

Article

Enhancing Spatial Orientation and Map-Reading Skills: Using Mental Maps and VR in Field Trips for Geography Students

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Abstract

Enhancing spatial orientation and map-reading skills is a cornerstone of geography education, yet the comparative efficacy of physical versus virtual reality learning environments (VRLEs) remains a subject of ongoing debate. This study evaluates the development of navigational competencies through a counterbalanced crossover experimental design involving 20 geography and geography teacher major students. Participants performed standardized spatial tasks, including bearing calculation and distance estimation, in both the volcanic landscape of the Tapolca Basin, Hungary, and its smartphone-based 360-degree virtual reality (VR) counterpart. To assess longitudinal retention and cross-modal transfer, a three-month interval was maintained between the two learning phases, supported by a robust pre-test/post-test framework. Results indicate that while both environments are susceptible to spatial distortions driven by the visual dominance of physiographic landmarks, VR-based training effectively scaffolds the cognitive frameworks required for real-world navigation. The findings confirm that spatial mental models acquired in a virtual setting possess significant cognitive resilience, as navigational accuracy was maintained over the three-month interval. In conclusion, this research justifies a hybrid pedagogical approach, where immersive digital simulations serve as a preparatory tool for physical fieldwork. The synergy of both modalities is essential for cultivating the resilient spatial intelligence required for professional geographic practice.

Keywords: virtual reality (VR); virtual reality learning environment (VRLE); virtual field trip (VFT); spatial orientation; map-reading; geography education; collaborative learning; crossover design; Balaton Uplands

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1. Introduction

The purpose of our research is to find the most optimal ways for the integration of virtual reality (VR) technology in geography teaching. Our previous findings highlighted

the advantages as well as the disadvantages of including virtual reality in the geography curricula of primary and secondary level public education [1]. This encouraged us to test our own developed virtual reality environment in higher education. The current study focuses on the role virtual reality learning environments (VRLEs) and virtual field trips (VFTs) could play in improving map-reading skills and enhancing spatial abilities. To assess this, university students studying geography at BSc level, as well as geography teacher majors, were the subjects of the research. The primary aim was to gather empirical data on the effectiveness of VR activities in complementing or substituting real-time field trips.

Virtual reality is being introduced into education because students are familiar with it and motivated by it due to its popularity in non-educational settings. VR gamification enhances student engagement, which improves subject perception and learning. It allows learners to understand biological, chemical, and technical processes through visual demonstrations, to virtually witness historical events, to travel to any region of the world while studying geography, or to interact with solar systems and other planetary systems [2]. In sum, VR provides access to unreachable environments—like outer space or the human anatomy—offering unique perspectives that deepen understanding and boost student engagement [3]. By integrating sequential activities into a virtual environment, in terms of geography, VR can make learning even more impactful and exciting without the need for real-time field trips [2]. Therefore, virtual reality holds immense potential to revolutionize geography teaching, specifically in the realms of spatial orientation and map-reading skills. As a cost-effective alternative to physical models or real-time field trips, it enables educational institutions to create virtual environments accessible to multiple students simultaneously [3]. Nevertheless, the use of virtual reality in environmental education has not yet been explored extensively compared to other subjects [4], though some of the pioneering works proved to be effective in this field [5–9].

Furthermore, VR in education can enhance collaborative learning, allowing learners to interact with their peers and the virtual environment, making the experience more active, and in general has proven to be an effective tool for learning geography [10]. It can additionally offer students a personalized learning experience by allowing them to explore the virtual world at their own pace and in the way they prefer [3]. Vert and Andone [11] highlight that from a constructivist point of view, virtual reality provides students with an active role in their learning as it provides experiential and case-based learning [12], as well as social interaction. Technically, learners can explore the learning contents in an immersive environment by operating VR devices, stimulating their interest in learning, and enhancing their learning effectiveness [9] constructively and collaboratively.

Building on prior international research, this study examines how VR interacts with spatial orientation and map-reading skills, specifically focusing on the durability of spatial models and map-to-terrain alignment. While spatial orientation is a broad concept that encompasses landmark recognition, place-name memorization, and self-positioning, this empirical analysis specifically focuses on two quantifiable metrics: distance estimation and directional accuracy. Rather than providing a comprehensive assessment of all spatial skills, the study compares student performance in pre- and post-tests to evaluate the comparative effectiveness and sequencing of on-site real-time field trips and classroom-based VR activities. This focused approach allows for a clearer understanding of long-term knowledge retention (measured over a three-month interval), distinguishing it from the short-term novelty effects of VR. To achieve this, a brief literature review summarizes the findings of previous works related to the key terminological approaches used during the research, followed by a detailed explanation of the locational parameters and methodology. The results section analyzes interpoint distance and direction angles to assess

selected spatial orientation skills within the sample area. Finally, the discussion interprets these findings, while the conclusion outlines potential directions for future research.

2. Literature Review

Using VR in geography lessons has become more frequent recently, although there are various limits and doubts regarding its more general application both in terms of device and methodology. In addition to the technological and methodological limitations, there are also medical and social concerns which are even more difficult to overcome [1]. Despite these challenges, the pedagogical potential of VR, particularly in overcoming the cognitive limitations of traditional classroom settings, remains a primary focus of recent research [13–15]. Spatial reasoning is a critical cognitive ability, encompassing skills like disembedding and spatial visualization, which are fundamental for success in geoscience and various STEM fields [16].

Resource constraints, accessibility issues, and safety concerns often limit the frequency and scope of traditional field excursions, necessitating the exploration of alternative learning modalities. Virtual field trips, powered by virtual reality technology, address many of these limitations by providing immersive and interactive learning environments that can replicate aspects of physical fieldwork without the associated logistical challenges [17]. While traditional field trips face logistical constraints, VR provides a controlled environment specifically suited for developing spatial orientation. This aligns with the argument of Edler et al. [15], who underscore that VR scenarios should be intentionally structured to adopt such competence-oriented learning. Specifically, VR environments can immerse users within an artificially generated setting, presenting realistic 360-degree scenes and objects that trigger human perception with potentially lasting effects on learning [13].

Corroborating these views, Hurrell et al. [18] underscore the transformative role of VFTs in geography higher education. In their perspective paper, they argue that while VR provides a powerful alternative to traditional excursions, its effectiveness lies in how it complements physical fieldwork to develop core geographical competencies. Moreover, the development of spatial thinking and orientation skills can be significantly enhanced through the use of game-engine-based virtual environments, which offer a powerful first-person perspective for landscape representation [19].

2.1. Spatial Orientation: Improving Map-Reading Skills

Within a Spanish higher educational context Carbonell-Carrera and Saorin [20] emphasize the fundamental role of cognitive maps in finding a route in a real-world or virtual environment. Their findings align with the earlier conclusions of Waller et al. [21], suggesting that VR training is not inherently more efficient than traditional map-reading for acquiring spatial orientation. However, the authors also acknowledge the rapid evolution of VR technology, a trend that has significantly accelerated in recent years. Indeed, Carbonell-Carrera et al. [19] have since demonstrated that immersive virtual environments can significantly enhance spatial orientation and three-dimensional (3D) visualization skills. This shift aligns with Johanesen et al. [16] and Edler et al. [15], suggesting that modern VR now offers a robust platform for developing spatial reasoning. These advancements open new perspectives for research, questioning whether contemporary, high-immersion VR can now surpass or more effectively complement traditional cartographic methods in fostering complex spatial orientation skills.

A recurring theme in this literature is the potential for gender differences in spatial skill acquisition. Lim [22], using a constructivist approach with QuickTime VR and cylindrical panoramas, reported that male students performed better in map-reading tasks based on pre- and post-test interventions. In contrast, more recent studies researchers

argue that there are no detectable gender differences in spatial orientation skills when using modern VR interfaces, suggesting that increased immersion may help level the playing field for all learners [20]. To ensure such effectiveness, VR-based learning environments must adhere to specific quality criteria. In this regard, our research draws on the quality factors for VR-based spatial learning techniques proposed by Patel and Vij [23]. Specifically, we focus on “Spatial Awareness”—defined as the user’s orientation and constancy of position within the environment during and after navigation—and “Information Gathering”, which refers to the ability to obtain critical environmental data while navigating. These factors are highly relevant to our study, as they directly influence the success of map-reading and orientation tasks within the virtual field trip.

