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REAsmash-ET: a methodological framework for combined cognitive and motor assessment through eye-tracking and kinematic metrics in immersive VR search-and-reach task

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Abstract

Background Virtual Reality (VR) Serious Games (SGs) can provide a functionally relevant framework to capture cognitive and motor dynamics. Their interactive and engaging nature improves compliance, measurement reliability and allows for more frequent evaluations. Additionally, VR SGs enable the parallel collection of multiple types of data within a single session. We present REAsmash-ET, an immersive VR adaptation of the REAsmash SG, grounded in Feature Integration Theory (FIT) and integrating eye-tracking (ET) and upper limb kinematic (UL) analyses. REAsmash-ET introduces a novel methodological framework for the simultaneous assessment of attentional and motor functions in VR.

Methods REAsmash is an interactive search-and-reach task designed to elicit structured visual exploration and UL motor responses under varying target-distractor saliency conditions. Custom algorithms extract metrics on visual search strategies and UL motor efficiency. Three age groups of adult healthy participants (n = 15 each) were included to test the feasibility and methodological consistency of the task and its metrics. Relative Response Time (RRT) and ET metrics were analyzed using ANOVA with factors: age group (20–39, 40–59, 60–80 years), target-distractor saliency (high vs. low), and number of distractors (11, 17, 23). Kinematic metrics were analyzed by age group and response hand (dominant vs. non-dominant).

Results REAsmash-ET differentiated visuomotor performance across task conditions. RRT and ET metrics showed significant effects of saliency, number of distractors, and their interaction, consistent with FIT. Age-related differences emerged in both RRT and visual search efficiency. Kinematic analyses revealed slower and less efficient movements in older participants, with effects of hand dominance.. The results support the robustness and feasibility of REAsmash-ET as a methodological framework.

Conclusions The results support the robustness and internal consistency of REAsmash-ET as a methodological framework for the integrated assessment of visual attention and UL motor control in immersive VR. The task's ability to

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capture visuomotor variability and its multidimensional approach highlight its potential for future research and clinical applications in both healthy and clinical populations.

Registry number This study was registered at ClinicalTrials.gov (NCT04694833).

Keywords Eye tracking, Virtual reality, Spatial attention, Distractor inhibition, Cognitive evaluation, Upper limb kinematics, Cognitive-motor interaction

Background

Context

With around 80 million survivors worldwide, stroke is the primary cause of long-term disability in developed countries [1] and the third cause of long-term disability worldwide [2]. Stroke prevalence is expected to further increase in the next years [3, 4]. Despite improvements in post-stroke care, survivors typically present a combination of long-term cognitive and motor deficits [5].

Estimates of cognitive impairment among stroke survivors remain uncertain and highly variable, with prevalence in the acute/sub-acute stages ranging from 24 to 80% [6], partially explained by a lack of consensus in assessment protocols [7]. Comprehensive cognitive assessments are not systematically performed on a routine basis in clinics [8, 9], due to the limited number/availability of neuropsychologist specialists trained for cognitive assessment. Access to stroke-specific cognitive rehabilitation services in community settings is also limited, further reducing cognitive follow-up chances in the post-discharge phase [10].

Furthermore, clinical presentations of cognitive impairments in stroke survivors typically involve multiple cognitive functions (such as visuospatial abilities, inhibition, memory, executive functioning [11–15]) with great variability in survivors' cognition and brain lesion profiles [16]. This variability further complicates assessment and, as a consequence, the rehabilitation process [5, 17].

Classical neuropsychological testing procedures, such as paper-and-pencil tests, often diverge from real-world demands, as they rarely provide complex and dynamic scenarios, and are susceptible to practice effects [18]. Computerized cognitive assessments can provide quantitative data such as speed and response consistency [18], however, they typically require long administration times, and often lack motivational appeal [18, 19]. Furthermore, computerized cognitive assessments are usually conducted in 2D environments that do not reflect real-life interactions. In this context, assessment of visuospatial attention appears to be more sensitive when performed in immersive virtual reality (iVR) compared to traditional paper-and-pencil tests [20]. Gamifying computerized cognitive assessments can improve participant engagement, while maintaining the accuracy of quantitative data collection [21].

Motor deficits, intended as loss or limitation in muscle control or reduced mobility [22] are well-documented in the literature, affecting approximately 80% of stroke survivors [23]. Consistent evidence indicates that over 75% of survivors experience persistent Upper Limb (UL) impairment during the chronic stage [24]. UL impairments can result in difficulties with reaching and grasping abilities [25], limiting individuals' autonomy to accomplish Activities of Daily Living (ADLs) [26]. For UL motor evaluation, the literature recommends several tests (e.g., Fugl-Meyer Assessment [27], Box and Block Test [28], and Action Research Arm Test [29]) [30]. These tests align with the International Classification of Functioning, Disability and Health (ICF) [31] framework, serving as reliable and valid tools in post-stroke assessment [32]. These tests are widely used worldwide, providing a reliable picture of the functional condition of the UL affected by stroke [32]. However, despite their strong measurement properties [33, 34], most of these clinical assessments exhibit floor and ceiling effects [35].

These effects can be attributed to several well-known limitations [36]: (i) limited sensitivity. Most assessments use ordinal scales, which may not detect minor yet clinically significant improvements during rehabilitation [37]; (ii) lack of movement quality analysis. Traditional tests focus on task completion but do not provide detailed insights into movement characteristics such as speed, smoothness, or coordination [38]. These kinematic parameters could help distinguish between active restorative movements and compensatory strategies [39] and (iii) observer-dependent variability. Some assessments rely heavily on clinical observation, introducing subjectivity and inter-rater variability, which can affect the consistency and reliability of assessment outcomes [40].

Integrating kinematic analysis can help address these limitations, enhancing the precision and objectivity of motor function evaluation [41]. However, introducing these technologies into clinical practice faces challenges related to clinical utility, including high costs, the need for specialized equipment and trained personnel, time-consuming data processing, and the absence of standardized, easy-to-use protocols suitable for everyday healthcare settings [42]. Furthermore, kinematic metrics are typically not collected during training (in-game), but only during specific assessment tasks performed outside the training sessions [43].

Differences in addressing motor and cognitive deficits may be related to the traditional approach of managing cognitive and motor impairments as distinct issues, with motor recovery often being the primary goal [44]. However, the combined presence of motor and cognitive disabilities further reduces individual autonomy in ADLs and quality of life, increasing caregiver dependency and reducing social participation [45]. These findings highlight the critical need for reliable and routine cognitive assessments and neuropsychology practice in post-stroke care, as frequently advocated in the literature [46]. Increasing evidence points to a strong connection between cognitive and motor functions, supporting the importance of integrating cognitive assessment with quantitative (kinematic) evaluation of residual motor abilities in stroke [47]. A large body of studies has shown that cognitive functions, such as attention and visuospatial abilities [48], play a crucial role in guiding motor performance, motor learning, and overall recovery [49].

Notably, recent evidence suggests that simulating ADLs in controlled settings provides a meaningful framework for assessing cognitive-motor interaction, as these tasks require the simultaneous engagement of motor control, attention, executive functioning, and memory [50].

The first challenge for both neuroscientific research and clinical settings is thus to propose a consistent, objective, and reliable assessment of both cognitive and motor impairments, integrated into the overall rehabilitation process to facilitate the development of personalized and effective rehabilitation programs, while ensuring clinical utility through feasible, accessible, and time-efficient tools that can be easily implemented in routine clinical practice.

Through the integration of different technologies including Virtual Reality (VR), Eye-Tracking (ET) and motion tracking sensors, Serious Games (SGs) offer a novel interactive approach to assess both cognitive and motor functions [51, 52]. SGs are, by definition, games (i.e., gamified tasks) designed with a primary purpose beyond entertainment [53], often aimed at facilitating learning, incorporating challenging tasks to keep participants motivated [54]. They enable the collection of extensive quantitative (e.g., response times and number of fixations) and qualitative data (e.g., task strategies or behavioral patterns inferred from gaze trajectories) during task execution, increasing the potential to capture subtle motor and attentional differences.by capturing real-time information on performances [55]. Additionally, as with computerized assessment [56], the randomization of stimulus presentation can help minimize practice effects while ensuring consistency and standardization across individuals.

REAsmash-ET is a SG we developed for investigating and objectifying visual search through the integration of ET technology into our original SG, the REAsmash [57]. REAsmash-ET enables precise measurement of cognitive visual-spatial attention interactions within compact 3D Regions of Interest (ROIs) representing the stimuli in a fully immersive VR environment. The REAsmash-ET presents stimuli in a horizontal playing field, matching the orientation of traditional paper and pencil tests, and the orientation of a consistent part of the ADLs [58]. From a technical perspective, this orientation presents challenges in fine-tuning the algorithm for raw ET data interpretation, as both accuracy and precision are strongly influenced by the spatial distance of the stimulus (i.e., whether it is located close to or far from the observer relative to the horizontal axis) [59]. This paper aims to address these challenges, demonstrating suitability for capturing and analyzing gaze behavior in dynamic, horizontally structured settings.

We aim to propose our serious game as a tool for studying different components of visuospatial attention involved in a target search-and-reach task, including distractor inhibition and working memory, reflected by the tendency to fixate repeatedly on distractors or return to them during visual exploration.

We further leveraged the built-in features of VR systems to analyze motor performance data, including speed, precision, and smoothness of the UL response.

Before introducing the REASmash-ET, we describe an overview of the two main technologies employed in this project: iVR and ET.

Fully immersive VR (iVR)

Definition of fully iVR

Fully iVR generally refers to technologies designed to create an engaging interactive, three-dimensional, multisensory environment by employing Large Projection Systems (LPSs), Cave Automatic Virtual Environments (CAVEs) or Head-Mounted Displays (HMDs) [60]. SPSs consist of large screens that project the virtual environment onto a display surface. A CAVE is a room equipped with four to six projection screens that, when viewed with 3D glasses, create a continuous and immersive visual experience. This setup is further improved with head-tracking sensors and speakers to provide audio stimuli [60]. HMDs are wearable devices equipped with integrated screens, head-tracking sensors, and auditory feedback systems [60]. Their strong clinical utility relies on their portability, ease of use, and minimal setup requirements, which make them well-suited for hospitalized patients, outpatient care, and potentially even home-based rehabilitation [61–63]. In contrast to other immersive VR systems that require complex and expensive infrastructures, HMDs offer a practical and scalable solution for routine clinical applications.

Interest of fully iVR in neurorehabilitation

Fully iVR enables the design of safe, fully immersive 3D virtual environments, typically difficult or impossible to replicate within a clinical setting, such as street-crossing or virtual supermarkets [64]. These environments can provide a multisensory experience, combining visual, auditory, and motor stimulation, which allows for customized levels of challenge and engagement tailored to individuals with varying severities and types of deficits [65, 66]. The field of motor assessment has played a pioneering role in integrating new technologies into clinical practice [67]. A growing body of literature supports the use of iVR for rehabilitative purposes in post-stroke, highlighting its potential to enhance engagement, functional outcomes, and therapy adherence [68].

Interest of iVR in assessment

iVR technologies have been demonstrated as valuable tools for evaluating complex and/or multiple tasks [69, 70]. In particular, the introduction of reliable kinematic measures during iVR tasks reinforces traditional practices by providing objective data [71]. Kinematic analysis is now a well-recognized methodology for quantifying motor-related metrics [72]. Fully iVR-based cognitive assessment showed greater accuracy than conventional paper-and-pencil methods [73]. HMDs allow for the consistent recreation of ideal testing conditions, independent of the real environment, enabling excellent session standardization with minimal disruption from real-world stimuli and excellent clinical utility [61–63, 74]. Modern devices allow for the integration of various types of data, including behavioral outcomes, kinematic measures and gaze metrics. These data streams can be used independently (e.g., kinematics to assess motor execution or gaze metrics to evaluate attention and decision-making) but can also be combined to explore the interaction between cognitive and motor domains in ecologically valid, task-based scenarios [75]. This characteristic makes these tools particularly valuable in complex assessment settings, such as post-stroke, where different types of deficits often coexist and are interdependent.

