Eurographics Conference on Visualization (EuroVis) 2025
W. Aigner, N. Andrienko, and B. Wang
(Guest Editors)

COMPUTER GRAPHICS *forum*
Volume 44 (2025), Number 3

Embedded and Situated Visualisation in Mixed Reality to Support Interval Running

A. Li [1], C. Perin [2], J. Knibbe [1], G. Demartini [1], S. Viller [1], M. Cordeil [1]

[1] The University of Queensland, Australia
[2] University of Victoria, Canada

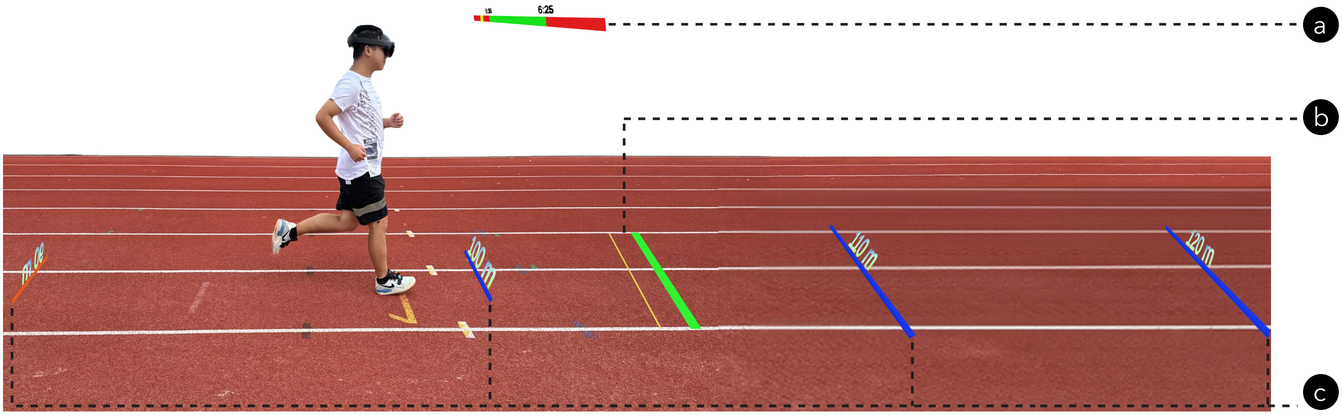

Figure 1: *A third person view illustration of the visualisations we have designed to support immersive interval running: (a) a Speedometer situated in front of the runner's viewpoint, (b) a LaserBeam embedded on the track and moves in front with the runner, and (c) the ShrinkingLines technique, also embedded onto the track but is static and uses a shrinking animation on the line to convey pace.*

Abstract

We investigate the use of mixed reality visualisations to help pace tracking for interval running. We introduce three immersive visual designs to support pace tracking. Our designs leverage two properties afforded by mixed reality environments to display information: the space in front of the user and the physical environment to embed pace visualisation. In this paper, we report on the first design exploration and controlled study of mixed reality technology to support pacing tracking during interval running on an outdoor running track. Our results show that mixed reality and immersive visualisation designs for interval training offer a viable option to help runners (a) maintain regular pace, (b) maintain running flow, and (c) reduce mental task load.

CCS Concepts

• ***Human-centered computing*** → ***Empirical studies in visualization;***

1. Introduction

Running has become increasingly data-driven, with both athletes and enthusiasts using smartwatches and phones to track their performance in real-time. This data is used to directly inform the ongoing training. However, checking data while running is cumbersome; runners often need to press physical buttons or perform gestures to select the right information, and hold the watch or phone up to read the data. This both interrupts their arm motion, breaking their running flow [KWFB15], and diverts the runner's attention from the environment to the display [MTBJ17]. In the worst case, this can lead to tripping or collision hazards. Moreover, limited by the display space, data visualisations on smartwatches and phones are compact and make it difficult to keep track of the metric of interest or to display multiple metrics simultaneously [BBB*19].

Mixed Reality (MR) could solve these problems. It seamlessly integrates visual information directly into the surrounding environment, affording a larger display area and more in-situ and unobtrusive access to data [EI17, TWD*18]. Existing attempts to use

MR for running, however, have (1) not focused on data visualisation [TBL*15, IAOL19, LDL*20], (2) not made use of the spatial capabilities of an MR device [HHKK22], and (3) provided no or limited evaluation [TBL*15, IAOL19, HHKK22]. To address these gaps, we evaluate the spatial capabilities afforded by modern MR headsets with canonical theories in immersive visualisation [WJD17, TWD*18] to present running data more efficiently to runners in real-time, outdoor settings. We introduce three visualisation techniques for running in MR, illustrated in Figure 1: (1) *Speedometer*, a virtual cockpit-style visualisation with a pace gauge displayed in front of the runner; (2) *LaserBeam*, a reference line anchored on the ground in front of the runner with a moving line to display the current pace (inspired by laser-projected systems used by elite marathon runners [Cae17]); and (3) *ShrinkingLines*, shrinking lines embedded every 10 meters along a running track that runners have to reach as they disappear.

We present the first use of an MR device outside on a running track and evaluate our immersive designs with an interval training task. We measured pace irregularity, state of flow, task load index, and preferences for a pace-focused task in which participants were asked to maintain a target pace during an interval training session on a running track. Our findings reveal that:

- Immersive visualisations can provide a valid alternative to traditional wearable-based visualisations in supporting outdoor running training.
- Immersive, embedded visualisations such as LaserBeam and ShrinkingLines support greater pace accuracy and user experience than the less embedded cockpit-style Speedometer.
- Efficient visualisation designs for running training should consider the trade-offs between perceived and actual performance.
- Though bulky and not ready for real-life use, MR headsets are a viable research tool for outdoor track-running.

2. Related Work

2.1. Running with Pace Tracking Technology

Running is one of the most popular exercises for its simplicity, accessibility and benefits in improving body health [HJPvMV15]. Many commercial applications support runners to track their pace while running, including Strava [Str], Nike+ [Nik], and RunKeeper [run]. Runners often use them together with physical trackers or smartwatches such as Garmin [gara], Fitbit [fit], and Polar [pol] to access running data in real-time [IBL*20].

Instant feedback through real-time visual cues when performing physical activities is beneficial [AHBI17, JM14, TN15]. This body of research largely focuses on hand-held or on-body devices, and on visual representations that range from simple texts [MII*04], to texts and icons [dOO08, MCPM11], to task- and data-specific charts [OFM06, NJT14, SKK*20, NAR*21]. and gamified visual elements [BC08, BC10]. During running, the main task is to run, not to read a visualisation [KWFB15, YBVI22]. While these systems provide real-time data access to various extents, they are obtrusive to access because runners have to hold or flick their devices to visually access the information [JM14, KGRL21]. To alleviate the obtrusiveness of accessing data while running, prior research has proposed to i) enhance the glanceability of visual elements, with simplified visual elements, highlighted in-demand information, promoting a faster reading of the data while running [dOO08, GPK*16, NSLM*19, SKK*20, NAR*21]; and to ii) reposition pace feedback to a more salient place is another common approach to reduce obtrusiveness. Nike recently demonstrated the project "Breaking2" [Cae17] aimed at finishing a marathon in two hours. A laser was mounted on a vehicle that drove at a constant pace and projected a line ahead of the marathon runners to show the target pace. The embedding and repositioning of running pace have also been explored with drones [MM15, BBJ*21], robots [TKR14], and wearables such as shoes [CWKH18] and textiles [MGF14].

