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Eye tracking in virtual reality for neurorehabilitation: a narrative perspective on needs, challenges, and pathways beyond game engines

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Virtual reality (VR) systems with integrated eye tracking offer a powerful way to study and support sensorimotor and cognitive function in neurorehabilitation. Eye movements provide a high-bandwidth window onto information processing, visuomotor integration, cognitive load, and affect, while immersive VR enables more ecologically valid yet controllable tasks spanning visual exploration, movement execution, object interaction, and social exchange. This narrative review synthesizes recent work on eye tracking in VR for neurorehabilitation, focusing on three application domains: assessment, intervention, and supportive design, together with the technical and governance requirements needed to make these systems clinically meaningful and ethically responsible. We highlight how the dominant implementation pattern of integrated headsets streaming preprocessed gaze rays into game engines introduces black-box processing, frame-bound timing, and limited calibration control that pose threats to validity, reproducibility, and cross-site comparability. We review emerging workarounds, including modular architectures that decouple sensing and rendering, explicit latency benchmarking and cross-modal synchronization, adaptive and implicit calibration approaches, and privacy-by-design frameworks from digital phenotyping and metaverse healthcare. Taken together, the evidence suggests that eye-tracked VR is already capable of supporting informative assessments and promising interventions, but that realizing its full potential for neurorehabilitation will require a shift toward architectures that support transparent control over sampling, calibration, timing, and data governance, as well as handling eye tracking data as both a sensitive clinical signal and a protected form of personal data.

KEYWORDS
eye tracking, virtual reality, neurorehabilitation, game engine, data quality, latency and synchronization, data governance and privacy

1 Introduction

Eye movements provide a rich, high-bandwidth window into cognition and action (Carter and Luke, 2020). Eye tracking records where, when, and in what sequence gaze is directed during a task. Because high-acuity vision is confined to the fovea, we constantly move our eyes to bring relevant information into this small region of the visual field (Findlay and Gilchrist, 2003; Rayner, 1998; Rayner, 2009). Although gaze does not fully reflect peripheral processing or covert attention (Rosenholtz and Williams, 2024), it provides a measurable record of overt sampling that can be used to infer which information is selected for detailed analysis under attentional demands, perceptual constraints, and cognitive influences such as memory, language, and decision-making (Just and Carpenter, 1980; Henderson and Ferreira, 2013; Land and Hayhoe, 2001). With millisecond-level temporal resolution, eye tracking can reveal how cognition unfolds over time rather than only its final outcome. Moreover, many aspects of fixation timing and saccade execution are not under explicit conscious control. Individuals may decide what to look at in general terms, but the detailed pattern of fixations and saccades is largely reflexive (Clarke et al., 2017; Kok and Jarodzka, 2017). This makes eye tracking a useful way to access non-conscious aspects of information processing.

Virtual reality (VR) is increasingly used for neurorehabilitation, offering controllable and engaging environments that can be tailored for assessment and training (e.g., (Tuena et al., 2020; Capobianco et al., 2024)). Immersive tasks can be designed to probe visuospatial exploration, movement execution, postural control, and cognitive functions while resembling meaningful everyday activities such as navigation, object interaction, or social exchange (Hougaard et al., 2021; Uimonen et al., 2024; Neugebauer et al., 2024b). Immersive eye-tracking paradigms in VR have also been evaluated under deliberately challenging sensory conditions, including reduced acuity, restricted visual fields/tunnel vision, and other impairment-like degradations such as scotomas or blur (Jones et al., 2020; Neugebauer et al., 2024a; Barbieri et al., 2024; Krösl et al., 2020). Across these studies, VR eye tracking remains usable and produces interpretable measures in gaze and performance that are consistent with established expectations from vision science and clinical observations, supporting the construct validity and practical feasibility of VR eye tracking under degraded sensory conditions.

It is important to acknowledge that VR is not a perfect proxy for physical viewing because head-mounted displays impose perceptual and sensorimotor constraints. These include restricted field of view, display optics that can alter depth cues, and oculomotor demands such as vergence and accommodation. Even when virtual scenarios preserve task structure and visual parameters, these factors can shift scanning strategies and other visual behaviors relative to comparable real-world settings (Kollenberg et al., 2010; Hoffman et al., 2008; Pastel et al., 2021; Cheng and Chukoskie, 2025). However, despite these differences, studies supported that functionally relevant gaze signatures can still be preserved when VR closely matches task structure and action demands (Drewes et al., 2021; Brument et al., 2019; Uimonen et al., 2024; Belger et al., 2025; Kaiser et al., 2022; Cheng and Chukoskie, 2025). With integrated eye tracking, VR adds detailed, context-rich measures of gaze and eye–head–limb coordination during functional tasks, which can complement conventional clinical scales and can help characterize underlying visuomotor strategies.

Most eye-tracking integrated VR systems used in research and early clinical deployments rely on a similar technical stack. Integrated head mounted displays with embedded eye trackers stream preprocessed gaze data into commercial game engines such as Unity or Unreal through software development kits. This ecosystem has lowered the barrier to entry and enabled rapid prototyping of immersive assessments and interventions, but it also introduces constraints that matter for neurorehabilitation. Eye tracking data are usually exposed as filtered gaze rays and event summaries rather than as raw camera signals. Key algorithmic details, such as how pupil and corneal reflection features are detected, how samples are filtered or interpolated, and how calibration models are fit and updated, are encapsulated inside vendor software and are not under researcher control (Clay et al., 2019; Adhanom et al., 2023). In addition, gaze updates are typically tied to the engine's rendering loop. This frame-bound design can introduce extra latency, temporal variability, and downsampling relative to the native tracker rate, which complicates precise alignment of eye movements with visual updates, kinematics, or physiological signals (Choi et al., 2018; Stein et al., 2021; Hou et al., 2024).

Beyond these technical issues, clinical deployment raises additional requirements for privacy and governance. Eye tracking data can reveal biometric identity and sensitive information about cognitive and affective state, which places them closer to clinical records than to ordinary interaction logs from a privacy and regulatory perspective (Liu A. et al., 2019; Kröger et al., 2020; Steil et al., 2019; David-John et al., 2021). Work on the privacy implications of eye tracking and VR emphasizes that gaze patterns can support user identification and inference of personal attributes, and argues that future systems will need stronger guarantees around consent, data minimization, and access control than are typically provided by current VR platforms. In regulated settings, longitudinal use of VR eye tracking also demands robust metadata, versioning, and audit trails so that changes in hardware, software, or task logic can be traced when interpreting outcomes.

This paper focuses on eye tracking in VR for neurorehabilitation and outlines what is needed for these systems to be technically sound, clinically meaningful, and ethically responsible. We first connect clinical use cases to the underlying eye-movement metrics and technical constraints, then examine how current game engine–based pipelines and commercial headsets support or limit these goals. Finally, we highlight implementation strategies and emerging alternatives that can reduce latency, improve data quality and synchronization, and bring privacy and data governance practices closer to clinical expectations. Together, these sections aim to clarify where current practice already supports gaze-based neurorehabilitation, where game engine-centric approaches fall short, and how alternative architectures can better align immersive eye tracking with clinical needs.

2 Methods

2.1 Overall approach and scope

This article is conceived as a narrative, critical review. The aim is not to exhaustively catalogue all studies that combine VR and eye tracking, but to integrate three strands of work that are often discussed in isolation: 1) clinical applications of VR and eye tracking in neurological and neurodevelopmental populations; 2) technical literature on eye movement metrics, sampling, calibration, and timing in VR; and 3) emerging work on privacy, security, and data governance for immersive and sensor-rich systems. The emphasis is on clarifying requirements and trade-offs for neurorehabilitation, using representative examples to illustrate key points rather than attempting a comprehensive census of all available systems and trials. To support this narrative synthesis, we conducted a structured literature search and then used backward and forward citation chaining. We did not conduct a formal systematic review, apply a predefined risk-of-bias tool, or perform a meta-analysis, because our aim is to integrate constraints across clinical, technical, and governance domains rather than estimate pooled effects.

2.2 Literature search and selection

To identify relevant work, we drew primarily on peer-reviewed journal articles and conference proceedings indexed in databases such as PubMed, Web of Science, IEEE Xplore, ACM Digital Library, and Scopus. Searches combined terms related to virtual reality and extended reality ("virtual reality," "VR," "XR," "head-mounted display"), eye tracking ("eye tracking," "eye movements," "gaze," "pupil," "blink"), and clinical or neurorehabilitation contexts ("stroke," "brain injury," "cerebral palsy," "autism," "ADHD," "neurorehabilitation," "rehabilitation," "digital therapeutics"). Additional queries targeted technical and governance aspects, including phrases such as "game engine structure," "motion-to-photon," "Lab Streaming Layer," "multimodal synchronization," "VR privacy," "metaverse healthcare," "digital phenotyping," and "data governance."

We prioritized work published from 2018 onward, reflecting the period in which integrated eye-tracking headsets and contemporary VR rehabilitation systems became widely available, while including earlier foundational studies on eye movement metrics, sampling requirements, and pupil and blink physiology when needed to ground technical arguments. Only studies and perspectives available in English were considered.

Across databases, the structured searches returned approximately 413 records. After removal of duplicates, approximately 335 unique records remained for title/abstract screening. We reviewed approximately 247 records in detail based on relevance to the review scope and inclusion criteria. The final synthesis includes 211 sources.

2.3 Inclusion criteria and organization

Studies were included if they met at least one of the following criteria: 1) used VR or closely related immersive technologies with integrated eye tracking in populations relevant to neurorehabilitation (e.g., stroke, traumatic brain injury, neurodegenerative conditions, cerebral palsy, autism, ADHD or other neurodevelopmental disorders); 2) reported technical evaluations of eye tracking in VR headsets or game engine–based pipelines with implications for sampling, calibration, accuracy, precision, or latency; 3) described architectures or toolkits for multimodal VR experiments that addressed synchronization and timing between eye tracking and other biosignals; or 4) offered conceptual, empirical, or architectural analyses of privacy, security, and data governance for VR, metaverse, or digital phenotyping systems that can reasonably inform gaze-based VR neurorehabilitation.