Eye-tracking

The elementary components of gaze movements and definition of eye-tracking

The elementary components of gaze movements while free viewing, reading or visual searching for a target are classically distinguished by fixations and saccades [76]. Fixations occur when the gaze remains relatively stable for a sufficient period, allowing cognitive processing of the stimulus upon which the gaze persists [77]. Saccades, on the other hand, are ballistic movements of the eye between two fixation points, during which limited cognitive interaction is possible [77]. There is a third category of eye macro-movements named 'smooth pursuit', which occurs when a visual pursuit of a moving stimulus is required [78].

ET technology refers to the measurement of eye movements to understand where an individual's visual attention is directed [79]. It is based on the principle that eye movements are used to bring the visual area to be explored into the center of the visual field (i.e., the foveal region), where the highest concentration of photoreceptors enables detailed visual processing [80, 81].

Various types of eye-tracking technologies are available today. A broad classification based on device setup divides ET technologies into two groups: remote and wearable systems. Remote ET systems are typically used in screen-based studies, enabling natural computer interaction while collecting gaze data without physical contact [82]. However, while they simplify data handling, remote systems are restricted to fixed locations and may produce gaps or artefacts if participants move their heads excessively [83].

Wearable or head-mounted ET systems, such as headbands, glasses, and helmet-mounted devices often feature a secondary scene camera capturing the participant's field of view [84]. These devices enable free movement during experiments and are valued for their binocular vision accuracy [41]. Mobile ET technologies are particularly suitable for real-world studies, although tracking peripheral gaze is less precise, and gaze data must be recorded in the scene camera's coordinate system due to the lack of a fixed reference frame [82].

An innovative system is represented by iVR-ET HMDs [85], a particular type of mobile device with ET systems built into HMD for fully iVR. As recently suggested by Kaise et al. [73], this novel technology provides an unprecedented opportunity in visual exploration, allowing the capture of detailed and accurate temporal and spatial data cross the entire visual field while allowing for full-body movements improving ecological validity.

Interest of ET in neurorehabilitation

ET is a well-established technology in the field of cognitive neuroscience [31] and offers significant potential in neurorehabilitation due to its ability to track and analyze visual attention in real time and across different types of tasks. Studies using ET have been used for assessment in peri-personal (i.e., within arm's reach) [86–88] and extra-personal (i.e., beyond arm's reach) spaces [89, 90] paving the way for studies that co-investigate eye-hand interaction. In terms of stimuli, the literature reports wildly different setups, including elementary geometrical shapes [91], everyday photographs [92, 93] and videos [94], and more complex stimuli [95]. Different tasks have been employed, such as reading tasks [96], free viewing [92], and visual search tasks [97]. In the neurorehabilitation field, these types of tasks can be fine-tuned to target specific cognitive functions, including spatial and sustained attention, distractor inhibition, and working memory, increasing real-world applicability through ecological design.

Interest of ET in assessment

ET technology provides a valuable tool for the assessment of visual attention by measuring parameters such as the number and distribution of fixations [73, 98], promoting a deeper understanding of cognitive and motor interactions [75]. Additionally, ET presents a non-verbal, less cognitively demanding approach for monitoring disease progression in individuals with cognitive deficits [75].

ET technology demonstrated its validity in various experimental setups, allowing researchers to assess attentional mechanisms across different contexts and task demands in controlled and naturalistic environments [99]. Furthermore, emerging evidence [100] indicates that ET data aligns closely with established cognitive evaluation methods, suggesting its potential as a tool for assessing severity and monitoring recovery in neurological conditions. Despite advancements in ET technology, its adoption in clinical settings remains limited [101].

REASmash-ET

Our research team developed REAsmash [102], a SG adaptation of the classic fairground and arcade game Whac-A-Mole built within a structured paradigm that provides an advanced gamified adaptation of a well-established cognitive paradigm based on Treisman and Gelade's Feature-Integration Theory (FIT) of attention [103]. FIT distinguishes between high- and low-saliency target-distractor conditions. In high target-distractors saliency, the target is prominent among the distractors and attention is directly drawn to the target stimulus through pre-attentive bottom-up "parallel search" [104]. In low-saliency conditions, individual stimuli need to be recognized as distractor stimuli and inhibited prior to target detection. This process is defined by "serial search" [104]. Parallel search times remain unaffected by distractor number, whereas serial search times increase with increased distractor number due to the need for more individual distractors to be inhibited.

The primary objective of REAsmash was to evaluate the impact of target-distractor salience on visual search efficiency during a structured search-and-reach task, with a focus on visuospatial attention and distractor inhibition measures. To this end, we analyzed behavioral outcomes including error and omission rates and response time for successful trials (see Materials section). The test supports adjustable saliency conditions and has demonstrated cognitive stability when transitioning from classical 2D stimuli to complex 3D cartoon-like animated VR presentations [105]. The iVR version integrates UL kinematic tracking and has been shown to enable precise motor performance evaluation [106, 107].

Previous research on visual exploration has predominantly employed non-immersive VR, focusing on static panoramas [92, 108, 109] or 2D visual search tasks [98, 110–115]. These studies indicate that fixation duration is influenced by target-distractor similarity, perceptual difficulty, and stimulus density, with similarity increasing fixation time and salience capturing attention. The REAsmash-ET aims to extend this knowledge by proposing, for the first time, ET measurements of visual search during a fully iVR SG, replicating the FIT and without body movement restrictions.

In the following sections, we present the REAsmash-ET methodological framework, including a detailed explanation of the tasks as well as the strategies for processing ET and UL kinematic data. We also provide descriptive ET and motor performance data across the three age groups.

Materials and methods

REAsmash SG

The REAsmash [57, 105, 106] was developed using Unity 2019.3 in C# and featured a cartoon-like 3D garden within a VR environment. The garden contains 24 molehills (6 columns and 4 rows) placed on an active playing surface of 150×100 cm. The task was built on a Whac-a-mole game that is widely known and intuitively understood thereby facilitating accessibility even for individuals with cognitive or comprehension difficulties. A cartoon-style was adopted to minimize both the emotional impact of a game that could otherwise appear violent and the risk of cybersickness [116, 117]. The number of stimuli was defined based on the playing field size and stimulus dimensions, which allowed a maximum of 24 items (1 target and 23 distractors). From this configuration, two additional levels were created with progressively fewer distractors (17 and 11), thereby providing a controlled manipulation of distractor number and saliency across game levels (consistent with FIT). In total, seven levels were implemented: one baseline level with no distractors and six experimental levels crossing two target-distractor saliency conditions (high vs. low) with three distractor set sizes (11, 17, and 23). This structure allowed for systematic modulation of task difficulty while maintaining experimental control and ensuring sufficient data points to detect both within- and between-subject variability. Moreover, the seven-level configuration provides an optimal trade-off between ability to capture performance changes and overall task duration, making it suitable for future clinical applications.

The task was designed to assess participant response times and accuracy in identifying a target stimulus, a mole wearing a red miner's helmet. The target stimulus appears pseudo-randomly, appearing once from each molehill (24 positions) during each of the seven trial levels, with each game level composed of 24 trials. In the baseline condition (level 0), no distractors are presented, whereas in the high-saliency target-distractor contrast conditions (levels 1 to 3), the target appears alongside distractor moles wearing blue miner's or horned helmets. In the low-saliency contrast conditions (levels 4 to 6), distractors wear either blue miner's helmets or red horned helmets, sharing a conjunction of features with the target (Fig. 1). Across levels one to six, 11, 17, or 23 distractors accompany the target, creating stimulus sets of 12, 18, or 24 elements, respectively, with 2, 3, or 4 stimuli per column. In high-saliency contrast levels, blue miner's and blue horned helmet distractors are equally distributed (i.e., 6, 9, and 12 per type in the 3 levels). In the 3 low-saliency levels, blue distractors with horns are replaced by red distractors with horns. We use the collider engine from Unity to detect responses. Every region of interest (i.e. the hammer, the target and the distractors) is matched to a 3D collider, and a response is defined by the collision between the hammer and target or distractor.

VR equipment

Participants were immersed in the virtual environment using an HMD (model: HTC Vive Pro Eye®, nominal field of view ≈110° according to manufacturer specifications; effective horizontal field of view ≈98° as reported in the literature [118], with a per-eye resolution of 1440 × 1600 pixels) and one hand-held controller. Participants interacted naturally with the scene, without body movement restrictions, by means of a virtual 3D hammer operated using the controller. The HTC Vive Pro Eye® uses two fixed infrared stations to create a calibrated tracking environment. These base stations emit structured infrared signals, which are detected by sensors on the HMD and controller to ensure accurate spatial positioning. The HTC Vive Pro Eye® provides eye-tracking accuracy of 0.5–1.1° at 120 Hz [119], with empirical validation showing mean accuracy ≈1.23° and RMS precision ≈0.62° [120]. Tracking via SteamVR of the Vive Pro Eye® controllers in static conditions has shown spatial errors on the order of a few millimeters to about a centimeter, depending on axis and setup [121, 122]. The HMD was connected to an Alienware® × 15 R2 laptop, which acted as the primary computing unit, managing software execution. This setup allowed real-time monitoring of the participant's field of view on the laptop display while ensuring stable system performance. Previous validation work has shown that the HTC Vive Pro Eye® provides high precision tracking with low latency (~ 22 ms), but that absolute positional accuracy can be affected by changes in the reference plane after temporary loss of tracking [121].

Procedure

Before the experiment, participants received written and verbal instructions. They were then seated on a standard four-legged office chair without wheels or armrests, equipped with an HTC Vive Pro Eye® and a controller in their response hand. Participants were asked to remain seated throughout the VR session. The proximal edge of the playing surface was located approximately 20 cm in front of the player's eyes in the orthogonal projection, with an eye-playing field center distance of 75 cm (see Figure S1 and Table S1 in the supplementary material for further details about visual angle subtended by the playing field and angular separation between stimuli).

They were allowed to lean forward from the backrest, while remaining seated with both feet on the ground.. Eye-tracking calibration was performed using the built-in VIVE Pro Eye® procedure, and assisted by the experimenter. On-screen messages guided the participant to

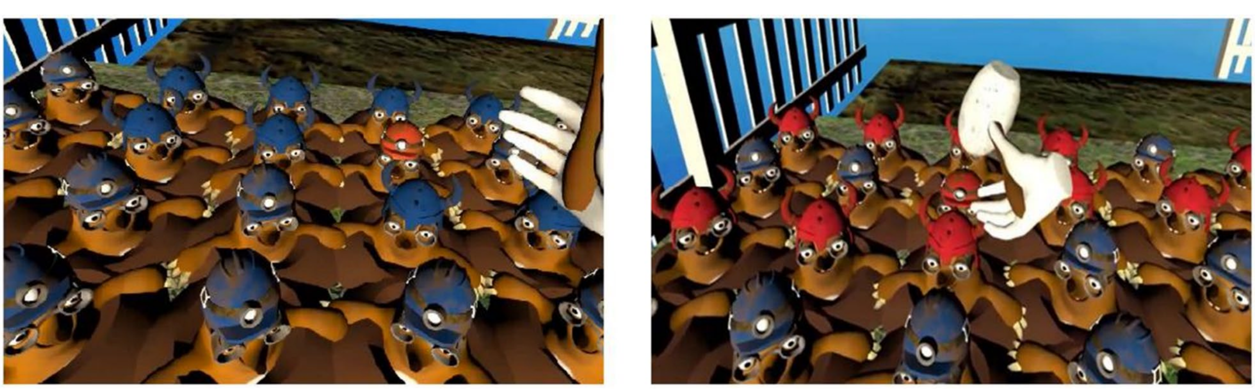

Fig. 1 Target-distractor search stimuli. On the left a frame form level 3 (i.e., high target-distractor salience condition) with 23 distractors wearing horned or miner's blue helmets and, on the right, level 6 (i.e., low target-distractor salience) with 23 distractors, wearing red helmets with horns or blue miner's helmets

wear the headset in the correct position, adjust the interpupillary distance, and follow a moving dot with their gaze as prompted by the system.