In line with the specific dimensions identified above, this study narrows its empirical focus to the ability to translate 2D cartographic information into 3D spatial mental models. Consequently, our assessment of spatial orientation is centered on these specific cognitive transitions rather than evaluating overall navigational proficiency or general spatial intelligence.

2.2. Spatial Orientation: Enhancing Spatial Ability

Spatial ability and learning achievement have been discussed in psychological and educational contexts for many years [23,24]. The formal study of geography is essential for training students to recognize and apply spatial relationships, which are analytical tools that require a sense of location and place [25]. Spatial intelligence is an important component of thinking that students must possess, and maps play a key role as a medium for learning geography, which can improve students’ spatial intelligence [26]. Spatial thinking includes representation, representational transformation, and spatial reasoning, all of which are important for finding locations and reading maps [27].

Improving spatial skills can be achieved through training in both real and virtual environments, with no significant difference between the two [28]. Game environments have demonstrated potential for improving spatial abilities [19]. Dedicated VR courses have demonstrated significant gains in students’ spatial abilities, particularly among undergraduate STEM students [29]. This suggests that VR can offer a compelling alternative or supplement to traditional field methods by providing flexible, accessible, and engaging learning experiences that foster crucial spatial competencies [30].

However, challenges such as high costs, infrastructural constraints, and teacher training gaps hinder widespread adoption, necessitating strategic implementation to overcome these obstacles [1]. In this sense, Edler et al. [15] underscore that VR scenarios in geography teaching should explicitly foster competence-oriented learning—including spatial orientation, analysis of natural and socioeconomic processes, and evaluation and action competencies. This perspective is supported by the results of a longitudinal study by Carbonell-Carrera and Hess Medler [31], which experimented with survey learning and wayfinding activities to track long-term spatial skill development.

A critical dimension of this spatial skill development is the cognitive transformation between allocentric (map-based) and egocentric (perspective-based) representations [32,33]. Spatial perspective-taking (SPT) is fundamental to this process, as it requires students to mentally align the static, top-down information of a map with the dynamic, first-person viewpoints experienced during navigation in both virtual and real-world environments [34]. Recent research suggests that the ability to reconcile these different frames of reference is essential for successful spatial orientation and the formation of accurate mental models [35]. Consequently, our research integrates these theoretical frameworks by examining how the sequence of VR and field-based activities influences the stability and alignment of these internal representations [36–38].

Building upon these findings, our study specifically focuses on the durability of spatial models as a core component of spatial ability. While spatial reasoning encompasses various skills, we prioritize the assessment of how well students can retain and retrieve spatial relationships over time, moving beyond immediate post-test results to explore the long-term cognitive impact of integrated VR and field excursions.

2.3. Teaching–Learning Strategies

Modern educational methodologies increasingly emphasize the integration of student activities and technology to enhance spatial reasoning and discovery-based learning. The integration of constructivist approaches and collaborative learning has become fundamental in developing spatial literacy, particularly in the context of map-reading and orientation. According to Lim [22], learning is most effective when students are active participants in constructing their own cognitive frameworks rather than passive recipients of geographical data. By employing collaborative strategies, educators can facilitate an environment where social interaction and peer-to-peer problem-solving reinforce the internalization of spatial relationships, making the abstract task of orientation more intuitive and grounded in shared experience.

Building on these pedagogical foundations, modern technology such as virtual reality and virtual field trips offers immersive platforms for inquiry-based learning. Chen and Chen [39] demonstrate through the VALID project that VR-based environments significantly enhance spatial ability by allowing learners to interact with three-dimensional space in ways that traditional media cannot. This technological shift is most effective when paired with structured active-learning strategies; for instance, Parkinson et al. [40] applied Think-Pair-Share activities within VFTs to encourage students to transition from individual discovery to collaborative reflection. Furthermore, Di and Zheng [41] argue that spatial ability can be strengthened with virtual technologies acting as efficient external tools that yield better outcomes in stimulating and facilitating students' spatial ability/reasoning. Collectively, these strategies bridge the gap between theoretical spatial concepts and practical, technology-enhanced application, providing the methodological framework for the empirical investigation presented in this study.

3. Materials and Methods

3.1. Location for Testing Spatial Orientation—Real World

Lake Balaton is one of Hungary's most popular and most visited tourist regions, the northern part of which is bordered by the Balaton Uplands. This area is delineated by the southwestern sections of the Transdanubian Mountains, which are composed of three discrete regions: the Balaton Uplands, the Tapolca Basin, and the Keszthely Mountains, extending from the northeast. We selected the remnant hills of the Tapolca Basin as our focus area.

The Tapolca Basin is mainly surrounded by remnant hills of volcanic origin, which were formed approximately 4 million years ago when basalt lava erupted through the surface. The distinctive topography of these remnant hills, such as Badacsony, Mt. Szent György, Csobánc, and Gulács (Figure 1), encompasses a wide array of unique shapes, including cones, coffins, and truncated cones giving a unique character to the surrounding landscape. The southern part of the basin was once part of Lake Balaton, while the northern region features a Miocene limestone plateau with karst formations and caves, including the Tapolca Lake Cave. The Tapolca Basin is a popular tourist destination due to its scenic beauty, geological values, and rich winemaking traditions, with vineyards stretching out at the foot of the remnant hills. The varied surface of the basin, with its alternating mountains and plains, creates a unique natural environment. To evaluate how students

interact with this specific geographic setting, a comparative experimental framework was established.

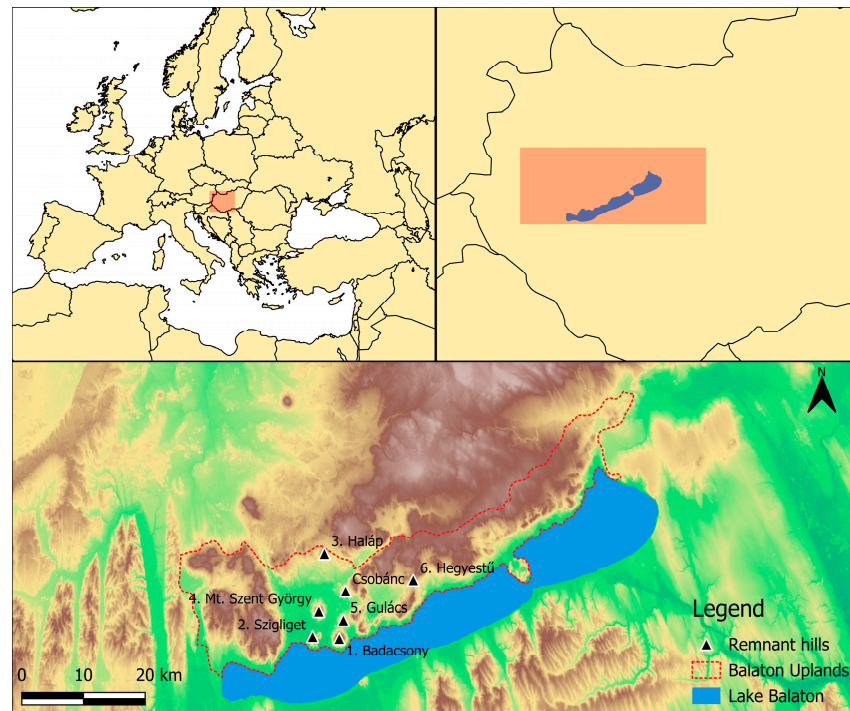


Figure 1. Study area used for spatial orientation task.