Our work embraces the aforementioned methods by incorporating abstract visual representations for real-time and target pace, and integrating data visualisation in the surrounding physical space. In addition, we overcome the limitations of small displays by leveraging the immersive space of MR, which further reduces the obtrusiveness of accessing data while running.

2.2. Immersive Visualisation for Sports and Exertion

Immersive Analytics (IA) [DMI*18] research (i.e, the exploration of the benefits of immersive technology for visualisation and analytical tasks) has recently expanded to sports and exertion [LYBP20, LSY*21, LCB*23, WYX*23]. The "Visualisation in Motion" framework [YBVI22, Yao24], that defines scenarios where relative motion exists between a person and a visualisation [GBYI24], stresses the potential of IA in accommodating moving users to moving or static visualisations. Our research contributes to a deeper understanding of visualisation scenarios in this space: we aim to understand how moving users with moving visualisations (showcased with Speedometer and LaserBeam in subsection 3.1 and subsection 3.2) and moving users with static visualisations (showcased with ShrinkingLines in subsection 3.3) perform in a running task.

Immersive visualisation has been explored to provide instant visual feedback in sports and exertion. In Virtual Reality (VR) environments, virtual items or avatars were spatially referenced in a cycling context [ML20] and a virtual watchface was attached to controllers for displaying physiological data in a tennis context [GB21]. In Augmented/Mixed Reality (AR/MR) environments, real-time situated trajectories for basketball training [LSY*21] and indoor workouts [WYX*23] were shown to improve user performance and experience. Yet, researchers have stressed the needs to i) investigate the effects of different placements on immersive visualisations in motion [WYX*23], and to ii) explore a wide range of contexts to build a comprehensive understanding of the benefits of immersive visualisations [LYBP20]. Our research looks at the benefits of immersive visualisation for running, an activity that features greater exertion and larger movement area compared to contexts explored in previous studies.

A handful of studies have investigated the use of immersive technologies for running – with research efforts focusing more on personable visualisations for self-reflection in training contexts [PVS*18]. JoggAR [TBL*15] is an AR exergame that uses in-game spatial objects to motivate runners – yet there was no evaluation of the system. In another VR exergame [IAOL19], players jogged and jumped in place to dodge virtual obstacles – but the research does not focus on visualisation. Lu et al. [LDL*20] studied the effect of placement of a visual interface on participants' capability to pace with a virtual avatar at a walking speed while performing discretionary and monitoring tasks. However, the primary task was not running and the interface did not include pace-related information. Simon [Sim23] used QR codes attached around a runner's physical environment while running on a treadmill and scanning a QR code would display running-related information. This required active detection of QR codes and was constrained to a stationary environment. Closest to our work, Hamada et al. [HHKK22] designed avatar pacers with different visibility options on AR glasses and measured workload and running cadence regularity of participants. There are three key differences with our work. First, Hamada et al. [HHKK22] looked at gamifying running with avatars, and we focus on more standard, data-driven training techniques. Second, the avatar position was fixed in front of the participant's point of view, regardless of their head movement, and we do explore the spatial positioning in AR. Third, while their participants did run outdoor with AR glasses, their task was a simple pacing task on a straight path, and our study involves a more challenging and dynamic interval training task on a real oval running track for a realistic distance and a realistic amount of time.

2.3. Situated Analytics

Situated Analytics (SA) [ETM*15, TWD*18] is a subset of IA research that supports visualisation and analysis "right here, right now", by placing data visualisations spatially or temporarily close to their referent. In their definition, the authors left the term "close" loosely defined on purpose, as spatial situatedness lies on a continuum [WJD17, TWD*18]. SA offers many opportunities for mobile usages with the mobile and spatial capability empowered by MR headsets [EI17]. Multiple categorisations of the design space for *situated visualisations* [Whi09, WJD17, TWD*18, LSS24, SBB*24] together provide three types of *placement* of a visualisation in the physical scene: **Display-referenced** visualisations are situated on the screenTheir appearance stays the same regardless of the angle they are viewed from; **Body- or Object-referenced** visualisations are anchored to the user's entire body or other objects in the scene; **World-referenced** visualisations are situated on the surrounding environment rather than on objects.

Aside from placement, these categorisations describe the level of situatedness on a continuum [WJD17, TWD*18, LSS24]. Situated visualisations are merely near their referents in the scene, whereas embedded visualisations directly overlap with their referents. Embedded visualisations are more integrated with the physical environment, therefore revealing information closely related to sub-components in the environment [TWD*18]. We use these existing frameworks to inform our designs and propose immersive visualisations for each of the three placement types. We also align our visualisations with representative points along the continuum of situatedness (Figure 5) in order to study their relative merits.

The gaps we identified in previous work on immersive running data visualisation are twofold: 1) evaluations do not focus on visualisation [IAOL19, LDL*20] or are conducted in constrained lab environments [IAOL19, Sim23], and 2) lack of visualisation situatedness [HHKK22]. In this work, we strive for ecological validity by conducting a study on a real-life outdoor running track, only adding MR as a new factor. We collect objective (pace data) and subjective (cognitive load, state of flow and preferences) measures and provide three immersive visualisations that afford in-situ pace feedback, including two visualisations embedded on the track.

3. Design & Implementation of Immersive Pace Visualisations

MR allows the display of information anchored on defined surfaces or in the space surrounding the runner. This can alleviate the obtrusiveness of monitoring data on a device like a watch [JM14, KGRL21]. To further explore the potential benefits of MR in supporting data-driven running, we focus on the pacing activity, in which runners seek to maintain a predefined target pace. The literature guides immersive MR designs along a continuum of situated and embedded visualisation [WJD17, TWD*18, LSS24]. In Willett et al.'s definitions [WJD17], situated visualisations are "in proximity to data referents" while embedded visualisations are situated visualisations that are "spatially coinciding with data referents". This continuum allows us to explore different situated and embedded strategies to place pace visualisations during a running activity; a visualisation can be placed in front of the runner in the peripersonal space (i.e., in a situated fashion) or displayed as an overlay on the running track (i.e., in an embedded way).

We first go through our design exploration of a set of visualisation techniques, inspired by real-life practices and experiences, along the continuum of situatedness. Then, we describe our journey to find the suitable hardware that not only tracks accurate real-time running pace, but also provides reliable spatial mapping for the display of running visualisation during running.

