legal responsibility, and workflow integration remain unresolved barriers[19,87]. Dataset bias is a related concern. Most studies discussed in this review report performance in relatively homogenous, single-center populations, and the extent to which these models would perform equitably across different ethnicities, age groups, or healthcare settings has rarely been tested directly. Integration into existing clinical workflows presents a further practical barrier, since even a well validated tool offers little benefit if it disrupts examination time, requires unavailable infrastructure, or is not trusted by the clinicians expected to use it. For tele-optometry in particular, successful deployment will depend not only on algorithm performance but also on connectivity, cost, user training, and acceptance by clinicians and patients[22,80].

Taken together, these challenges confirm that AI currently functions best as a support tool rather than a replacement for expert BVD assessment. Importantly, this is not simply a matter of waiting for better algorithms, the translation of research stage models into validated, interpretable, and clinically integrated systems will require coordinated progress on standardized diagnostic criteria, multicenter validation, and regulatory clarity, in addition to continued technical refinement[18,22,88].

Future Direction In clinical practice, BVD is never diagnosed from a single test and future AI system should be built with this in mind. AI systems for BVD assessment should integrate multiple clinical parameters including eye movements, ocular alignment, stereoacuity, accommodation, symptoms, and clinical history into a single interpretable output rather than relying on isolated measurements[18,22,42]. Such multimodal frameworks better reflect the clinical complexity of BVD, where no single test is diagnostically sufficient.

However, technological development of this kind cannot substitute for parallel progress on the methodological gaps identified throughout this review. A clear priority is the development of standardized, consensus-based diagnostic definitions and outcome measure for non-strabismic BVD, without which AI models will continue to be trained on inconsistent labels and validated against incomparable reference standards[10,31]. Equally important is the establishment of multicenter validation studies and normative databases across diverse age groups, ethnicities, and clinical settings, since most AI models discussed in this review have been tested in limited, single center populations[19,27,87]. Prospective studies testing whether AI-assisted diagnosis actually improves referral decisions, treatment outcomes, or time to diagnosis in real world practice are still lacking, and would offer a more meaningful test of clinical value than accuracy metrics alone.

Portable and explainable AI tools represent another important area for development, particularly for tele-optometry and home based monitoring. Smartphone, wearable, and cloud based AI systems can extend BVD care to primary and remote settings[42,62,80]. However, the clinical adoption of these tools will depend on transparency. Clinicians must be able to interpret, justify, and trust AI-generated outputs before these

tools can be responsibly integrated into diagnostic practice[87-88]. Clearer explainability, regulation, and medico-legal guidance will likely shape how soon these tools reach routine clinical use.

CONCLUSION

AI has emerged as a promising adjunct in the assessment and diagnosis of binocular BVD. Evidence across eye tracking, ocular alignment, vergence, accommodation, stereoacuity, and disorder specific diagnosis consistently points towards improvements in objectivity, clinical efficiency, and accessibility of care. Perhaps one of the most valuable contribution lies in reducing reliance on subjective patient responses, an advantage that may be especially meaningful in children, patients with neurodevelopmental difficulties, and settings where access to specialist eye care is limited. Most of the current evidence is still at an early and largely exploratory stage. Concerns around small and demographically limited datasets, lack of external validation, inconsistent diagnostic criteria, and limited model interpretability remain unresolved. These are not minor technical issues, they directly affect whether clinicians can trust and act on AI-generated outputs in everyday practice. Current evidence is mostly limited to accuracy and feasibility data. There is still little proof that AI improves real world outcomes, efficiency, or decision making in BVD care, and this should be kept in mind before drawing firm conclusions. Addressing them will require deliberate investment in well designed, multicenter validation studies and a commitment to building systems that are transparent in their reasoning.

Ultimately, the role of AI in binocular vision care is not to replace the clinician but to support better and earlier clinical decisions. Achieving this will depend on turning promising prototypes into tools that are validated for real world use.

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