Prior to each trial, two red squares, aligned with the center of the playing field, appeared in front of the participant. One square contained an eye pictogram and the other contained a hammer pictogram. To initiate each trial, participants were required to fixate on the eye-square and position the virtual hammer on the hammer-square (Fig. 2). Once correctly aligned, the squares turned green and disappeared, signaling the start of the trial. This procedure ensured consistent starting coordinates of both gaze and hammer prior to each trial response. At the beginning of the SG, participants were instructed to hit the target stimulus as quickly as possible with the virtual hammer while ignoring the distractors. The response hand had to be the same for all game levels. Once the 7 game levels were completed, the task was repeated with the other hand following a 5-min pause. The response hand order was randomized.

Stimuli were presented for a maximum duration of seven seconds, with omissions recorded if no response was made, and errors recorded if the participant struck a distractor instead of the target. A correct response was defined as the virtual hammer colliding with the target within the seven-second time window, terminating the trial and initiating the next trial. Participants completed a 10-trial practice session to familiarize themselves with the VR environment, and a 10-s rest period was provided between each trial block (level). The experiment progressed from the easiest condition (no distractors) to the most difficult (23 low-saliency distractors). The full session, including all trial blocks and breaks, lasted approximately 20 min per hand.

Outcome measures were organized into three domains: (i) task performance, including Relative Response Time (RRT), omission rates, and error rates; (ii) eye-tracking, including cumulative and mean fixation time on distractors, as well as the number of capture and re-capture fixations; and (iii) upper limb kinematics, including mean and peak velocity, smoothness (SPARC), and coefficient of variation of velocity. This structured framework enabled the parallel assessment of attentional and motor performance within the same immersive VR task, while the following sections detail the feature extraction strategies for ET and UL data.

Eye-tracking data processing strategy: the semi-adaptive dispersion-threshold approach

Raw ET data were tracked with the integrated ET system of the HTC Vive Pro Eye®. The HMD recorded head position and gaze point relative to the 3D colliders of the VR stimuli at a sampling frequency of 50 Hz. The stimuli represented the ROIs. ET data were recorded from the start of each trial (i.e., when the participant reached the initial position and the two squares turned green and disappeared) until the trial ended (i.e., manual response or end of the 7 s allowed per trial). The spatial and temporal positions of head and gaze points constituted the raw ET dataset, stored as “CSV” files on the headset's hard drive for each participant.

To study gaze behavior, we employed a revised version of the dispersion-threshold algorithm by Llanes-Jurado et al. [123]. Starting from the original algorithm [123], we first resolved coding bugs related to the computation of gaze vectors [124] and then implemented further refinements to improve data accuracy and robustness (explained below). The original dispersion-threshold algorithm analyses consecutive gaze points according to fixed Angular Dispersion (A_D), where A_D is defined as the angle between two gaze vectors originating from the eyes and reaching two consecutives gaze points. Depending on the distance (d) between the eyes and the stimuli, a fixed A_D can lead to variations in Linear Dispersion (L_D), defined as the linear distance between two consecutive gaze points (Fig. 3). This consideration implies a major

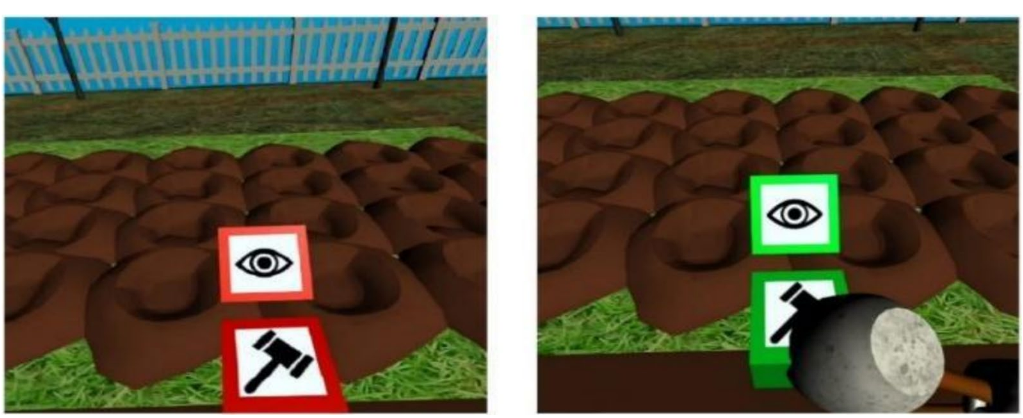

Fig. 2 The starting position. Before each trial, the participants viewed the 24 empty molehills and two reference squares, one with an image of an eye that they had to fixate, and one with an image of a hammer, on which they placed their virtual hammer. This enabled a consistent starting point for each trial

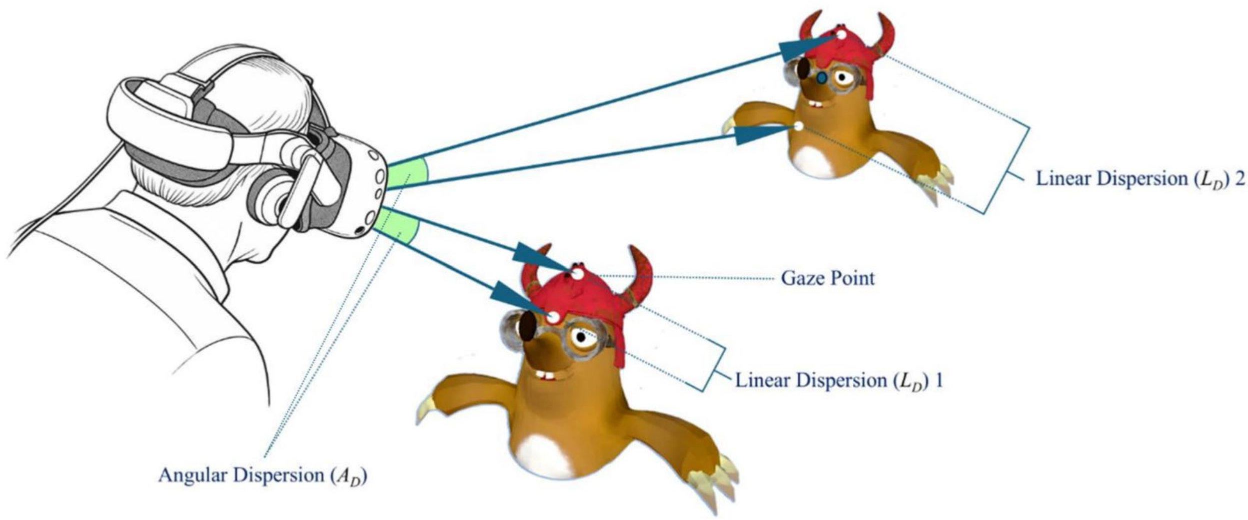

Fig. 3 Variation in Linear Dispersion (L_D) at constant Angular Dispersion (A_D). The white dots indicate two consecutive gaze points on a distractor. Angular Dispersion (A_D) is defined as the angle (in green) between two gaze vectors (blue arrows) originating from the eyes and extending to the respective gaze points. The illustration demonstrates that, with a constant A_D between gaze points, the Linear Dispersion (L_D) between the two dots can greatly vary depending on the distance between the observer and the stimulus. In this example, L_D1 refers to the dispersion on a closer distractor (first row), whereas L_D2 corresponds to a more distant distractor (fourth row) from the participant's perspective

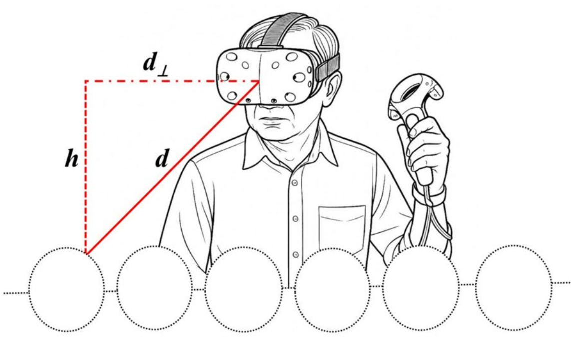

Fig. 4 Computation of eyes-ROI distance. Graphical 3D representation of d computation, with $d_\perp$ representing the orthogonal distance between the eyes and each ROI and h the height difference between the eyes and the ROI. The virtual objects (i.e., the playing field and the moles) are schematically represented with dotted black lines

limitation to the application of fixed A_D for our task (or any tasks to stimuli oriented on the horizontal plane) where ROIs are spatially compact (13 × 16 cm) and vary in retinal size according to d from less than 0.5 to 1.5 m.

To increase the accuracy of gaze data interpretation in our task, we implemented a semi-adaptive A_D approach. Specifically, different A_D values were applied within predefined d ranges, ensuring that gaze points were spatially analyzed under a consistent L_D while accounting for variations in eyes-ROI distance.

Basing our calculations on anthropometric norms of human height and proportions [125], we derived d for each ROI as $d = \sqrt{d_\perp^2 + h^2}$, here $d_\perp$ represents the orthogonal distance between the eyes and the stimuli ROI and h is the height difference between the eyes and the ROI. Our analysis was centered on the position of the mole helmets, which served as the distinguishing feature among the stimuli (Fig. 4).

For the REASmash-ET setting, d was estimated to range from approximately 45 cm to 130 cm according to the ROI position on the playing field. We then divided the playing field into three distinct 8 ROIs zones based on d: (i) proximal; (ii) intermediate and (iii) distal. The average d was approximately 60 cm for the proximal zone, 90 cm for the intermediate zone, and 120 cm for the distal zone (Fig. 5).

To ensure a constant L_D across the three zones, A_D was calculated as a function of d for a given L_D, using the formula $A_D(d) = 2 \cdot \tan^{-1}(L_D/d)$. We tested the A_D for L_D of 1.5, 2, and 2.5 cm (Fig. 6). An L_D in the range of 1.5 to 2.5 cm allows us to discriminate fixations on specific features within the stimuli, such as horns.

The literature suggests A_D between 1° and 2° for visual search tasks similar to the REASmash-ET [126]. A L_D of 2 cm was the only value that fell within the suggested A_D range for d values consistent with our task: an A_D around 2° was needed for an eyes-ROI mean distance of 60 cm (proximal zone) and an A_D around 1° was needed for an eyes-ROI mean distance of 120 cm (distal zone). We then calculated the A_D for an L_D of 2 cm with an eyes-ROI mean distance of 90 cm (intermediate zone) and found an A_D of 1.3° (Fig. 7).

