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ORIGINAL ARTICLE

Effects of physical walking on eyes-engaged target selection with ray-casting pointing in virtual reality

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Abstract
Target selection in virtual reality (VR) is usually carried out with the need of visual attention. While target selection in VR has been extensively investigated in non-walking activities (e.g., sitting or standing), there have been few studies about eyes-engaged target selection during walking in virtual environments. Therefore, we conducted a comprehensive study to explore the effects of physical walking (as an independent variable with low, medium and high speeds) on eyes-engaged selection tasks with targets (three target sizes and three target depths) in two experiments: targets fixed in the virtual environment (Experiment One) and targets fixed to the virtual body (Experiment Two), respectively. Results showed that for Experiment One, the low walking speed led to the significantly longest task completion time, while the medium and high speeds had similar task completion time. For Experiment Two, higher walking speed led to longer task completion time. In both tasks, error rate significantly increased as walking speed increased. The effects of walking speed also varied across target size and target depth. We conclude our study with a set of design implications for target selection tasks when walking in VR environments.

Keywords Virtual reality · Target selection · Physical walking · Ray-casting selection · Eyes-engaged interaction

1 Introduction

Target selection is a fundamental task in virtual reality (VR) interactions. VR, by its possibility to simulate a real-world experience, supports diverse interaction scenarios in which target selection is commonly an indispensable component. For example, in a virtual workshop, virtual tools around a user have fixed positions relative to the user. The user can select tools with visual attention. The process helps the user to build a spatial memory of the virtual tools. With such a memory, the user could select a tool without looking at it (Yan et al. 2018; Zhou et al. 2020). Another example is that a gamer can aim at and shoot a target while standing or walking in a VR gaming environment (Cashion et al. 2012).

Target selection tasks in VR can be classified into four categories according to two dimensions: motor activity (walking or non-walking) and visual attention (eyes-free or eyes-engaged) (Table 1). The motor activities include

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Table 1 Categories of target selection tasks in VR

	Non-walking activity	Walking activity
Eyes-engaged selection	Ray casting: e.g. Argelaguet and Andujar (2013), Mine (1995), Bowman et al. (2001), Grossman and Balakrishnan (2006), Poupyrev et al. (1996), Steinicke et al. (2006), Tu et al. (2019), Liu et al. (2020), Takashina et al. (2021), Khanwalker et al. (2016), Gao et al. (2019)	Ray casting: None
	Virtual hand: e.g. Lin and Woldegiorgis (2017), Teather and Stuerzlinger (2011), Lubos et al. (2014), Argelaguet and Andujar (2013), Machuca and Stuerzlinger (2018), Barrera Machuca and Stuerzlinger (2019), Poupyrev et al. (1996), Vanacken et al. (2007), Cashion et al. (2012)	Virtual hand: Chiovetto and Giese (2013)
Eyes-free selection	Virtual hand: Yan et al. (2018), Wu et al. (2021), Gao et al. (2019)	Virtual hand: Zhou et al. (2020)

non-walking (e.g., sitting or standing) and walking ones. Target selection in VR during walking differs from non-walking for two main aspects. First, when engaging in target selection tasks during walking, users need to balance the efforts dedicated to the walking activity and the target selection task. This requires higher demands on the sensory-motor system to achieve successful target acquisition relative to sitting or standing (Bergstrom-Lehtovirta et al. 2011). Second, target selection during walking involves more factors to consider compared to sitting or standing. Walking speed is an important factor of walking behaviors, which may affect target selection performance (Bergstrom-Lehtovirta et al. 2011; Lin et al. 2007). In addition, the walking activity varies in locomotion behaviors, such as walking speed (fast or slow) or walking styles like walking in place (Nilsson et al. 2018, 2014) or walking on treadmill (Nilsson et al. 2014; Powell et al. 2011). Existing work has shown that locomotion behaviors could influence target selection efficiency (Bergstrom-Lehtovirta et al. 2011). These factors would make it more challenging to acquire targets during walking than non-walking activities. Also, these factors, in combination of target-related factors (e.g., target depth, size and layout), would make target selection during walking a more complicated interaction behavior than target selection in non-walking activities. Regarding the dimension of visual attention (i.e., user's visual focus on target selection Yan et al. 2018; Zhou et al. 2020), target selection tasks can be performed in either eyes-free or eyes-engaged modes. Eyes-engaged target selection requires a close coupling between visual and motor spaces, while eyes-free target selection does not rely on visual attention (e.g., in a virtual workshop, an engineer grabs and selects a virtual tool surrounding him without looking at it Yan et al. 2018; Zhou et al. 2020). Such a difference of visual requirements may affect target selection efficacy. In summary, the four categories represent typical target selection tasks in VR with unique interaction characteristics.

Ample research has investigated target selection in non-walking activities with eyes-engaged (e.g., Argelaguet and Andujar 2013; Mine 1995; Tu et al. 2019; Lu et al. 2020; Yu et al. 2020; Batmaz and Stuerzlinger 2021; Batmaz et al. 2020) or eyes-free methods (Yan et al. 2018; Gao et al. 2019; Wu et al. 2021) (Table 1). Nonetheless, there are relatively fewer studies looking at target selection while walking. Existing work has fundamentally investigated eyes-free target acquisition during walking in VR (Zhou et al. 2020), which examined target selection performance using the virtual hand technique (i.e., directly acquire targets with hand) with the consideration of target placements (the spatial layout of the targets), reference frames for target layout (using the head or torso), and locomotion patterns (i.e., standing still, walking in a straight line, and walking around a curve). However, the study did not investigate selection tasks with eye engagement during walking (Zhou et al. 2020). While a previous study of motor behavior concerned eyes-engaged target selection with arm pointing in VR while walking (Chiovetto and Giese 2013), it was focused on kinematic patterns of joint co-variation when performing such a task, rather than user performance. Overall, there is no generalizable, controlled empirical study into eyes-engaged target selection in VR while walking by taking walking speed and target-related factors (e.g., depth, size and layout) into account.

Therefore, we conducted a fundamental study to look into eyes-engaged target selection with ray-casting pointing during walking in VR. We considered two types of target selection tasks and carried out two experiments correspondingly. One is selection of targets that are fixed in the virtual environment. This is a common task in VR such as aiming at and shooting a target during walking in a gaming scene. The other task type is selection of targets that are fixed in the virtual body when walking. Such a task can be found in scenarios such as acquiring weapons around the body in a game. Experiment results showed that selection performance depended on walking speed. The effects of walking speed varied between the two task types and target-related factors such as target depth and size.

The contributions of our study are threefold. First, we presented a comprehensive study that analyzed the effects of physical walking speed on target selection with ray-casting pointing in VR. Second, we analyzed target selection performance with the consideration of walking speed, target size, and target depth based on experimental data collected. Third, our work contributes new empirical evidence and theoretical results that provide fundamental support for VR interface design with target acquisition during walking.

2 Related work

Our work is based on previous studies of target selection and virtual walking in VR, which are reviewed below.

2.1 Target selection in VR

There are a considerable number of studies related to target selection in VR. We summarize them according to the four categories in Table 1. We refer the reader to Argelaguet and Andujar (2013) for a detailed review.

2.1.1 Eyes-engaged selection in non-walking activities

Eyes-engaged target selection during sitting or standing mainly relies on two techniques: virtual-hand and ray-based ones.

Virtual hand selection is a straightforward way to acquire targets in a reachable area with a virtual hand manipulated by users. However, such a method works only for selection of objects inside the working space unless decoupling mechanisms are introduced (Argelaguet and Andujar 2013). The interaction performance of virtual hand selection could be affected by factors related to the ergonomics of direct interaction, including interaction duration, hand and arm postures, frequency of movements, and comfort (Lubos et al. 2014; Argelaguet and Andujar 2013). In particular, as stereo display deficiencies may hinder depth perception (Machuca and Stuerzlinger 2018; Barrera Machuca and Stuerzlinger 2019; Lin and Woldegiorgis 2017; Lubos et al. 2014; Teather and Stuerzlinger 2011), virtual hand selection like the Go-Go (Poupyrev et al. 1996) and the virtual point cursor (Vanacken et al. 2007) could not provide enough precision when selecting distant and dense objects (Cashion et al. 2012).

Ray-based techniques specify a target of interest based on a virtual ray cast from a hand-held controller, a tracked hand or even an eye. A target is selected if it intersects with the ray when a trigger event is issued (Argelaguet and Andujar 2013). Compared to virtual hand techniques, ray-based techniques support longer-distance object selection with relatively less physical movement (Mine 1995), thus has become a major selection method in current commercial VR devices (e.g., Oculus Rift and HTC Vive). Previous studies have demonstrated the effectiveness of ray-casting selection over virtual hand selection (e.g., Bowman et al. 2001; Grossman and Balakrishnan 2006; Poupyrev et al. 1996; Steinicke et al. 2006). Due to the popularity and advantage of ray-casting selection, we used it for target selection during walking in VR.

The evaluation of ray-based techniques needs to take into account many target-related factors. The survey paper by Argelaguet and Andujar (2013) summarized a set of factors such as target width, target depth and target layout. The survey paper by Bergström et al. (2021) also revealed that 70.4% and 55.6% of target selection studies in VR considered the variables of target position and size, respectively. The study of ray-casting crossing vs. pointing showed that target depth and size would impact target selection performance (Tu et al. 2019). Regarding target layout, the half-cylinder design with ray-casting pointing has been widely used in previous studies (Liu et al. 2020; Takashina et al. 2021; Khanwalker et al. 2016; Gao et al. 2019). Accordingly, our work considered both target size and target depth in experiment design.

2.1.2 Eyes-free selection in non-walking activities

Eyes-free target selection refers to acquiring targets without eye engagement. It mainly relies on the sense of spatial perception and proprioception. Yan et al. (2018) carried out a study to examine user performance of eyes-free target selection in VR. In their experiment, participants acquired targets located on both sides of their body while reporting to an experimenter when a changing character appearing in the front turned to a target character. Their work indicated that the eyes-free approach had a shorter selection time and less fatigue and motion sickness than the eyes-engaged approach. A follow-up study further investigated target layouts for eyes-free acquisition. Experiment results indicated that high acquisition accuracy and low task load were achieved when the target position is in front or to the side of the user, or at the same level as the users' torso (Wu et al. 2021). Another follow-up study demonstrated that additional feedback (e.g., auditory or haptic) significantly reduce acquisition errors for eyes-free target selection in VR (Gao et al. 2019).

2.1.3 Eyes-free selection in the walking activity

In the walking activity, the limbs produce rhythmic oscillations to maintain gait stability (e.g., walking posture) (Chiovetto and Giese 2013). The faster users walk, the higher oscillation frequency their limbs have. In addition, when a hand is engaged in target selection tasks, hand oscillation would also affect the accuracy of target-reaching operations

(Chiovetto and Giese 2013). Overall, the combinational effects of hand and body oscillation during walking may alter target selection performance. A study conducted by Zhou et al. (2020) examined target selection performance using the virtual hand technique by considering target layout, reference frames for target layout (using the head or torso), and locomotion patterns (i.e., standing still, walking in a straight line, and walking around a curve). Their study demonstrated that target acquisition may be more challenging for users when walking than when standing still. Inspired by their work, we conducted the present study to explore target selection with eye engagement during walking in VR.

2.1.4 Eyes-engaged selection in the walking activity

Target selection with visual engagement during walking has attracted much attention in mobile interaction (e.g., Bergstrom-Lehtovirta et al. 2011; Lin et al. 2007). However, there is limited research on eyes-engaged selection during walking in VR. Chiovetto and Giese (2013) conducted a study to investigate target selection with arm pointing in VR while walking. But its focus was on kinematic patterns of joint co-variation when performing such a task, rather than user performance.