Studies that used eye tracking without VR (for example, conventional desktop-based tasks) were generally excluded unless they provided essential background on eye movement metrics or physiology that directly informed the technical requirements discussed. Likewise, VR rehabilitation studies without eye tracking were included selectively when they provided critical context on clinical effectiveness, patient and clinician acceptability, or implementation frameworks that shape how eye tracking could be added. Included sources were organized into three strands: clinical applications, technical measurement and pipeline considerations, and governance, and synthesized to derive cross-cutting requirements and trade-offs relevant to eye tracking-integrated VR neurorehabilitation.

3 Eye tracking and VR in neurorehabilitation

3.1 Eye tracking and VR for assessments

By combining immersive, ecologically meaningful tasks with gaze recorded over predefined areas of interest (AOIs), VR eye tracking can characterize how individuals explore, monitor, and act within their visual environment, making it especially useful for assessing visuospatial deficits and visual field loss. Hougaard et al. (2021) developed VR midline judgment and target detection tasks with gaze logging and found that eye-movement-based measures (e.g., horizontal bias, failures to explore contralesional space) differentiated spatial neglect subtypes more sensitively than conventional paper-and-pencil tests. Uimonen et al. (2024) introduced a VR task battery with integrated eye tracking for acute stroke, demonstrating that even patients with "mild" neglect by standard measures show pronounced asymmetries in visual search and fixation density in VR. Brouwer et al. (2022) used a naturalistic VR simulation and applied machine-learning classifiers to gaze features. In their sample, gaze patterns distinguished stroke patients with and without spatial neglect from healthy controls. Eudave and Vourvopoulos (2025) extended this direction by combining VR, eye tracking, and mobile electroencephalogram to map spatial attention, showing that abnormal gaze distributions co-varied with electrophysiological markers of right-hemisphere dysfunction in unilateral neglect.

VR-based cognitive and motor assessments also use eye tracking to better characterize underlying mechanisms in neurodivergent populations. Capobianco et al. (2024) reviewed VR neurorehabilitation interventions and highlighted studies using immersive virtual classrooms where eye tracking was employed to measure attentional distraction in children with ADHD, for example, by quantifying time spent looking at irrelevant stimuli that would be hard to capture reliably with more traditional methods. Cheng and Chukoskie (2025) observed that autistic individuals can spend more time scanning the broader environment and fixating on task-irrelevant information during movement execution. Simmons et al. (2024) used a collaborative VR environment and found that the presence of a virtual partner altered the timing of gaze behaviors and gross motor actions, and modulated physiological arousal and blink rate in autistic individuals differently than in non-autistic controls. Because VR can present rich, precisely controlled visual scenes, when combined with adequate eye movement data, it supports detailed measurement of gaze patterns in context, and may offer advantages for targeting attention, memory, visuospatial, and motor abilities, and even speech-related processes compared with non-VR approaches (Mikhailenko et al., 2022).

3.2 Eye tracking and VR for interventions

Eye tracking has also been integrated into VR interventions. Cinnera et al. (2024) developed a VR protocol with eye-tracking biofeedback for unilateral neglect. Patients received immediate visual feedback when their gaze failed to explore contralesional targets. In this early study, stroke participants tolerated the system well and showed systematic shifts in exploration patterns over training sessions. A complementary eye-movement training paradigm for chronic neglect used smooth-pursuit-like gaze tasks with real-time feedback and reported improvements in visual exploration measures and neglect severity scores after multiple sessions, suggesting that repeated eye-movement practice in VR can at least modify how patients scan their environment. Neugebauer et al. (2024b) conducted a crossover randomized controlled trial in patients with retinitis pigmentosa using an open-source VR gaze-training program that encouraged systematic scanning of the visual scene. Navigation performance in real-world obstacle courses improved significantly more during the VR gaze-training phase than during a control phase, indicating that training gaze strategies in VR can transfer to everyday mobility.

On the cognitive side, VR interventions have been tested for visual processing, memory, and executive function across neurological and aging populations, and eye tracking is increasingly used to make these therapies adaptive. Szczepocka et al. (2024) evaluated a VR-based cognitive training program in healthy older adults and reported improvements in visual memory and sustained attention compared with a control condition. Razzak et al. (2025) examined a VR program for autistic participants that used eye tracking to monitor engagement over repeated sessions; time-series analysis of gaze showed consistent engagement and appropriate cognitive load, supporting the feasibility of using gaze metrics to titrate difficulty in social and attentional training. Capobianco et al. (2024) similarly noted VR eye-tracking tasks used to quantify attentional distraction in children with ADHD, which could be repurposed into training by providing immediate feedback when gaze drifts from task-relevant cues.

3.3 Eye tracking and VR for supportive design

Beyond assessments and interventions, eye tracking in VR broadly enables supportive design choices that make digital environments more accessible (Kiefer et al., 2017). For people with visual field loss, VR perimetry and gaze-contingent display can be extended into assistive tools. For example, by magnifying or enhancing contrast only where the user is currently looking, or by highlighting obstacles that fall into regions inferred to be affected by visual field loss. Sipatchin et al. (2021) demonstrated that, despite reduced precision in the far periphery, commercial VR headsets are a plausible platform for some gaze-contingent visual enhancement and home-based monitoring tasks for individuals with visual loss, as long as task design takes these technical limitations into account. Neugebauer et al. (2024b) developed a VR gaze training for retinitis pigmentosa and illustrated how such systems can be distributed as open-source tools to support sustained, home-based practice.

In motor impairment, gaze can also act as an alternative input channel for VR interfaces. Individuals with limited hand function can select targets, issue commands, or navigate menus via dwell-time or pursuit-based interaction, reducing reliance on conventional controllers. Chen and Hou (2022) showed that gaze and eye-hand coordination features can be used to recognize a user's interaction intention (e.g., upcoming selection or teleportation) in head-mounted VR, which could help future systems distinguish between exploratory looking and deliberate control. Severitt et al. (2025) compared several gaze- and head-based interaction methods in VR and reported trade-offs between precision and user preference, underscoring that gaze-only interaction is not universally optimal but can be competitive when carefully configured.

For neurodivergent users, supportive design also includes using gaze as a safety and tolerability signal. Reviews of VR rehabilitation and clinical VR usability report discomfort of cybersickness, sensory overload, and other adverse effects, and these issues need to be monitored carefully in clinical use (Tuena et al., 2020; Voinescu et al., 2021). In autism and other neurodevelopmental conditions, studies of VR multisensory environments and social-skills training similarly emphasize that benefits often co-exist with risks of sensory overwhelm or discomfort, and that careful calibration and monitoring are essential (Schmidt et al., 2021; Yi et al., 2025). In this context, eye tracking could help detect early signs of disengagement or distress such as increased blink rate, avoidance of specific stimuli, or sudden changes in exploration patterns. These signals have been proposed as one of several signals that could drive automatic adjustments to the VR experience, for example, by simplifying scenes, reducing motion, altering color schemes, or introducing breaks (Adhanom et al., 2023; Stokes et al., 2022). This capability may be particularly important for autistic individuals, children with ADHD, and individuals with acquired brain injury, who may have limited capacity or opportunity to verbalize discomfort during a session but are frequently the target populations for these interventions (Voinescu et al., 2021; Sarai et al., 2025).

4 Technical and clinical requirements for eye tracking VR applications in neurorehabilitation

To provide useful information for neurorehabilitation research and clinical practice, eye tracking in VR has to meet a set of technical and clinical requirements. Below, we outline the eye-movement metrics most relevant to neurorehabilitation and the implications for sampling, data quality, and calibration. We then summarize additional requirements for privacy, metadata, and governance for clinical deployment.

4.1 Eye movement metrics of interest in neurorehabilitation

Eye movement records are commonly described as sequences of fixations and saccades. A fixation is a period during which gaze remains relatively stable at a location, and a saccade is the rapid movement that links two consecutive fixations. Typical observers produce roughly 3–5 saccades per second, with rates vary with perceptual and cognitive demands (Fischer and Weber, 1993). Saccade peak velocity and amplitude follow a characteristic "main sequence" relationship (Carpenter, 1989) that is approximately linear up to about 15–20°, and this relationship has been shown to vary with age and in several neurological or psychiatric conditions (Choi et al., 2014; Reppert et al., 2015). These basic events enable analyses including regions or AOIs, fixation-density heat maps, and scan-path analyses that describe the sequence and timing of fixations, and saccades (Mahanama et al., 2022), which provide understanding in visual information processing, visuomotor coordination, and decision-making processes (Schuetz and Fiehler, 2022; Wolf and Ueda, 2021).

Beyond fixations and saccades, smooth pursuit eye movements are another important class of oculomotor behavior for neurorehabilitation (Kerkhoff, 2000). Smooth pursuit refers to the continuous tracking of a slowly moving target. Measures such as pursuit gain, latency, and the presence of catch-up saccades provide sensitive indices of visuomotor integration and cortical–subcortical control (Barnes, 2008). The saccade and smooth pursuit systems work in concert to track objects in dynamic scenes (Krauzlis, 2004), with predictability of the target motion and timing of an aligning saccade impacting the latency for smooth pursuit onset (Bahill and McDonald, 1983). Abnormal pursuit has been reported across several neurological and psychiatric conditions, including schizophrenia, Parkinson's disease, and other movement disorders, and is often interpreted as a marker of disrupted motion processing and fronto-striatal or cerebellar dysfunction (O'Driscoll and Callahan, 2008; Lencer and Trillenberg, 2008).