Following the spatial definition of fixation based on the dispersion of gaze points, we then evaluated fixation using temporal criterion. This is necessary to ensure that

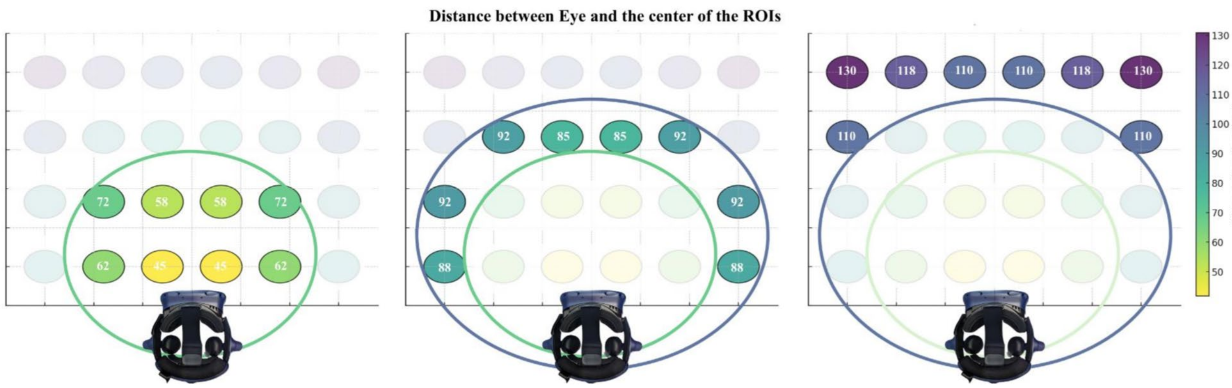

Fig. 5 Division of the playing field into three zones according to the average distance between eyes—ROIs. Visual representation of the d (i.e., eyes-ROI distances) in centimeters across the playing field. The three graphics illustrate the classification of ROIs into proximal (**a**), intermediate (**b**), and distal (**c**) zones, based on their estimated distances from the participant's eyes. Colors indicate the measured distance in centimeters, with warmer shades representing shorter distances and cooler shades representing longer distances

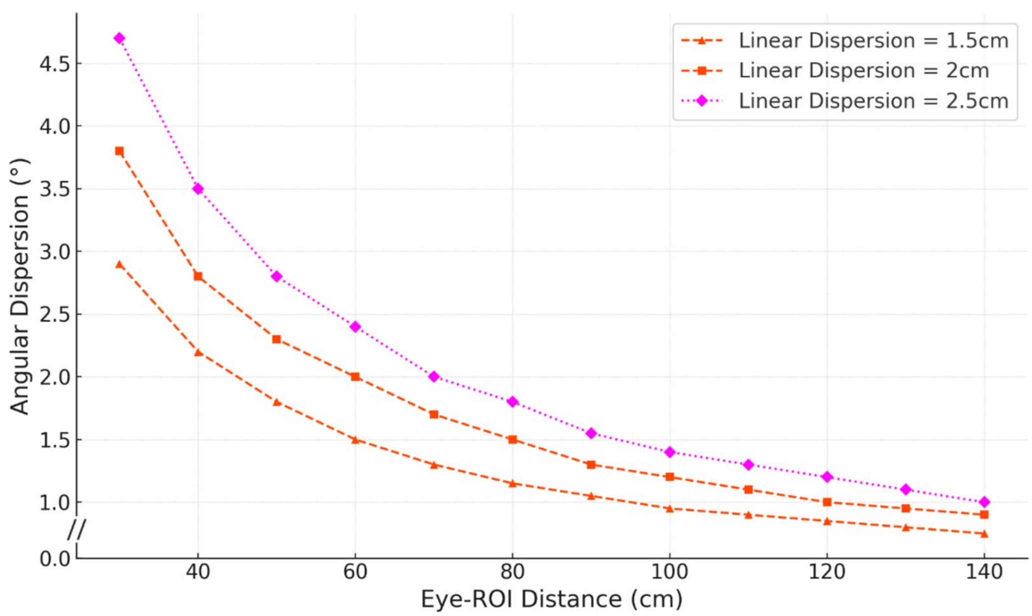

Fig. 6 Relationship between Angular Dispersion (A_D) and Eye-ROI Distance (d) across different Linear Dispersion (L_D) conditions.. Graphical representation of the relation between A_D, d and L_D. As d increases, the required A_D decreases to maintain a constant L_D with shorter L_D requiring smaller A_D

the gaze remains sufficiently stable for a minimum duration, allowing cognitive engagement with stimuli located within the foveal region. In accordance with the literature [126–131], we set the time threshold at 100 ms to exclude false positives and micro-fixations that do not reflect cognitive visual engagement with stimuli. True fixations were gaze points remaining within $A_{D,}$ whereas saccades were implicitly classified as any gaze movements that did not meet the fixation criteria. For each fixation, duration was calculated as the time difference between fixation onset and offset, corresponding to the time between the first and the last gaze point classified within the fixation. Fixation location was calculated by determining the 3D coordinates of the centroid (i.e., the average spatial position of all gaze points belonging to the same fixation). Fixated objects were identified by projecting the binocular gaze vector into the virtual scene. When multiple intersections with colliders occurred, the collider with the shortest distance from the gaze origin was selected.

To test the reliability of our ET data, we contrasted distractor fixation duration metrics to behavioral outcomes. This approach permitted to make hypotheses grounded on the FIT to verify the efficacy of REAsmash-ET to detect real cognitive interactions on compact 3D VR stimuli. In high target-distractor saliency trials, the time spent fixating distractors was expected to be close to zero (parallel search). In contrast, in low saliency trials, a positive correlation was expected between the number of distractors and the ET metrics, reflecting visual serial search.

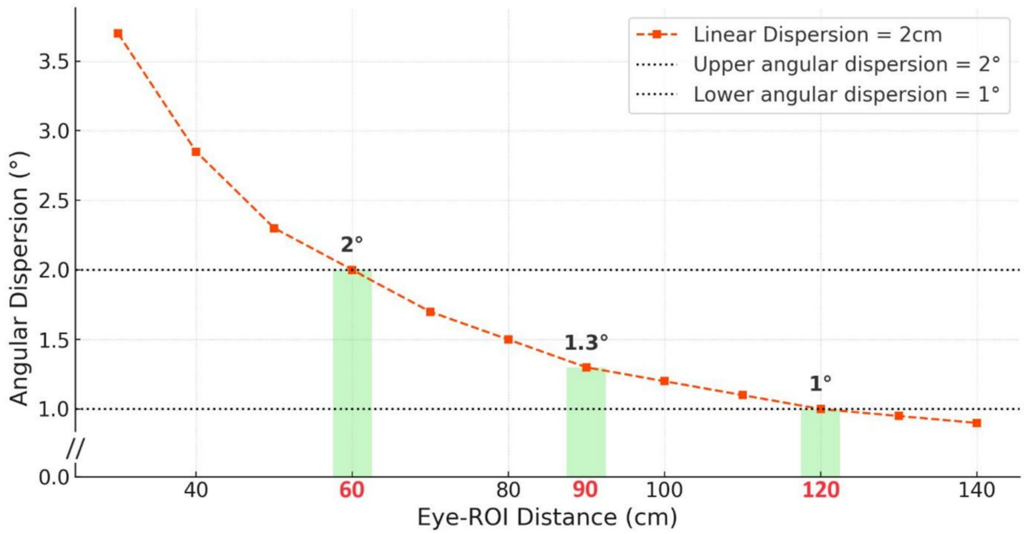

Fig. 7 The Angular Dispersion (A_D) for the three zones of the playing field. A L_D of 2 cm corresponds to: (i) a A_D of approximately 2° for d of the proximal zone (60 cm), (ii) a A_D of approximately 1.3° for d of the intermediate zone (90 cm) and (iii) a A_D of approximately 1° for d of the distal zone (120 cm)

The spatio-temporal computation of the ET data made it possible to study overlapping fixations. We defined capture fixations as two or more consecutive fixations on the same stimulus (i.e., the gaze remains locked on a single object without shifting to others) [51, 75] and re-capture fixations as instances where the gaze returns to a stimulus after having shifted to one or more different stimuli [92, 132, 133]. An augmented number of capture fixations likely suggests difficulties in disengaging attention from a stimulus (i.e., a distractor inhibition impairment) [94, 132, 134] while an augmented number of re-capture fixations has been interpreted in the literature as a possible marker of spatial working memory impairment [92, 132, 133]. Although there is relative consensus regarding the underlying pathological mechanisms of overlapping fixations [92, 94, 132], to date there are no norms regarding these ET metrics. We hypothesized an age effect related to a general decrease in visual exploration efficiency with age [135].

The semi-adaptive dispersion-threshold algorithm described here constitutes a general-purpose solution for gaze data analysis in 3D environments with variable eye-to-stimulus distances.

Upper limb kinematic data processing strategy

As for the ET data analyses, we only considered data of successful trials. The 3D position of the controller used for manual responses collected from the stimuli appearance to manual response with a sampling rate of 60 Hz. UL kinematic raw data were stored as export files (.csv) on the headset's hard drive for each participant.

This strategy made it possible to study the metrics of UL movement in the temporal window corresponding to response time. Kinematic data were then analyzed using a custom program developed in Python [136]. We first performed a visual inspection of the controller's 3D position over time to ensure data reliability. To reduce acquisition noise, a fourth order Butterworth filter (sampling frequency = 60 Hz; cut-off frequency = 10 Hz) was applied to each dataset. Then, for each consecutive time point, we calculated the Euclidean distance traveled in 3D space and divided it by the time interval (s), to compute the instant velocity signal ($v(t_i)$). For each trial, we calculated in 3D space: (i) Mean velocity; (ii) Peak velocity; (iii) Spectral arc length (SPARC) and (vi) Coefficient of variation of the velocity.

$$Meanvelocity = \frac{\Delta_d}{\Delta_t}$$

Mean velocity, computed as the mean rate of change position (Δ_d/Δ_t), was calculated from the beginning of the trial to the manual response.

$$Peakvelocity = max(v(t_i))$$

Peak velocity corresponded to the maximal instant velocity ($v(t_i)$) within a trial.

$$SPARC = -\int_0^{\omega_c}\left[\left(\frac{1}{\omega_c}\right)^2 + \left(\frac{d\widehat{V}(\omega)}{\omega_c}\right)^2\right]^{\frac{1}{2}} d\omega;$$

$with \widehat{V}(\omega) = \frac{V(\omega)}{V(0)}$ and

$\omega_c = min\left\{\omega_c^{max}, min\left\{\omega, \widehat{V}(r) < \overline{V} \forall r > \omega\right\}\right\}$

SPARC is a smoothness metric ranging from -∞ to 0, with higher values corresponding to a smoother movement. It consists in the arc length of the spectrum of the normalized instant velocity signal ($\widehat{V}(\omega)$) [137, 138]. To compute SPARC, we first applied a fast Fourier transform (FFT) to the instant velocity signal in order to obtain its amplitude spectrum as a function of frequency. The spectrum was then normalized by dividing all amplitudes by the maximum amplitude value, scaling the curve from 0 to 1. We computed the arc length of this normalized spectrum within a defined frequency range (ωc to ωmax). Finally, a negative sign was applied to the resulting arc length, so that larger arc lengths (i.e., more irregular and less smooth velocity profiles) correspond to lower SPARC values, while smoother movements yield higher SPARC values.

$$Coefficientofvariationofthevelocity = \frac{SD(v(t_i))}{meanvelocity}$$

Coefficient of variation of the velocity is another smoothness metric ranging from 0 to 100% with lower values corresponding to a smoother movement. The metric is a ratio between the standard deviation (SD) of the instant velocity ($v(t_i)$) and the mean velocity.