In summary, existing VR studies have looked into eyes-engaged target selection in the non-walking activity, and also eyes-free target selection in the non-walking and walking activity. However, few studies have focused on target selection with visual engagement in the walking activity. In particular, few studies have paid attention to perform such a task with ray-casting pointing by comprehensively considering walking speed and target-related factors. Some applications are related to target acquisition while walking in VR. For instance, in a VR game named "Virtuix Omni Coin Rush," players need to collect as many coins (placed in varying depths) as possible in a limited time on a straight road[1]. Another example is a first-person shooter game called "VINDICTA," where players could shoot enemies while walking on a straight path[2]. Given the wide range of applying eyes-engaged target selection in VR application design, it is worth investigating eyes-engaged target selection while walking in VR.

2.2 Virtual walking in VR

Virtual walking is a type of locomotion performed to navigate virtual environments. There are numerous studies conducted to achieve natural and effective virtual walking. We review them from the two directions below. A thorough review can be found in Nilsson et al. (2018).

2.2.1 Virtual walking techniques

Virtual walking in VR can be achieved through either gait-enabled or gait-free approaches. The former generally requires users to walk in the real world to cause virtual movements in VR (Nilsson et al. 2018), while the latter usually relies on predefined body-part movements while standing in place (Gao et al. 2021). The gait-enabled approach is more natural to perform, as it is consistent with users' behavior of navigating their surroundings on foot in the daily life. Also, this approach can be executed with relative ease and without assigning much explicit attention to the performed movements. Therefore, we focus on this approach of virtual walking in VR.

There are many methods proposed for virtual walking in VR. One common way is real walking, which allows users to walk in a physical space to navigate a virtual environment. The most natural and straightforward way to perform real walking generally adopts a physical space that has the same size as a virtual environment (Usoh et al. 1999; Zhou et al. 2020; Sayyad et al. 2020). While this type of real walking produces a high sense of presence, it is not feasible for large-scale virtual environments with restricted tracked physical environments.

Therefore, many alternative methods have been proposed to mimic real walking without dedicated room space. Redirected walking is a method which allows users to navigate through a large virtual environment while physically remaining in a room-scale workspace (Bruder et al. 2015; Bozgeyikli et al. 2019). However, if redirected walking is applied in a smaller workspace, the manipulation of virtual camera motions in VR would become noticeable, which could influence walking experience in VR (Bruder et al. 2015).

Another common method is the use of linear treadmills to realize virtual walking in VR. Such a method has been adopted to investigate the perception of physical walking speed in VR (Nilsson et al. 2014; Powell et al. 2011; Banton et al. 2005), study VR-based rehabilitation with treadmills (Feasel et al. 2011; Kassler et al. 2010; Fung et al. 2006), simulate an infinite surface using multi-linear treadmills (Iwata 1999), examine the kinematics of the coordination of pointing during locomotion (Chiovetto and Giese 2013). Other devices include motorized floor tiles which cancel users' forward walking by moving in the opposite direction of walkers' direction (Iwata et al. 2005) and a human-sized hamster ball that could simulate walking in a semi-natural way (Medina et al. 2008).

Some body-centric walking methods have been proposed as well. The tapping-in-place method was designed

[1] https://www.youtube.com/watch?v=wGpsQCddjwY.

[2] https://store.steampowered.com/app/597770/VINDICTA/.

to achieve natural walking by tapping each heel against the ground but without breaking contact with toes (Nilsson et al. 2013, 2014). The walking-in-place (WIP) technique allows users to alternately lift the foot to move forward (Nilsson et al. 2018, 2014; Tregillus and Folmer 2016). Follow-up studies also improved the performance of WIP with methods such as machine learning models (Wendt et al. 2010), deep networks (Hanson et al. 2019) and a LLCM-WIP system (Feasel et al. 2008), aiming to alleviate latency existed in WIP algorithms.

Our study used a linear treadmill to simulate real walking as previous studies also used linear treadmills to investigate target selection while walking (Bergstrom-Lehtovirta et al. 2011; Chiovetto and Giese 2013; Schildbach and Rukzio 2010). It is a commonly used method and easy to deploy. In addition, the linear treadmill could enable participants to walk at a relatively constant speed. Participants could walk at different speeds by changing the speed of the treadmill, so that we can control the factor of walking speed in our experiment.

2.2.2 Mapping between physical walking and virtual motion

To facilitate natural walking experiences, it is important to establish a proper mapping between physical walking and virtual motion. Many studies have employed visual gains (optic flow multipliers) (Powell et al. 2011; Nilsson et al. 2014), step frequency (Nilsson et al. 2014), the displacement of headset (Zhou et al. 2020; Suma et al. 2007; Abtahi et al. 2019) or lower-body locomotion techniques (Suma et al. 2012; Gao et al. 2021) to achieve a suitable mapping between walking in the physical world and motion in the virtual environment. These studies can be further classified into two aspects: non-isometric and isometric mappings.

The non-isometric mapping means that the walking speed in physical environments differs from that in virtual environments. Studies of the non-isometric mapping are mainly related to perceptual walking speed and locomotion design. Previous studies showed that perceived natural speeds in VR were usually underestimated (Schneider et al. 2018; Powell et al. 2011; Nilsson et al. 2014, 2015; Janeh et al. 2017, 2017). Powell et al. (2011) suggested that the range of visual gain in 1.55 - 2.41 was perceived as normal. Many studies have adopted non-isometric mappings in locomotion design. For example, the walking-in-place technique (Nilsson et al. 2018, 2014; Tregillus and Folmer 2016), a common approach that users alternately lifted each foot from the ground to perform locomotion, used a non-isometric mapping to achieve efficient locomotion (Nilsson et al. 2013). In addition, other locomotion techniques employed nonlinear transfer functions to control walking speed (e.g., seven league boots Interrante et al. 2007) or dynamically changed non-isometric mappings according to different locomotion algorithms (e.g., redirected walking techniques Suma et al. 2012).

Studies also examined isometric mapping, i.e., the walking speed in the real world is equal to that in VR. This is a natural mapping between walking in the physical world and motion in the virtual environment, as it enables a coupled correlation between the physical space and the virtual space (Nilsson et al. 2018). The use of isometric mapping has been widely adopted in goal-directed walking (Janeh et al. 2017, 2017; Kannape et al. 2014), target selection (Chiovetto and Giese 2013; Zhou et al. 2020), rehabilitation (Feasel et al. 2011), as well as navigation and wayfinding in VR (Suma et al. 2007). Hence, our study adopted isometric mapping between walking speed in the physical world and the virtual environment.

3 Experiment one: selection of targets fixed in the virtual environment

In this experiment, we investigated the effects of physical walking on selecting targets fixed in the virtual environment. During walking, target position relative to users would vary depending on users' motion.

3.1 Apparatus

The experiment was conducted on a computer with an Intel core i7 8700 CPU (3.2 GHz), 16GB RAM and Geforce GTX-1060 graphics card, running Microsoft Windows 10. We used an Oculus Quest 2 with 1832×1920 resolution per eye and a 90 Hz refresh rate and a horizontal field of view of around 89° (±4°) to render the virtual environment. An Oculus controller was used to perform target selection tasks. A quest link cable was used to connect Quest 2 with the computer to run the experiment program, which was developed with Unity 2020 in C#.

Participants walked on a treadmill with a running area of 122×42 cm to simulate natural walking. This method has been adopted in many studies of locomotion in VR (Chiovetto and Giese 2013; Sloot et al. 2014; Choi et al. 2015; Feasel et al. 2011).

3.2 Participants

Fifteen participants (8 males, aged 20–27) from the local university took part in the experiment. All were right-handed and had normal vision or corrected to normal vision. Five of them had experience with VR interaction.

3.3 Experiment design

The experiment followed a within-subject repeated-measures design. The independent variables and dependent variables are as follows.

3.3.1 Independent variables

The independent variables were walking speed, initial target depth and target size. The independent variables are described below.

Walking speed is participants' gait speed during the experiment. It had three levels: 1.4 m/s, 1.1 m/s and 0.8 m/s. The high speed was 1.4 m/s, which is regarded as the average walking speed for adults (Choi et al. 2015; Yao et al. 2014). We selected 0.8 m/s as the low speed. This speed was also used in previous studies of target selection in VR (Chiovetto and Giese 2013). The speed of 1.1 m/s was selected as the medium speed.

There are two main reasons why we did not use the non-walking condition in our experiments. First, the focus of the study was on the effect of physical walking on target selection in VR. Therefore, our experiment design adopted three walking speeds (low, medium, and high) but not the non-walking condition. Such a design is consistent with many previous studies of investigating how physical walking affects target selection (e.g., Lin et al. 2007; Schildbach and Rukzio 2010). Second, our pilot study with 4 participants showed that the non-walking condition significantly outperformed the walking condition with the low speed in terms of task completion time (non-walking: M = 0.90 s, SD = 0.05 s; low speed: M = 1.09 s, SD = 0.09 s)($F_{1,3} = 26.45, p < 0.05, \eta_p^2 = 0.90$) and error rates (non-walking: M = 2.51 %, SD = 1.27 %; low speed: M = 6.15 %, SD = 1.37 %)($F_{1,3} = 43.01, p < 0.01, \eta_p^2 = 0.94$). It is relatively straightforward to expect such results as walking requires higher motor control abilities, which would lead to a worse target selection performance (Bergstrom-Lehtovirta et al. 2011; Lin et al. 2007; Schildbach and Rukzio 2010). We therefore did not include the non-walking condition in experiment design.

The movement speed of the viewpoint (virtual camera position) in VR was the same as the walking speed. This is a straightforward mapping (1:1) between body movements to virtual viewpoint displacement (i.e., user's viewpoint in VR). The movement speed of the virtual viewpoint was kept constant in a trial to simulate a constant walking speed in the virtual environment. A pilot study with 4 participants showed that the 1:1 mapping could offer a natural walking experience in this experiment.

There are three main methods to control walking speed: a treadmill (Bergstrom-Lehtovirta et al. 2011; Lin et al. 2007; Sloot et al. 2014), instruction to maintain a particular speed (Yatani and Truong 2009), and a human pace-setter (Kane et al. 2008). We adopted the first one for three main reasons. First, it is feasible for use to control walking speed. We conducted a pilot study to exam participants' walking speed on the treadmill under three setting speeds of the treadmill. Two HTC Vive trackers were attached to the participants' shoes using a buckled elastic strap. Based on the position of the two trackers, we calculated the stride length of each step and the time used for each step. Then we calculated the velocity of each step by using the step length divided by the time. The walking speed of a participant was the average value of all step velocities. Our results showed the walking speed was 0.86 m/s (SD = 0.06 m/s) for the low treadmill speed (0.8 m/s), 1.07 m/s (SD = 0.09 m/s) for the medium treadmill speed (1.1 m/s) and 1.39 m/s (SD = 0.17 m/s) for the high treadmill speed (1.4 m/s). Generally, participants' walking speed on the treadmill is close to the setting speed of the treadmill, indicating that our method is acceptable in speed control. Second, compared to other methods, such as instruction to maintain a particular speed (Yatani and Truong 2009) and a human pace-setter (Kane et al. 2008), the use of a treadmill would not distract participants' attention when selecting targets in VR. Third, the use of a treadmill has been used in many previous studies on target selection while walking (e.g., Bergstrom-Lehtovirta et al. 2011; Chiovetto and Giese 2013; Ng and Brewster 2013). The participants only performed rectilinear walking in this experiment (Fig. 2d), because this is a common locomotion behavior for investigating user performance of target selection Bergstrom-Lehtovirta et al. 2011; Chiovetto and Giese 2013; Schildbach and Rukzio 2010.