In addition to individual fixation, saccade, or smooth pursuit events, information-theoretic measures such as gaze or scan path entropy quantify how predictable or exploratory a person's gaze pattern is over time, capturing whether fixations repeatedly return to a small set of locations or are distributed more broadly across the scene (Krejtz et al., 2016). Higher or lower gaze entropy has been linked to differences in cognitive state and task strategy, and recent work suggests that entropy-like measures can help distinguish observer states and characterize the richness of visual exploration in both typical and clinical populations (Wollstadt et al., 2021; Nasri et al., 2024).

However, detailed work on smooth pursuit and gaze-entropy metrics in neurorehabilitation remains relatively rare. In part because they require relatively high data quality and complex analysis pipelines, most clinical applications still rely on simpler fixation- and AOI-based measures (Hill et al., 2015; Klinke et al., 2015; Liu K. P. et al., 2019; Kaiser et al., 2022; Holmqvist et al., 2023; Dunn et al., 2024; Adhanom et al., 2023). Systematic reviews of spatial-neglect rehabilitation identify smooth pursuit eye-movement training as promising, but they also emphasize small samples, heterogeneous protocols, and a generally low level of evidence, with many studies lacking instrumented eye-movement recording altogether (Hill et al., 2015; Klinke et al., 2015; Liu K. P. et al., 2019; Kaiser et al., 2022). For gaze entropy, prior work has highlighted substantial conceptual and methodological ambiguities (e.g., sensitivity to AOI definition, sampling irregularity, missing data, and time-window choice) and the need for clearer standardization of analysis choices (Shiferaw et al., 2019), while related applied studies have so far used entropy primarily in human-factors and performance-monitoring domains rather than in clinical neurorehabilitation (Lanini-Maggi et al., 2021).

For eye tracking in VR head-mounted displays, it is also important to note that eye-movement detection and classification methods from conventional desktop eye tracking do not carry over directly. In immersive setups, gaze can be represented in multiple reference frames, such as eye rotation in the head, head orientation in the world, or a combined gaze-in-world vector. The chosen reference frame affects how fixations, saccades, and pursuit should be defined and interpreted when the head is moving (Bischof et al., 2024). In practice, head motion and headset optics can distort velocity- and dispersion-based features used by common event detectors, motivating VR-specific processing choices and threshold tuning; related head-mounted work also highlights measurement dependencies that are negligible on desktop systems (e.g., gaze-angle effects on pupil size) and the need to consider large eye–head gaze shifts when quantifying natural behavior (Petersch and Dierkes, 2022; Hooge et al., 2024; Moreno-Arjonilla et al., 2024).

In addition to gaze position, eye tracking provides pupil and blink measures that are often relevant in neurorehabilitation, as they can index aspects of physiological arousal or information processing. Pupil size is typically interpreted as reflecting a combination of tonic and phasic responses. Tonic changes index slower shifts in arousal or alertness, while phasic changes are brief dilations linked to particular events or processing demands (Sun et al., 1983; Wass et al., 2015; Peysakhovich et al., 2017). Pupil data are challenging to interpret because illumination changes also drive pupil responses, and arousal measures can be modulated by lighting (Raiturkar et al., 2016). Despite these limitations, pupil data have been used as an indirect marker of subjective task difficulty and cognitive load. Pupil dilation is linked to activity in the locus coeruleus–norepinephrine system, which plays an important role in arousal and cognitive control (Laeng et al., 2012; Burkhouse et al., 2015; Bast et al., 2021; Chevalier et al., 2015). In clinical contexts, pupil measures help interpret pupillary responses in mental and motor tasks. For example, autistic individuals may have both hypoarousal and hyperarousal when attending to social stimuli (Lydon et al., 2016), and patients with schizophrenia have shown reduced pupil dilation during action preparation, suggesting a reduced phasic arousal signal (Thakkar et al., 2018).

Blinks provide another useful signal. Non-voluntary blinks are typically divided into spontaneous and reflexive blinks. Reflexive blinks are evoked by external stimuli as a protective response, while spontaneous blinks are those that occur in the absence of such explicit triggers (Valls-Sole, 2019). Spontaneous blinks are most commonly studied because they have been linked to a range of information-processing functions, including attention and working memory (Müller et al., 2007; Schumacher et al., 2013; Groman et al., 2014). Blink-based measures have also been used to evaluate internal state. For example, spontaneous blink rate can increase under stress or negative affect in social or emotional recollection tasks (Shin et al., 2015; Maffei and Angrilli, 2019; Eckstein et al., 2017; Gotlieb et al., 2021; Jongkees and Colzato, 2016). Several studies have reported that increased eyeblink rate reflects rising fatigue (Borghini et al., 2014; Gergelyfi et al., 2015). In contrast, spontaneous blink rate has been found to decrease when participants are highly engaged in demanding tasks involving memory operations and sustained attention (Brefczynski-Lewis et al., 2011; Paprocki and Lenskiy, 2017).

4.2 Technical requirements for the relevant metrics

The technical requirements for eye tracking depend strongly on the research or clinical question, because different eye-movement metrics have different temporal and spatial characteristics (Nyström et al., 2025). When fast eye movements such as saccades and smooth pursuit onset detections are of interest, higher sampling rates become more important. Sampling frequencies of at least 200–300 Hz are often recommended for accurate estimation of saccade peak velocities and fixation-to-pursuit transitions (Juhola et al., 1985; Inchingolo and Spanio, 2007). Smooth pursuit has lower temporal frequencies than saccades, so for estimating pursuit gain and velocity profiles in common tasks with target speeds under about 40 deg s^{-1}, stable sampling in the 60–120 Hz range is usually adequate, although higher rates can improve onset timing and noise suppression (Nyström et al., 2025).

Information-theoretic gaze metrics such as gaze entropy depend less on micro-dynamics and more about unbiased transition counts between AOIs. In this case, a tracker with stable sampling and explicit timestamps is more important than ultra-high frequency, because entropy estimates are sensitive to sampling irregularity, AOI definition, and time-window choice (Shiferaw et al., 2019). At lower sampling rates (< 120Hz), estimated peak velocities tend to be lower than expected (Mack et al., 2017), although some work have argued that 50 Hz can be sufficient when appropriate upsampling strategies are used (Wierts et al., 2008). However, if the goal is simply to determine whether a participant fixated particular objects in a scene, a 30 Hz sampling rate may be sufficient: this provides one position estimate every 33.3 ms, and fixations typically last longer than 100 ms, so several samples within the same image region can be enough to infer a fixation. Similarly, relatively low sampling rates are usually adequate for studies focused on pupil dilation, as the arousal-related signal changes over seconds (Othman and Romli, 2016; Dalmaijer, 2014).

The Shannon–Nyquist sampling theorem provides a useful theoretical reference point (Shannon, 1949), a continuous-time signal that contains only frequencies below x Hz can be represented without loss of information if it is sampled at more than 2x Hz. Because most eye-movement signals contain their dominant frequencies below about 100 Hz (Findlay, 1971; Nyström et al., 2021), this reasoning suggests a minimal sampling frequency of around 200 Hz if one aims to capture all information in principle. In practice, researchers prefer higher sampling rates when they are available and feasible. Denser sampling can improve the temporal precision of estimates such as saccade onset and offset, which can increase statistical power (Andersson et al., 2010). Higher sampling rates can also be useful when the goal is to predict saccade landing position and pursuit onset as early and accurately as possible (Han et al., 2013), which is particularly relevant in gaze-contingent applications.

Data quality is another central concern in neurorehabilitation research and application. Eye-tracking data are accurate when measured gaze positions are close to the true gaze position, and precise when repeated measurements under the same conditions are consistent (Reingold, 2014). These notions are closely analogous to validity and reliability. In neurorehabilitation, it is especially relevant because participants may have atypical head posture, involuntary movements, visual-field deficits, or difficulty maintaining fixation.

Calibration is therefore critical. It is the point where researchers and clinicians have the greatest leverage over data quality, and spending extra time to obtain a good calibration generally pays off over the remainder of the session (Carter and Luke, 2020). Because data quality can degrade over time, for example, due to small changes in head position, headset slippage, or lighting changes, it is often good practice to include multiple calibration or validation checks within a session. When high spatial accuracy is needed, more frequent recalibration may be warranted. For example, when inferring fixations on small AOIs, supporting gaze-contingent interactions, or estimating smooth pursuit gain and gaze-entropy, calibration accuracy is especially important because even modest drift, noise, or intermittent tracking can shift gaze across AOI boundaries and distort continuous-path statistics even when nominal sampling rates are adequate.

4.3 Clinical and regulatory requirements: privacy, metadata, and versioning

As VR eye tracking moves toward neurorehabilitation deployment, data governance becomes a practical requirement. Eye movements and pupil signals can reveal identity and a wide range of sensitive attributes. Eye-tracking data can be used to infer biometric identity (Munoz et al., 1998; Zhang and Le Meur, 2018), emotional state (Armstrong and Olatunji, 2012), and cognitive processes (Duchowski et al., 2018; Bradley, 2009; Raiturkar et al., 2016), and allows rich insights into psychological attributes, such as neurological (Leigh and Zee, 2015) and behavioral disorders (Mundy, 2018). In VR and AR, González and Bozkir (2024) argued that eye-tracking data will often qualify as “special categories of personal data” under the EU General Data Protection Regulation.