3.2. Creating Virtual Location—Virtual World

The digital counterpart of the physical study area was developed to facilitate the virtual component of this sequential training. We created the virtual location that serves as the basis for the “virtual field” using a DJI Mini 2 UAS. For data recording, we used the DJI Fly “Sphere” Panorama function, during which the drone took 26 images in a spherical pattern, which DJI Fly then used to automatically create a 360° image with a resolution of 4096*2048pxl. We uploaded the resulting 360° image (Figure 2) to Google Photos for further use. To provide an immersive experience during the virtual field trip, the 360-degree panoramas were accessed via students’ smartphones and viewed through Cardboard VR headsets. This mobile VR approach was chosen for its high accessibility and ease of integration into geography classrooms. Students inserted their mobile devices into the headsets, allowing them to explore the panoramic scenes of the Tapolca Basin through head-tracking, which simulated a 360-degree field of view. This setup enabled a cost-effective yet immersive interaction with the volcanic landscape, facilitating the observation of the remnant hills’ unique morphology from a first-person perspective.



Figure 2. Panoramic image taken with a DJI Mini 2 drone in Csobánc, used for spatial orientation tasks.

Having established both the physical and virtual platforms, a standardized set of navigational challenges was applied across both environments.

3.3. Experimental Design and Pedagogical Sequence

The study employed a counterbalanced crossover experimental design to compare the efficacy of physical and virtual learning environments in developing spatial orientation skills. To ensure a rigorous longitudinal comparison, participants were selected based on their consistent attendance across all testing phases over the three-month period. This resulted in a final sample of 5-5 participants per group, specifically filtered for data completeness (Figure 3).

Participants were divided into two cohorts to mitigate order effects and ensure the internal validity of the findings:

- Group 1 (Field-First): Participated in an in situ (real-time) field lecture using traditional map-and-compass navigation, followed by a delayed VR post-test three months later.
- Group 2 (VR-First): Engaged with the virtual location and assignment sheets first, subsequently validating their spatial hypotheses through an in situ field post-test three months later.

The VR intervention was conducted using smartphone-based Cardboard headsets (providing a 360-degree immersive field of view) to stimulate the locational parameters of the Csobánc area. The VR intervention followed a structured pedagogical sequence. Participants were first briefed on the technical handling of the smartphone-based Cardboard headsets and the navigation within the 360-degree environment. To prevent potential symptoms of motion sickness and maintain cognitive focus, each VR session was limited to approximately 15–20 min of immersive viewing. During this immersion, students were required to perform active spatial perspective-taking (SPT) tasks. Specifically, they were instructed to perform visual scanning tasks, such as identifying the remnant hills (e.g., Badacsony, Csobánc) and correlating their relative positions with the physical orientation markers provided on their assignment sheets. This guided exploration ensured that the virtual experience was not merely passive viewing but a goal-oriented spatial analysis, mirroring the cognitive demands of the subsequent or previous real-world field

trip. The pre-tests and post-tests consisted of distance estimation and direction accuracy or bearing calculations. By administering pre-tests and post-tests across both modalities, the research evaluates whether the spatial mental model constructed in a virtual environment is as resilient as one formed through physical, kinesthetic experience in the field.

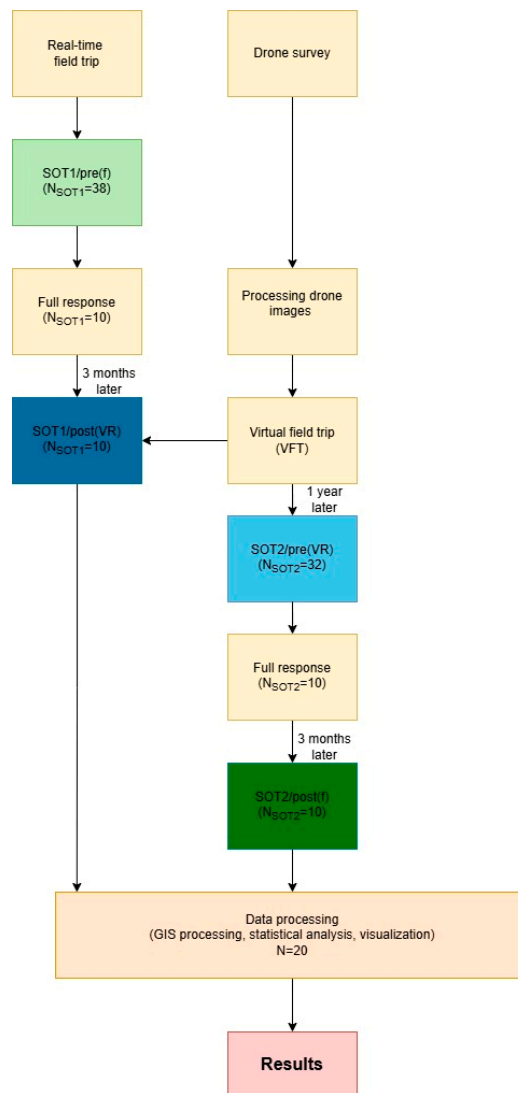


Figure 3. Flowchart of the experimental design and pedagogical sequence, illustrating the longitudinal crossover methodology between real-time and virtual field trips.

3.4. Spatial Orientation Task

To evaluate the students' SPT abilities, a specific spatial orientation task (SOT) was designed. This task was administered in two sequences, hereafter referred to as SOT1 and SOT2. The task was based on a map published by the Balaton Uplands National Park [42]. The students involved in the study received this map of the Tapolca Basin for the preliminary lecture held in Csobánc. Based on this, they used the topographic map and compass to orient themselves during the lecture. The goal was to estimate the spatial distances and directions between Csobánc and the six other reference mountains, all of which are clearly visible from Csobánc itself. We recorded the actual geodetic distances and compass directions, as well as the angles of direction marked in geographic information software (Table 1) and used these to evaluate the accuracy of the students' answers.

Table 1. Distances and direction angles of the remnant hills from Csobánc.

	Distance (m)	Direction Angle (°)
Badacsony	7765.46	192.30
Szigliget	9111.57	215.95
Haláp	6985.45	330.61
Mt. Szent György	5417.10	233.35
Gulács	4671.81	184.42
Hegyestű	11,120.75	80.73

After a 30–45 min lecture, students received their assignment sheets. These were blank maps divided into a 2×2 km grid with a north orientation, on which Csobánc was marked as their “position” and the grid covered the entire Tapolca Basin. The task sheet was created in QGIS 3.28.10 software in the HD72/EOV (EPSG: 23700) projection system. The reason for this was that we wanted to use the local projection system with which the students were the most familiar with, and it is simpler for distance measurement and estimation as the projection system is meter-based. The quantitative data derived from these performance tasks and pre-test and post-test results were subsequently subjected to comparative analysis.

3.5. Spatial and Statistical Analysis

The spatial analysis was based on the points marked during the pre-test and post-test, which the students placed on blank maps (Figure 4) as the geographical location of the six remnant hills relative to their own position. From the completed worksheets, five representative samples per grade level were selected using stratified sampling, taking into account the type of educational program and the number of marked points. These selected maps were georeferenced using linear (affine) transformation in QGIS 3.38.2 software. These selected maps were georeferenced using linear (affine) transformation in QGIS 3.38.2. Field control points (GCPs) were defined based on clearly identifiable and stable features, including grid intersections and well-defined topographic features. The points were evenly distributed across each map, with particular attention to the corners of the map to minimize local distortions. A total of nine GCPs were used per map, consisting primarily of grid intersections, supplemented with additional stable reference features where necessary. The average RMS error across all maps was 0.19 m, with values ranging from 0.016 m to 0.33 m (standard deviation: 0.14 m). We then created vector elements from the points marked by the students, which allowed us to determine the exact distance differences in meters using the QGIS Distance Matrix operation, while the direction angle differences were recorded manually.

The data obtained from the distance matrix were divided into three categories for statistical analysis.

1. Points and Csobánc—distance and direction angle differences between student points and the actual reference point (Csobánc) [distance (m), direction angle (°)];
2. Points and remnant hills—the distance and direction angle between pairs of marked remnant hills [distance (m), direction angle (°)];
3. Points marked during the pre- and post-tests—Euclidean distance differences between points assigned to the same hill in the pre- and post-tests [distance (m)].

Descriptive statistical analysis [mean, standard deviation (SD), median] of the data sets obtained was performed using PAST Statistics software, and the extent of spatial variations was also examined. The results provided an opportunity to quantitatively evaluate the effectiveness of the learning process, i.e., improvement in orientation accuracy, and to explore spatial patterns.