As previous studies of target selection in VR (Zhou et al. 2020; Lu et al. 2020), targets were spheres which appeared at different spatial locations in front of participants' viewpoint in VR. Target size refers to the actual physical size of targets in VR environments, which was defined as the diameter of the target (Bergström et al. 2021). Based on (Tu et al. 2019), we selected three sizes: 20 cm, 25 cm and 30 cm. Our pilot study with three participants showed that targets of 15 cm size resulted in error rates greater than 50% for the walking speed of 1.4 m/s. This indicates that selection tasks with such targets would be very challenging for participants. Therefore, we set the small target size as 20 cm. Note that although the physical size of a target was kept constant in a trial, the visual size of the target (i.e., perceived size by the user Poupyrev et al. 1998) would vary along with the change of the distance between the participant's viewpoint and the target. Such a design is consistent with the most realistic interaction scenarios in VR.

Initial target depth was defined as the distance between the target's center and the view point (virtual camera's position in VR) (Fig. 1a) at the beginning of a trial. There were three levels: 0.8 m, 2.5 m and 3.5 m. According to Oculus

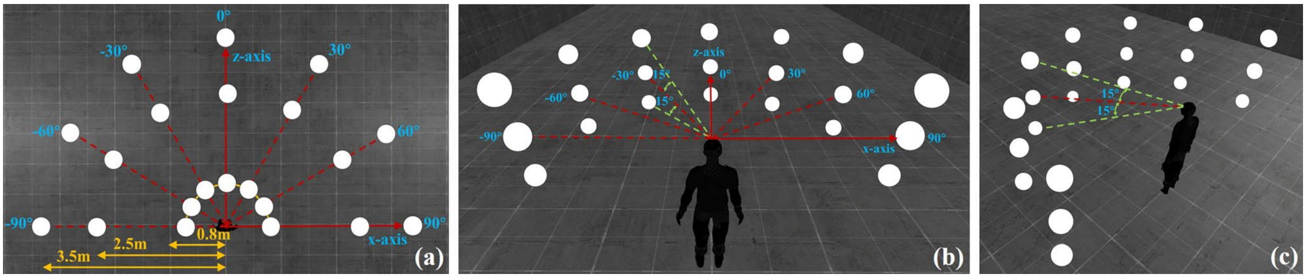

Fig. 1 Target layout in the virtual environment. **a** Target positions (white spheres) from an overhead view in the three depths (i.e., 0.8, 2.5 and 3.5 m). *Z*-axis is the default orientation of the virtual camera in VR. Note that there are three layers at a target position but only one can be seen due to view angle. **b** Back view of 21 targets in the medium depth. Note that targets in other two depths have the same layout. **c** Lateral view of the target layout in the medium depth

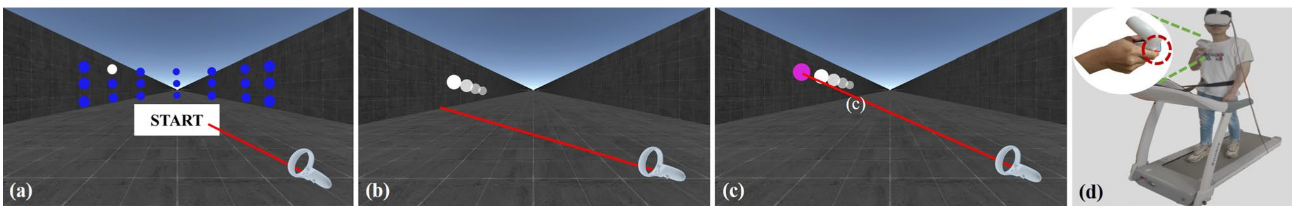

Fig. 2 Experiment interfaces and environment. **a** Before the start of a trial, the white ball in the mini target layout roughly indicates the location of the target to be selected relative to others. **b** The target is moving during the task process. **c** When the ray cursor moves into the target, it changes to pink. **d** A participant is walking on a treadmill with a belt tied around the waist and the console for safety reasons. Inset: close-up of the Oculus Touch controller. To confirm a selection, the participant presses the button highlighted in a dotted red circle

VR best practices guidelines (Yao et al. 2014), the most comfortable range of depths for a user to look at in the Oculus Rift was between 0.75 and 3.5 m. We therefore selected 0.8, 2.5 and 3.5 m as the shallow, medium, and deep depths, respectively. In addition, target depths of 0.8 m and 3.5 m are the representative peripersonal distance and extrapersonal distance used in (Armbrüster et al. 2008).

For each initial target depth, twenty-one positions were specified on a half cylinder with the default y axis of the virtual camera as the axis and the target depth as the radius (Fig. 1b). The half-cylinder design has been widely used in previous studies of ray-casting pointing (Liu et al. 2020; Takashina et al. 2021; Khanwalker et al. 2016; Gao et al. 2019). The twenty-one positions were equally divided into seven groups. The seven groups were spaced evenly on the cylinder, ranging from W (−90°) to E (90°) in 30° increments. This formed seven target angles (i.e., −90°, −60°, −30°, 0°, 30°, 60, and 90°). For each group, a position was on the default *x-z* plane of the virtual viewpoint (horizontal view), and the other two positions were on two sides of the *x-z* plane with an angle of 15° (Fig. 1c). Since the best display of field should not be larger than 15–20° of a visual angel where users are looking Yao et al. (2014), we set the top and bottom target layers with 15° angle offset from the horizontal view.

In an experimental trial, a target was randomly located at one of the twenty-one positions in one initial target depth. To indicate the position of the target, at the beginning of an experimental trial, we rendered a mini position layout in front of the participant's viewpoint with the target position highlighted in white and others colored blue (Fig. 2a). The design of the mini position layout was based on (Yan et al. 2018). This design would alleviate the effects of target searching, which could be a time-consuming task and may bias the result of target selection time. A pilot study with four participants showed that this method could help them locate targets without much effort. Participants needed to click the "start" button to begin a trial.

The virtual scene was an enclosed corridor with a width of 8 m and infinite length (Figs. 2a–c). Such a setting was designed based on previous studies of target selection in VR (Tu et al. 2019; Cashion et al. 2012).

3.3.2 Dependent variables

The dependent variables were task completion time, error rate, distance between the ray and the target center, target re-entry number, and controller's moving distance. Task completion time was defined as the interval between clicking the start button and successfully acquiring the target. Target

Table 2 Experiment One: average time (s), error rate (%), target re-entry number and controller's moving distance (m) for different target depths in each walking speed

Target depth (m)	0.8			2.5			3.5		
Speed (m/s)	**0.8**	**1.1**	**1.4**	**0.8**	**1.1**	**1.4**	**0.8**	**1.1**	**1.4**
Time (s)	0.81	0.80	0.79	1.06	1.02	0.99	1.22	1.17	1.14
	(0.07)	(0.09)	(0.09)	(0.10)	(0.09)	(0.07)	(0.15)	(0.13)	(0.11)
Error Rate (%)	2.43	6.14	13.33	5.71	9.37	14.34	13.02	15.56	23.33
	(1.55)	(3.85)	(7.27)	(4.18)	(4.41)	(6.16)	(5.59)	(5.74)	(6.99)
Target Re-entry Number	1.03	1.05	1.07	1.19	1.21	1.23	1.34	1.36	1.39
	(0.02)	(0.03)	(0.03)	(0.10)	(0.10)	(0.09)	(0.17)	(0.15)	(0.15)
Controller's Moving Distance (m)	0.37	0.43	0.47	0.35	0.39	0.41	0.36	0.40	0.42
	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)

Note that bold numbers indicate different levels ofindependent variables (i.e., target depth, target size, speed).

acquisition was successful if the selection ray intersected the target sphere when pressing the button of the controller (Figs. 2c and d). Otherwise, a selection error occurred. Error rate was calculated as the ratio of the number of unsuccessful trials to the number of total trials. A target re-entry happened when the ray cursor entered and then left the target. Target re-entry number was the average number of target re-entry. Controller's moving distance is the total moving distance of the controller from starting to completing a selection task. As previous studies (Serrar et al. 2014; Lu et al. 2020), the distance was obtained in the Unity in which 1 unit is approximately equal to 1 meter in the real world (Yao et al. 2014).

3.4 Task and procedure

Participants first read and signed a consent form which included their demographic data and VR experience. They then wore an Oculus HMD on their head and held the controller with their dominant hand. Before starting data collection, we instructed participants to practice selection tasks while walking on the treadmill with the three walking speeds, respectively. They could do practice tasks several times until they felt comfortable with the tasks. For safety reasons, the treadmill was equipped with two lateral bars (Fig. 2d). In addition, a black belt wrapped around the waist was tied to the console of the treadmill to enhance participants' safety. After the initial walking training phase, participants could maintain their balance on the treadmill well, so that the lateral bars during the experiment were rarely used.

During the data collection phase, the order of the three walking speeds was counterbalanced across participants using a Latin Square. Each walking speed had 2 blocks of 9 sets of target depth-size combinations. For each set of combination, participants were required to acquire a target in each of the 21 target positions. The order of 189 trials in a block (21 target positions × 9 combinations) was randomized. For all trials in a walking speed, participants kept walking at the specified speed on the treadmill. A trial started when the start button under the mini layout was clicked (Fig. 2a). The viewpoint moved forward at the same speed as the walking speed (Fig. 2b). Participants needed to acquire the target with the ray cursor as fast and accurately as possible. When the ray cursor moved into the target area, the target turned from white to pink to provide visual feedback as an aid in selection (Fig. 2c). In case of an error, an error tone sounded to remind participants to redo the trial until a successful selection was made. To alleviate fatigue, participants took a 1-minute break between 30 trials in a block, 1-minute break between blocks, and a 3-minute break between the condition of walking velocity. In summary, the experiment consisted of 15 participants × 3 walking velocities × 2 blocks × 3 target depths × 3 target sizes × 21 target positions = 17010 trials.

3.5 Result and analysis

For the combinations of 3 walking speeds × 3 target depths × 3 target sizes, we first removed the outliers (1.91 % of the data) with more than three standard deviations from mean time. The data of task completion time, target re-entry number and controller's moving distance passed the Kolmogorov–Smirnov test (*alpha* = 0.05) for normality of the distribution, so we analyzed these data with repeated-measures ANOVA and post hoc comparisons with Bonferroni adjustment. As the data of error rate were not normally distributed, we applied the method of generalized estimating equations to data analysis as suggested in Wobbrock and Kay (2016). Whenever Mauchly's test indicated that the assumption of sphericity had been violated ($p < 0.05$), the Greenhouse & Geisser method was applied for correction. We checked the learning effect across 2 blocks in our experiment. For completion time, there was no significant difference between the 2 blocks

Table 3 Experiment One: average time (s), error rate (%), target re-entry number and controller's moving distance (m) for different target depths and target sizes in each walking speed

Target size (m)	0.2			0.25			0.3		
Speed (m/s)	**0.8**	**1.1**	**1.4**	**0.8**	**1.1**	**1.4**	**0.8**	**1.1**	**1.4**
Time (s)	1.10	1.06	1.04	1.02	0.99	0.96	0.97	0.94	0.92
	(0.10)	(0.09)	(0.07)	(0.09)	(0.09)	(0.06)	(0.08)	(0.08)	(0.07)
Error Rate (%)	10.63	15.77	24.76	7.14	8.94	16.72	3.39	6.35	9.52
	(5.89)	(6.00)	(8.51)	(3.50)	(3.92)	(6.54)	(2.47)	(3.81)	(5.93)
Target re-entry number	1.25	1.27	1.34	1.17	1.20	1.20	1.14	1.15	1.16
	(0.12)	(0.12)	(0.11)	(0.08)	(0.09)	(0.07)	(0.07)	(0.06)	(0.08)
Controller's moving distance (m)	0.38	0.42	0.45	0.36	0.40	0.43	0.35	0.40	0.42
	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)

Note that bold numbers indicate different levels ofindependent variables (i.e., target depth, target size, speed).

for the three walking speeds (all $p > 0.05$). The mean values and standard deviations are shown in Tables 2 and 3.