Clinical systems also require robust metadata and provenance. In healthcare, data provenance is typically defined as a record of where data came from, how they were generated, and how they have been processed over time (Ahmed et al., 2023). This supports version control and auditable logging for clinical decision-making or for regulated digital therapeutics. Regulatory guidance for electronic records stresses the need for audit trails that record who created, modified, or accessed a record, along with timestamps and justifications for changes (Food and Drug Administration, 2018). Related work on data provenance similarly emphasizes auditability and traceability as key to detecting errors, supporting inspections, and ensuring that automated systems can be scrutinized when needed (Ahmed et al., 2023). For VR eye tracking, this implies more than encrypt and pseudonymize gaze data, but also maintain transparent records of why data were collected, how long they will be stored, and conditions they may be reused, along with updates to task content, rendering engines, gaze-mapping algorithms, and scoring rules should be versioned. Patient-level records should store which versions were in effect at each session so outcomes can be interpreted consistently across time and sites.

5 Tools available for VR eye tracking research

Most VR eye-tracking work in neurorehabilitation is built on a common integration stack. Commercial headsets generate a gaze signal that is processed by the vendor runtime and then delivered into VR applications through game engines and software development kit (SDK) interactions. Below we summarizes the main components of that stack and how gaze information is typically delivered to VR tasks.

5.1 Commercially available VR headsets with eye tracking

Eye tracking in VR headsets typically relies on the same infrared pupil center and corneal reflection identification technology used in many remote and desktop eye trackers, adapted to the limited space and optical geometry inside a headset (Ugwitz et al., 2022). A growing ecosystem of commercially available head-mounted displays now combines VR with embedded eye tracking, and these devices have become the default choice for many laboratories and clinical applications. Recent surveys describe a core set of integrated systems, including HTC Vive Pro Eye, Varjo VR-1 and VR-3, Fove-0, and standalone devices such as Pico Neo 3 Pro Eye, Oculus Quest Pro, as well as add-on solutions like Pupil Labs modules (Adhanom et al., 2023; Moreno-Arjonilla et al., 2024).

Embedded eye tracking performance is shaped by headset hardware constraints. Typical sampling rates for embedded eye trackers in VR range from about 60 to 200 Hz, with vendor-reported delays between 15 and 52 ms and end-to-end latencies between 45 and 81 ms (Adhanom et al., 2023; Stein et al., 2021). Limited by camera placement and optical design, most headsets use a display behind optical lenses to cover a visual field of approximately 100–110° (Sipatchin et al., 2021). Eye tracking integrated VR head-mounted displays such as the HTC Vive Pro Eye typically yield median central accuracies closer to 1–2° with precision in the sub-degree range, and show substantially worse performance at eccentricities beyond 20–25° (Schuetz and Fiehler, 2022; Sipatchin et al., 2020; Adhanom et al., 2023). In addition, data quality can differ substantially depending on setup, procedure, and participant characteristics, which is especially relevant in clinical populations where ocular physiology, glasses, fatigue, or atypical oculomotor control may affect tracking (Groman et al., 2014; Ehinger et al., 2019; Hessels et al., 2015; Hutton, 2019; Nyström et al., 2013).

These constraints make task-specific validation important even with commercial-ready-to-use VR eye tracking systems. For example, Sipatchin et al. (2020); Sipatchin et al. (2021) documented systematic degradation in accuracy and precision toward the periphery and under head-free viewing, underscoring the need for application-specific testing. Lamb et al. (2022) reported that gaze accuracy and precision vary systematically with stimulus distance and cautioned that relying on vergence to estimate gaze depth in VR can introduce biases, which complicates the interpretation of depth-related effects in three-dimensional tasks.

5.2 Game engines and the integration stack for VR eye tracking

Game engines are the dominant software infrastructure for VR applications. Systematic reviews of VR visualization and serious games consistently identify Unity and Unreal are the most widely used platforms for immersive environments in both research and industry (Checa and Bustillo, 2020; Korkut and Surer, 2023). Game engines provide ready-made solutions for many foundational tasks involved in building games, virtual environments, and digitally augmented scenes (Jungherr and Schlarb, 2022; Paul et al., 2012; Christopoulou and Xinogalos, 2017; Mishra and Shrawankar, 2016). Core components typically include a rendering engine, a physics engine, and a math or numerics engine. These components coordinate scene updates such as object motion and collision, lighting and shadows, and other graphical and physical effects needed to produce a coherent virtual scene (Angra et al., 2022). In VR, these engines are typically configured to support stereoscopic rendering, head-tracked interaction, and headset runtimes rather than representing a separate software category.

In most current systems, VR eye tracking is delivered to Unity or Unreal as a processed data stream rather than raw camera images (Ugwitz et al., 2022). At the device level, near-infrared cameras inside the headset capture images of the eyes at the tracker's internal sampling rate. Vendor runtimes detect features such as the pupil center and corneal reflections, estimate gaze direction for each eye, and then fuse these estimates into a combined binocular gaze vector. These pipelines usually include proprietary filtering and data quality handling, for example, temporal smoothing, interpolation across short dropouts, and removal of low confidence samples (Clay et al., 2019; Ugwitz et al., 2022).

On the engine side, gaze is often accessed through vendor-provided SDK. Engine-side code typically queries the integration layer during runtime updates and receives the most recent available gaze estimate along with quality indicators. If the eye tracker runs faster than the display, several internal samples can be collapsed into a single frame level update, and any samples that occur between frames are not directly exposed to the engine. Gaze is then mapped onto virtual objects or scene elements using application logic or SDK-provided mapping utilities, enabling common endpoints such as gaze-triggered events or estimates of which objects were attended.

Implementation details can differ across runtimes and SDKs even when the underlying headset is the same. Schuetz and Fiehler (Schuetz and Fiehler, 2022) collected gaze data in Unity with HTC Vive Pro Eye. They used manufacturer-provided scripts and recorded each session twice, once via SteamVR and once via the Tobii XR SDK. In both cases, they accessed per-frame gaze vectors delivered by the respective SDKs, showing that the same headset-level signal can be wrapped in different engine-side application interfaces without changing the underlying hardware measurements. Some SDKs also provide optional object-mapping layers that go beyond simple ray–collider intersection. For example, Liu et al. evaluated a Tobii object-mapping approach that combined gaze rays with scene information and compared it to a ray–collider baseline, finding differences in how targets were assigned near edges and for small, adjacent objects (Liu et al., 2023).

6 Limitations of game engine-based pipelines for VR and eye tracking in neurorehabilitation

Neurorehabilitation applications depend on reliable gaze measurement, interpretable event detection, precise alignment between gaze, task events, and other signals, and regulation alignments. However, the common headset–SDK–engine stack can constrain reliability, reproducibility, and clinical interpretability. This section focuses on limitations that are especially consequential for neurorehabilitation studies and early clinical deployments.

6.1 Black box processing and its impact on data reliability and reproducibility

In the common game engine and proprietary SDK systems, developers typically can only access the preprocessed outputs. The underlying stages are usually hidden from users, and details of the algorithms and parameter choices are not publicly documented (Clay et al., 2019; Adhanom et al., 2023). This means that researchers working inside engines such as Unity or Unreal rarely know which samples were discarded, how missing data were interpolated, or how filtering alters the timing and spatial profile of saccades, fixations, or pupil traces. Josupeit (2022) argues that open-source access to raw data and code is a key advantage for transparency and reproducibility in VR research. In neurorehabilitation, this becomes particularly important because many customized analyses and clinical validation steps are not possible without access to raw eye tracking data. It also complicates efforts to assess validity in clinical populations or to compare results across hardware generations and software versions (Clay et al., 2019; Josupeit, 2022).

Interoperability further complicates reproducibility. Across VR ecosystems, eye tracking is exposed through vendor-specific SDKs and runtimes that differ in data formats, timestamp conventions, coordinate frames, and event definitions. This fragmentation often forces device-specific analysis pipelines. For example, Tobii reports gaze using a head-unit coordinate system tied to the headset (Tobii, 2023), Varjo reports eye positions and gaze directions in a headset coordinate system with a defined origin between the eyes (Varjo, 2025), and Pupil Labs maps gaze into the world-camera coordinate system and commonly exports additional normalized coordinates for surfaces or AOIs (Pupil Labs, 2025). These representational differences matter because core outcomes in neurorehabilitation research, such as AOI dwell time, scan path structure, eye-head and eye-hand coordination can shift depending on coordinate conventions, mapping assumptions, and event logic.

A related challenge is that analysis choices from desktop eye tracking do not transfer cleanly to head-mounted VR. In head-mounted settings, gaze is inherently coupled to head motion and changing reference frames. Meaningful measures often require explicit transformations among eye-in-head, head-in-world, and gaze-in-world representations, along with geometry-aware mappings such as intersecting gaze rays with 3D scene geometry or defining AOIs on surfaces rather than a fixed display (Bischof et al., 2024; Sidenmark and Gellersen, 2019). Event detection and derived metrics can therefore be more sensitive to noise, sampling jitter, and coordinate transforms than in desktop paradigms, particularly when the available signal has already been filtered and downsampled within the SDK-engine stack (Bischof et al., 2024).

Methodological and validation studies underline how this opacity can limit reliability, validity, and reproducibility. Nyström et al. (2025) and Niehorster et al. (2025) noted that vendor software can differ substantially in filtering and event classification, and that these differences can change derived metrics even when the hardware is identical. Hessels and Hooge (2019) showed that precision and data loss vary widely across participants, sessions, and operators, and argued that without visibility into processing steps it is difficult to know whether poor data quality reflects the hardware, the recording setup, or the participant's behavior. Moreno-Arjonilla et al. (2024) surveyed eye tracking in VR and documented wide variation in reported accuracy and precision across devices and studies, noting that inconsistent reporting and limited access to raw signals complicate comparisons across system. Device-focused evaluations similarly showed that spatial accuracy, precision, and data loss can change with background luminance, headset slippage, locomotion, and other factors, and that these effects are mediated by vendor-specific detection and filtering strategies that are not fully described (Awasthi et al., 2024; Aziz et al., 2024). Building on this, Dunn et al. (2024) proposed a minimal reporting guideline for eye tracking studies and emphasized the need to account for variability and hidden processing in commercial systems to support reproducibility.