3.1. Display-referenced Speedometer

We aim to design immersive visualisations that are less obtrusive to runners' flow. Our first design is a relocation of the pace visualisation on watch faces to a more salient and less disruptive space in MR. For this, we choose a typical pace alarm watch face on Garmin [gara], turning it into a Speedometer visualisation that is displayed in the space in front of the user in a head-up-display, cockpit-style [EI17]. This immersive visualisation results in a gauge that displays both the target and actual pace in a fixed range of $\pm$ 10 seconds (Figure 2). The runner should align their current pace (the yellow block in Figure 2) within the target range (the green zone in Figure 2), which corresponds to $\pm$ 5 seconds of the target pace. The visualisation is placed 5 meters away and 20 degrees above the runner's horizontal field of view, avoiding visual clutter with the physical environment [KMHS19, SRGD22],

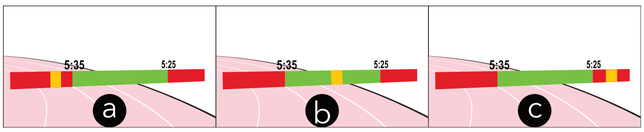

Figure 2: *Speedometer with the runner being: a) slower than the target pace, b) within the target pace, c) faster than the target pace.*

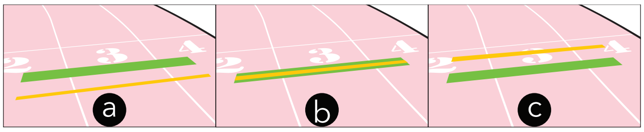

Figure 3: *LaserBeam with the runner being: a) slower than the target pace, b) within the target pace, c) faster than the target pace.*

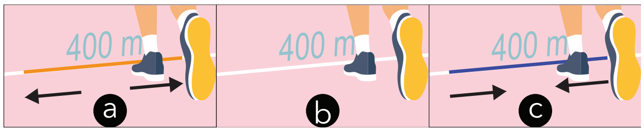

Figure 4: *ShrinkingLines with the runner being: a) slower than the target pace, b) within the target pace, c) faster than the target pace.*

and within the maximum comfortable viewing angle for MR HMDs [Alg15]. To reduce motion sickness, the movement of the visualisation is linearly interpolated to follow head movements. This visualisation is situated and is always visible with a fixed orientation and position relative to the runner's view.

3.2. Body/Object-referenced LaserBeam: Adapting a Projection Technique to MR Running

This design incorporates embodied techniques into the Speedometer, resulting in a more embedded LaserBeam design. The placement of the LaserBeam was inspired by Nike's "Breaking2" projection technique [Cae17], where a car-mounted projector casts a beam ahead of a group of runners, indicating the target pace (subsection 2.1). Our setup does not include an additional moving referent like a car. Instead, we adapt the technique from the perspective of individual runners, anchoring the visualisation to the runner's body. We introduce 2 beams (Figure 3), with the green beam indicating the target pace, and the yellow beam the current pace. The width of the green beam represents the difference between the per-second distances resulting from the upper and lower bounds of the target pace range ($\pm$ 5 seconds of the target pace). The yellow beam has a fixed width of 0.01 meter. The beams are spatially mapped on the ground in front of the runner, based on the per-second distance resulting from the target (for the green beam) or the current pace (for the yellow beam). The LaserBeam visualisation is a more embedded version of the Speedometer, as it coincides with the surface of the track in the physical environment, indicating pace with real-scale reference to the running track.

3.3. World-referenced ShrinkingLines: An Exploration Towards more Embeddedness

This design is the result of our exploration of the more embedded side of the continuum of situatedness; it is perceived as being completely integrated into the physical environment. The orientation and position of this visualisation remain stable when the runner moves around the track, or changes their point of view, which creates a fully spatially embedded visualisation. The distance markers with ShrinkingLines (Figure 4) resemble the physical lines on a running track that runners rely on for pacing and racing. Instances of the visualisation are placed along the path of a 400-meter running track at regular intervals. This differs from the characteristics of Speedometer and LaserBeam, that are referenced to the runner and can be used anywhere regardless of the running path. In contrast to the other two visualisations, ShrinkingLines is not an iteration over existing techniques. ShrinkingLines, however, is grounded in previous research that tells us that introducing additional objectives and minimising movements foster engaging running experiences [MTBJ17]. We introduce an *additional objective* as the runner has to reach the location of the visualisation as it shrinks out by a specific time, making the visualisation both spatially and temporally coincide with the environment. When the runner starts running, the closest situated line in front of them starts shrinking. We apply a shrinking animation aligned with the target pace. When the runner reaches the line, they are on target pace if the line exactly vanishes, ahead of target pace if there is still a remaining part of the line, and behind target pace if the line starts growing backwards in orange (Figure 4). Ideally, when finishing a lap, if the runner's pace remained close to the target pace, they should see minimal visual cues along the track, as if they had run naturally without any technological assistance. The distance between instances and the number of simultaneously displayed instances are both configurable. For the purpose of our study, the spawning distance between instances is set to 10 meters. This is to afford a strong sense of stereo distance, which is optimal at 10 meters afar and gradually falters afterwards in the pass-through HMD [Alg15]. The number of instances is set to 3 to avoid excessive visual clutter. We made a one-to-one virtual model based on the first lane of the track at our university, with reference to the map imagery of the actual track in Mapbox Unity. Users perform a manual alignment of the virtual and the actual track to spawn the visual instances.

3.4. Hardware Experimentation

We tested three different MR devices to find the best solution in terms of spatial tracking, visual quality of both physical and virtual elements, and wearing comfort while running. These features, especially spatial tracking, were deemed essential for research to study the design of immersive running visualisations outdoors, as LaserBeam relies on a stable spatial tracking in large environments.

We tested a pair of **XReal Light AR glasses** [xre] for its wearing comfort and spatial capability. It was the lightest device and wore like a normal pair of glasses; the see-through lenses allowed the user to see the actual environment clearly, but the upper edge was blocked by its sensors and cameras, resulting in the smallest field of view for both virtual and physical environments among all tested devices; though it was capable of anchoring virtual objects in space, its tracking was unstable and lagging while the user was in movement. It was thereby insufficient for our purpose.

We then tested with a **Microsoft HoloLens 2** [Hol], for its better spatial tracking ability and visual quality. It was heavier than the XReal Light but could still be worn in comfort while running; it was see-through, but the virtual objects were too faded when used outdoors; its spatial tracking, although better than XReal's, remained insufficient when the user was running.