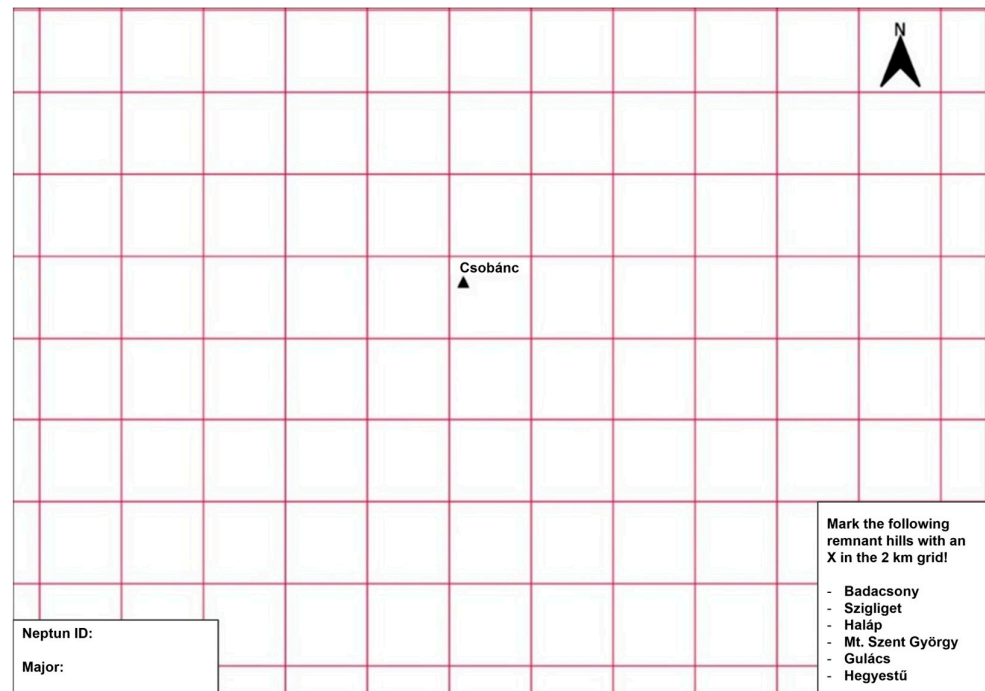


Figure 4. Blank map divided into 2 × 2 km grid with Csobánc marked as the viewpoint.

4. Results

4.1. Analysis of Interpoint Distance and Direction Angles in the Assessment of Spatial Orientation Skills

4.1.1. Badacsony

The spatial accuracy of the responses of the students participating in the study was examined in the case of Badacsony based on the criteria presented earlier, with particular regard to the order of the tests and the location of the points in relation to the references. We separated the locations of the points marked by the students in relation to Csobánc based on the order of the tests (Figure 5, Table 2).

The members of Group 1 completed the pre-test in the field and the post-test in VR. The pre-test results indicated a significant initial underestimation of distance relative to the reference point. Participants in this sequence made only minimal corrections toward the reference point during the post-test. However, the relative stability of the mean direction angle suggests that the initial field experience provided a foundational spatial framework that persisted even when transitioning to the immersive virtual environment. Although the perceived distance remained underestimated compared to the actual location, the field experience significantly contributed to the overall accuracy of the spatial representation.

In Group 2, where VR was used as a pre-test, the results were characterized by higher initial variance in directional angles. Nevertheless, the subsequent post-test conducted in the field resulted in a relative convergence toward the actual geographical locations. This difference, evidenced by the harmonization of mean and median values (Table 2), confirms that the in situ field trip was significantly more effective in refining and strengthening the mental mapping process than the virtual stimulation on its own.

We also analyzed the position of the points assigned to Badacsony in relation to the actual location of the reference mountain according to the test sequences (Figure 6). In Group 1, although the distance remained underestimated during the pre-test, in the post-

test there was a shift in the median values and directional accuracy, suggesting a consolidation of spatial knowledge over time.

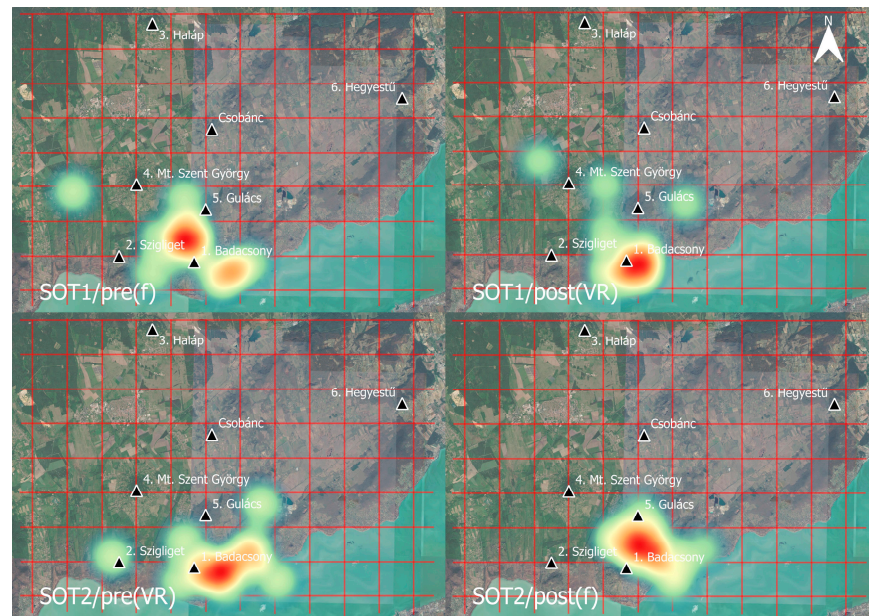


Figure 5. Comparative heatmaps of student-marked locations for Badacsony. The maps illustrate the spatial distribution and point density across the two experimental sequences: SOT1 (field pre-test vs. VR post-test) and SOT2 (VR pre-test vs. field post-test). Brighter (red) areas indicate higher point density, reflecting the most common student estimations relative to the actual landmarks (black triangles). (SOT: spatial orientation task, f: field; VR: virtual reality.).

Table 2. Descriptive statistics of distance and direction angle estimations for Badacsony across the test sequences (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

Badacsony			Mean	SD	Median
SOT1	pre-test (Field)	Distance (m)	7396.74	1475.55	7661.24
		Direction angle (°)	194.29	22.40	191.81
	post-test (VR)	Distance (m)	7039.45	1637.29	7372.24
		Direction angle (°)	193.12	26.34	187.88
SOT2	pre-test (VR)	Distance (m)	7710.56	1347.21	7799.27
		Direction angle (°)	161.46	55.88	176.35
	post-test (Field)	Distance (m)	6700.43	1180.71	6703.23
		Direction angle (°)	177.35	12.59	179.61

Note: SOT = spatial orientation task.

The points of Group 2 were generally more consistent, suggesting that the field experience reinforced previously acquired knowledge. The field-based post-test results were closer to the actual situation, with remarkably closer values. These findings suggest that the in situ field trip reinforced the previously gained knowledge during the preliminary VFT session, thus resulting in a more accurate mental reproduction.