Participants

Participants were recruited between July 2023 and April 2024 through the University of Louvain participation panel and social media groups in Belgium and Italy. All the participants gave their written informed consent prior to the beginning of the study. The protocol was approved by the Saint Luc-UCL Hospital-Faculty Ethics Committee (Belgium) (2015/10FEV/053) prior to the initiation of the study and registered on clinicaltrial.gov (NCT04694833). The participants had normal or corrected to normal vision and no neurological, psychiatric or orthopedic disorders potentially affecting compliance or limiting upper limb functionality. The REAsmash-ET instructions were presented in French or Italian depending on the location of testing, and the insufficient understanding of any of these languages was a further exclusion criterion. All participants were naïve to our SG and to iVR.

To explore differences in age, we divided participants into three age-based groups, each consisting of 15 participants, ensuring a balanced number of left-handed individuals and different genders. Groups were composed as follow: Group 20–39 years, 7 females, 1 left-handed, average age of 24.6 years (SD = 4.52); Group 40–59 years, 7 females, 2 left-handed, average age of 49.9 years (SD = 5.93) and Group 60–80 years, 6 females, 1 left-handed, average age of 69.6 years (SD = 3.88).

Data analyses

All statistical analyses were conducted using SPSS 27.0 (IBM®). The normality of residuals was verified using the Shapiro–Wilk test and in case of significant deviations, data were also log-transformed to assess robustness against potential violations of normality assumptions. Since the results of the ANOVAs were unchanged, we report here the analyses on the untransformed data for clarity. Outlier exclusion was performed using the conventional ± 3 SD rule, applied separately within each age group for each dependent variable (e.g., response times, fixation metrics, kinematic measures). Specifically, trials with values exceeding the mean ± 3 SD of the distribution for that group and variable were removed. The significance threshold was set at α = 0.05, and Bonferroni corrections were applied for post-hoc comparisons when appropriate.

Replicating recent publications using REAsmash [105], we selected mean Relative Response Time (RRT) as the main dependent variable for behavioral outcomes. RRT was calculated by subtracting the average response time in the baseline condition (level 0, without distractors) from each response in levels 1 to 6. This measure reflects the additional cognitive cost associated with increasing distractor number and decreasing target-distractor saliency.

To test REAsmash-ET for detecting fixations, we verified the FIT on eye-tracking outcomes. For this purpose, the primary dependent variables were (i) the total cumulative fixation time on distractors per trial and (ii) the mean fixation duration on distractors per trial. Secondary metrics included (iii) the number of distractors with at least one capture fixation and (iv) the number of distractors with at least one re-capture fixation. Concerning UL kinematics, the dependent variables included (i) mean velocity, (ii) peak velocity, (iii) SPARC and (iv) the coefficient of variation of velocity.

Only successful trials were analyzed for RT, gaze metrics and UL kinematics. Outlier exclusion was performed applying the standard practice of using a three SD confidence interval filter within each age group.

For RRT and gaze metrics, repeated-measures ANOVAs were performed on the dependent variables, with (i) target-distractor saliency (high vs low) and (ii) number of distractors (11, 17, 23) as within-subject independent variables, and (iii) age group (20–39, 40–59, 60–80 years) as a between-subject independent variable.

For kinematic data, the response hand (dominant vs. non-dominant) was chosen as within-subject independent variable. This within-subject factor was intended to assess the ability of kinematic metrics to detect physiological motor asymmetries, even in neurologically healthy individuals. Age group was a between-subject independent variable.

Table 1 The error and omission rates of the 3 groups

Age group	Omissions (number, %)	Errors (number, %)	Outliers removed (number, %)	Anticipatory responses
20–39 years	8 (0.2%)	5 (0.1%)	62 (1.2%)	None
40–59 years	34 (0.7%)	11 (0.2%)	92 (1.8%)	None
60–80 years	77 (1.5%)	27 (0.5%)	121 (2.4%)	None

In the presence of significant interactions, separate ANOVAs were conducted within the independent variables concerned by the interaction effect. Due to their low frequency, omissions and errors were reported in the Results section, without further statistical analysis.

Results

All participants completed the experiment. In a general feedback discussion session with the participants after the study, they all described the experimental tasks as non-stressful and engaging. No participants asked to stop the experiment prematurely or to extend the rest periods. No serious and non-serious adverse events, such as cybersickness or epileptic seizures, occurred.

Behavioral outcomes

Concerning behavioral outcomes, each participant (age) group contributed a total of 5,040 trials (7 levels × 24 trials × 15 participants × 2 hands) for a total data set of 15,120 trials. The error and omission rates are presented in Table 1.

Outlier RTs were removed from the successful trial dataset of each group, causing the removal of 62 trials (1.2%) for the 20–39 years group, 92 trials (1.8%) for the 40–59 years group, and 121 trials (2.4%) for the 60–80 years group. No anticipatory responses (i.e., responses faster than 250 ms) were observed in any group (See Table 1).

The ANOVA for mean RRT demonstrated significant main effects of target-distractors saliency (F (1,42) = 1897.68, $p < 0.001$, η2 = 0.98) and distractor number (F (2,84) = 276.46, $p < 0.001$, $\eta^2 = 0.87$), with longer RTs observed in the low saliency condition and with increasing numbers of distractors. A significant effect of group (F (1,42) = 19.35, $p < 0.001$, $\eta^2 = 0.48$) was also found. Multiple interactions were also statistically significant: (i) target-distractors saliency and distractor number (F (2,84) = 234.56, $p < 0.001$, $\eta^2 = 0.85$); (ii) target-distractors saliency and group (F (2,42) = 23.10, $p < 0.001$, $\eta^2 = 0.52$) and (iii) target-distractors saliency, distractor number and group (F (4,84) = 3.12, $p = 0.019$, $\eta^2 = 0.13$) (Fig. 8). No other significant main effects and interactions were found.

To analyze the interaction between target-distractors saliency and distractor number, separate ANOVAs were run for high versus low saliency condition. The ANOVA for the high saliency condition showed no significant differences for numbers of distractors on mean RRT (F (2,84) = 2.41, $p = 0.1$, $\eta^2 = 0.05$). In contrast, the ANOVA for the low saliency condition showed a significant distractor number effect (F (2,84) = 281.24, $p < 0.001$, $\eta^2 = 0.87$), with RRT increasing with increased numbers of distractors (M = 912.01 ms, SD 29.15; M = 1216.79 ms, SD 29.16 and M = 1428.05 ms, SD 26.50 with 11, 17 and 23 distractors, respectively).

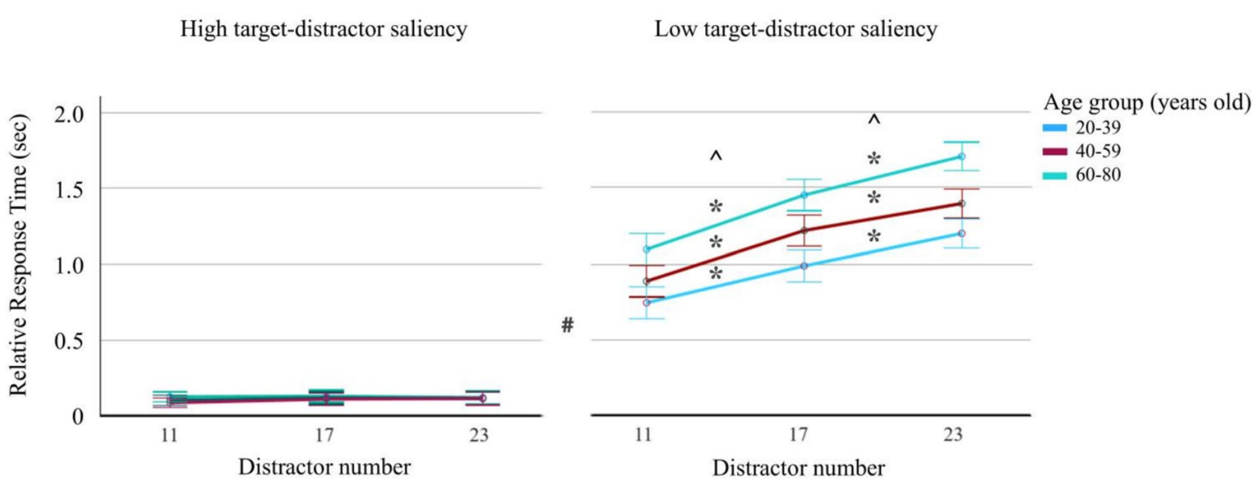

Fig. 8 Mean RRT (seconds) for independent variables of target-distractor saliency, number of distractors and group. The left graph illustrates the high saliency condition, while the right graph shows the low saliency condition. Error bars represent 95% confidence intervals. Blue lines indicate participants aged 20–39 years, purple lines represent those aged 40–59 years, and green lines represent participants aged 60–80 years. Hash symbols ('#') indicate significant main effects of saliency; Carets ('^') indicate significant main effects of the number of distractors and Asterisks ('*') indicate significant main effects of age group. Results confirmed the classic FIT pattern, with a significant increase in mean RRT as the number of distractors increased only under low saliency conditions. Additionally, a significant age effect was observed in the low saliency condition

Concerning the interaction between target-distractor saliency and age group, these analyses demonstrated a significant group effect only in the low saliency condition (F (2,42) = 24.49, $p < 0.001$, $\eta^2 = 0.54$). No significant group effect was found in the high saliency condition (F (2,42) = 0.353, $p = 0.70$, $\eta^2 = 0.02$). Mean RRT for high target-distractor saliency conditions were 96.96 ms (SD 18.42), 103.93 ms (SD 18.42) and 118.42 ms (SD 18.42) for age groups 20–39, 40–59 and 60–80, respectively. Mean RRT for low target-distractor saliency conditions were 976.13 ms (SD 43.86), 11,165.84 ms (SD 43.86) and 1411.88 ms (SD 43.86) for age groups 20–39, 40–59 and 60–80, respectively, showing increased RRT with age.

For the three-way interaction between target-distractor saliency, distractor number and group (i.e., the FIT effect versus age group), separate ANOVAs per group, confirmed the FIT effect in the three groups (F (2,28) = 53.25, $p < 0.001$, $\eta^2 = 0.79$; F (2,28) = 66.62, $p < 0.001$, $\eta^2 = 0.83$ and F (2,28) = 128.62, $p < 0.001$, $\eta^2 = 0.90$ for group 20–39 years, 40–59 years and 60–80 years, respectively). This interaction shows that the age effect was specifically apparent in the low target-distractor saliency condition.

ET outcomes

Statistical analyses on ET metrics were performed on a dataset of 12,752 trials corresponding to the total dataset of levels with distractors minus 208 trials consisting of errors and omissions. No trials were excluded because of incorrect gaze starting position. We excluded 161 trials (1.26% of the initial dataset) that didn't end with a fixation of the target. The distractor fixation dataset was composed of 14,489 measures.

Concerning the main ET outcomes (i.e., total cumulative time spent fixating on distractors and mean distractor fixation time), we then excluded 85 outliers (2.2%) for group 20–39 years, 104 outliers (2.1%) for group 40–59 years, and 112 outliers (1.9%) for group 60–80 years. The final dataset was thus composed of 14,188 valid measures. Although the main analyses reported in the manuscript focused on fixation duration, for descriptive purposes we also provide, in the supplementary material, 3D plots of fixation counts across the playing field (Figure S2). These visualizations illustrate the relative distribution of attention across stimulus positions.

Total cumulative time spent fixating on distractors per trial

We found a significant main effect of (i) target-distractors saliency (F(1, 42) = 219.581, $p < 0.001$, $\eta^2 = 0.839$) and (ii) distractor number (F(1, 42) = 150.102, $p < 0.001$, $\eta^2 = 0.781$), with longer cumulative time spent fixating on distractors for low saliency condition and with increasing number of distractors (Fig. 9).