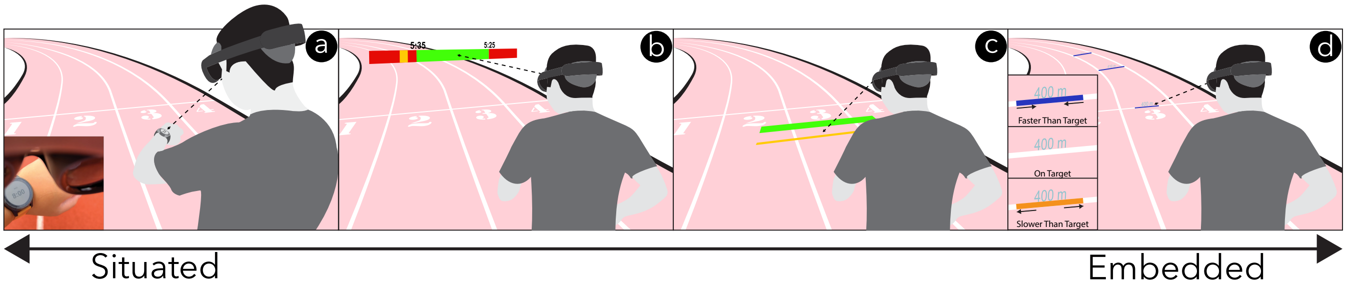

Figure 5: *We compared four conditions, ranked accordingly along the continuum of situatedness/embeddedness: a) Watch (baseline in our study): Situated on the runner's wrist, b) Speedometer: Situated to the display of the HMD, c) Laserbeam: Situated to the runner's body while embedding into the ground in front, d) ShrinkingLines: Embedded to the track the runner is running on.*

We eventually decided to prototype immersive visualisations with a **Meta Quest Pro** [Met]. Although being the bulkiest among the three, we were still able to wear it and run at ease (tested in pilot studies), which was acceptable for research purposes; it featured RGB colour pass-through, compared to the other two optically see-through devices, although had lower clarity to the physical environment, but the largest field of view, and higher opaqueness for virtual objects when used outside; most importantly, it had stable spatial tracking, even in a large and bright outdoor environment.

3.5. Speed Calculation

For visualisation designs implemented in the immersive environment, runners' speeds are computed in real-time based on the global position of the headset in Unity's coordinate system. The position data of the headset is available in 3D vectors and is recorded at a default frame rate of 72 Hz. Correspondingly, speed can be deduced from the horizontal distance moved (along the X and Z axis in the Unity's coordinates) and the time passed since the last frame. We increase the temporal window for speed calculation as the per-frame value often gets very sensitive upon even subtle head movements. We tested 3 temporal windows at a length of 1 second, 3 and 5 seconds and decided to update the speed once per second.

4. Exploratory User Study

Our user study aimed to explore the relative merits of our immersive designs for pace tracking in interval running. Study participants were asked to sustain two different target paces over intervals, with the help of each of the three conditions we described in section 3: Speedometer, LaserBeam, and ShrinkingLines. We report on participants' performance in each condition, focusing on the irregularity of the running pace; as well as subjective participant experiences through measures such as task workload, preference, and the flow state of runners as a proxy measure of obtrusiveness. We obtained ethics approval from our university.

4.1. Baseline - Watch

We used a watch-based pace tracker as a reference condition of the current practice to compare performance with the new immersive designs. Participants wore the head-mounted display in the watch condition for two reasons: (1) it makes it consistent with other conditions where participants have to wear the head-mounted display to visualise data in mixed reality, and (2) we needed the headset to track participants pace across all conditions. Our study is of an exploratory nature and we acknowledge that this has limitations, that we discuss further in section 5. We tried implementing a virtual watch and various ways to attach it virtually to users' wrists, including updating its position with hand-tracking, controller-tracking, and gaze-tracking. Hand- and controller-tracking were unstable and lagging during outdoor use. In pilot testing without the headset, we observed how runners do not bring their watch up to the middle of their vision, but instead briefly glance down at their watch in the lower corner of their visual field. This occurs while wearing a headset such as a Meta Quest Pro with light blockers removed. Participants flicked their wrists and could easily peek through the gap to access information on the watch without the need to fully reorient their head (Figure 5a). We also note that the watch condition fits into the situated end of the continuum (Figure 5a). While the watch supports pace tracking and is a situated display, we are not considering representing data visually on it as text representations are still the dominant representation of data on smart watches [IBL*20, KWP24]; we only used it as a reference for standard pace tracking. Due to the study's exploratory nature, we prioritised ecological validity by displaying only the current pace. This ensures maximum readability of the pace given the limited display space on the watch.

4.2. Participants

We recruited 20 participants who self-identified as regular runners. We discarded data from four participants because they did not complete all conditions in one session due to headset malfunction (P20) and environmental or personal conditions (P8, P18), and because they were unable to maintain the target pace in three out of four conditions due to fatigue (P10), making the data an outlier. The 16 remaining participants were 10 males and 6 females aged 18–44 years. 3/16 participants ran less than an hour a week, 11/16 one to three hours a week and 2/16 three to five hours a week. Participants self-reported their expertise in running and in AR/VR on a 1–5 Likert scale. The average score resulted in 2.5 (SD=1.17) for running and 1.6 (SD=1.17) for AR/VR.

4.3. Interval Running Task

Participants completed one 6-interval running task per condition. They were asked to alternate running at a high-intensity pace ($Pace_{High}$) for 50 seconds and at a low-intensity pace ($Pace_{Low}$) for 50 seconds. They were asked to repeat this pattern three times, for a total of 3 intervals at $Pace_{High}$ and 3 intervals at $Pace_{Low}$. Audio prompts were provided in the headset at the beginning of every interval, to remind participants of the interval target pace. Participants could choose between speed (in kilometers per hour) and pace (in minutes per kilometer) as the metric to receive in the audio prompts. Participants changed intensity upon hearing audio prompts. These prompts consisted of a voice recording stating the next target pace, followed by four beep sounds. Participants were instructed to adjust their pace upon hearing the last beep sound – a common signal used on running watches in workout modes.

We selected this interval running task for three reasons. First, this is an ecologically valid task, because it is a popular workout among runners. Second, it is highly customisable and dynamic, as it requires runners to alter pace frequently at fixed times/distances and for predetermined durations/distances. This allows us to study multiple instances of pace changes and the effect of conditions on pace changes. This is in contrast to tasks that simply require running at the same pace for some time – for which experienced runners would rely less on visual aids to maintain their pace. Third, interval running allows runners to quickly enter target training zones and achieve training outcomes in a relatively short amount of time compared to regular aerobic jogging ('base' runs). This ensures the user study is conducted in a time-effective manner, without compromising the quality of the collected data. We used 5:30 min/km (10.91 km/h in speed) for $Pace_{High}$, and 7:30 min/km (8 km/h in speed) for $Pace_{Low}$. We arrived at these values based on the results from several pilot studies, indicating that these were different enough to require significant changes in pace, and that they were feasible by experienced runners (we tested higher paces but pilot participants struggled to maintain their effort across the four conditions).