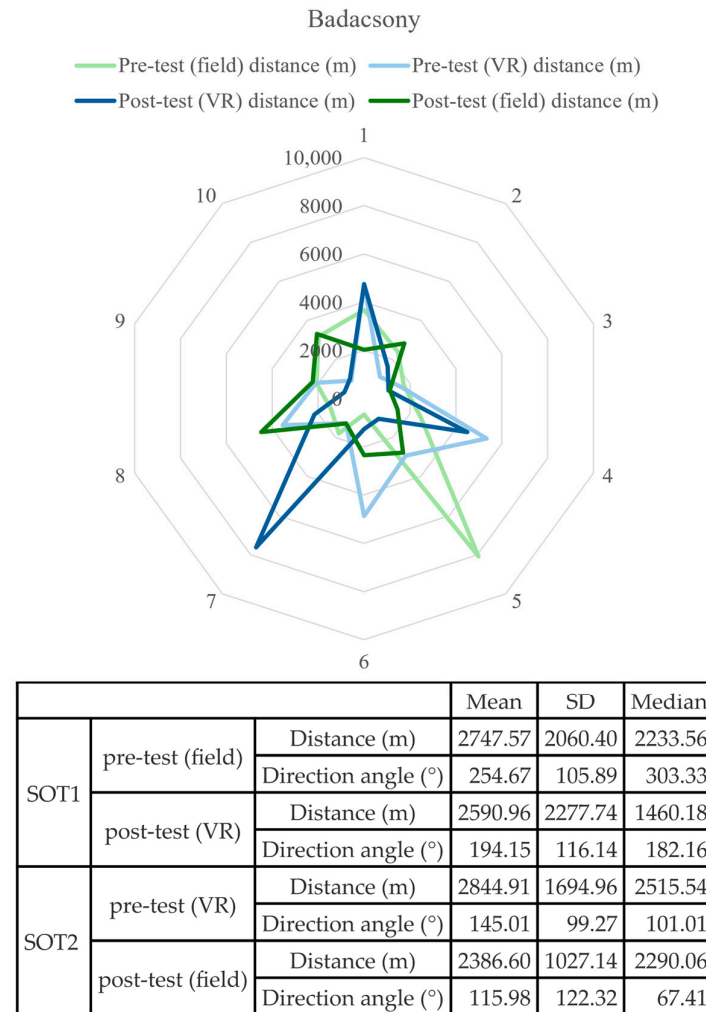


Figure 6. Spatial distribution of individual student responses (radar chart) and corresponding descriptive statistics for distance and direction angle estimations regarding Badacsony (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

4.1.2. Szigliget

When examining the spatial accuracy and location of points identified by students as Szigliget, the results of the post-tests were closer to their actual geographical position than those of the pre-tests (Figure 7, Table 3).

In Group 1, the virtual post-test showed an increase in mean and median distances compared to the field pre-test, although with a higher variability (SD).

In contrast, in Group 2 the VR pre-test and field post-test results showed a similar pattern, while in the field post-test both the mean and median values approximated the actual distance of 9111.57 m and the standard deviation of the points decreased. Regardless of whether these results were recorded in the field or VR environment, during the pre- or post-test, each was an underestimated distance value.

The direction angles between the points marked as Csobánc and Szigliget showed a similar trend. During the field pre-test, the results were characterized by higher variability, while in the VR post-test, the average direction angle approached the actual value and the standard deviation significantly decreased. In the VR pre-test, the reference point was marked with a similar direction angle, and variance; however, during the post-test, the

determination of the direction of the points improved significantly, showing more concentrated values and a lower standard deviation.

The location of the student points showed that they perceived the actual geographical location of Szigliget differently in both field and virtual reality conditions.

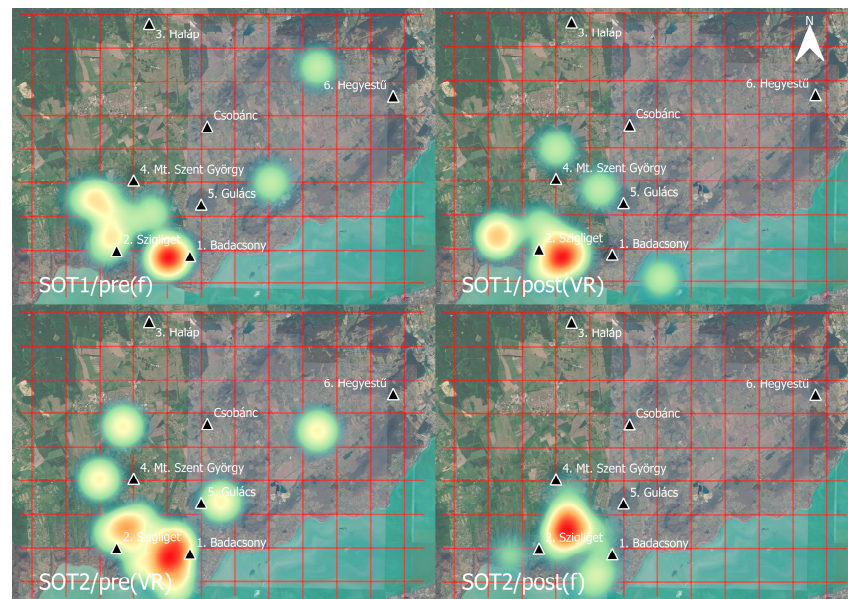


Figure 7. Comparative heatmaps of student-marked locations for Szigliget. The maps illustrate the spatial distribution and point density across the two experimental sequences: SOT1 (field pre-test vs. VR post-test) and SOT2 (VR pre-test vs. field post-test). Brighter (red) areas indicate higher point density, reflecting the most common student estimations relative to the actual landmarks (black triangles). (SOT: spatial orientation task, f: field; VR: virtual reality.).

Table 3. Descriptive statistics of distance and direction angle estimations for Szigliget across the test sequences (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

Szigliget			Mean	SD	Median
SOT1	pre-test (field)	Distance (m)	7605.89	1213.232	7915.77
		Direction angle (°)	190.956	54.46647	205.64
	post-test (VR)	Distance (m)	8209.17	2175.653	8776.21
		Direction angle (°)	213.48	21.96453	209.755
SOT2	pre-test (VR)	Distance (m)	7280.31	1606.855	7188.2
		Direction angle (°)	170.075	55.03445	177.935
	post-test (field)	Distance (m)	7811.08	1492.864	7371.19
		Direction angle (°)	217.172	27.38674	210.885

Note: SOT = spatial orientation task.

During the field pre-test, the points were placed at a considerable mean distance and direction angle around Szigliget (Figure 8). The standard deviation and median values for both distance and direction angle reflected significant initial spatial uncertainty. In the VR post-test, the average distance between the marked points decreased accompanied by a reduction in both standard deviation and the median values. Only a minor change was observed in the average values of the direction angles, although the variability of these estimates also showed a downward trend.

The trend was similar for the second pair of measurements. During the VR pre-test, the estimated location of the points showed higher mean distances, while during the field

post-test, these values significantly decreased. Both the standard deviation and the median values changed similarly, with both metrics decreasing notably in the in situ field environment. In the case of direction angles, a strong shift towards the east was observed between the pre-test and post-test results.

Overall, it can be said that in the case of Szigliget, the differences between the pre- and post-tests showed a tendency to improve, especially in distance estimation.

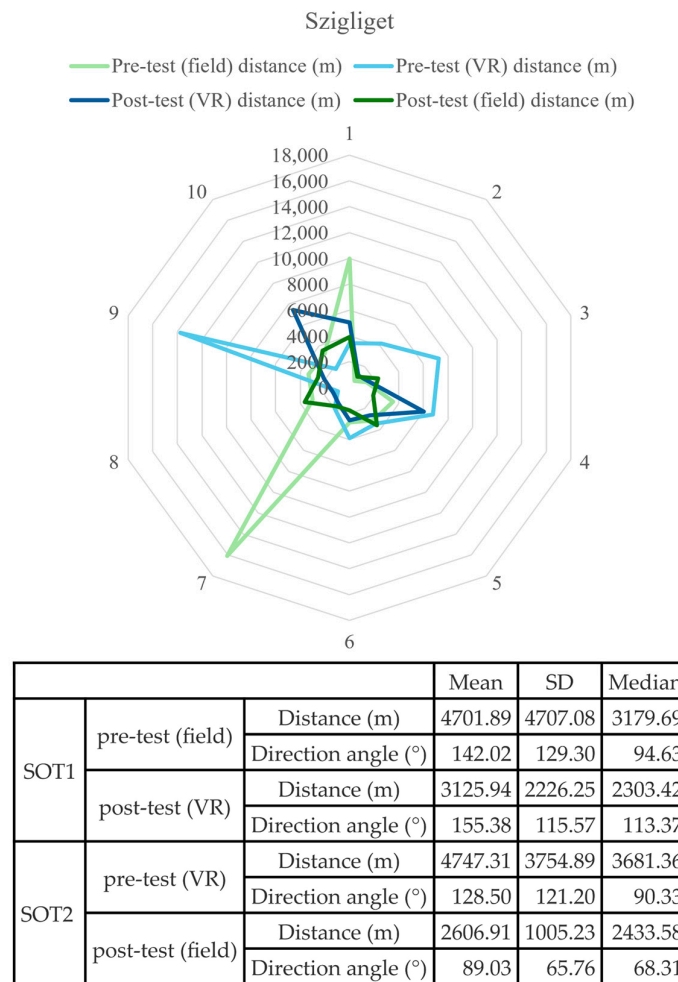


Figure 8. Spatial distribution of individual student responses (radar chart) and corresponding descriptive statistics for distance and direction angle estimations regarding Szigliget (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

4.1.3. Haláp

In the case of Haláp, moderate discrepancies can be observed between the actual location of the remnant hill and the points marked by the students (Figure 9, Table 4).