3.5.1 Task completion time

Walking speed had a significant main effect on task time (Table 4). The post hoc tests revealed that the low speed (M = 1.03 s, SD = 0.09 s) had significantly longer times than both medium (M = 1.00 s, SD = 0.09 s) and high speeds (M = 0.97 s, SD = 0.07 s) ($p < 0.01$). However, there was no significant difference between the medium and high speeds ($p = 0.38$). Target depth had a significant main effect on task time (Table 4). Task time increased as target depth increased (shallow depth: M = 0.80 s, SD = 0.08 s; medium depth: M = 1.02 s, SD = 0.09 s; deep depth: M = 1.18 s, SD = 0.13 s) (all $p < 0.01$). Target size had a significant main effect on task time (Table 4). The small target size led to the longest time (M = 1.07 s, SD = 0.08 s), followed by the medium size (M = 0.99 s, SD = 0.08 s) and the large size (M = 0.94 s, SD = 0.07 s) (all $p < 0.01$).

There were significant interaction effects between walking speed and target depth (Table 4). However, there was no significant interaction effect between walking speed and target size (Table 4). Also, there was no significant interaction effect between speed, target depth and target size (Table 4). We further analyzed the effect of target depth and size on task time on a per speed basis.

While walking speed did not have a significant main effect on task time for the shallow depth, it had a significant main effect on task time for the medium and deep depths (Table 5). As shown in Fig. 3a, the three speeds had similar task times in the shallow depth (all $p > 0.68$). For the medium depth, the low speed had significantly longer times than the medium and high speed (both $p < 0.05$), while the medium speed and the high speed did not significantly differ in task time ($p = 0.14$). For the deep depth, the low speed had significantly longer times than the high speed, and the medium speed had significantly longer times than high speed (both $p < 0.01$), but the low speed and the medium speed did not significantly differ in task time ($p = 0.10$).

For the three levels of target sizes, walking speed had a significant main effect on task time (Table 5). For the small size, the low speed had significantly longer times than both medium and high speeds (both $p < 0.05$), while the medium and high speeds had similar times ($p = 0.89$) (Fig. 3b). For both medium and large target sizes, the only difference was found between the low and medium speeds (both $p < 0.01$) (Fig. 3b).

3.5.2 Error rate

Walking speed had a significant main effect on error rate (Table 4). As expected, the higher the walking speed, the higher the error rate (high speed: M = 17.62 %, SD = 6.45 %; medium speed: M = 10.35 %, SD = 3.89 %; low speed: M = 7.05 %, SD = 3.46 %) (all $p < 0.01$). Target depth had a significant main effect on error rate (Table 4). The shallow depth (M = 7.30 %, SD = 3.50 %) resulted in the smallest error rate, followed by the medium depth (M = 9.81 %, SD = 4.56 %) and the deep depth (M = 17.30 %, SD = 5.60 %) (all $p < 0.01$). Target size had a significant main effect on error rate (Table 4). Error rate decreased with the increase of target size (small size: M = 17.05 %, SD = 6.34 %; medium size: M = 10.93 %, SD = 4.09 %; large size: M = 6.42 %, SD = 3.56 %) (all $p < 0.01$).

There was a significant interaction effect between walking speed and target depth, and between walking speed and target size (Table 4). There was a significant interaction effect between speed, target depth and target size (Table 4). Due to these interaction effects, we further analyzed the effect of walking speed for each target depth and size.

For the three target depths, walking speed had a significant main effect on error rate (Table 5). Generally, the high speed had significantly higher error rates than the medium

Table 4 Experiment One: Repeated-measures ANOVA results and generalized estimating equations results for the main effects and interaction effects

	Main effect			Interaction effect		
	Walking speed	Target depth	Target size	Walking speed × Target depth	Walking speed × Target size	Walking speed × Target depth × Target size
Time	$F_{2,28} = 8.98$	$F_{1.08,15.07} = 92.62$	$F_{1.39,19.44} = 332.59$	$F_{2.40,33.60} = 4.56$	$F_{4,56} = 1.93$	$F_{8,112} = 4.56$
	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p = 0.12$	$p = 0.99$
	$\eta_p^2 = 0.39$	$\eta_p^2 = 0.87$	$\eta_p^2 = 0.96$	$\eta_p^2 = 0.25$	$\eta_p^2 = 0.12$	$\eta_p^2 = 0.07$
Error rate	$.\chi^2(2) = 188.72$	$.\chi^2(2) = 196.31$	$.\chi^2(2) = 108.63$	$.\chi^2(4) = 9.86$	$.\chi^2(4) = 64.85$	$.\chi^2(8) = 17.69$
	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.05$	$p < 0.01$	$p < 0.05$
Target	$F_{2,28} = 8.69$	$F_{1.15,16.07} = 60.99$	$F_{1.31,18.36} = 66.84$	$F_{4,56} = 0.22$	$F_{4,56} = 4.13$	$F_{8,112} = 0.30$
Re-entry	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p = 0.93$	$p < 0.01$	$p = 0.97$
Number	$\eta_p^2 = 0.38$	$\eta_p^2 = 0.81$	$\eta_p^2 = 0.83$	$\eta_p^2 = 0.02$	$\eta_p^2 = 0.23$	$\eta_p^2 = 0.02$
Controller's	$F_{2,28} = 100.30$	$F_{1.10,15.45} = 18.78$	$F_{2,28} = 82.80$	$F_{4,56} = 10.01$	$F_{4,56} = 2.28$	$F_{8,112} = 1.91$
Moving	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p = 0.07$	$p = 0.07$
Distance	$\eta_p^2 = 0.88$	$\eta_p^2 = 0.57$	$\eta_p^2 = 0.86$	$\eta_p^2 = 0.42$	$\eta_p^2 = 0.14$	$\eta_p^2 = 0.12$

Table 5 Experiment One: Repeated-measures ANOVA results and generalized estimating equations results for the main effects of walking speed in each target depth and target size

	Main effect					
	Target depth			Target size		
	Shallow	Medium	Deep	Small	Medium	Large
Times	$F_{2,28} = 0.85$	$F_{2,28} = 12.94$	$F_{2,28} = 57.75$	$F_{2,28} = 8.64$	$F_{2,28} = 9.11$	$F_{2,28} = 6.05$
	$p = 0.44$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
	$\eta_p^2 = 0.06$	$\eta_p^2 = 0.48$	$\eta_p^2 = 0.81$	$\eta_p^2 = 0.20$	$\eta_p^2 = 0.39$	$\eta_p^2 = 0.30$
Error rate	$.\chi^2(2) = 77.23$	$.\chi^2(2) = 99.94$	$.\chi^2(2) = 119.06$	$.\chi^2(2) = 154.71$	$.\chi^2(2) = 90.18$	$.\chi^2(2) = 36.15$
	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Target	$F_{2,28} = 10.76$	$F_{2,28} = 3.68$	$F_{1.44,20.11} = 2.49$	$F_{2,28} = 12.53$	$F_{2,28} = 2.38$	$F_{2,28} = 0.90$
Re-entry	$p < 0.01$	$p < 0.05$	$p = 0.10$	$p < 0.01$	$p = 0.11$	$p = 0.42$
Number	$\eta_p^2 = 0.43$	$\eta_p^2 = 0.21$	$\eta_p^2 = 0.15$	$\eta_p^2 = 0.47$	$\eta_p^2 = 0.15$	$\eta_p^2 = 0.60$
Controller's	$F_{2,28} = 69.32$	$F_{2,28} = 63.53$	$F_{2,28} = 54.98$	$F_{2,28} = 77.39$	$F_{2,28} = 83.25$	$F_{2,28} = 93.66$
Moving	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Distance	$\eta_p^2 = 0.83$	$\eta_p^2 = 0.82$	$\eta_p^2 = 0.80$	$\eta_p^2 = 0.85$	$\eta_p^2 = 0.86$	$\eta_p^2 = 0.87$

speed and the low speed (all $p < 0.01$), and the medium speed had significantly higher error rates than the low speed (all $p < 0.05$) (Fig. 4a).

For the three target sizes, walking speed had a significant main effect on error rate (Table 5). In general, the low speed had significantly lower error rate than the fast speed (all $p < 0.01$) (Fig. 4b). For both the small size and the medium size, the medium speed had significantly lower error rate than fast speed (both $p < 0.05$), but similar error rate for the large size ($p = 0.20$) (Fig. 4b). For both the small and the large sizes, the low speed had significantly lower error rate than the medium speed (both $p < 0.01$), but similar error rate for the medium size ($p = 0.10$) (Fig. 4b).

3.5.3 Target re-entry number

Walking speed had a significant main effect on target re-entry number (Table 4). The higher the walking speed, the greater the target re-entry number (high speed: M = 1.23, SD = 0.08; medium speed: M = 1.21, SD = 0.08; low speed: M = 1.19, SD = 0.09) (all $p < 0.01$). Target depth had a significant main effect on target re-entry number (Table 4). The deep depth (M = 1.36 , SD = 0.15) had a significantly higher target re-entry than the medium depth (M = 1.21 , SD = 0.09) and the shallow depth (M = 1.05, SD = 0.02) (both $p < 0.05$). However, the shallow depth and the medium depth had a similar target re-entry number

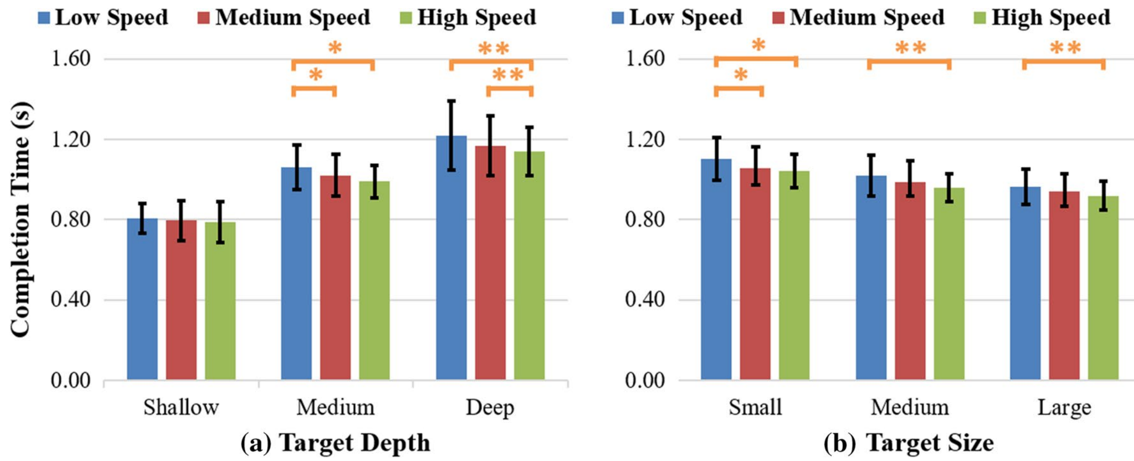

Fig. 3 Experiment One: task completion time for each walking speed in different **a** target depths, and **b** target sizes. * and ** represent $p < 0.05$ and $p < 0.01$, respectively. Error bars represent 0.95 confidence interval