The two-way interaction between target-distractors saliency and distractor number (FIT effect) was also significant (F(2, 42) = 114.497, $p < 0.001$, $\eta^2 = 0.732$). Post hoc analyses showed a significant main effect of distractor number in both (i) high saliency condition (F(1, 42) = 26.050, $p < 0.001$, $\eta^2 = 0.383$), and low saliency condition (F(2, 42) = 135.864, $p < 0.001$, $\eta^2 = 0.764$).

We also found a significant effect of group (F(2, 42) = 3.231, $p = 0.050$, $\eta^2 = 0.133$) with older age groups showing longer cumulative fixation times on distractors.

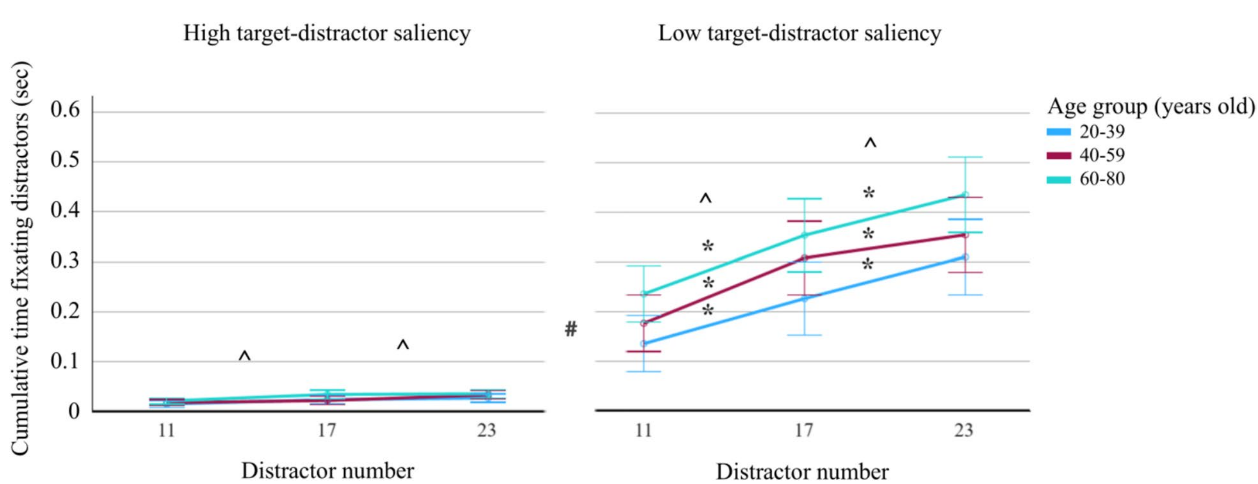

Fig. 9 Total cumulative time spent fixating on distractors (seconds) for independent variables of target-distractor saliency, number of distractors and group. The left graph illustrates the high saliency condition, while the right graph shows the low saliency condition. Error bars represent 95% confidence intervals. Blue lines indicate participants aged 20–39 years, purple lines represent those aged 40–59 years, and green lines represent participants aged 60–80 years. Hash symbols ('#') indicate significant main effects of saliency; Carets ('^') indicate significant main effects of the number of distractors and Asterisks ('*') indicate significant main effects of age group. Results showed a significant main effect of target-distractors saliency, with longer cumulative fixation times in low saliency condition. A significant increase in mean cumulative fixation time was also observed as the number of distractors increased, for both high and low saliency conditions. Additionally, a significant age effect was observed in the low saliency condition

The interaction between target-distractor saliency and group was also significant ($F(2, 42) = 3.231$, $p = 0.050$, $\eta^2 = 0.133$). The effect of saliency was most pronounced in the group of 60–80 years, where the mean increased from $M = 0.031$ ($SD = 0.003$) in high saliency to $M = 0.342$ ($SD = 0.032$) in low saliency. A similar pattern was observed in group 40–59 years, with an increase from $M = 0.025$ ($SD = 0.003$) to $M = 0.280$ ($SD = 0.032$). In group 20–40 years, the effect was less marked, with means rising from $M = 0.022$ ($SD = 0.003$) to $M = 0.225$ ($SD = 0.032$).

The ANOVA for the high saliency condition showed a significant main effect of distractor number ($F(1, 42) = 26.050$, $p < 0.001$, $\eta^2 = 0.383$), with longer cumulative fixation times on distractors with increasing number of stimuli. For high saliency condition, the effect of group was not significant, ($F(2, 42) = 1.656$, $p = 0.203$, $\eta^2 = 0.073$).

The ANOVA for the low saliency condition showed a significant main effect of distractor number ($F(2, 42) = 135.864$, $p < 0.001$, $\eta^2 = 0.764$), with longer cumulative fixation times on distractors with increasing number of stimuli. A significant main effect of group ($F(2, 42) = 3.278$, $p = 0.048$, $\eta^2 = 0.135$) was also observed. For low target-distractor saliency, a significant main group effect was found between group 20–40 years and group 60–80 years ($F(1, 28) = 5.537$, $p = 0.026$, $\eta^2 = 0.165$), with older age groups showing longer cumulative fixation times on distractors. The other pairwise comparisons between groups did not reveal any statistically significant differences. (Fig. 9, supplementary Table S2 lists the reference values for each condition).

Mean distractor fixation time

We did not find a significant main effect for target-distractors saliency ($F(1, 42) = 1.015$, $p = 0.320$, $\eta^2 = 0.024$), or distractor number ($F(1.738, 72.984) = 2.874$, $p = 0.070$, $\eta^2 = 0.064$). Similarly, there was no significant main effect of group ($F(2, 42) = 0.390$, $p = 0.679$, $\eta^2 = 0.018$).

None of the interactions reached significance, including the three-way interaction of saliency, distractor number, and group ($F(4, 84) = 0.798$, $p = 0.354$, $\eta^2 = 0.050$) (Fig. 10, supplementary Table S3 lists the reference values for each condition).

Distractor capture fixations

Concerning the distractor capture fixations number analysis, the total dataset was composed of 14,216 measures. A three SD confidence interval filter was applied, removing 333 outliers. The analyses showed significant main effects for (i) target-distractors saliency ($F(1, 42) = 376.624$, $p < 0.001$, $\eta^2 = 0.900$) and (ii) distractor number ($F(1, 42) = 162.394$, $p < 0.001$, $\eta^2 = 0.795$). The interaction between saliency and distractor number was also significant ($F(1, 42) = 122.214$, $p < 0.001$, $\eta^2 = 0.744$). Separate ANOVAs for saliency showed a significant main effect of distractor number for both high ($F(2, 42) = 38.872$, $p < 0.001$, $\eta^2 = 0.481$) and low saliency conditions ($F(2, 42) = 145.793$, $p < 0.001$, $\eta^2 = 0.776$) (Fig. 11, supplementary Table S4 lists the reference values for each condition), with increasing number of capture fixations on distractors with increasing number of stimuli. For the between-subjects effects, the main effect of group was not significant ($F(2, 42) = 2.032$, $p = 0.144$, $\eta^2 = 0.088$) and there were no significant interactions with group.

Distractor re-capture fixations

Concerning the distractor re-capture fixations number analysis, the total dataset was composed of 614 measures.

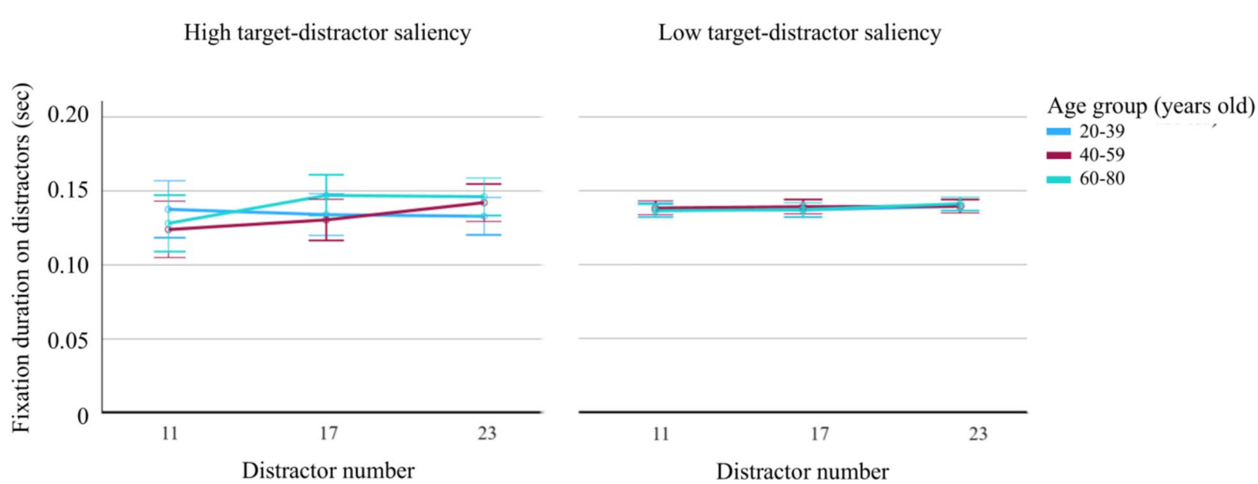

Fig. 10 Mean fixation duration (seconds) for independent variables of target-distractor saliency, number of distractors and group.. The left graph illustrates the high saliency condition, while the right graph shows the low saliency condition. Error bars represent 95% confidence intervals. Blue lines indicate participants aged 20–39 years, purple lines represent those aged 40–59 years, and green lines represent participants aged 60–80 years. No significant main effects or interaction were observed

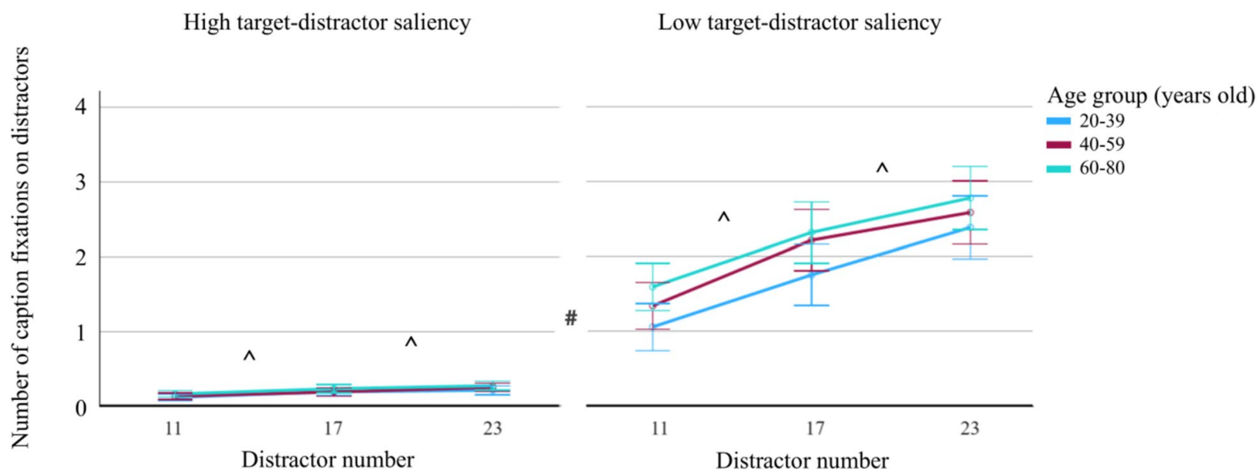

Fig. 11 Mean number of caption fixations on distractors for independent variables of target-distractor saliency, number of distractors and group. The left graph illustrates the high saliency condition, while the right graph shows the low saliency condition. Error bars represent 95% confidence intervals. Blue lines indicate participants aged 20–39 years, purple lines represent those aged 40–59 years, and green lines represent participants aged 60–80 years. Hash symbols ('#') indicate significant main effects of saliency; Carets ('^') indicate significant main effects of the number of distractors and Asterisks ('*') indicate significant main effects of age group. Results showed a significant main effect of target-distractors saliency, with higher number of capture fixations in low saliency condition. A significant increase in mean number of capture fixations as the number of distractors increased was also observed for both high and low saliency conditions. No age effect was observed