4.4. Procedure and Apparatus

Participants were first given an overview of the research and asked to fill a consent form, and a demographic survey. Then, participants underwent a 5-minute warm-up, before they were fitted with the headset, adjusted the interpupillary distance, and selected one of two running metrics (minutes per km or kilometers per hour). Then, they were introduced to the first condition. To minimise fatigue and learning effects, the order of conditions was balanced using a 4x4 Balanced Latin Square. Participants spent one minute familiarising themselves with the visualisation condition in a training run that featured the same target paces as for the recorded trial, but only 4 intervals of 15 seconds each. After training, participants performed the interval running task as described in subsection 4.3. Once participants had completed the 6 intervals of 50 seconds each (5 minutes in total), an audio cue and a text message appeared to notify them to stop. Participants then filled out a post-condition questionnaire (subsection 4.5), and were asked if they had any other comments in an open-ended question. We provided water and participants were given time to rest, each time before they repeated the introduction, training and task with the three other conditions. At the end of the study, participants ranked the four conditions according to their preferences. The study lasted around one hour. Participants wore a Meta Quest Pro HMD and a Garmin Vívoactive® 4 smartwatch [Garb]. The Meta Quest Pro HMD hosted all the Speedometer, LaserBeam and ShrinkingLines conditions, which were implemented with Unity 2022.3.5f1. The Garmin smartwatch showed the Watch condition, displaying the speed/pace value derived from GPS + GALILEO signals. For the ShrinkingLines condition, participants performed a manual alignment of the virtual and the actual track to spawn the visual instances. The study was conducted outdoors on a standard 400m running track.

4.5. Data Collection and Measures

To measure objective performance, we recorded time, speed, and distance travelled every second via the Meta Quest Pro HMD. Subjective assessments were gathered via the Core Flow Scale [MJ08] and the NASA Task Load Index (NASA-TLX) [HS88] for each condition. The Core Flow Scale is a condensed questionnaire designed and used for assessing people's flow state. The flow state is a psychological state described as optimal, extremely rewarding and characterised by complete absorption in an activity [JM96]. Being in the flow state is often associated with high performance and satisfaction; and people in the flow state encounter experiences such as losing track of time, feeling in total control, experiencing challenges that match skill level, and merging action with awareness [JM96, MJ08]. A higher level of flow experienced by a runner reflects a better ability to balance between the challenge of the task and the runner's skills [JM96]. The Core Flow Scale [MJ08] we used in this study featured 10 questions that assessed the level of flow from the following aspects: balance of challenge and skill, merging action and awareness, having clear goals, receiving unambiguous feedback, concentration on the task, sense of control, loss of self-consciousness, time transformation, and autotelic experience [MJ08]. We used the NASA-TLX to measure the amount of effort participants spent completing the task in each condition. The NASA-TLX measures the workload via the magnitude of the demands in the mental, physical, temporal, performance, effort, and frustration aspects. A lower score in an aspect suggests a lower human cost of maintaining performance [HS88].

4.6. Data Analysis and Results

We analysed the collected data with Bootstrapping [KG13], using the mean of the repetitions as the aggregated for each participant and for each condition. We report the results using confidence intervals (CIs) rather than $p-$values, following recommendations for statistical practices in HCI and visualisation (e.g., [Cum14, Dra16, BBB*19, BLIC20]), and interpret them using effect sizes through both visual inference and Cohen's d [Coh88]. All analyses were performed with 95% CIs. All bootstrap CIs were computed with 2000 replicates and the BCa method [KG13]. For the interpretation of the statistical significance of the overlap of CI bars, we refer to [KA13]. Here we focus on reporting significant differences.

Pace Irregularity. It is the average difference between participants' actual speed (Figure 6) and the target speed for each condition, calculated as follows:

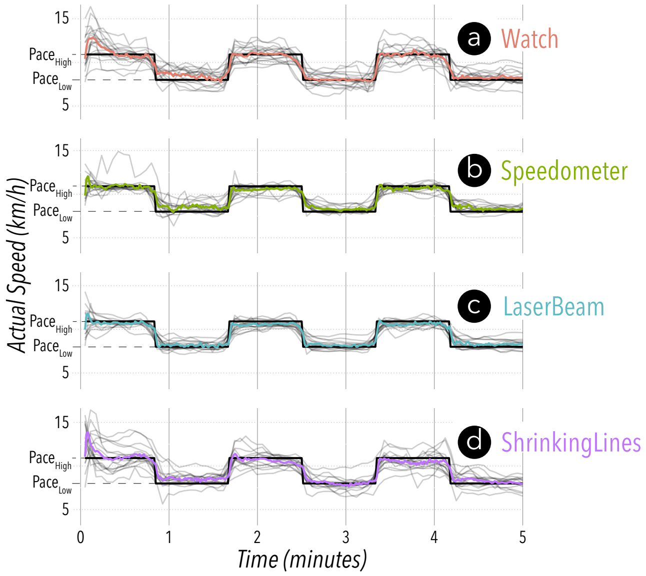

Figure 6: *Pace irregularity data. Black lines show target speeds (alternating between $Pace_{High}$ and $Pace_{Low}$). Grey lines show the actual speed of participants. Coloured lines show the average speed across all participants.*

$$diff \leftarrow \frac{\sum_{n=1}^{N(\tau)} abs(\Delta(S_\tau, T_\tau))}{N(\tau)}$$

where $N(\tau)$ is the total number of time frames in a condition. S_τ, T_τ denote the actual and target speed at time frame τ respectively.

We excluded speed measurements from the first 2 seconds of the task, as participants started still. We also removed 23 outliers created by tracking issues, where a sharp increase or drop in speed was observed in an isolated time frame. We also considered whether the difference in speed calculation between the speed displayed in the immersive conditions and the speed displayed in the Watch condition would affect the results, and concluded that this difference is negligible (see Appendix A for details). Figure 7 shows bootstrapped means of pace irregularity overall (a) as well as broken down by at $Pace_{Low}$ (b) and at $Pace_{High}$ (c), as well as pairwise comparisons. Pairwise comparisons show that pace irregularity was smaller with Speedometer than with Watch, with LaserBeam than with Watch, with Speedometer than with ShrinkingLines, and with LaserBeam than with ShrinkingLines (the CI do not overlap with 0). All differences show a large effect, with Cohen's d values between 1 and 2. The difference between LaserBeam and Watch is particularly substantial (Cohen's d close to 2) – this corresponds to pace with Watch being 0.3 km/h more irregular than with LaserBeam – a difference of large practical significance for an interval training task. The actual difference in pace was more substantial when the target speed was $Pace_{High}$ (Figure 7c).