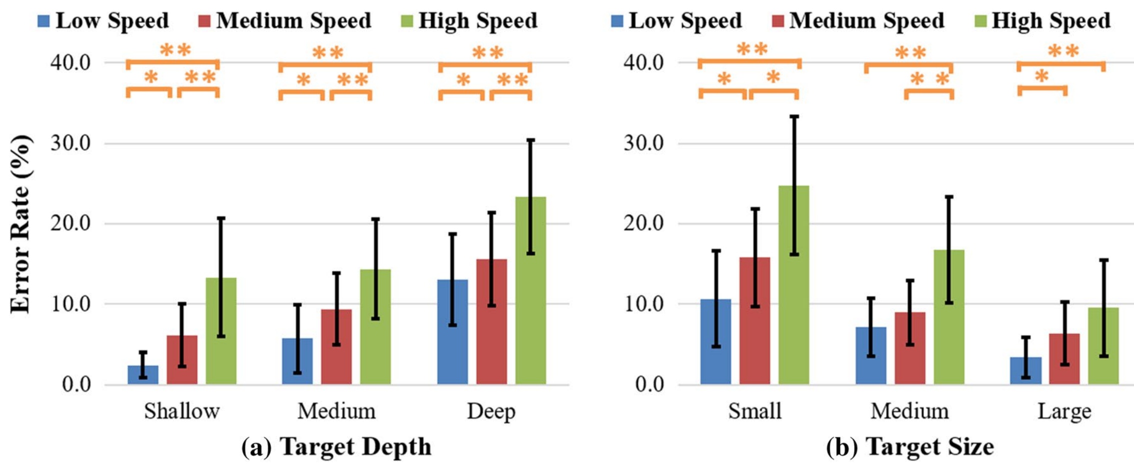

Fig. 4 Experiment One: error rate for each walking speed in different **a** target depths, and **b** target sizes. * and ** represent $p < 0.05$ and $p < 0.01$, respectively. Error bars represent 0.95 confidence interval

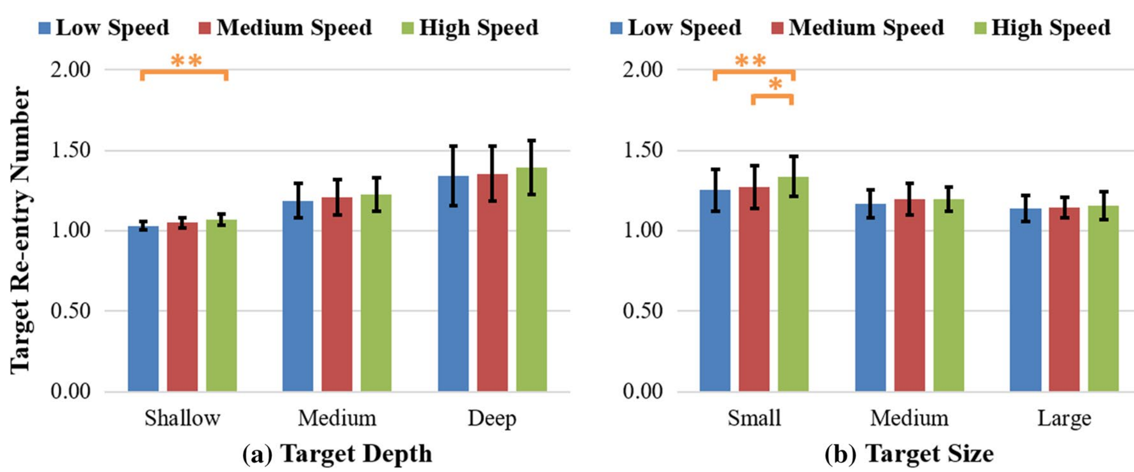

Fig. 5 Experiment One: target re-entry number for each walking speed in different **a** target depths, and **b** target sizes. * and ** represent $p < 0.05$ and $p < 0.01$, respectively. Error bars represent 0.95 confidence interval

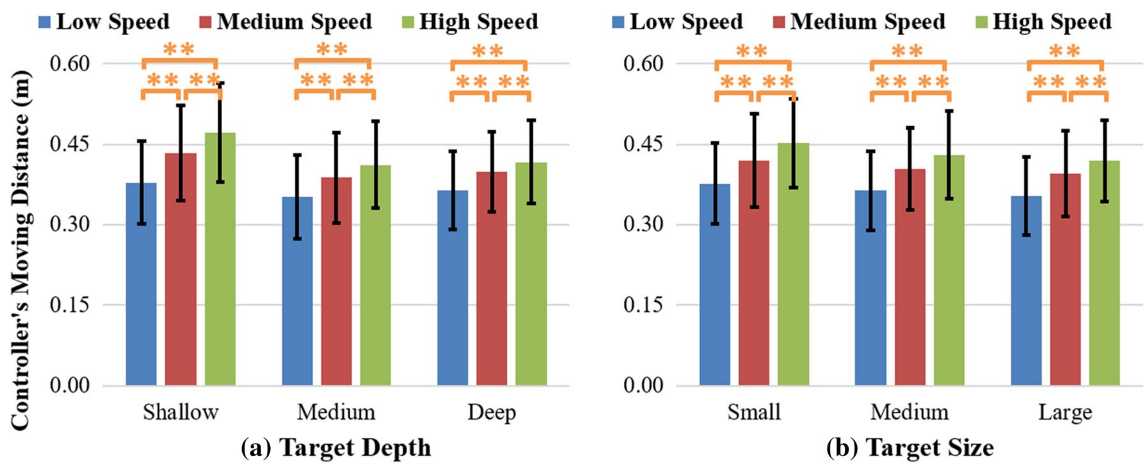

Fig. 6 Experiment One: controller's moving distance for each walking speed in different **a** target depths, and **b** target sizes. * and ** represent $p < 0.05$ and $p < 0.01$, respectively. Error bars represent 0.95 confidence interval

($p = 0.43$). Target size had a significant main effect on target re-entry number (Table 4). As expected, the larger target size, the lower target re-entry number (small size: M = 1.29 , SD = 0.11; medium size: M = 1.19, SD = 0.07; large size: M = 1.15, SD = 0.06) (all $p < 0.01$).

There was a significant interaction effect between walking speed and target size (Table 4). However, there was no significant interaction effect between walking speed and target depth, and between walking speed, target depth and target size (Table 4). Due to these interaction effects, we further analyzed the effect of walking speed for each target size and target depth on a per speed basis.

For the shallow depth and the medium depth, walking speed had a significant main effect on target re-entry number, but no significant main effect for the deep depth (Table 5). Overall, the three speeds had a similar target re-entry number in the deep depth and the medium depth (all $p > 0.08$) (Fig. 5a). For the shallow depth, the high speed had a significantly higher target re-entry number than the low speed ($p < 0.01$), but the medium speed and the low speed, and the medium speed and the high speed did not significantly differ in target re-entry number (both $p > 0.08$) (Fig. 5a).

While walking speed did not have a significant main effect on target re-entry number for the medium size and the large size, it had a significant main effect for the small size (Table 5). As shown in Fig. 5b, the three speeds had similar target re-entry number in the medium size and the large size (all $p > 0.21$). For the small size, the high speed had a significantly higher target re-entry number than the medium speed and the low speed (both $p < 0.05$), but the medium speed and the low speed had a similar target re-entry number ($p = 0.82$).

3.5.4 Controller's moving distance

Walking speed had a significant main effect on controller's moving distance (Table 4). Generally, the higher the walking speed, the larger the controller's moving distance (low speed: M = 0.37 m, SD = 0.07 cm; medium speed: M = 0.41 m, SD = 0.07 cm; high speed: M = 0.43 m, SD = 0.07 cm) (all $p < 0.01$). Target depth had a significant main effect on controllers' moving distance (Table 4). The farther the depth, the smaller the controllers' moving distance (shallow depth: M = 0.43 m, SD = 0.08 cm; medium depth: M = 0.38 m, SD = 0.07 cm; deep depth: M = 0.39 m, SD = 0.07 cm) (all $p < 0.05$). Target size had a significant main effect on controller's moving distance (Table 4). The larger target size, the smaller controller's moving distance (small size: M = 0.42 m, SD = 0.07 cm; medium size: M = 0.40 m, SD = 0.07 cm; larger size: M = 0.39 m, SD = 0.07 cm) (all $p < 0.05$).

There were significant effects between walking speed and target depth, but no significant interaction effects between walking speed and target size, and between walking speed, target depth and target size were found (Table 4). We further analyzed the effect of target depth and size on controller's moving distance on a per speed basis.

For the three levels of target depths, walking speed had a significant main effect on controller's moving distance (Table 5). Overall, the higher the walking speed, the larger the controller's moving distance (all $p < 0.01$) (Fig. 6a).

For the three levels of target sizes, speed had a significant main effect on controller's moving distance (Table 5). In general, the controller's moving distance increased as the increase in walking speed (all $p < 0.01$) (Fig. 6b).

Table 6 Experiment Two: average time (s), error rate (%), target re-entry number and controller's moving distance (m) for different target depths in each walking speed.

Target depth (m)	0.8			2.5			3.5		
Speed (m/s)	**0.8**	**1.1**	**1.4**	**0.8**	**1.1**	**1.4**	**0.8**	**1.1**	**1.4**
Time (s)	0.80 (0.10)	0.80 (0.08)	0.80 (0.09)	1.10 (0.15)	1.12 (0.13)	1.15 (0.14)	1.29 (0.19)	1.33 (0.19)	1.40 (0.19)
Error rate (%)	0.63 (0.66)	0.53 (0.55)	0.74 (1.07)	3.17 (2.58)	5.61 (4.30)	6.83 (3.29)	6.67 (4.20)	11.06 (5.21)	16.88 (7.18)
Target re-entry number	1.02 (0.02)	1.02 (0.02)	1.02 (0.02)	1.15 (0.07)	1.17 (0.08)	1.23 (0.11)	1.30 (0.11)	1.41 (0.16)	1.57 (0.23)
Controller's moving distance (m)	0.28 (0.08)	0.28 (0.08)	0.29 (0.07)	0.33 (0.10)	0.33 (0.09)	0.35 (0.10)	0.36 (0.12)	0.36 (0.10)	0.39 (0.11)

Note that bold numbers indicate different levels ofindependent variables (i.e., target depth, target size, speed).

3.6 Discussion

Our results showed that walking speed had significant main effects on task completion time, error rate, target re-entry number, and controller's moving distance. Generally, the low walking speed led to the significantly longest task time, while the medium and high speeds had similar task time. Error rate, and target re-entry number significantly increased as walking speed increased, indicating that participants could select targets more accurately with the low walking speed.

Walking speed significantly interacted with target depth in terms of the four dependent variables. The three levels of walking speed had similar time performance in the shallow target depth. As target depth increased, higher walking speed tended to result in shorter selection time. This may be because participants usually selected targets when targets were close to the view point in VR where targets would be visually enlarged. Higher walking speed can lead to higher motion of targets in VR, hence targets would take shorter times to reach the vicinity of the view point. Overall, higher walking speed tended to have higher error rates, higher target re-entry number. It would be more challenging to select targets when walking faster.

There was an interaction effect between walking speed and target size. Generally, the low walking speed had better performance than the medium and high walking speeds. Such performance advantages were more marked in the small target size than the other two target sizes.

4 Experiment 2: selection of targets fixed to the virtual body

In this experiment, we investigated the effects of physical walking on selecting targets fixed to the virtual body. During walking, target position did not change relative to users' position in the virtual environment.

4.1 Apparatus and participants

The experiment device was the same as Experiment One.