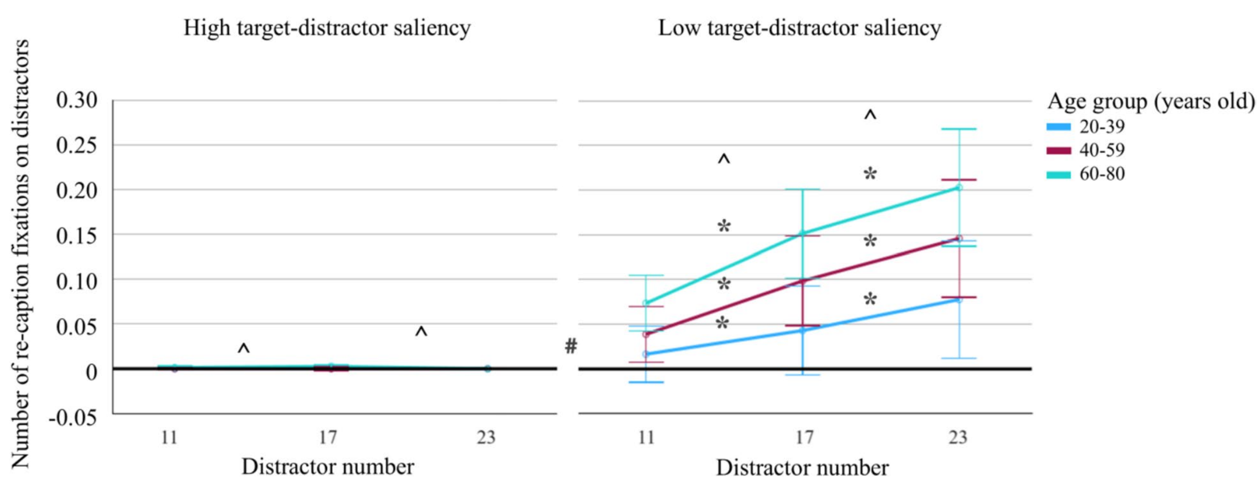

Fig. 12 Mean number of re-caption fixations on distractors for independent variables of target-distractor saliency, number of distractors and group. The left graph illustrates the high saliency condition, while the right graph shows the low saliency condition. Error bars represent 95% confidence intervals. Blue lines indicate participants aged 20–39 years, purple lines represent those aged 40–59 years, and green lines represent participants aged 60–80 years. Hash symbols ('#') indicate significant main effects of saliency; Carets ('^') indicate significant main effects of the number of distractors and Asterisks ('*') indicate significant main effects of age group. Results showed a significant main effect of target-distractors saliency, with higher number of re-capture fixations in low saliency condition. A significant increase in mean number of re-capture fixations was also observed as the number of distractors increased, for both high and low saliency conditions. Additionally, a significant age effect was observed in the low saliency condition

A three SD confidence interval filter was applied, removing 3 outliers from group 60–80 years.

We found a significant main effect for (i) target-distractors saliency ($F(1,42) = 57.307$, $p < 0.001$, $\eta^2 = 0.577$) and (ii) distractor number ($F(1,42) = 27.634$, $p < 0.001$, $\eta^2 = 0.397$).

The interaction between saliency and distractor number was also significant ($F(1, 42) = 27.925$, $p < 0.001$, $\eta^2 = 0.399$). Posthoc analyses showed that the ANOVA for the high saliency condition showed no significant main effect of distractor number ($F(2,42) = 1.000$, $p = 0.372$, $\eta^2 = 0.023$), whereas the ANOVA for the low saliency condition showed a significant main effect of distractor number ($F(2, 42) = 27.845$, $p < 0.001$, $\eta^2 = 0.399$), with increasing number of re-capture fixations on distractors with increasing number of stimuli.

A significant main effect of group ($F(2,42) = 5.256$, $p = 0.009$, $\eta^2 = 0.200$) was found. However, the interaction between distractor number and group was not significant, ($F(4, 42) = 1.231$, $p = 0.306$, $\eta^2 = 0.055$) (Fig. 12, supplementary Table S5 lists the reference values for each condition).

Kinematic outcomes

As for ET metrics, statistical analyses on kinematic metrics were performed on a dataset of 12,752 trials. A three SD confidence interval filter was applied to each variable. After filtering, the number of valid trials per metric was as follows: Mean Velocity (12,648 trials), Peak Velocity (12,571 trials), SPARC (12,390 trials), and Coefficient of Variation of Velocity (12,501 trials).

Mean velocity

We found a significant main effect for (i) response hand ($F(1,42) = 5.320$, $p = 0.026$, $\eta^2 = 0.112$) and (ii) group ($F(2,42) = 20.488$, $p < 0.001$, $\eta^2 = 0.494$). The interaction between group and response hand was not significant ($F(2,42) = 0.559$, $p = 0.576$, $\eta^2 = 0.026$). The significant main group effect showed differences between: (i) group 20–39 years and group 40–59 years ($F(1, 28) = 17.591$, $p < 0.001$, $\eta^2 = 0.386$), (ii) group 40–59 years and group 60–80 years ($F(1, 28) = 5.746$, $p = 0.023$, $\eta^2 = 0.170$) and (iii) group 20–40 years and group 60–80 years ($F(1, 28) = 41.797$, $p < 0.001$, $\eta^2 = 0.599$), with a gradual reduction in mean velocity as the group's mean age rises (supplementary Table S6.a.b list the reference values for group and response hand).

Peak velocity

A significant group effect ($F(2,42) = 9.733$, $p < 0.001$, $\eta^2 = 0.317$) was observed, but no response hand effect ($F(1,42) = 3.156$, $p = 0.083$, $\eta^2 = 0.070$) and no interaction between group and response hand ($F(2,42) = 0.876$, $p = 0.424$, $\eta^2 = 0.040$). The significant main group effect showed differences between: (i) group 40–59 years and group 60–80 years ($F(1, 28) = 6.046$, $p = 0.020$, $\eta^2 = 0.178$) and (ii) group 20–39 years and group 60–80 years ($F(1, 28) = 20.721$, $p < 0.001$, $\eta^2 = 0.425$), with a gradual reduction in peak velocity as the group's mean age rises (supplementary Table S7).

SPARC

Group ($F(2,42) = 0.917$, $p = 0.407$, $\eta^2 = 0.042$) and response hand ($F(2,42) = 0.025$, $p = 0.876$, $\eta^2 = 0.001$) effects were not significant. The interaction between group and response hand was also not significant ($F(2,42) = 1.911$, $p = 0.161$, $\eta^2 = 0.083$).

Coefficient of variation of the velocity

Group ($F(2,42) = 0.413$, $p = 0.664$, $\eta^2 = 0.019$) and response hand ($F(2,42) = 0.030$, $p = 0.862$, $\eta^2 = 0.001$) effect were not significant. The interaction between group and response hand was also not significant ($F(2,42) = 0.101$, $p = 0.905$, $\eta^2 = 0.005$).

Discussion

This study aimed to present REAsmash-ET, a methodological framework for the integrated assessment of visuospatial attention and UL motor control in iVR. Through the combination of behavioral outcomes, ET metrics and kinematic analysis within a structured search-and-reach task, we tested three main hypotheses. First, based on FIT, we hypothesized that behavioral outcomes, specifically RTs, would vary as a function of target-distractor saliency, number of distractors. Second, we hypothesized that eye-tracking metrics would reflect differences in visual search strategies under different task conditions. Third, we hypothesized that kinematic metrics would capture variations in motor performance associated with hand dominance, providing complementary information on UL function. We also hypothesized an age effect on RT, ET metrics and motor control.

The behavioral outcomes confirmed the reliability of our SG in replicating the FIT in a different HMD setup relative to previous studies with REAsmash [57, 105, 106]. We observed progressively longer RTs as the number of distractors increased, but only in the low salience target-distractor condition. This effect was accompanied by a clear age-related decline in RRT specifically for the low salience target-distractor condition. Consistent with previous studies employing REAsmash on healthy participants [102, 105, 106], the frequency of errors and omissions remained very low, confirming the reliability of the task.

Overall, ET metrics confirm the REAsmash-ET as an effective framework for measuring the cognitive cost of visual search under different stimuli conditions and assessing visual exploration strategies. In accordance with the FIT, the total fixation time spent on distractors showed a significant interaction between target-distractor salience and the number of distractors, with progressively higher values when the number of distractors increased for the low salience condition. While statistical significance for distractor number was observed for some ET dependent variables in high salience conditions, these effects were much smaller than the effects in the low salience conditions (see the accompanying figures and tables in the supplementary material), and likely clinically irrelevant. In the high salience conditions, the time spent looking at distractors remained close to zero regardless of the distractor number. This finding confirms that participants detected the target with minimal engagement of distractors, likely relying on bottom-up processes typical of parallel search [94, 104].

In low-salience conditions, consistent with top-down processing involved in visual serial search [94, 104], the effect of distractor number was both robust and clinically relevant. In this low saliency condition, compared to the 11-distractor level, the mean total cumulative time spent fixating on distractors increased by 62% and 100% with 17 and 23 distractors respectively.

The emergence of group differences further supports the ability of REAsmash-ET in detecting subtle variations in visual attention performance across the lifespan, even in a healthy population. This is consistent with previous evidence showing that ageing is associated with reduced visual search efficiency, particularly in tasks requiring serial attentional processes, with older adults exhibiting slower response times and altered gaze patterns when confronted with increased visual complexity [139].

Regarding the mean duration of distractor fixations, no significant effects were found for target-distractor saliency, distractor number, or age group, nor were any interactions observed. Results on distractor fixation duration suggest that, while task complexity influences how often participants fixate on distractors, the length of each fixation remains substantially stable, regardless of search difficulty or age in healthy individuals. As suggested by previous research [140, 141], under conditions of time pressure, as in the REAsmash-ET, fixation durations may remain stable regardless the stimuli set (i.e., features and number of distractors), likely due to limited time for attentional adjustment. This feature of REAsmash-ET is expected to provide a valuable framework for future comparisons between individuals with cognitive impairments and normative data from healthy controls. The present findings allow us to speculate that in the presence of cognitive impairments, individuals may exhibit longer average fixation durations. This may indicate a reduced ability to adapt to the temporal constraints of the task, which requires exploring as many stimuli as possible within a limited time window, while maintaining an organized search path and ensuring sufficient accuracy in distractor detection and inhibition.

While disruptive effect of distractors on performance is well established, with numerous replications in the literature [142, 143], yet no tool for assessing distractor inhibition is available in routine clinical practice. From a clinical standpoint, prolonged fixations on distractors may serve as a marker of impaired distractor inhibitory control, which in patients could manifest as slowed information processing and greater susceptibility to interference in everyday tasks. REAsmash-ET ability to elicit and assess distractor inhibitory control is thus particularly valuable in stroke survivors, where deficits in attentional control can hinder functional recovery and daily performance [144].