During the field pre-test, in Group 1, the standard deviation and median values showed a relatively stable positioning. However, in the VR-based post-test, these values increased, suggesting that the virtual environment did not facilitate the spatial identification of Haláp for all individuals. The mean and median direction angles changed dramatically between the two measurements, which suggested that a significant proportion of students determined a completely different direction, presumably due to the lack of reference points that are easy-to-identify in VR space.

The results of the reverse test pair, performed by students in Group 2, showed a pattern opposite to the previous one. In the VR pre-test, the average distance, median, and standard deviation values were similar to the previous VR post-test median value, while in the field post-test, the average distance decreased significantly, with the median and standard deviation values also decreasing significantly. The results of the direction estimates showed a large standard deviation during the pre-test and even more so during the field post-test, even though the median value of the VR post-test was only slightly below the actual direction angle.

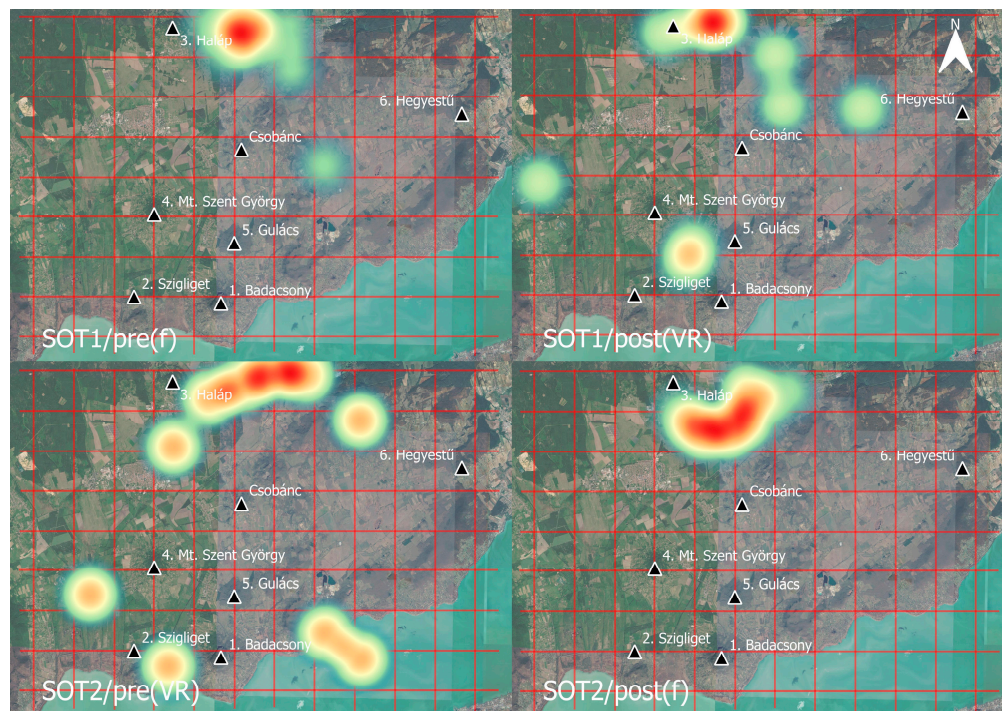


Figure 9. Comparative heatmaps of student-marked locations for Haláp. The maps illustrate the spatial distribution and point density across the two experimental sequences: SOT1 (field pre-test vs. VR post-test) and SOT2 (VR pre-test vs. field post-test). Brighter (red) areas indicate higher point density, reflecting the most common student estimations relative to the actual landmarks (black triangles). (SOT: spatial orientation task, f: field; VR: virtual reality.).

Table 4. Descriptive statistics of distance and direction angle estimations for Haláp across the test sequences (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

Haláp			Mean	SD	Median
SOT1	pre-test (field)	Distance (m)	5636.25	876.891	5674.36
		Direction angle (°)	135.691	165.2751	31.91
	post-test (VR)	Distance (m)	6254.08	1822.756	6384.62
		Direction angle (°)	217.487	131.0067	233.7
SOT2	pre-test (VR)	Distance (m)	7238.24	1655.805	7199.7
		Direction angle (°)	148.25	124.1228	144.935
	post-test (field)	Distance (m)	4739.81	899.2236	4479.5
		Direction angle (°)	206.902	170.7719	327.36

Note: SOT = spatial orientation tasks.

The students' results showed significant spatial variation compared to the actual situation in Haláp (Figure 10). In the field pre-test, the median and standard deviation values

indicate that while some students marked the location relatively accurately, others made significant errors. During the VR post-test, the average distance increased, accompanied by a significant increase in the median and standard deviation values. The average direction angle of the points in both measurements was oriented east-southeast relative to the actual location.

When comparing the VR pre-test and field post-test, an inverse pattern can be observed. In the pre-test, the average distance was characterized by an extremely high standard deviation and median value, while the field post-test resulted in significantly lower values, suggesting that the points were placed closer to their actual location. This improvement was confirmed by the direction angles, as the standard deviation decreased notably.

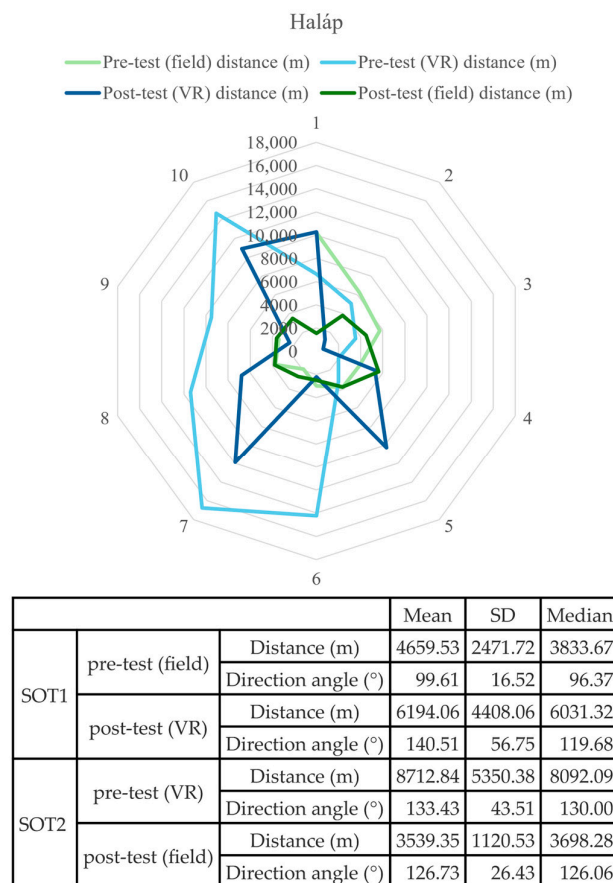


Figure 10. Spatial distribution of individual student responses (radar chart) and corresponding descriptive statistics for distance and direction angle estimations regarding Haláp (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

In the case of Haláp, it can be clearly stated that the results of the tests carried out in the field environment showed greater accuracy in determining distance and direction angle, even though shorter distances were given during distance estimation, and the spatial dispersion of the points was also lower.