Fifteen participants (7 males, aged 20–26) took part in Experiment Two. Eleven of them took part in Experiment One. Note that Experiment One and Two were conducted on a different date. Two of the four new participants had experience with VR interaction.

4.2 Experiment design and procedure

The experiment design was similar to Experiment One. The only difference was that the task in this experiment requires selection of targets fixed to the virtual body, rather than fixed in the virtual environment as in Experiment One. As the purpose of our study was not to compare the results of these two tasks, we did not deliberately design Experiment One and Two in a way for result comparison. This is why the two experiments were carried out on different dates with overlapping participants.

4.3 Result and analysis

For the combinations of 3 walking speeds × 3 target depths × 3 target sizes, we first removed the outliers (2.36% of the data) with more than three standard deviations from mean time. Data analysis adopted the same methods as Experiment One. We checked the learning effect across 2 blocks in our experiment. For completion time, there was no significant difference between the 2 blocks for the three walking speeds (all $p > 0.05$). The mean values and standard deviations are shown in Tables 6 and 3.

4.3.1 Task completion time

Walking speed had a significant main effect on task time (Table 8). The high speed (M = 1.12 s, SD = 0.14 s) had significantly longer times than the medium speed (M = 1.09 s, SD = 0.13 s) ($p < 0.01$) and the low speed (M = 1.06 s, SD = 0.14 s) ($p < 0.05$), and the medium speed had significantly longer times than the low speed ($p < 0.05$). Target depth had a significant main effect on completion time (Table 8). The shallow depth (M = 0.80 s, SD = 0.09 s) had the shortest time, followed by the medium depth (M = 1.13 s, SD = 0.14 s) and the deep depth (M = 1.34 s, SD = 0.19 s) (all $p < 0.01$). Target size had a significant main effect on task time (Table 8). Task time decreased as target size increased (small: M = 1.20 s, SD = 0.04 s; medium: M = 1.07 s, SD = 0.03 s; large: M = 1.00 s, SD = 0.03 s) (all $p < 0.01$).

There was an interaction effect between walking speed and target depth, and between walking speed, target depth and target size (Table 8). However, there was no significant interaction effect between walking speed and target size (Table 8). We further analyzed the effects of walking speed on task time for each target depth and size, respectively.

For the shallow target depth, walking speed did not have a significant main effect on task time (Table 9). Overall, the three speeds had similar task time (all $p = 1.0$). For the medium and deep depths, walking speed had a significant main effect on task time (Table 9). As shown in Fig. 7a, for the deep depth, the low speed had significantly shorter times than both medium and high speeds (both $p < 0.05$), and the medium speed had significantly shorter times than the high speed ($p < 0.05$). For the medium depth, the high speed had significantly longer times than the low speed and the medium speed (both $p < 0.05$), while the low speed and the medium speed had a similar task time ($p = 0.05$).

For the three levels of target size, walking speed had a significant main effect on task time (Table 9). As illustrated in Fig. 7b, the low speed had significantly shorter times than the high speed across the three sizes (all $p < 0.01$). The low speed had significantly shorter times than the medium speed for the small size ($p < 0.05$), but similar times for the medium and large sizes (all $p > 0.05$). The medium speed had significantly shorter times than the high speed for the large size ($p < 0.05$), but similar times for the small and medium sizes (all $p > 0.06$).

4.3.2 Error rate

Walking speed had a significant main effect on error rate (Table 8). Error rate increased as walking speed increased (low: M = 3.49%, SD = 2.13%; medium: M = 5.73%, SD = 3.08%; high: M = 8.15%, SD = 3.59%) (all $p < 0.01$). Target depth had a significant main effect on error rate (Table 8). The deep depth (M = 11.53%, SD = 3.08%) resulted in the highest error rate, followed by the medium depth (M = 5.20%, SD = 3.07%) and the shallow depth (M = 0.63%, SD = 0.57%) (all $p < 0.01$). Target size had a significant main effect on error rate (Table 8). The small size (M = 9.21 %, SD = 4.38%) had significantly higher error rates than the medium size (M = 5.03%, SD = 2.36%) and the large size (M = 3.14 %, SD = 1.95%) (all $p < 0.01$), and the medium size had a significantly higher error rates than the large size ($p < 0.01$).

There was an interaction effect between walking speed and target depth, between walking speed and target size, and between walking speed, target depth and target size (Table 8). Due to these interaction effects, we further analyzed the effect of walking speed on error rate for each target depth and target size.

For the shallow target depth, walking speed did not have a significant main effect on task time (Table 9). Overall, the three speeds had similar task time (all $p = 1.0$) (Fig. 8a). However, for the medium depth and the deep depth, walking speed had a significant main effect on error rate (Table 9). The low speed had significantly lower error rates than both medium and high speeds (both $p < 0.01$) (Fig. 8a). Compared to the high speed, the medium speed had lower error rates in the deep depth ($p < 0.01$), but similar error rates in the medium depth ($p = 0.46$) (Fig. 8a).

For the three levels of the target size, walking speed had a significant main effect on error rate (Table 9). Overall, the low speed had significantly lower error rates than the medium speed and the high speed (all $p < 0.05$), and the medium speed had significantly lower error rates than the high speed (all $p < 0.05$) (Fig. 8b).

4.3.3 Target re-entry number

Walking speed had a significant main effect on target re-entry number (Table 8).The higher the walking speed, the higher the target re-entry number (low speed: M = 1.16, SD = 0.05; medium speed: M = 1.20, SD = 0.08; high speed: M = 1.27, SD = 0.11) (all $p < 0.01$). Target depth had a significant main effect on target depth (Table 8). Target re-entry number increased as target depth increased (shallow depth: M = 1.02, SD = 0.01; medium depth: M = 1.19, SD = 0.08; deep depth: M = 1.43, SD = 0.15) (all $p < 0.01$). Target size had a significant main effect on target re-entry number (Table 8). Target re-entry number decreased with the increase in target size (all $p < 0.01$).

There were interaction effect between walking speed and target depth, between walking speed and target size, and between walking speed, target depth and target size (Table 8). Due to these interaction effects, we further analyzed the effect of walking speed for each target depth and target size.

While walking speed did not have a significant main effect on target re-entry number for the shallow depth, it had a significant main effect on target re-entry number for the medium depth and the deep depth (Table 9). In general, the three walking speeds had similar target re-entry number in the shallow depth (all $p > 0.5$) (Fig. 9a). The high speed had a significantly higher target re-entry number than the medium low speeds for the medium depth and the deep depth (all $p < 0.05$), while the low speed and the medium speed did not significantly differ in the medium depth ($p = 0.44$) (Fig. 9a).

For the three levels of target sizes, walking speed had a significant main effect on target re-entry number (Table 9). Overall, for the small size, the target re-entry number increased as the increase in walking speed (all $p < 0.01$) (Fig. 9b). For the medium size and the large size, the high speed had significantly higher re-entry numbers than the low speed (both $p < 0.05$), while the low speed and the medium speed had similar target re-entry numbers (both $p > 0.12$) (Fig. 9b). For the medium size, the high speed had a significantly higher target re-entry number than the medium speed (Fig. 9b).

4.3.4 Controller's moving distance

Walking speed had a significant main effect on controller's moving distance (Table 8). The post hoc tests revealed that the high speed (M = 0.32 m, SD = 0.10 m) had a significantly larger distance than the medium speed (M = 0.33 m, SD = 0.09 m) and the low speed (M = 0.34 m, SD = 0.09 m) (both $p < 0.05$), while the latter did not significantly differ in controller's moving distance ($p = 0.93$). Target depth had a significant main effect on controller's moving distance (Table 8). The farther depth, the larger controller's moving distance (shallow depth: M = 0.28 m, SD = 0.08 m; medium depth: M = 0.34 m, SD = 0.10 m; deep depth: M = 0.37 m, SD = 0.11 m) (all $p < 0.01$). Target size had a significant main effect on the distance (Table 8). As expected, the distance decrease with the increase in target size (small size: M = 0.34 m, SD = 0.10 m; medium size: M = 0.33 m, SD = 0.09 m; large size: M = 0.32 m, SD = 0.09 m) (all $p < 0.01$).

There were interaction effects between walking speed and target depth, and between walking speed, target depth and target size, but there was no interaction effect between walking speed and target size (Table 8). We further analyzed the effect of walking speed on the distance for each target depth and size, respectively.

While the walking speed did not have a significant main effect on the distance for the shallow depth, it had a significant main effect on the distance for the medium and deep depth (Table 9). Generally, three speeds had similar controller's moving distance in the shallow depth (all $p > 0.50$) (Fig. 10a). For the medium and deep depth, the high speed had significantly larger controller's moving distance than the medium and low speed (all $p < 0.50$), but the medium speed and the low speed did not significantly differ (both $p = 1.00$) (Fig. 10a).

For the three levels of target sizes, walking speed had a significant main effect on controller's moving distance (Table 9). As shown in Fig. 10b, the three walking speeds had similar controller's moving distance for the small size (all $p > 0.05$). For the medium and large size, the high speed had a significantly larger controller's moving distance than the medium speed (both $p < 0.50$), but the low and medium speeds did not significantly differ (both $p > 0.65$). In addition, the high speed had a significantly larger controller's moving distance than the medium speed for the medium size ($p < 0.50$).

4.4 Discussion

Generally speaking, target selection performance significantly declined with the increase in walking speed: higher walking speed led to longer task time, higher error rate and target re-entry number and controller's moving distance.

Walking speed significantly interacted with target depth for the four dependent variables. When targets were placed in the shallow depth, the three levels of walking speed had similar performance in terms of the four dependent variables. In fact, a previous study also indicated that when the target depth was less than 1 virtual cubit (approximately 0.7 m), participants had similar task completion time when selecting targets for different target sizes (Poupyrev et al. 1998). When targets were located in the medium and deep depths, the low walking speed tended to have shorter task time and lower error rates than the other two walking speeds, indicating an overall better performance with the low walking speed. In addition, the low walking speed resulted in smaller target re-entry numbers compared to the other two walking speeds. It was easier to control the ray cursor to select targets while walking at a low speed.

5 General discussion

5.1 Effects of physical walking on target selection

In this study, we evaluated the effects of physical walking on target selection in terms of the four variables: task completion time, error rate, target re-entry number and controller's moving distance. These variables represent a comprehensive understanding of how target selection performance in VR would be affected by physical walking. We discuss the analysis results of these variables below.

In both experiments, walking speed had significant effects on task completion time. However, such effects varied across the two task types. In experiment one, target selection time was inversely proportional to walking speed, while the reverse held true in experiment two. In experiment one, targets would approach participants' viewpoint more quickly for higher walking speed, hence enabling a faster selection performance. In experiment two, targets were stationary relative to the virtual body. Hence, when participants walked

Table 7 Experiment Two: average time (s), error rate (%), target re-entry number and controller's moving distance (m) for different target sizes in each walking speed

Target size (m)	0.2			0.25			0.3		
Speed (m/s)	**0.8**	**1.1**	**1.4**	**0.8**	**1.1**	**1.4**	**0.8**	**1.1**	**1.4**
Time (s)	1.17 (0.17)	1.19 (0.17)	1.24 (0.16)	1.04 (0.13)	1.07 (0.12)	1.10 (0.13)	0.98 (0.12)	0.99 (0.11)	1.02 (0.13)
Error rate (%)	5.66 (3.56)	9.21 (5.65)	12.75 (5.03)	3.23 (2.29)	4.55 (1.98)	7.30 (4.26)	1.59 (1.36)	3.44 (2.57)	4.39 (2.35)
Target re-entry number	1.03 (0.02)	1.29 (0.11)	1.68 (0.23)	1.02 (0.01)	1.17 (0.08)	1.36 (0.14)	1.01 (0.01)	1.10 (0.06)	1.24 (0.10)
Controller's moving distance (m)	0.34 (0.11)	0.34 (0.10)	0.36 (0.10)	0.32 (0.10)	0.32 (0.10)	0.34 (0.09)	0.31 (0.09)	0.31 (0.08)	0.33 (0.09)

Note that bold numbers indicate different levels ofindependent variables (i.e., target depth, target size, speed).