Building on these considerations, we analyzed the results related to overlapping fixations with a focus on serial search. These metrics allowed us to further investigate whether and how REAsmash-ET can detect the efficiency of visual exploration from a spatial perspective (i.e., spatial distribution of a sequence of fixations). Concerning capture fixations, our results suggest that the likelihood of consecutive fixations on the same distractor increases with the number of distractors on the playing field, regardless of the age of the participant. According to the literature, a pathological number of capture fixations likely indicates difficulties with attentional disengagement [94, 132, 134]. However, our data suggests that during complex search tasks, capture fixations are present even in healthy controls. This consideration calls for the introduction of normative data if the aim is to introduce these metrics in cognitive assessment.

Although re-capture events were extremely rare, significant age-related differences emerged, particularly between younger and older participants. These differences reflect subtle variations in spatial exploration efficiency, highlighting the capacity of REAsmash-ET in detecting age-related changes in attentional control, reinforcing its value beyond clinical diagnostics. These results support the proposed methodological approach and confirm its potential for use in both normative research and clinical adaptation for assessing visual attention in naturalistic goal-directed immersive settings.

Overlapping fixation patterns mirror clinical profiles commonly observed in patients with right hemisphere stroke [145] or frontal executive dysfunction [146]. Clinically, excessive capture or re-capture fixations may signal inefficient allocation of (inhibitory) attentional resources and working memory, linked to disorganized visual exploration after stroke. An increase in capture fixations indicates difficulty disengaging from irrelevant stimuli, reflecting impaired distractor inhibition. Increased recapture fixations (i.e., perseveration) [94, 132, 134] is caused by a combination of visuospatial working memory and the inability to correctly inhibit a previously viewed distractor [92, 132, 133]. These findings highlight the potential of REAsmash-ET for fine-grained diagnostic assessment.

Concerning UL speed metrics, findings align with previous works with REAsmash [136], showing that both mean and peak velocity slow with age. As expected, the dominant UL was faster than the non-dominant one, confirming the ability of REAsmash to detect asymmetries in motor performance even within healthy participants.. However, the lack of significant interaction between age and response hand suggests that age-related slowing occurs equally in both ULs. Movement smoothness, measured by SPARC, was not significantly affected by age or response hand, indicating that older adults maintain relative smooth trajectories despite moving more slowly. Similarly, movement consistency, assessed through the coefficient of variation of velocity, remained stable across age groups and response hand. These findings highlight the value of REAsmash-ET in detecting age-related motor changes while distinguishing between declines in movement speed and the preservation of movement quality. The stability of smoothness and consistency is particularly relevant, as their deterioration is typically associated with pathological motor impairment rather than healthy ageing. These results may serve as an initial reference point for exploring motor performance in clinical populations, particularly in conditions characterized by unilateral motor deficits. Beyond statistical differences across age groups, these kinematic measures provide clinically relevant insights into motor efficiency. By revealing diminished motor control in older participants, reductions in peak velocity highlight the capacity of these measures to discriminate within the healthy spectrum, thereby underscoring their value for probing pathological motor deficits, as documented in post-stroke populations [43, 147, 148]. Importantly, these continuous, objective measures should overcome the floor and ceiling effects of traditional ordinal scales, supporting the development of more precise and individualized assessments of motor recovery complementary to conventional clinical assessments.

Unlike previous iVR-ET studies, which have predominantly focused on passive or non-motor visual exploration tasks, REAsmash-ET combines active motor responses with structured visual search, allowing the simultaneous investigation of attentional and motor dynamics within a single naturalistic goal-directed immersive framework [149]. By interpreting the results within this clinical framework, REAsmash-ET emerges not only as a methodological innovation but also as a tool that can contribute to advancing neurorehabilitation practice by supporting the integrated assessment of cognitive and motor functions within a single task.

Limitations

The present study aimed to define a framework for the extraction and interpretation of eye-tracking metrics in a structured search-and-reach task. As a preliminary investigation of the reliability of a novel methodological approach, we acknowledge that the present study has several limitations. Because only healthy participants were included, the present study does not allow us to draw conclusions regarding the ability of REAsmash-ET to detect motor deficits or to capture cognitive-motor interference effects that typically occur in clinical populations, such as stroke. The next step will be to test REAsmash-ET in a post-stroke population, where aspects such as consistency, sensitivity, reliability, and convergent validity with established gold-standard assessments will be systematically addressed. Preliminary results also suggest a potential age-related effect even among healthy individuals, particularly in visual search patterns such as recapture fixations. However, the sample size of the present study was not designed to establish normative data, and these findings are therefore not conclusive. Future studies will include larger samples to further investigate the effect of age on overlapping fixations.

Although participant groups were balanced for gender, no statistical analyses were conducted to investigate gender-related effects. This choice was based on previous findings and theoretical frameworks, such as the FIT, which suggest that cognitive and attentional processes involved in the primary task are unlikely to be influenced by gender [103]. Therefore, gender was not considered a critical factor for the current research aims. Nevertheless, we acknowledge that gender may still play a role in other dimensions, such as technology use or task engagement, and future studies should consider exploring these aspects more specifically.

Recent work with REAsmash has shown that HMD hand controllers can provide reliable and sensitive kinematic measures to capture training-related changes in motor learning [136]. However, it remains a limitation that VR-based kinematics are not fully equivalent to real-world movements, as the use of such controllers may influence natural motor execution. The absence of physical object interaction and reduced haptic feedback can subtly affect movement trajectories, especially during the deceleration and endpoint phases [150].

Implications and perspectives

We consider REAsmash-ET a task of functional relevance, as it engages naturalistic goal-directed visuomotor behavior under standardized conditions. REAsmash-ET offers a robust and flexible framework for studying the interplay between cognitive and motor processes in immersive VR contexts. By combining behavioral, eye-tracking and UL kinematic data within structured task manipulations, it enables a multidimensional investigation of visual search, attentional control, and motor execution. This makes it a valuable tool for fundamental research on how attention and action co-regulate under time and performance constraints.

From a clinical perspective, REAsmash-ET holds strong potential for assessing the interaction between cognitive functions frequently impaired in stroke survivors. For example, its metrics on distractor engagement and fixation dynamics may support the identification of attentional disengagement difficulties, such as those observed in USN [134]. Moreover, the framework could help explore how spatial working memory and selective attention interact during visual exploration, offering insights into compensatory mechanisms or deficits in goal-directed behavior. By highlighting individual profiles of cognitive-motor interplay, REAsmash-ET may inform targeted assessments and personalized rehabilitation strategies in clinical populations.

As a planned extension of the REAsmash-ET framework, we aim to further investigate the interplay between cognitive and motor processes by segmenting upper limb kinematic data into distinct phases relative to eye-tracking events. Specifically, we will distinguish (i) a first scanning phase, during which stimuli are displayed on the field but the target has not yet been fixated; (ii) a second phase, starting from the first fixation of the target and extending to the manual response / the end of the trial. By contrasting post-stroke patients with healthy controls, this approach will allow us to explore in greater detail how cognitive demands and motor execution interact across task stages, thereby providing a more precise characterization of cognitive-motor interference under dual-task conditions. Furthermore, future analyses will leverage the recorded head coordinates to disentangle the relative contributions of head and eye movements to gaze deployment in REAsmash-ET.

While this study was limited to healthy participants, the results support the potential clinical utility of REAsmash-ET as a single-task framework integrating information that currently requires multiple assessment tools. For instance, visuospatial attention is typically evaluated through subtests of the TAP battery [151], while upper limb function is assessed with scales such as the Fugl-Meyer Assessment [27]. REAsmash-ET offers the possibility to capture both domains simultaneously and, importantly, provides metrics on distractor inhibition, a cognitive ability for which no standardized clinical test is currently available. This integrated approach could therefore streamline assessment protocols, while future studies in clinical cohorts will be needed to confirm its applicability and diagnostic value.

An additional advantage of REAsmash-ET is its ease of use, which minimizes the learning curve for clinical personnel and facilitates rapid implementation in rehabilitation settings. Unlike classical non-immersive systems, which would require the parallel use of external eye-tracking devices and additional kinematic sensors to obtain the same range of information, REAsmash-ET provides an integrated solution that captures behavioral, oculomotor, and kinematic data with a single device.

In addition, we are currently developing a fully adaptive algorithm in which AD tolerance is continuously adjusted to the average distance between eyes and consecutive gaze points. This approach is designed to keep LD constant within a physiologically meaningful AD range and to account for individual differences (e.g., height, posture), thereby supporting more robust and individualized fixation detection in future implementations of REAsmash-ET.

Beyond its application in post-stroke assessment, our main target population, the REAsmash-ET framework may also have utility in other neurological conditions, such as mild cognitive impairment and early-stage dementia, where deficits in distractor inhibition, spatial and non-spatial attention have often been reported [152]. Its multidimensional approach could contribute to the early identification and characterization of attentional and working memory dysfunctions across clinical populations.

In terms of ET algorithm, our semi-adaptive approach aims to provide a generalizable solution for fixation detection in immersive 3D environments, by adapting the angular dispersion threshold based on the average eye-to-stimulus distance. Unlike purely spatial (Euclidean) methods that require precise 3D gaze coordinates, this method can be applied in situations where such data are unavailable, as long as an approximate stimulus distance is known or can be assumed.

Conclusions

This study introduced REAsmash-ET, a novel and generalizable methodological framework for combined cognitive and motor assessment in iVR. By combining behavioral outcomes, ET and UL kinematic measures within a naturalistic goal-directed search-and-reach task, REAsmash-ET enables the simultaneous investigation of attentional and motor control and their interaction.

The framework's structure, data processing pipeline, and convergence with theoretical predictions from FIT support its robustness and feasibility or future applications.

Beyond its current implementation, REAsmash-ET is designed to be flexible and scalable, making it suitable for adaptation to other tasks, patient groups, or rehabilitation contexts. Taken together, these findings highlight the value of a multidimensional, theory-driven approach for advancing research and clinical assessment of motor–cognitive interactions in both healthy and neurological populations.

Abbreviations

(UL)	Upper Limb
(ADLs)	Activities of Daily Living
(ICF)	International Classification of Functioning, Disability and Health
(VR)	Virtual Reality
(ET)	Eye-Tracking
(SGs)	Serious Games
(ROIs)	Regions of Interest
(iVR)	Immersive VR
(LPSs)	Large Projection Systems
(CAVEs)	Cave Automatic Virtual Environments
(HMDs)	Head-mounted displays
(FIT)	Feature-Integration Theory
(A_D)	Angular Dispersion
(*d*)	Distance between the eyes and the stimuli
(L_D)	Linear Dispersion
(SPARC)	Spectral arc length
(RRT).	Relative Response Time

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12984-025-01844-0.

Additional file1 (DOCX 38 kb)

Additional file2 (DOCX 576 kb)

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Author contributions

GS designed the presented study, analyzed the data, interpreted the results and wrote the paper. GE, TL and MGE created the REAsmash, interpreted the results of the present paper, and helped write the paper. MM and NB interpreted the results of the present paper and helped write the paper. All authors contributed to editorial revisions in the manuscript. All authors read and approved the final manuscript. All authors have participated actively in the work and accepted responsibility for all aspects of the work.

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Availability of data and materials

The datasets used during the current study are openly available in the open data archive of University of Louvain (https://doi.org/10.14428/DVN/GWVH3W).

Declarations

Ethics approval and consent to participate

The protocol was approved by the Saint Luc-UCL Hospital-Faculty Ethics Committee (Belgium) (2015/10FEV/053) prior to the initiation of the study and registered on clinicaltrial.gov (NCT04694833).

Competing interests

The authors declare no competing interests.

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