Black-box constraints also extend to calibration. In most commercial integrations, calibration is usually implemented as a short, point-based procedure that assumes a cooperative, neurotypical user who can maintain stable fixation and follow targets on command (Adhanom et al., 2023). The underlying calibration modeling, adaptation rules, and quality checks are encapsulated inside the SDK, and developers have limited options beyond triggering a new calibration or accepting the current state (Clay et al., 2019; Adhanom et al., 2023; Ugwitz et al., 2022; Niehorster et al., 2025). These assumptions can become problematic in neurorehabilitation and neurodivergent populations, where stable fixation and functional binocular coordination may not hold. Binocular-vision differences such as strabismus, amblyopia, or vergence insufficiency are common in neurodivergent groups. For example, in ADHD children, 36% showed reduced positive fusional vergence and 20% had a receded near point of convergence (Solé Puig et al., 2015; Clavé and Torrents, 2025). In autistic individuals, ophthalmologic and orthoptic exams report strabismus in approximately 4%–15% and convergence difficulties in about 13%–26%. (Longo et al., 2023; Gutiérrez et al., 2022). Similar oculomotor and binocular-vision disruptions are also prevalent in clinical groups such as cerebral palsy, stroke, and concussion (Rowe, 2010; Herron et al., 2025). In these cases, calibration can appear successful algorithmically while still introducing systematic bias in gaze estimates, compromising gaze accuracy and the interpretability of downstream analyses (Ferracini et al., 2025). Motor impairments, atypical oculomotor

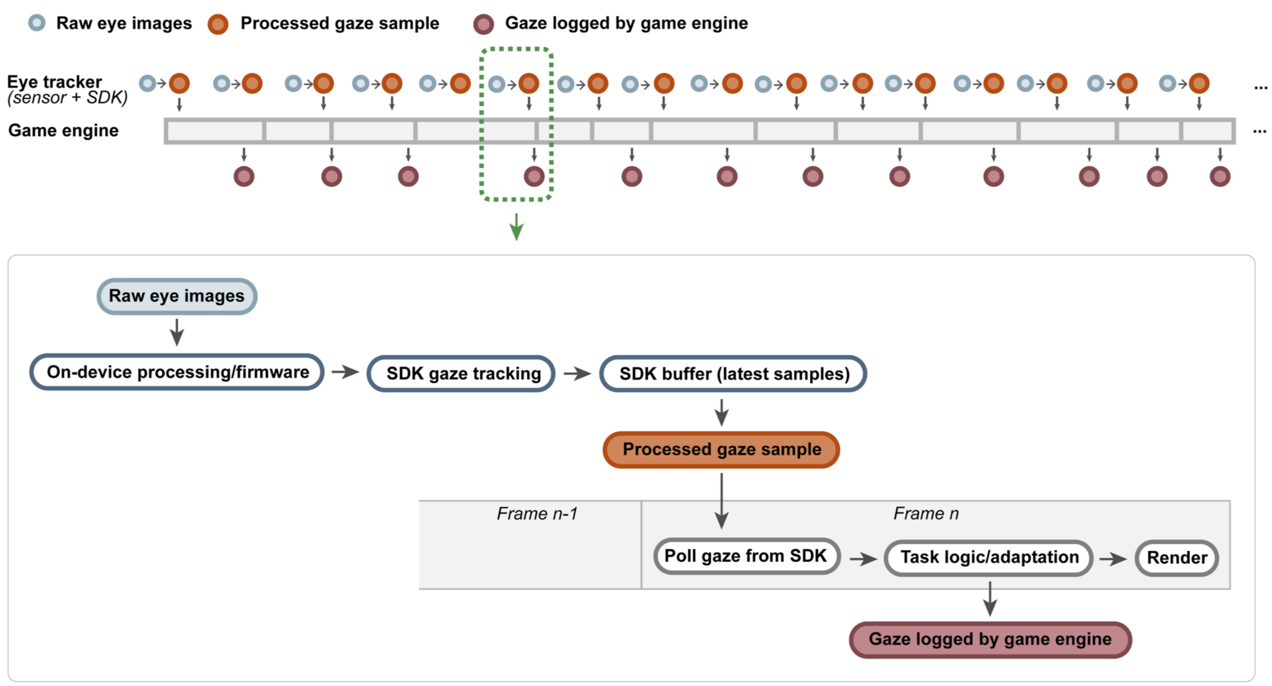

FIGURE 1
Simplified illustration of the temporal relationship between the eye tracker and the game engine. The eye tracker continuously converts raw eye camera images into processed gaze samples. The game engine runs a separate frame loop whose rate can fluctuate with scene complexity and system load; it queries the eye-tracking software once per frame, uses the most recent available sample in its task logic, and logs one gaze sample per frame. Because these timelines are not synchronized and the frame rate can vary, the delay between when gaze is measured and when it is used and logged is itself variable and not captured by nominal sampling-rate or latency specifications.

patterns, fatigue, or sensory sensitivities can further reduce calibration stability and tolerability in clinical sessions.

Empirical work underscores the role of individual differences and the need to monitor effective gaze error over time. Liu et al. (2024) reviewed personal calibration issues in video oculographic eye tracking and emphasized that individual differences in eye anatomy, head pose, and behavior can create substantial variability in calibration quality. They also note that these issues are amplified in children and clinical populations, who may not be able to follow instructions or maintain stable fixation. Leharanger et al. (2023) similarly report that autistic individuals often require multiple sessions to become comfortable with mixed reality headsets and eye tracking tasks, underscoring the need for extended familiarization and flexible calibration procedures in neurodivergent populations. Fernandes et al. (2024) showed in a controlled VR study that degrading eye tracking accuracy leads to measurable declines in performance and subjective experience during gaze-based interaction. They argue that systems should monitor and manage effective gaze error over time, rather than assuming that a single initial calibration remains valid throughout a session.

6.2 Game loop coupling, latency, and temporal variability

A central component of a game engine is the game loop, which controls how the game state is updated and rendered in real time. In most engines, the loop repeatedly processes input, updates the simulation, and renders the next frame, creating the impression of smooth, continuous interaction. Different loop designs exist, including fixed time step, variable time step, semi-fixed, event-driven, and asynchronous loops, each with advantages and disadvantages for performance and responsiveness (Mileff, 2023). Regardless of the specific pattern, each iteration of the loop corresponds to a frame, and many Unity and Unreal-based eye tracking integrations update gaze in lockstep with this loop.

Frame-bound access introduces a transformation of the gaze stream that can change both effective sampling and timing. Hou et al. (2024) examined mismatches between the eye tracker sampling rate and the Unity frame rate and reported dropped or duplicated eye-tracking samples and discrepancies between tracker timestamps and engine-derived timestamps when gaze is accessed per frame. Stein et al. (2021) measured delays using Unity scripts recommended by manufacturers, so that the reported values already reflect engine timing behavior. When the eye tracker samples at 100–120 Hz and the engine renders at 72–90 Hz under variable load, a frame bound logging strategy effectively decimates the eye tracking stream to the engine's instantaneous frame rate and re-timestamps samples according to when the render loop happens to run. From the perspective of any analysis that uses engine-side logs, the device's advertised sampling rate is therefore a poor proxy for the effective temporal resolution of the data unless gaze is acquired and time-stamped outside the render loop or through a dedicated synchronization layer. Figure 1 illustrates the temporal relationship between the eye tracker and the game engine, showing how continuous gaze sampling is folded into a frame-based loop on the application side.

For neurorehabilitation, latency is not only a comfort issue but also a validity constraint. Many research projects rely on accurate temporal information between gaze, visual updates, and other physiological or kinematic signals. A growing body of empirical work has benchmarked the delays introduced by the game engine's own update and rendering loops. Choi et al. (2018) introduced a time-sequential motion-to-photon measurement system and showed that latency in a head-mounted display increased from a minimum of 46.55 ms to a maximum of 154.63 ms as scene complexity and system workload rose, again measured with external encoders and photodiodes rather than engine timestamps. Hou et al. (2024) examined multiple VR headsets' eye-tracking characteristics in Unity and showed that while average sampling rates were close to manufacturer specifications, devices exhibited bimodal sampling-frequency distributions that reflected interactions between the eye tracker's internal timing and Unity's frame-update loop. This coupling implies that gaze samples are effectively snapped to engine frame boundaries. Also, gaze-contingent paradigms for saccadic suppression, trans-saccadic learning, and foveated rendering typically require that display changes occur within a few tens of milliseconds of the relevant eye movement, otherwise key perceptual effects weaken or disappear (Stein et al., 2021; Albert et al., 2017). Albert et al. (2017) quantified this for foveated rendering, reporting end to end eye to photon latencies of around 31–35 ms in their baseline condition, and showing that adding 40–150 ms of additional eye tracking latency dramatically reduced the range of foveation levels that remained perceptually acceptable. Stein et al. (2021) similarly argue that effective gaze-contingent displays in head-mounted systems should not delay stimuli much beyond the saccade duration plus a few tens of milliseconds, based on the time course of saccadic suppression and related phenomena. When game engine-dependent jitter, clock differences between devices, and network delays for remote deployments are added on top of eye tracker latency, the total timing uncertainty impacts the data validity for neurorehabilitation research and applications.