4.1.4. Mt. Szent György

The students solved the spatial location of Mt. Szent György relatively accurately in both test pairs (Figure 11, Table 5).

In Group 1, during the field pre-test, the average distance was underestimated compared to the actual distance, although the average direction angle closely followed the actual direction. The standard deviation values also indicated that the majority of points were marked in a consistent direction and location. During the VR post-test, the average distance values indicated that the points were almost correctly determined, while the direction estimates showed greater deviation, both in terms of average value and standard deviation.

A comparison of the VR pre-test and field post-test, performed by Group 2, clearly shows the effect of prior knowledge. In the pre-test, the average distance between points reflected a large overestimation with a large spatial standard deviation, as also indicated by the mean, standard deviation, and median of the direction angles. In the field post-test, these points and the subsequent statistical analysis confirmed that the students performed with minimal distance and angle deviations, showing a significant refinement in spatial precision.



Figure 11. Comparative heatmaps of student-marked locations for Mt. Szent György. The maps illustrate the spatial distribution and point density across the two experimental sequences: SOT1 (field pre-test vs. VR post-test) and SOT2 (VR pre-test vs. field post-test). Brighter (red) areas indicate higher point density, reflecting the most common student estimations relative to the actual landmarks (black triangles). (SOT: spatial orientation task, f: field; VR: virtual reality.).

Table 5. Descriptive statistics of distance and direction angle estimations for Mt. Szent György across the test sequences (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

Mt. Szent György			Mean	SD	Median
SOT1	pre-test (field)	Distance (m)	4893.95	1532.711	4499.55
		Direction angle (°)	251.667	16.3904	251.14
	post-test (VR)	Distance (m)	5554.01	1972.753	5031.37
		Direction angle (°)	268.876	37.13321	263.02
SOT2	pre-test (VR)	Distance (m)	6509.71	2083.055	6229.38
		Direction angle (°)	182.778	47.32579	187.125
	post-test (field)	Distance (m)	5514.37	1182.83	5548.41
		Direction angle (°)	240.365	10.79157	240.655

Note: SOT = spatial orientation task.

During the field pre-test, the average deviation showed that, based on their relative position, students overestimated the distance compared to the actual position of the mountain (Figure 12). The standard deviation was relatively low, reflecting the uniform responses of the students.

In the VR post-test, the distance increased significantly. This change reflects the distorting effect of VR space, which often results in the overestimation of distances and the shifting of reference points. The greater standard deviation indicates increasing uncertainty in estimates, which can be attributed to visual differences in the VR experience.

In the VR pre-test, the average deviation and the direction angle indicated a significant standard deviation in the spatial position of the mountain. In contrast, in the field post-test, the distance decreased, representing the most accurate spatial identification. This indicates that the students significantly refined their mental reproduction of the mountain's position as a result of the exercise.

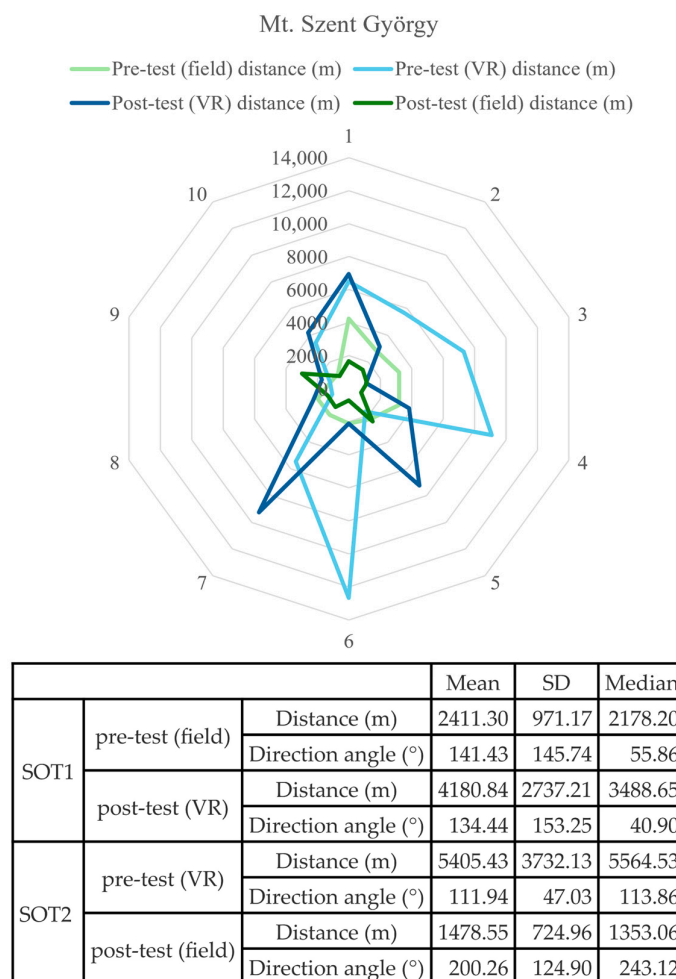


Figure 12. Spatial distribution of individual student responses (radar chart) and corresponding descriptive statistics for distance and direction angle estimations regarding Mt. Szent György (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

The differences between the two environments clearly demonstrate the benefits of learning and adaptation processes. While the pre-tests showed greater errors, including both underestimations and overestimations, the post-tests were closer to the actual position in terms of both distance and direction angle.

4.1.5. Gulács

The results obtained in determining the position of Gulács fit well with the pattern previously identified, particularly with regard to the direction angle differences between field and VR measurements, which are more extreme in this case than in previous ones (Figure 13, Table 6).

Based on the field pre-test results, Group 1 students positioned the mountain relatively uniformly but further away and in a southeasterly direction, a trend supported by the standard deviation values. In the VR post-test, the mean and median distances increased further, while the mean direction angle shifted, with the median value barely exceeding the correct direction angle. The standard deviation of the points also increased significantly, confirming the spatial pattern.

At the same time, a comparison of the VR pre-test and field post-test results in Group 2 showed a marked improvement.

The field post-test resulted in the most accurate distance estimation in this test pair compared to the VR pre-test. A similar refinement in representation was also observed in the determination of directions, with the median direction angle showing a positive shift. The smaller standard deviation also suggested that VR prior knowledge and field repetition significantly increased the efficiency of spatial orientation.

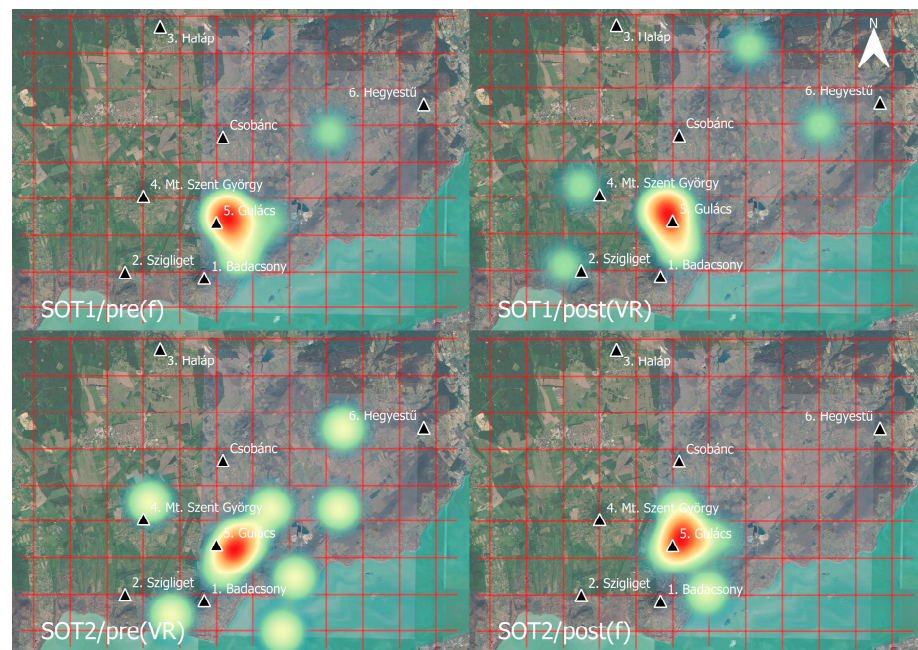


Figure 13. Comparative heatmaps of student-marked locations for Gulács. The maps illustrate the spatial distribution and point density across the two experimental sequences: SOT1 (field pre-test vs. VR post-test) and SOT2 (VR pre-test vs. field post-test). Brighter (red) areas indicate higher point density, reflecting the most common student estimations relative to the actual landmarks (black triangles). (SOT: spatial orientation task, f: field; VR: virtual reality.).