Task Workload. We measured task workload with NASA-TLX on a 20-point scale. We ran Cronbach's α test (a measure of consistency) for each condition. The α value revealed higher consistency with ShrinkingLines (α=0.713), then Speedometer (α=0.622), LaserBeam (α=0.598), and Watch (α=0.576). Figure 8a shows bootstrapped means and pairwise comparisons for the aggregated NASA-TLX score, and Figure 8b–g shows the score for each dimension of the NASA-TLX. Pairwise comparisons in Figure 8a show that LaserBeam required a smaller amount of overall workload than Watch and than Speedometer. This translates into about 43% less overall workload with LaserBeam than with Watch and than with Speedometer – a large effect, confirmed by Cohen's d (1.05 between Watch and LaserBeam, 1.01 between Speedometer and LaserBeam). There is also evidence that ShrinkingLines required a smaller amount of overall workload than Watch (Cohen's d=0.69) and than Speedometer (Cohen's d=0.68). Note that the effect is slightly smaller than for LaserBeam. Pairwise comparisons in Figure 8b–g tell us which individual dimensions caused the observed differences in the total score:

- **Mental demand (b):** LaserBeam requires less mental demand than Watch (Cohen's d=0.97) and than Speedometer (Cohen's d=0.98). ShrinkingLines requires less mental demand than Speedometer (Cohen's d=0.73). The effect size between LaserBeam and Speedometer is particularly strong, with the mental demand for Speedometer nearly doubling that with LaserBeam.
- **Performance (e):** Participants indicated better performance with LaserBeam than with Watch (Cohen's d=1.04) and than with Speedometer (Cohen's d=1.07). They also indicated better performance with ShrinkingLines than with Watch (Cohen's d=0.65) and than Speedometer (Cohen's d=0.69) – lower scores mean better performance. The effect comes strongest with around 67% better perceived performance with LaserBeam than with Watch or Speedometer.
- **Effort (f):** Participants spent less effort with LaserBeam than with Watch (Cohen's d=0.96) and than with Speedometer (Cohen's d=0.98); and less effort with ShrinkingLines than with Speedometer (Cohen's d=0.56).
- **Frustration (g):** Participants were less frustrated with LaserBeam than with Watch (Cohen's d=1.17) and than with Speedometer (Cohen's d=1.25); and less frustrated with ShrinkingLines than with Watch (Cohen's d=0.72) and than with Speedometer (Cohen's d=0.88). The differences were substantial, especially between LaserBeam and Speedometer, with the average score for Speedometer tripling that for LaserBeam.

We found no significant differences in physical and temporal demand, as all CIs were close to or overlapped with 0 (Figure 8c,d).

Flow State. We gathered participants' experience of flow in each condition with the 10-question Core Flow Scale. The questions were measured with 5-point Likert Scales, ranging from strongly disagree to strongly agree. Cronbach's α test showed great reliability with α values of 0.944 for Watch, 0.923 for Speedometer, 0.945 for LaserBeam, and 0.965 for ShrinkingLines. We converted the Likert ratings to points from 1 (strongly disagree) to 5 (strongly agree), and aggregated the rating of all questions for each participant. Figure 9 shows bootstrapped means of the overall flow score for each condition, and pairwise comparisons. It shows that participants were more "in the flow" with LaserBeam than with Watch (Cohen's d=0.93) and than with Speedometer (Cohen's d=0.79), and more "in the flow" with ShrinkingLines than with Watch (Co-

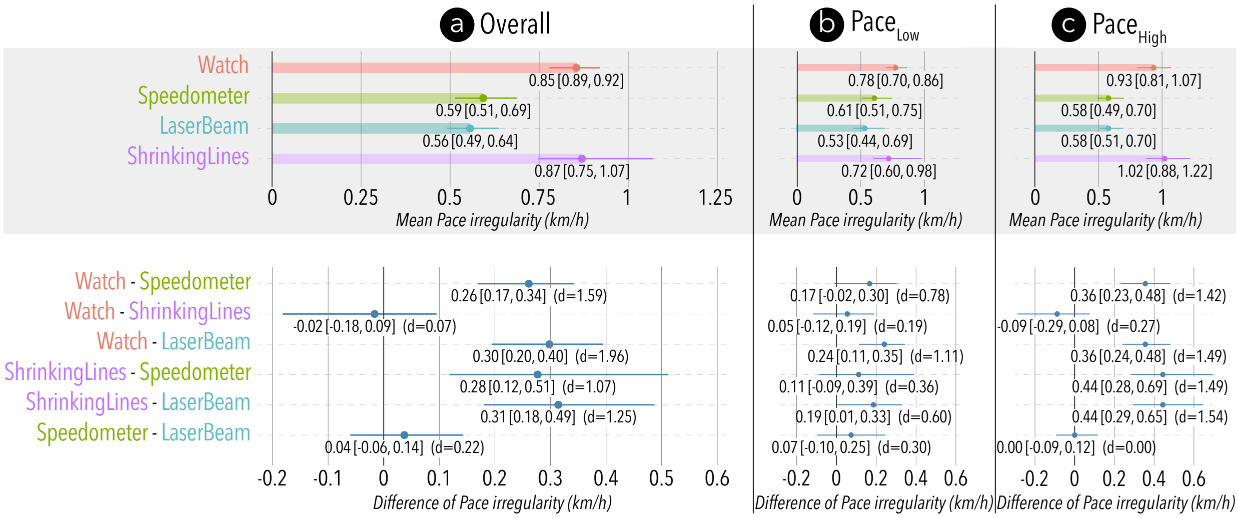

Figure 7: *Bootstrapped mean pace irregularity with the four conditions (top, light-grey background) and bootstrapped mean differences between conditions (bottom, white background). Bars show 95% CI. Mean estimates and CI values are shown below each bar, with Cohen's d indicated in brackets for the pairwise comparisons.*