6.3 Privacy and data governance

The VR security and privacy literature indicates that current commercial VR platforms handle sensor streams very differently from clinical data. Major VR SDKs such as OpenVR, Oculus Platform, and WebXR provide limited or inconsistent mechanisms for permissioning and auditing relative to clinical expectations (Wu et al., 2023). VR devices may also continuously collect fine-grained nonverbal information, including body movements, gestures, and eye movements, which are highly identifying and predictive of user traits (Giaretta, 2025). From a data governance perspective, game engines expose this information to applications through ordinary sensor application programming interfaces, often without strong permission controls, encryption, or built-in logging policies. The same mechanisms that make it easy to prototype gaze-contingent interaction also make it easy for any engine-based application to stream clinically relevant behavioral data off the headset.

Clinical and mental health VR work have already raised concerns about this misalignment between current tools and clinical expectations. Parsons (2021) discussed ethical issues in using virtual environments for assessment and treatment of psychopathology, arguing that many VR deployments treat data governance as an afterthought and lack clarity on who has access to them, how long they are retained, and how consent and withdrawal are implemented when VR systems are deployed clinically. More recent papers on VR ethics echo these concerns, noting that headset logs can reveal intimate details about mental state and cognition and that current commercial ecosystems offer limited support for granular access control, audit trails, or patient-controlled data sharing (Giaretta, 2025; Abdrabou et al., 2025; Goulet et al., 2025). Rahartomo et al. (2025) surveyed work on metaverse security and privacy and found that most papers focus on individual attacks, defenses, or user studies, while only a small number propose comprehensive architectures that integrate authentication, access control, secure storage, and accountability mechanisms. Giaretta (2025) reached a similar conclusion for VR specifically, noting that research has concentrated on authentication schemes and particular attack vectors, while holistic discussions of data governance, logging infrastructures, and regulatory compliance remain rare. Unity or Unreal logs, often simple text files or cloud analytics streams, fall far short of the standards expected for electronic health records, which typically require encryption at rest and in transit, role-based access control, and verifiable audit logging. Researchers who need these properties must build bespoke solutions that sit alongside or outside the engine, which increases implementation burden and makes it harder to standardize best practices across neurorehabilitation studies.

7 Implementation key requirements: capabilities and workarounds

Given the constraints in SDK-level opacity, frame-bound access, and limited governance support, recent work has converged on practical implementation strategies that recover observability, improve timing fidelity, and increase robustness within today's commercial ecosystems.

7.1 Working around black-box eye tracking pipelines

Researchers have built workaround layers on top of the black-box interfaces to gain more control over representation, calibration, and downstream analysis. One common approach is to reduce cross-platform fragmentation by normalizing gaze and head-pose representations across devices. When supported, acquiring gaze through OpenXR provides a more standardized gaze pose interface that can be queried consistently across headsets (The Khronos Group, 2025; Unity Technologies, 2025). In parallel, modular logging stacks can help by attaching explicit metadata, such as units, coordinate frame, transforms, SDK or runtime versions, and perform coordinate harmonization outside the engine before analysis. Related community standards illustrate how this can scale. Motion-BIDS specifies a consistent representation for motion-capture data and coordinate metadata to support interoperability across systems (Jeung et al., 2024). Eye-tracking standardization within the BIDS ecosystem is also advancing through a formal community process (FieldTrip, 2025), with the goal of making continuous gaze samples and eye-tracking annotations portable across toolchains.

A second set of workarounds focuses on analyses methods that are more tolerant to noise and better matched to naturalistic, dynamic viewing conditions. VR-specific guidance emphasizes making reference-frame choices explicit and to computing metrics in frames that match the research question. For example, by separating eye-in-head from head-in-world contributions and using geometry-aware mappings when intersecting gaze with objects or surfaces (Bischof et al., 2024). A practical implementation pattern is to export gaze and head pose with enough metadata to reconstruct consistent coordinates, then apply classifiers outside vendor pipelines to standardize event detection across datasets. Dar et al., 2021 introduced REMoDNaV, which was designed for dynamic stimulation and prolonged recordings and provides robust classification of saccades, fixations, pursuits, and post-saccadic oscillations under noisier conditions than many classical threshold pipelines, making it a practical baseline for VR datasets after appropriate coordinate handling and preprocessing. Complementary work include strategies for improving automatic fixation detection under head motion (Drews and Dierkes, 2024) and noise-estimation approach for 3D binocular head-mounted tracking that can inform noise-aware preprocessing and threshold selection (Velisar and Shanidze, 2024).

Recent work on adaptive and implicit calibration offers a roadmap for moving beyond this static, engine-centric view, particularly in clinical contexts where calibration may need to be tailored rather than treated as a one-time prerequisite. Grillini et al. (2021) introduce continuous eye-tracking perimetry in which stimuli follow a pseudo-random walk and sensitivity maps are inferred from continuous gaze deviations using spatial-temporal integration and recurrent networks, demonstrating that calibration and assessment can be interleaved within a dynamic, task-embedded procedure. Implicit calibration methods extend this idea by eliminating explicit calibration phases. Kasprowski et al. (2019) proposed a “probable fixation targets” framework that uses knowledge of the visual stimulus to infer likely gaze targets and update the gaze-to-screen mapping continuously during interaction. Yang et al. (2023) presented vGaze system leverages saliency maps to select informative frames for opportunistic calibration on mobile devices, achieving continuous, saliency-aware calibration with accuracy on the order of a few degrees. Mygdalis and Dens (2024) describe an implicit, train-free calibration approach for appearance-based eye tracking that adapts deep models to individuals without explicit calibration trials, showing that subject-specific performance can be recovered from in-task gaze data alone. Li et al. (2022) introduce a calibration-error prediction model that uses features of raw gaze signals to forecast when calibration quality is likely to be poor, allowing systems to flag or adjust low-quality segments instead of treating all calibrated data as equally reliable. When binocular assumptions are unreliable, another practical direction is to relax those assumptions explicitly. Ferracini et al. (2025) proposed a custom monocular calibration approach designed to enhance eye-tracking accuracy, illustrating how calibration procedures can be adapted for users in whom standard binocular calibration may yield systematically biased gaze estimates. More broadly, these approaches highlight that calibration success should be evaluated not only by vendor-defined completion criteria but also by clinically relevant validation checks that can detect systematic bias and guide recalibration or alternative procedures.

Researchers also wrap commercial devices with more flexible calibration and validation controllers. The Titta toolbox and its extension provide adaptive calibration and validation workflows for Tobii trackers and supports synchronized access to Tobii Pro SDK data streams (Niehorster et al., 2020; Niehorster et al., 2025). Josupeit (2022) documented how the Pupil Labs add-on supports relatively transparent access to gaze streams and calibration routines within VR research workflows, lowering barriers to customizing calibration and data handling compared with closed commercial integrations.

Finally, several groups address degraded gaze quality at interaction time by making interfaces explicitly error-aware interaction techniques and providing fallback modalities. Sidenmark et al. (2023) proposed Weighted Pointer, which monitors eye tracking error in real time and automatically adjusts the contribution of gaze versus a secondary input such as a controller or head direction, ensuring that pointing remains usable even when gaze samples are noisy or missing. Earlier work on error-aware gaze interfaces for mobile devices also combined gaze with touch or other modalities, using signal quality estimates to decide when to trust gaze alone and when to rely more heavily on the fallback channel (Barz et al., 2018; Fernandes et al., 2024) degradation study complements this by quantifying how much gaze error can be tolerated in VR before interaction performance and subjective usability decline, providing concrete thresholds that adaptive calibration systems can target.

7.2 Timing, latency, and modular synchronization

To mitigate timing uncertainty introduced by frame-bound access and variable engine workloads, many groups have adopted modular synchronization frameworks that treat the game engine as just one client in a larger timing ecosystem. The Lab Streaming Layer (LSL) is widely used for this purpose. Kothe et al. (2025) describe LSL as a general-purpose framework for synchronized multimodal recording, in which each device or application streams time-stamped samples into a shared clock domain over the local network; LSL then handles clock offset estimation, jitter buffering, and stream alignment. Iwama et al. (2024) review two common issues in synchronized multimodal recordings, jitter and latency, and highlight that LSL-based approaches can reduce misalignment between devices and improve signal-to-noise ratios in averaged electrophysiological responses. A scoping review by Wang et al. (2023) shows that LSL has been widely adopted in VR research to synchronize eye tracking, electroencephalogram, motion capture, and controller data with Unity or Unreal front ends. In these studies, the engine typically publishes task events and receives decoded states, but the main data logging and timekeeping occur outside the engine, which allows gaze, electroencephalogram, and movement signals to be recorded at their native rates and aligned with VR events at millisecond precision.

Several platforms extend this approach into explicit modular architectures to integrate VR, gaze, and biosignals with explicit latency and synchronization handling. PhysioLabXR is a Python-based open-source platform designed for real-time multimodal experiments that integrate brain–computer interfaces and extended reality (Li et al., 2024). In this system, game engines work as front ends that connect via LSL, ZeroMQ, or gRPC to a central hub that acquires eye tracking, electroencephalogram, and other signals, performs online processing, and sends control messages back to the VR application. This design allows developers to benchmark and manage end-to-end delays in one place, while keeping the timing of each device independent of the game engine's rendering loop. Wang et al. (2023) notes that this pattern, in which XR applications act as clients of a dedicated synchronization and logging layer, is increasingly common in multimodal VR research.

Modular synchronization has also been extended beyond single laboratories. The LabLinking framework connects distributed laboratories, each with their own sensors and VR systems, into joint experiments by exchanging time-stamped events and data streams over middleware such as LSL (Schultz et al., 2024). In this setup, each lab can use its preferred acquisition hardware and game engine, while shared timing and communication infrastructure ensures that gaze, motion, and other signals remain aligned across sites.

From a neurorehabilitation perspective, these modular synchronization efforts provide practical solution to help keep latency and temporal variability within known bounds, and make it more straightforward to relate gaze events to motor behavior and clinical outcomes across sessions and sites.