Table 8 Experiment Two: Repeated-measures ANOVA results and generalized estimating equations results for the main effects and interaction effects

	Main effect			Interaction effect		
	Walking speed	Target depth	Target size	Walking speed × Target depth	Walking speed × Target size	Walking speed × Target depth × Target size
Time	$F_{2,28} = 15.27$	$F_{1.08,15.08} = 318.71$	$F_{1.09,15.31} = 159.13$	$F_{4,56} = 17.42$	$F_{4,56} = 2.01$	$F_{8,112} = 3.25$
	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p = 0.11$	$p < 0.05$
	$\eta_p^2 = 0.52$	$\eta_p^2 = 0.96$	$\eta_p^2 = 0.92$	$\eta_p^2 = 0.55$	$\eta_p^2 = 0.13$	$\eta_p^2 = 0.19$
Error rate	$.\chi^2(2) = 89.15$	$.\chi^2(2) = 80.23$	$.\chi^2(2) = 90.92$	$.\chi^2(4) = 146.83$	$.\chi^2(4) = 33.46$	$.\chi^2(8) = 194.16$
	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Target	$F_{2,28} = 25.29$	$F_{1.15,16.07} = 112.38$	$F_{1.16,16.26} = 96.48$	$F_{2.27,31.83} = 17.66$	$F_{4,56} = 8.42$	$F_{8,112} = 3.94$
Re-entry	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Number	$\eta_p^2 = 0.64$	$\eta_p^2 = 0.89$	$\eta_p^2 = 0.87$	$\eta_p^2 = 0.56$	$\eta_p^2 = 0.38$	$\eta_p^2 = 0.22$
Controller's	$F_{2,28} = 7.73$	$F_{1.03,14.47} = 59.25$	$F_{1.03,14.47} = 27.45$	$F_{2.19,30.62} = 5.99$	$F_{2.06,28.87} = 0.39$	$F_{8,112} = 3.12$
Moving	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p = 0.82$	$p < 0.01$
Distance	$\eta_p^2 = 0.36$	$\eta_p^2 = 0.81$	$\eta_p^2 = 0.66$	$\eta_p^2 = 0.30$	$\eta_p^2 = 0.03$	$\eta_p^2 = 0.19$

Table 9 Experiment Two: Repeated-measures ANOVA results and generalized estimating equations results for the main effects of walking speed in each target depth and target size

	Main effect					
	Target depth			Target size		
	Shallow	Medium	Deep	Small	Medium	Large
Time	$F_{2,28} = 0.29$	$F_{2,28} = 13.94$	$F_{2,28} = 19.30$	$F_{1.46,20.37} = 10.71$	$F_{2,28} = 13.38$	$F_{2,28} = 8.40$
	$p = 0.75$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
	$\eta_p^2 = 0.02$	$\eta_p^2 = 0.50$	$\eta_p^2 = 0.58$	$\eta_p^2 = 0.43$	$\eta_p^2 = 0.49$	$\eta_p^2 = 0.38$
Error rate	$.\chi^2(2) = 0.72$	$.\chi^2(2) = 42.18$	$.\chi^2(2) = 88.22$	$.\chi^2(2) = 57.85$	$.\chi^2(2) = 21.96$	$.\chi^2(2) = 38.69$
	$p = 0.70$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Target	$F_{2,28} = 0.68$	$F_{2,28} = 10.58$	$F_{2,28} = 22.80$	$F_{2,28} = 23.12$	$F_{2,28} = 12.25$	$F_{2,28} = 11.57$
Re-entry	$p = 0.52$	$p < 0.01$	$p < 0.10$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Number	$\eta_p^2 = 0.05$	$\eta_p^2 = 0.43$	$\eta_p^2 = 0.62$	$\eta_p^2 = 0.65$	$\eta_p^2 = 0.47$	$\eta_p^2 = 0.45$
Controller's	$F_{1.39,19.41} = 0.84$	$F_{2,28} = 5.67$	$F_{2,28} = 12.00$	$F_{1.20,16.84} = 5.59$	$F_{2,28} = 7.31$	$F_{2,28} = 6.06$
Moving	$p = 0.44$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$	$p < 0.01$
Distance	$\eta_p^2 = 0.06$	$\eta_p^2 = 0.29$	$\eta_p^2 = 0.46$	$\eta_p^2 = 0.29$	$\eta_p^2 = 0.34$	$\eta_p^2 = 0.30$

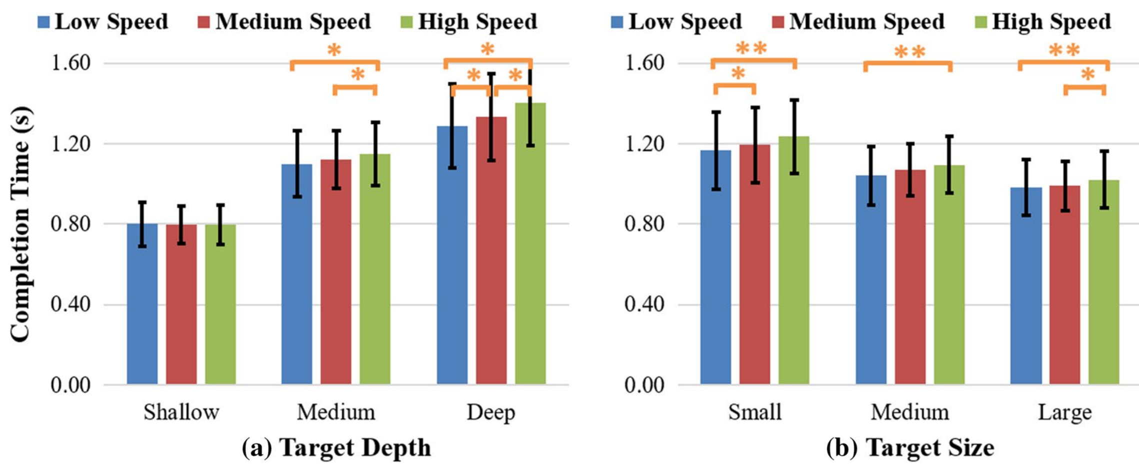

Fig. 7 Experiment Two: task completion time for each walking speed in different **a** target depths, and **b** target sizes. * and ** represent $p < 0.05$ and $p < 0.01$, respectively. Error bars represent 0.95 confidence interval

faster, it would be more difficult to manipulate the controller to select targets, probably due to higher stride frequency and rhythmic oscillation of the body (Chiovetto and Giese 2013). Some similar results can be found in both experiment one and two. First, the three walking speeds had similar task time in the shallow target depth. Second, when target size is larger than 25 cm (medium size), the low and medium speeds did not significantly differ in time. Third, the medium and high walking speeds generally had comparable task time across the three target sizes.

According to the analysis of error rate, in general, selection accuracy decreased as walking speed increased. In experiment one, the accuracy differences between the three walking speeds generally kept consistent for the three target depths and sizes. However, in experiment two, the accuracy differences between the three walking speeds varied depending on target depths. The three walking speeds resulted in similar selection accuracy for the shallow target depth, but different selection accuracy for the medium and deep target depths. The three walking speeds had significantly different selection accuracy across the three target sizes. Furthermore, the accuracy difference between the three walking speeds increased from the shallow to deep depths (Table 6), and also from large to small target sizes (Table 7).

Controller's moving distance and target re-entry number can be used to assess ease of selection in the two phases of target selection tasks, respectively. The former measure is related to the initial distance-covering phase, during which participants needed to move the ray cursor to the target's vicinity. If the controllers' moving distance is short, it means that participants could easily locate the ray cursor close to the target. The latter measure is related to the accuracy phase, during which participants needed to place the cursor inside the perimeter of the target. If the target re-entry number is small, it means that participants dedicated less effort to adjust the position of the controller to achieve precious selection. In experiment one, target re-entry number and controller's moving distance increased as walking speed increased. There were significant differences between the three walking speeds across the three target depths and sizes. However, the three walking speeds generally had similar target re-entry numbers across the three target depths and sizes. The results indicate that the time differences of the three walking speeds are mainly caused by the initial distance-covering phase, rather than the accuracy phase. Experiment two had different results of controller's moving distance and target re-entry number. In general, controller's moving distances of the three walking speeds were similar for the shallow target depth and the small target size, but the high speed significantly differed from the other two speeds for both medium and deep target depths, as well as both medium and large target sizes. For target re-entry number, the three walking speeds led to a similar performance for the shallow target depth, but significantly different performances for the other two depths. If targets are located in the shallow target depth, it is reasonable to expect a similar performance among the three walking speeds.

As the focus of our work is on target acquisition while walking, we did not consider standing and sitting in our experiments. But it is meaningful to explore how different motor activities like standing or sitting affect target selection performance in VR.

5.2 Participant number

We adopted the G*Power tool Faul et al. (2007) to conduct priori power analyses to determine the appropriate sample size (i.e., participant number) with given alpha power and effect size. The effect size set in G*Power was 0.40 (i.e., $\eta_p^2 = 0.14$ in SPSS), considered to be a large effect (the effect

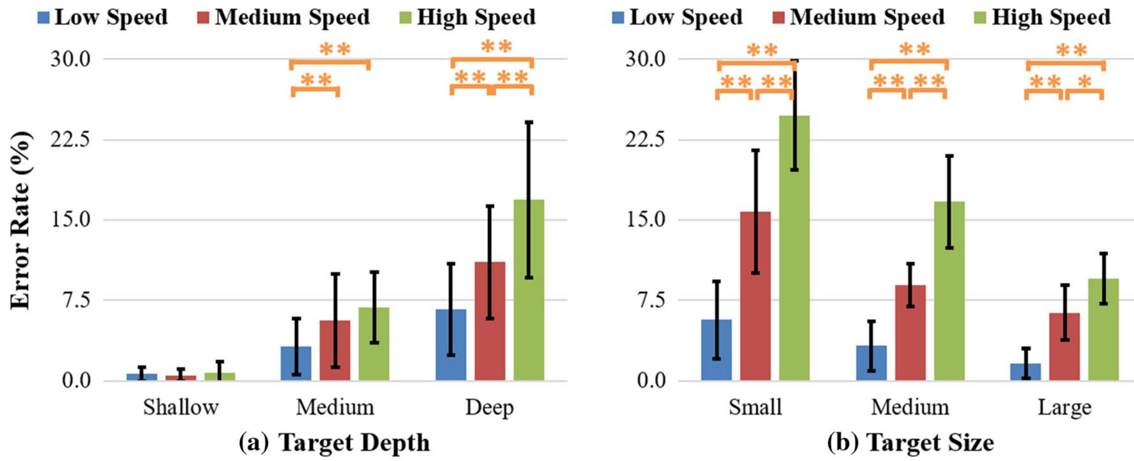

Fig. 8 Experiment Two: error rate for each walking speed in different **a** target depths, and **b** target sizes. * and ** represent $p < 0.05$ and $p < 0.01$, respectively. Error bars represent 0.95 confidence interval