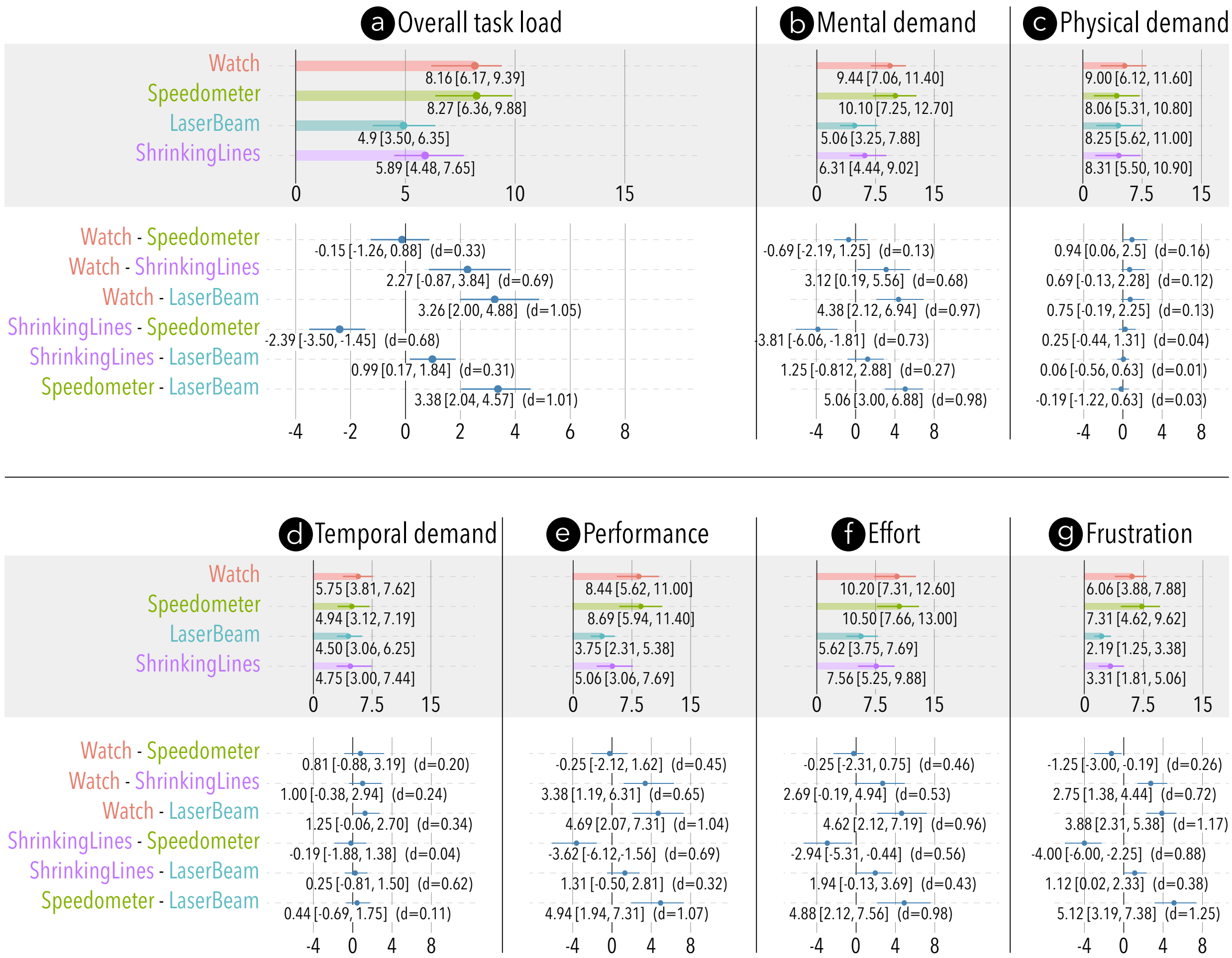

Figure 8: *Bootstrapped mean NASA-TLX score with the four conditions (light-grey background) and bootstrapped mean differences between conditions (white background). Bars show 95% CI. Mean estimates and CI values are shown below each bar, with Cohen's d indicated in brackets for the pairwise comparisons. The scores were measured on 20-point scales. The lower the score, the less effort to complete the task.*

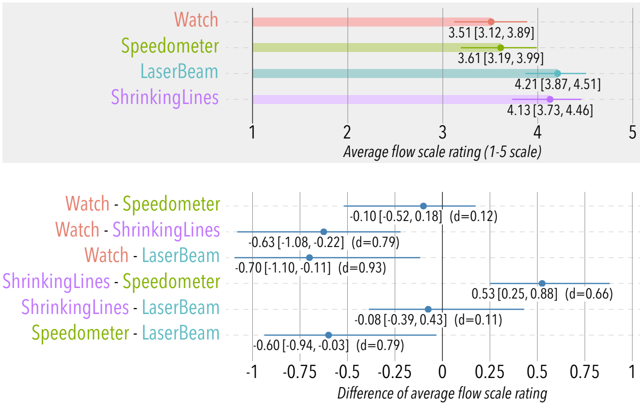

Figure 9: *Bootstrapped mean average participants' self-assessment of their flow experience with the four conditions (top) and bootstrapped mean differences between conditions (bottom). Bars show 95% CI. Mean estimates and CI values are shown below each bar, with Cohen's d indicated in brackets for the pairwise comparisons. Higher ratings mean easier task achievement.*

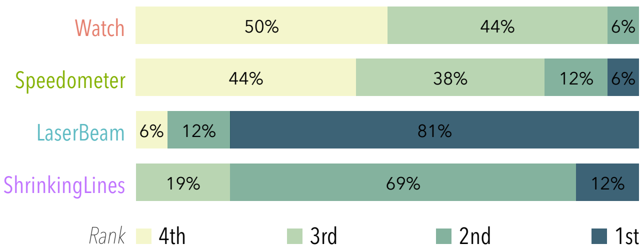

Figure 10: *Participants' preference ranking.*

hen's d=0.79) and than Speedometer (Cohen's d=0.66). Raw response data can be found in Appendix B.

Preference Ranking. Participants clearly preferred LaserBeam, then ShrinkingLines (Figure 10). They ranked Speedometer and Watch similarly, although Watch was the least preferred overall.

5. Discussion and Future Work

Immersive Visualisations Afford Accurate Pace Tracking. We wanted to understand whether immersive visualisations offer a viable alternative to a running watch. Our study showed similar, and even better results with the immersive designs for our interval pacing task. All three immersive visualisations achieved at least on par or better pace regularity (subsection 4.6) than the baseline watch condition. This is reflected in participants' raw performances shown in Figure 6. Noticeably, participants' speeds are less variable with LaserBeam and Speedometer, showing more stable pace regularity. Even though the difference in speed between conditions seems small, differences in deviation from the target speed are large. People are nearly 0.3 km/h more on the target speeds with LaserBeam than with the baseline Watch (Figure 7a). This effect is amplified with a higher target speed (Figure 7c), underscoring the benefits of immersive visualisations for high-intensity training. This echos results seen across other sports, such as immersive basketball shooting [LSY*21] and workout [WYX*23].

We must note, though, that the immersive designs displayed more information than the watch display – the baseline we used only showed the current pace and not e.g., the target pace, which was provided as an audio prompt before a target pace change. Besides, participants had to wear the headset while reading the pace data on the smartwatch. These may give advantages to the immersive visualisations in terms of both actual performance and experience. Indeed, with the baseline, participants may have to memorise the target pace, and peeking through the bottom gap of the headset to read the pace on the watch face is an annoyance. However, recent evidence [LSY*21] shows that the negative effect of wearing an HMD in a baseline condition on task performance can be mitigated through gradual adaptation – following that, we provided an introduction and training sessions for all the interfaces. Besides, our intent was not to prove the superiority of immersive visualisations over current practices but rather to investigate and compare the viability and usefulness of immersive visualisations to reduce obtrusiveness. Future studies could include a baseline condition without the headset and with more information given, for direct comparison with the current standard, as well as baseline conditions of existing MR designs such as a virtual avatar pacer [HHKK22]. Our approach used more abstract and simplified representations for the speed data, as compared to, e.g., ghost avatars, which yield greater visual occlusion and have been validated in prior studies [ML20, HHKK22].