7.3 Platform control and ethical data practices

Privacy concerns related to eye tracking applications have increased substantially in recent years (Bozkir et al., 2020; John et al., 2019; John et al., 2020; Kröger et al., 2020; Steil et al., 2019). In response, a growing body of work has begun to treat the gaze as a sensitive biometric and proposes mechanisms that reduce identifiability while preserving utility for interaction or analysis. At the sensor level, John et al. (2020) introduced a hardware based technique that optically degrades images collected by the eye tracker so that they are no longer suitable for iris authentication while preserving gaze tracking performance, reducing identification accuracy from 79% to 7% while maintaining usable gaze accuracy (Li et al., 2021). At the signal level, methods that replace raw gaze samples with aggregate representations such as saliency heatmaps (Liu A. et al., 2019) and event-level statistics (Bozkir et al., 2021; Steil et al., 2019; Fuhl et al., 2021) can reduce inference of protected attributes like gender or identity but still support many forms of analysis. Related approaches apply formal privacy guarantees to raw gaze streams by obfuscating where and when viewers look at specific AOIs while preserving analytic utility, bringing biometric identification closer to chance in benchmark evaluations (Li et al., 2021).

Because commercial VR ecosystems and game-engine pipelines are not designed to meet clinical governance expectations by default, it is useful to draw on patterns from mobile and wearable sensing frameworks that implement privacy and security by design. A systematic review by Kumar et al. (2021) surveyed 28 sensing frameworks and cataloged non functional features such as extensibility, data encryption, secure communication protocols, licensing, and documentation. Many of these platforms use Advanced Encryption Standard for data at rest and Transport Layer Security or Secure Sockets Layer for data in transit, and several adopt explicit pseudonymization strategies in which personally identifying information is removed, hashed, or stored on separate servers from sensor streams.

The Beiwe platform provides a concrete example from digital phenotyping that is widely used in psychiatry and neurology (Onnela et al., 2021). Data are encrypted at rest on the device, encrypted again in transit, and stored encrypted on the server using a hybrid asymmetric encryption scheme. Personally identifying fields are anonymized on device using a one-way hash with an added random system-generated code before upload, so the back end never receives raw identifiers. The only stable link between a participant and their data is a randomly generated study identifier managed by study staff, which simplifies compliance with de identification and data minimization requirements (Onnela et al., 2021). Similar principles appear in game-based cognitive assessment platforms such as COSMOS, which is a web platform where each gamified cognitive task has its own application specific relational SQL database to record user input, while a separate central authentication system assigns user data to unique identifier codes (Aeberhard et al., 2019). This separation allows gameplay to be linked longitudinally across tasks and sessions within a secure web framework without exposing direct identifiers in task level tables. The per game SQL databases are then connected via experience application programming interfaces to a learning record system backed by MongoDB, which serves as a visualization and query layer for administrators and researchers. Because the core data are stored in standard SQL tables, they can be accessed programmatically and analyzed with reusable query scripts, enabling retrieval and aggregation of behavioral measures across tasks. COSMOS has already been used as infrastructure for large scale cognitive assessment studies, in which centralized, queryable databases support analysis of performance metrics derived from gameplay (Rotaru et al., 2018). For VR neurorehabilitation, these design choices translate into practical requirements for handling gaze, motion, and interaction logs as protected behavioral health data.

Clinical deployments also benefit from access control and auditability that are explicit at the platform level rather than left to *ad hoc* application code. The LAMP protocol underlying the open source mindLAMP platform for digital phenotyping and interventions in mental health (Vaidyam et al., 2019). LAMP is developed as an application programming interface driven framework that represents patients, clinicians, activities, sensors, and survey events as resources in a JSON over HTTP model. Every API call consists of a verb (for example, "get" or "post"), a resource uniform resource locator, and a security token that encodes the authorization context, specifying which user or role is accessing which resource under which study permissions. The protocol includes a transaction audit log in which each modification to a resource is recorded, and responses can carry a live citation that links them back to the original access request and credentials. This structure makes it possible to reconstruct the full history of any data element, including who accessed or edited it and when, and provides built in support for rollback and data recovery (Vaidyam et al., 2019).

At larger scales, multi-site consortia increasingly encode ethical boundaries directly into their data operations infrastructure. Billah et al. (2025) describe a data operations architecture named Accelerating Medicines Partnership Schizophrenia that supports FAIR (Findability, Accessibility, Interoperability, and Reusability) stewardship across eight international sites and diverse data modalities, including REDCap clinical data, digital phenotyping apps, imaging, and audio and video. Their system uses the Phoenix directory structure (Gait, 1990) to separate "general" and "protected" data, with protected information (direct identifiers, raw audio and video, certain imaging metadata) stored in restricted areas and linked to de identified datasets via study keys. The open source Lochness tool (Harvard Neuroinformatics Research Group, 2022) pulls data from source systems through their APIs, maps them into Phoenix, and controls which data are synchronized to central repositories based on predefined sharing agreements. Only redacted or derived materials, such as transcribed and de identified text or averaged features, leave the originating institutions, and systems such as REDCap are configured with role based access control and detailed audit logs for all user activity.

8 Discussion

VR with integrated eye tracking is now increasingly accessible, but its role in neurorehabilitation is currently limited. This paper focuses on eye tracking as a critical sensing modality within VR neurorehabilitation, and examines how current implementation pathways, especially those built around commercial game engines, enable or constrain clinically meaningful use of gaze.

8.1 Technical feasibility, structural tensions, and clinical fit

From a hardware standpoint, many of the demands of neurorehabilitation research and early clinical use are achievable. Commercially available eye tracking VR headsets can provide 60–200 Hz sampling, 1–2° central-field accuracies, and below 100 ms end-to-end latencies, which is sufficient for a wide array of applications focused on fixations, dwell times, scan paths, and gaze-based interaction near the center of the visual field (Adhanom et al., 2023; Schuetz and Fiehler, 2022; Sipatchin et al., 2021; Stein et al., 2021; Ugwitz et al., 2022). Related work on VR-based vision-impairment simulation further supports that VR eye tracking can yield interpretable fixation and saccade measures even under degraded viewing, with systematic effects consistent with established vision-science expectations (Kasowski et al., 2023; David et al., 2021; Neugebauer et al., 2024a; Chow-Wing-Bom et al., 2020). Although challenges remain for precise work on saccadic or pursuit dynamics, perimetry, or micro-movements on current consumer headsets, these readily available devices are suitable for many neurorehabilitation paradigms that operate on moderate spatial and temporal scales (Adhanom et al., 2023; Stein et al., 2021; Schuetz and Fiehler, 2022). There is also now substantial evidence that VR-based interventions may improve motor and cognitive outcomes for people with stroke, cerebral palsy, and acquired brain injury, especially when tasks are tailored to specific impairments and when training is sufficiently intensive (Voinescu et al., 2021). In parallel, the broader VR eye tracking literature has expended across gaze-contingent interaction, foveated rendering, and attention-aware interfaces across domains ranging from entertainment to ophthalmology and human–computer interaction (Adhanom et al., 2023).

The central tension instead lies in how this hardware is exposed through proprietary SDKs and game engines. As detailed in Sections 5–6, commercial stacks commonly deliver vendor-preprocessed gaze estimates and event summaries once per rendered frame. This loop-bound design introduces additional delay and temporal variability on top of tracker latency, effectively downsampling the native eye movement signal to the engine's instantaneous frame rate and re-timestamping samples according to when the render loop happens to execute (Stein et al., 2021; Hou et al., 2024). This structure directly shapes what can be measured and how reliably it can be interpreted. Loop-bound access and undisclosed filtering can bias estimates of saccade or pursuit onset, peak velocity, and threshold-like outcomes, expecially under variable rendering or head motion (Choi et al., 2018; Stein et al., 2021; Hou et al., 2024). Collapsing multiple native samples into one frame-level update limits fine-grained oculomotor analyses and complicates alignment with kinematic or electrophysiological signals, even when the raw hardware would support it. This proprietary pipeline also freezes calibration into a short, one-size-fits-most procedure whose internal models and adaptation rules are hidden, leaving developers with little control beyond triggering or skipping calibration (Clay et al., 2019; Adhanom et al., 2023; Ugwitz et al., 2022; Niehorster et al., 2025). Black-box calibration and event classification further reduce the ability to diagnose and correct problems, compare results across devices or software versions, or reanalyze data with improved algorithms (Nyström et al., 2025; Moreno-Arjonilla et al., 2024; Hessels and Hooge, 2019). In principle, VR headset cameras and illumination could support richer timing diagnostics, continuous or implicit calibration, and task-specific quality monitoring. In practice, the engine-facing pipeline often collapses these possibilities into a single, opaque stream.

A further tension arises when eye-tracked VR is placed into a clinical or regulatory context. Privacy and security analyses of VR platforms consistently show that gaze, body movement, and interaction histories are highly identifying and predictive of user traits, yet most commercial SDKs expose these streams through ordinary sensor APIs without strong permissioning, encryption, or built-in audit trails (Giaretta, 2025; Wu et al., 2023; Rahartomo et al., 2025). In healthcare-oriented scenarios, Letafati and Otoum (2023) argue that multi-modal behavioral and physiological data will need protection mechanisms comparable to or stronger than current telehealth platforms, spanning secure communication, access control, and tamper-evident logging. Work on VR ethics and clinical VR similarly emphasizes that immersive systems blur the distinction between interaction logs and health records, and that consent, retention, secondary use, and cross-platform data sharing must be governed explicitly rather than left to default platform settings (Parsons, 2021; Abdrabou et al., 2025; Goulet et al., 2025; González and Bozkir, 2024).