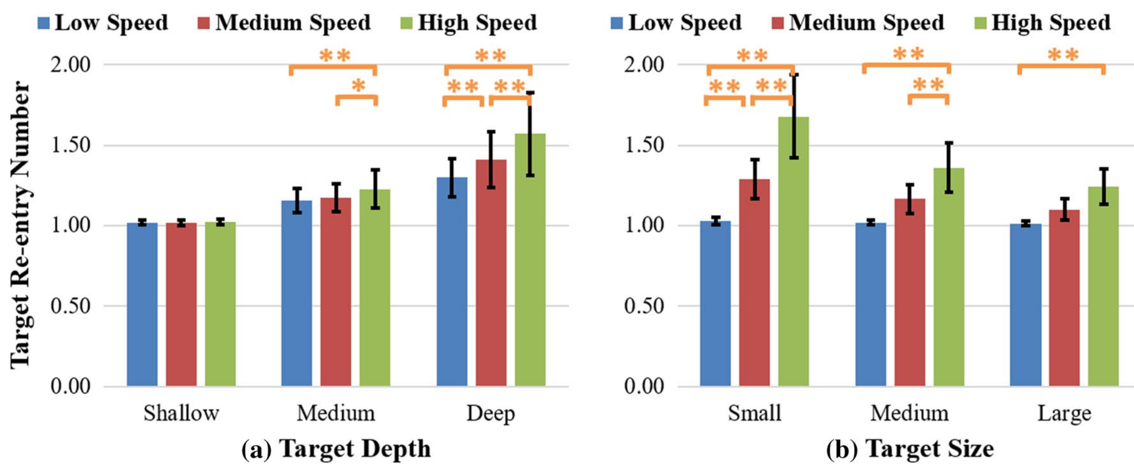

Fig. 9 Experiment Two: target re-entry number for each walking speed in different **a** target depths, and **b** target sizes. * and ** represent $p < 0.05$ and $p < 0.01$, respectively. Error bars represent 0.95 confidence interval

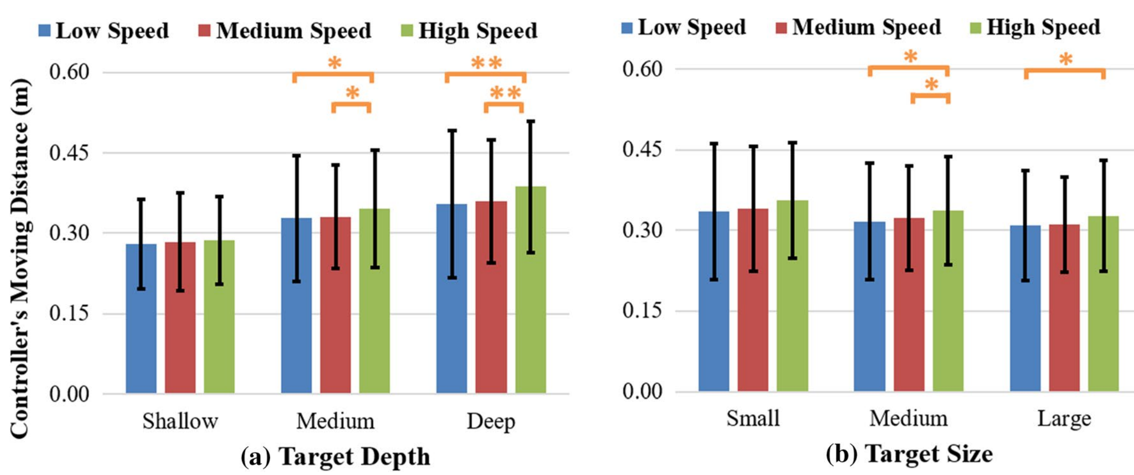

Fig. 10 Experiment Two: controller's moving distance for each walking speed in different **a** target depths, and **b** target sizes. * and ** represent $p < 0.05$ and $p < 0.01$, respectively. Error bars represent 0.95 confidence interval

sizes obtained in our data analysis are generally greater than this number). With an alpha = 0.05, power = 0.90, the sample size needed with this effect size is approximately 8 for the main effects (number of measurements = 9) and 15 for the interaction effects (number of measurements = 3). Thus, our proposed sample size of 15 should be adequate for the objectives of our study.

5.3 Mapping between physical walking and virtual walking

In this study, we adopted the 1:1 mapping between the physical walking speed and the virtual walking speed. It is a straightforward mapping and in line with our daily activities of navigating our surroundings on foot. Such a mapping method has been used in previous target selection studies (e.g., Chiovetto and Giese 2013; Zhou et al. 2020). For locomotion in VR, there are many mapping methods proposed in previous studies (e.g., Nilsson et al. 2013; Powell et al. 2011). Future work can investigate these mapping methods to extend our results to wider application scenarios.

5.4 Spatial reference frame

In both experiments, we fixed the reference frame of the target layout as participants' viewpoint (the head) in VR. This was to provide a comfortable view for target selection. Such a setting can also be found in many interactive scenarios in VR like shooting games. However, the use of the virtual body as the reference frame is also worth exploring. In particular, for selection of targets fixed to the virtual body, using the virtual body (torso) as the reference frame may be better than using the head, according to the study of eyes-free target selection during walking Zhou et al. (2020).

5.5 Omnidirectional walking

As a controlled laboratory study, we considered the factors of walking speed, target size, target depth and target layout. We did not include walking direction (rectilinear vs. omnidirectional walking) as an independent variable, as this would complicate our experiment design. Both experiments were carried out in the condition of rectilinear walking, because this is a common locomotion behavior for investigating user performance of target selection (Bergstrom-Lehtovirta et al. 2011; Chiovetto and Giese 2013; Schildbach and Rukzio 2010). Future work will examine how target selection would be affected by omnidirectional walking.

5.6 Virtual hand selection

This study focused on ray-based pointing as the method of target selection, as it is suitable for selecting remote targets with relatively less hand movements compared to virtual hand techniques (Mine 1995). In the future, it is also worth investigating the effects of physical walking on eyes-engaged target selection with virtual hand techniques given that such behavior is common in VR interaction as well (Chiovetto and Giese 2013).

5.7 VR and AR devices

We used the Oculus Quest 2 as the experiment apparatus. As another popular VR device, the HTC Vive has different device forms than the Oculus Quest 2. It is of interest to exam how different device forms would affect selection performance in future. We will also explore eyes-engaged target selection in AR environments while walking.

5.8 Linear Treadmills

In this study, we employed a linear treadmill as our experiment device for two main reasons. First, it is a common way to simulate a walking environment in VR. Linear treadmills have been used in many studies to realize virtual walking in VR, for example, investigating the perception of physical walking speed in VR (Nilsson et al. 2014; Powell et al. 2011; Banton et al. 2005), studying VR-based rehabilitation with treadmills (Feasel et al. 2011; Kassler et al. 2010; Fung et al. 2006), simulating an infinite surface using multi-linear treadmills (Iwata 1999), and examining the kinematics of the coordination of pointing during locomotion (Chiovetto and Giese 2013). In addition, some products can enable users to walk in VR with linear treadmills, such as SpaceWalkerVR[3] and K-01 Pod.[4] Some applications for these products are related to target acquisition while walking in VR. For instance, in a VR game named "Virtuix Omni Coin Rush," players need to collect as many coins (placed in varying depths) as possible in a limited time on a straight road Virtuix Omni Coin Rush. VR shooting games are also a popular application in which users need to select targets while walking. For example, in a first-person shooter game called "VINDICTA," players could shoot enemies while walking on a straight path VINDICTA. During the shooting process, players need to adjust their walking speed to perform precise shoots. For these application cases, our study could provide design implications for VR interaction design. It is worth noticing that apart from linear treadmills, omnidirectional treadmills (e.g., Omniverse ESPORTS,[5]) a mechanical device that allows users to walk in different directions, have also been employed to VR application design, such as architecture design while walking (Keung et al. 2021) or

[3] http://www.spacewalkervr.com/urunler/.

[4] https://aperiumreality.com/index.php/en/K01/.

[5] https://www.virtuix.com/omniverse-esports/.

shooting games while moving around (Wehden et al. 2021; Polechoński et al. 2020). As our study focused on target selection during rectilinear walking, we did not use omnidirectional treadmills. But in order to extend our results to a wider range, we plan to investigate target selection while walking in unconstrained directions with omnidirectional treadmills in future. Second, it is feasible for use to control walking speed. Our pilot study showed that participants' walking speed on the treadmill was close to the setting speed of the treadmill, indicating that the use of a treadmill is reasonable for walking speed control.

Admittedly, using a treadmill would lead to two main limitations of our study. One is that walking on a treadmill could not be as "natural" as real walking. We did not adopt the real-walking method as it usually relies on instructions (Yatani and Truong 2009) or a human pace-setter (Kane et al. 2008) to maintain a particular speed, which could distract participants' attention when selecting targets in VR. Instead, we used a treadmill as such a device could be a potential solution to achieve realistic simulation of natural locomotion (Cherni et al. 2020). We used a linear treadmill rather than an omni-directional treadmill due to straight paths in our experiments. The other limitation is that walking on a treadmill with a VR headset on the head is challenging for beginners, who may feel uncomfortable when performing experimental tasks. To alleviate this issue, participants walked on a treadmill with a belt tied around the waist and the console for safety reasons (Fig. 2d). After a short period of practice, participants could adapt to our experiment tasks.

6 Design implications

Based on the above discussion, we proposed the following design implications for target selection during walking in VR.

First, for selection of targets fixed in the virtual environment when walking, selection time varied directly with walking speed but selection accuracy varied inversely with walking speed. Interface designers need to take into account such a trade-off between selection time and accuracy. While walking fast in VR, improving selection accuracy should be the primary consideration, which can be accomplished by methods such as transferring targets close to the user or enlarging target size. For example, in a virtual workshop, an engineer walks around and checks whether products are assembled correctly. If the engineer walks faster, the size of products should become larger to enable higher selection accuracy. Another example, in a shooting game, if walking speed increases, telescopic sight with higher magnification should be employed to achieve a more precise aiming.

Second, for selection of targets adhered to the virtual body when walking, targets should be located in the shallow depth or closer (0.8 m) relative to the virtual body if possible, as target selection performance were better than other target depths and selection performance would not significantly change for different walking speeds. In the case of a virtual workshop, for virtual tools around the body of an engineer, frequently-used tools should be placed at a depth less than 0.8 m for the purpose of fast and accurate selection.

Third, when selecting targets attached to the virtual body, low walking speed generally had shorter selection time and higher selection accuracy than other speeds. If the user's walking speed exceeds 0.8 m/s, applications could prompt the user to slow down so as to achieve a fast and accurate target selection. For example, in a shooting game, if the player's walking speed exceeds 0.8 m/s, the game application could prompt the player to slow down when acquiring weapons around the body.

Fourth, the effects of walking speed on selection performance would vary when selecting targets fixed in the virtual environment or to the virtual body. Our study provides a detailed analysis of the differences, which could serve as a reference for VR interaction design during walking.

7 Conclusion

This study evaluated the effects of physical walking on eyes-engaged target selection with ray-casting pointing in virtual reality. Two experiments were carried out with selection tasks with targets fixed in the virtual environment and to the virtual body. Results show that walking speed significantly affected selection performance. Such effects varied across target depth, target size and the two selection tasks. The results have enriched the knowledge of target selection while walking in VR and also provided design implications for walking-based interface design in VR.

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Declarations

Consent to participant Participants were treated strictly in accordance with the National Statement on Ethical Conduct in Research Involving Humans. Written informed consent was obtained by all participants at the start of the first session.

Consent for publication Participants were informed that the results would be published in a way that their information could not be revealed.

Ethical approval Ethics approval was obtained from the Jinan University Ethics Committee prior to commencing the study.

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