LaserBeam Outperformed the Rest. Overall, participants had the most stable pace with LaserBeam at both target paces, objectively and subjectively. LaserBeam resulted in the highest accuracy (Figure 6 and Figure 7), required the least effort (Figure 8), was perceived as the least flow-disruptive (Figure 9) and was the preferred design overall (Figure 10). Similar approaches to LaserBeam have been proven useful, in particular Nike's 'Breaking2' project [Cae17], which we were inspired by; however, its deployment is costly and only used by elite runners. Our design makes such technology more accessible to ordinary runners in the foreseeable future when more lightweight and spatially capable devices such as Meta Orion [Ori] become commercially available.

We also found that embedded designs were less mentally demanding and frustrating than their counterparts (Figure 8b,g). These results indicate that embedded visualisations are promising for pace-tracking visualisation in MR. This is further supported by the preference for ShrinkingLines, which is also an embedded design that yields high runner satisfaction. The relative merits of embedded visualisations over co-located visualisations have great potential for applications in broader sports activities such as cycling and running in a variety of terrains and environments, but also activities like swimming, sailing and climbing. All those activities demand a continuous focus on the path or trajectory ahead, where relevant data could be naturally embedded.

Mismatch Between Actual and Perceived Performances. While the quantitative performance gains are noteworthy, runners' preferences and experiences are equally important. LaserBeam and ShrinkingLines received the most favourable subjective scores

(Figure 10). Interestingly, participants performed similarly with LaserBeam and Speedometer in terms of pace regularity, but the subjective ratings on performance drastically differed, especially in the NASA-TLX dimensions of mental demand, performance, and frustration (Figure 8). The embedded and embodied nature of LaserBeam may lead to more intuitive user experiences than Speedometer, reducing the perceived cognitive effort. Several participants commented on this cognitive effort with Speedometer, that the small range (± 10 to the target pace) shown in the wide cockpit made the visualisation *"too sensitive"* (P3, P6, P19) and caused them to pay more attention on the changes (P11, P12, P16, P19). This was also reflected in participants' experience of flow in which many disagreed they were able to control their pace (Appendix B-Q5,Q7). The mismatch between the granularity of the information and the size of the display space could account for the mismatch between people's actual and perceived performance. Besides, participants performed better with LaserBeam than with ShrinkingLines (Figure 6). With LaserBeam, a small relative motion exists between the orientation of the runner's view and the movement of the LaserBeam (which follows the orientation of the body), only requiring peripheral awareness so that runners can better focus on the horizon; whereas a larger relative motion exists between the runner and the fixed positions of the lines with ShrinkingLines. This contributes to the broader research agenda of visualisation in motion [YBVI22, Yao24], providing insights that the design of visualisation in motion might benefit from smaller relative motions.

According to Figure 6d, ShrinkingLines might have a sharper learning curve than the other conditions, as participants' speeds seemed to converge more towards the end. This learning curve might also be attributed to the design of ShrinkingLines. Unlike Speedometer and LaserBeam, which directly convey the target and the current pace, runners needed to interpret the shrinking rate of the line instances to perceive the target pace and reflect on their current pace. This could increase the response time for runners to make the right pace adjustment. Nonetheless, three participants (P1, P7 and P9) expressed that they would prefer to use ShrinkingLines for real training, while the other designs felt too "artificial". They explained that the natural embeddings of ShrinkingLines could help them recall the training scene when in real competitions where no visual assistance would be available. Our study was capped at 5 minutes per condition, and it would be interesting to see how they perform in a longer duration, and to investigate if spatially embedded designs help improve the transferability of learning [LSED24].

Towards Less Obtrusive Running Experience. Our design exploration of situated and embedded visualisations sheds light on future designs to achieve more unobtrusive running experiences. Across the four conditions tested, runners were more in the flow with visualisations that were more naturally embedded into their display area, and provided more granular representations of speed. This is also reflected by higher preferences given to LaserBeam and ShrinkingLines. However, being more in the flow is not always accompanied by better performance. ShrinkingLines, which seamlessly integrates into the large area of the track, fostered a more engaging and immersive running experience (Figure 9), but resulted in less accurate pacing (Figure 6 and Figure 7). Conversely, the Speedometer, which is attached to a more salient space on the front of the headset, resulted in better pace regularity than the baseline but was perceived as more obtrusive and cognitively demanding. These findings underscore the need to balance minimising obtrusiveness and maximising effectiveness in immersive visualisation design in exertion scenarios. Future efforts should explore adaptive approaches that dynamically adjust visualisation properties based on users' cognitive load, as demonstrated in prior work [LFH19]. In this research, we focused on communicating information through the visual channel. While out of the scope of this paper, including additional sensory modalities, e.g., audio and haptics, may further improve information throughput without increasing obtrusiveness.

Mixed Reality Headsets Are Good Proxies For Jogging Visualisation Research. Although our study revealed promising opportunities for integrating MR with running, in real practices, we do not recommend people run with current pass-through VR headsets because of known usability problems, including low see-through resolution, bulky design, lagging spatial tracking, discomfort when sweaty, and low adaptability to extreme outdoor conditions. One of our participants (P20) did not finish the study, for they chose to run at noon, and the high temperature (34 degrees Celsius) broke the headset's SLAM sensors. We did not experience significant motion sickness while wearing the headset, and no participant mentioned it explicitly. Although rapid movement did cause visual latencies, participants seemed to adapt quickly enough during the training and warm-up sessions for it not to be a problem worth mentioning. The data for three participants (P8, P10, P18) was not included in the analysis because they were too exhausted to complete the study at once. Nonetheless, we cannot rule out the aforementioned factors which may have compounded the cause of exhaustion. Nevertheless, this study provides insights into the future design possibilities of immersive visualisations for running, and there is much we can learn through additional design space explorations, more proof of concept prototypes, and other realistic studies – knowledge that will then be fully leveraged when more usable, less bulky and more accessible technology such as Meta Orion [Ori] is made available.

6. Conclusions

We have introduced and studied the design of three immersive visualisations – *Speedometer*, *LaserBeam* and *ShrinkingLines* – to support pace tracking for runners. We conducted an in-depth study of those immersive visualisation designs with 16 participants to understand their impact on performance, cognitive workload and state of flow; we found that immersive visualisations are a valid alternative for pace tracking. While MR technology is not yet completely mature in terms of miniaturisation and comfort, this study allows us to better understand the design space of immersive visualisation for runners. In particular, we found evidence that immersive embedded data representations improve performance and user satisfaction over the baseline. The LaserBeam design, inspired by elite runners' training, resulted in the best pace regularity, was most preferred, and was found to be least flow-disruptive. The ShrinkingLines design had more mixed results; while performance was inferior to that of the LaserBeam and Speedometer designs, it was still the second-most preferred. It was also perceived as less disruptive than the Watch and Speedometer, which indicates that more design efforts should be directed toward embedded visualisation designs.

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