Taken together, these observations suggest a nuanced position. On one hand, today's eye tracking and VR hardware is broadly adequate for most neurorehabilitation applications that target fixations, scan paths, and gaze-contingent interaction at moderate spatial and temporal scales. On the other hand, the way this hardware is wrapped by proprietary SDKs and game engines introduces latency, calibration rigidity, and opacity that lower data quality and restrict analysis, while the surrounding platform ecosystems treat gaze as an ordinary interaction signal rather than as sensitive health data. Bridging this gap will require not only incremental improvements in headset specifications but also deliberate re-design of software stacks and data pathways so that the full capabilities of the sensors can be used in a way that aligns with clinical, scientific, and regulatory expectations.

8.2 Beyond game engines: observability, modularity, and governance

The structural limitations of game engine–based pipelines point toward a broader architectural shift rather than simple incremental fixes. A first direction is to restore observability over the gaze signal by stepping around black-box abstractions. Open or semi-open stacks such as Pupil Labs add-ons and the Titta toolbox deliberately expose raw or minimally processed streams, calibration routines, and timing information, enabling task-specific calibration, continuous quality checks, and re-analysis with improved models (Niehorster et al., 2020; 2025; Josupeit, 2022). Toolkits and standardized benchmarking protocols, including simulators that inject controlled error into gaze streams, can quantify how hardware and filtering choices affect data quality and interaction performance (Adhanom et al., 2020; Kangas et al., 2020; Sidenmark et al., 2023; Fernandes et al., 2024). Combined with adaptive and implicit calibration techniques that run outside vendor SDKs, these approaches allow researchers to treat the headset as a sensor rather than a closed appliance, and to tailor calibration and quality monitoring to the constraints of neurorehabilitation populations (Kasprowski et al., 2019; Yang et al., 2023; Mygdalis and Dens, 2024; Li et al., 2022; Liu et al., 2024). These recommendations would improve software interoperability and cross-platform compatibility, making neurorehabilitation tools more robust to single system updates.

Another common thread across recent work is to treat the engine as a thin client for graphics and interaction, and to move critical functions, including timing, data access, calibration, and governance, into layers that sit alongside or outside game engines. In modular timing frameworks such as LSL, devices and applications stream time-stamped samples into a shared clock domain, allowing gaze, electroencephalogram, motion capture, and controller data to be aligned independently of the rendering loop (Kothe et al., 2025; Iwama et al., 2024; Wang et al., 2023). Platforms like PhysioLabXR and LabLinking extend this pattern by routing eye tracking and biosignals through central hubs or distributed nodes that handle acquisition and synchronization, while engines subscribe to processed states and events (Li et al., 2024; Schultz et al., 2024). In effect, these architectures keep end-to-end latency and jitter under explicit control, while still leveraging mature engines for task design and visual feedback.

A third direction concerns governance. Instead of letting engines write *ad hoc* log files or stream data directly to vendor analytics, several communities have converged on architectures in which the VR front end talks to a secure back end that enforces encryption, pseudonymization, and audit trails. Smartphone-based digital phenotyping platforms such as Beiwe and mindLAMP, and game-based cognitive assessment systems like COSMOS, demonstrate that high-volume behavioural data can be handled with healthcare-grade separation of identifiers, role-based access control, and versioned provenance (Onnela et al., 2021; Vaidyam et al., 2019; Aeberhard et al., 2019; Rotaru et al., 2018). Multi-site consortia such as AMP-SCZ go further by encoding ethical boundaries directly into directory structures and synchronization tools, ensuring that only de-identified or derived materials leave originating institutions and that all access is logged (Billah et al., 2025). Adapting these patterns to eye-tracked VR that treat the headset and game engine as user interfaces to a governed data layer may offer a practical route to reconcile the richness of gaze data with clinical expectations around privacy, traceability, and regulatory compliance.

Adopting such modular designs, however, comes with costs. They require additional infrastructure for networking and time synchronization, familiarity with real-time data streaming, and more careful documentation of hardware and software versions than single-engine setups. In clinical settings, modular pipelines must also integrate with hospital information security policies and electronic health record systems, which may constrain network architectures or data paths. At the same time, they offer clear benefits: critical logic for sampling, synchronization, logging, and data governance moves out of closed engine plugins and into configurable, auditable layers that can be tailored to regulatory and research needs. When combined with privacy-preserving data handling and explicit audit trails, these architectures provide a pragmatic way to use existing game engines for graphics and interaction, while ensuring that gaze and biosignals are recorded and governed with the fidelity expected of clinical measurements (Vaidyam et al., 2019; Onnela et al., 2021; Billah et al., 2025).

8.3 Translational considerations: populations, platforms, and protocols

A recurring theme across rehabilitation reviews is the gap between general VR evidence and the specific needs of neurorehabilitation populations. Umbrella and narrative reviews of VR rehabilitation systems report that VR can support more ecologically valid assessment and training, enhance motivation, facilitate intensive and repetitive practice, but also highlight small samples, heterogeneous tasks, limited follow-up, and inconsistent reporting of adverse events (Fernandez and Hui, 2022; Macchitella et al., 2023; Voinescu et al., 2021). This gap is likely even larger for eye-tracked VR: relatively few studies have examined how calibration, data quality, and gaze-contingent feedback behave in individuals who may have motor impairments, atypical oculomotor control, sensory sensitivities, or cognitive fatigue, even though these groups are prime targets for VR-based neurorehabilitation.

For many such users, standard eye-tracking application workflows may be uncomfortable or simply infeasible. Reviews of video-oculography emphasize that individual differences in eye anatomy, head pose, and behavior can create substantial variability in calibration quality, with children and clinical populations particularly affected (Liu et al., 2024; Hessels and Hooge, 2019). Work with autistic individuals and people with severe neurodevelopmental conditions similarly reports that extended familiarization and flexible protocols are often needed before participants can reliably engage with mixed reality headsets and gaze tasks (Leharanger et al., 2023). Degradation studies in VR show that as gaze error increases, both performance and subjective usability decline, supporting the need to monitor and manage effective gaze error over time rather than assuming that a single initial calibration remains valid (Fernandes et al., 2024).

Evidence from VR vision-impairment simulation studies offers a practical complement to this translational gap. Rather than serving as direct clinical analogs, these studies function as controlled stress tests that pair well-defined sensory degradations with immersive tasks and quantify how gaze structure, exploration strategies, and functional performance change under degraded input (Kasowski et al., 2023; David et al., 2021; Barbieri et al., 2024; Neugebauer et al., 2024a). Because the perturbations are interpretable, this literature can inform protocol-level choices that are otherwise underspecified in clinical-facing work, such as minimum validation checks, reporting conventions, and data-quality thresholds, and it can highlight when calibration and mapping assumptions remain stable versus when they break down (Kasowski et al., 2023).

The adaptive and implicit calibration methods reviewed earlier suggest one path forward: instead of treating calibration as a one-time prerequisite, they embed it into engaging tasks and update the gaze-to-display mapping continuously from behavior, saliency, or model-based predictions (Kasprowski et al., 2019; Yang et al., 2023; Mygdalis and Dens, 2024; Li et al., 2022; Niehorster et al., 2020; 2025). Translationally, these approaches will require careful clinical validation, but they offer a way to align calibration protocols with the attentional and sensory profiles of neurodivergent and neurologically impaired users, rather than forcing users to conform to the constraints of off-the-shelf workflows. Importantly, many current VR headset–SDK–engine stacks do not expose the raw signals or intermediate quality metrics needed to implement such adaptive procedures, reinforcing the argument that platform design, not hardware capability, is now a primary bottleneck.

At the platform and protocol level, the literature points toward hybrid architectures and governed data layers as pragmatic strategies for translation, but without a unified solution yet. Existing reviews of VR rehabilitation systems and telerehabilitation indicate that VR has been deployed in both inpatient and home-based programs, and that remote supervision is increasingly feasible, yet eye tracking is mentioned rarely and usually only in brief device descriptions rather than in detailed implementation or validation work (Voinescu et al., 2021; Macchitella et al., 2023). The implementation work reviewed here suggests that multimodal synchronization frameworks, together with privacy-by-design infrastructures are promising candidates to provide the multimodal data integration, provenance, and access governance that neurorehabilitation demands (Onnela et al., 2021; Vaidyam et al., 2019; Aeberhard et al., 2019; Rotaru et al., 2018; Kothe et al., 2025; Li et al., 2024; Billah et al., 2025).

8.4 Limitations and future directions

This paper focuses on selected strands of a rapidly evolving literature and is not a systematic review. We prioritized recent work on eye tracking in VR, neurorehabilitation applications, timing and synchronization, privacy, and security, which means that some relevant domains, such as telepresence for multidisciplinary care and long-term home monitoring, are only touched on indirectly. Much of the existing technical discussion is grounded in results from non-immersive, flatscreen setups, and standalone VR devices and mobile applications may introduce additional constraints and opportunities that warrant separate analysis. Finally, our emphasis on game engines and alternative modular architectures is shaped by the current research ecosystem; future commercial platforms may expose different APIs, timing behavior, and governance features.

Several concrete research directions emerge. First, there is a need for task- and population-specific validation studies that characterize eye tracking accuracy, precision, data loss, and latency in neurorehabilitation settings, including comparisons between engine-bound and modular logging pipelines and between laboratory, clinic, and home environments. Second, developers and clinicians should collaborate to define technical, protocol, and reporting standards for VR eye tracking in neurorehabilitation, building on existing data quality and reporting guidelines so that future trials can be compared and synthesized more reliably, and so that critical elements such as calibration procedures, logging architectures, and latency measurements are documented in a consistent way. Third, more work is needed at the level of policy, governance, and regulation to clarify how gaze in VR should be treated as health-relevant and privacy-sensitive data, to design and evaluate reference architectures for privacy-by-design data layers, and to align eye-tracked VR systems with existing legal frameworks and institutional practices around consent, data minimization, provenance, and patient control over data access and reuse.

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