Table 6. Descriptive statistics of distance and direction angle estimations for Gulács across the test sequences (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

Gulács			Mean	SD	Median
SOT1	pre-test (field)	Distance (m)	5137.19	970.0271	4916.66
		Direction angle (°)	161.215	31.24795	173.07
	post-test (VR)	Distance (m)	5807.94	1777.213	5854.52

SOT2	pre-test (VR)	Direction angle (°)	170.518	61.7691	186.78
		Distance (m)	6356.4	2031.452	6336.56
	post-test (field)	Direction angle (°)	158.913	45.50392	162.47
		Distance (m)	4828.23	1588.983	4662.03
		Direction angle (°)	174.24	11.04576	176.88

Note: SOT = spatial orientation task.

During the field pre-test, the points showed the smallest average deviation from their actual positions among the mountains examined so far (Figure 14). The median indicated that most students identified Gulács relatively accurately, although there was variation in individual responses. The deviation in direction angles can be considered concentrated, indicating the accuracy of the determination in the field. In contrast, in the VR post-test data, the average distance increased, and the average direction angle shifted. In relation to these values, the standard deviation indicated significant spatial uncertainty.

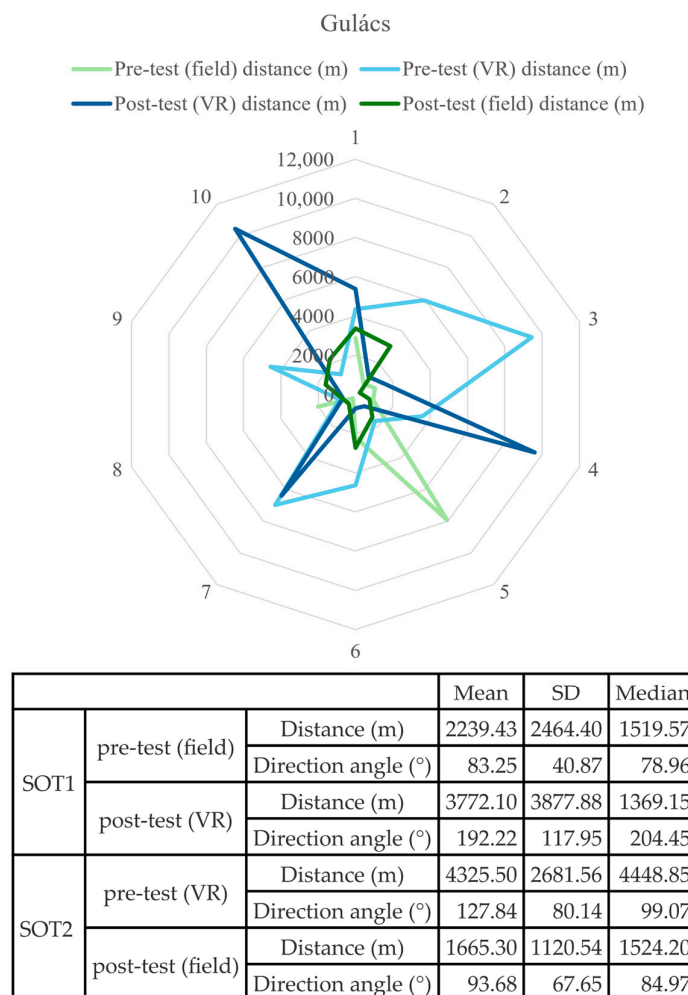


Figure 14. Spatial distribution of individual student responses (radar chart) and corresponding descriptive statistics for distance and direction angle estimations regarding Gulács (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

A comparison of the VR pre-test and field post-test also confirmed this pattern. Estimates made in the field showed a significantly smaller deviation than those made in the

VR environment. The median values of the direction angles also decreased, suggesting that localization in real space was more accurate.

4.1.6. Hegyestű

In the case of Hegyestű, there were significant discrepancies in the determination of distance and direction angle (Figure 15, Table 7).

In Group 1, based on the field pre-test results, the average distance, median, and standard deviation indicated that the students determined the actual spatial position of Hegyestű with a significant degree of uncertainty. The mean direction angles and large standard deviation also indicate variability in direction estimation, although the median value was close to the actual direction angle. During the post-test, the direction angle deviations covered a wide range, meaning that the VR experience did not improve, but rather increased spatial accuracy errors.

In Group 2, a comparison of the results and statistical data of the VR and field test pairs also revealed an interesting pattern. In the field post-test, the average distance value increased compared to the VR-based pre-test. The average direction angle changed toward a more accurate orientation, but due to the great distance and visual identifiability of Hegyestű, no significant improvement was detected in either distance or direction estimation.

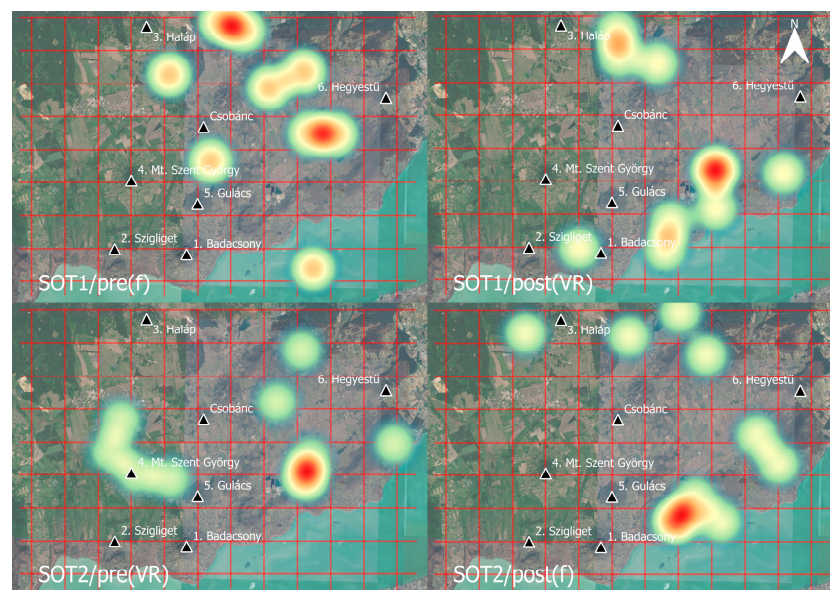


Figure 15. Comparative heatmaps of student-marked locations for Hegyestű. The maps illustrate the spatial distribution and point density across the two experimental sequences: SOT1 (field pre-test vs. VR post-test) and SOT2 (VR pre-test vs. field post-test). Brighter (red) areas indicate higher point density, reflecting the most common student estimations relative to the actual landmarks (black triangles). (SOT: spatial orientation task, f: field; VR: virtual reality.).

Table 7. Descriptive statistics of distance and direction angle estimations for Hegyestű across the test sequences (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

Hegyestű			Mean	SD	Median
SOT1	pre-test (field)	Distance (m)	6152.14	2498.367	6418.55
		Direction angle (°)	108.391	96.71759	93.2
	post-test (VR)	Distance (m)	6787.43	1816.49	6617.89
		Direction angle (°)	136.672	97.37922	123.275
SOT2	pre-test (VR)	Distance (m)	6440.65	2136.144	6369.39

post-test (field)	Direction angle (°)	153.814	78.22432	119.78
	Distance (m)	7471.49	1348.579	7293.47
	Direction angle (°)	117.593	85.35053	120.08

Note: SOT = spatial orientation task.

Based on the pre-test data, the standard deviation indicates that there was significant spatial error, and an incorrect identification pattern was observed in the entire sample group (Figure 16). The varied positions and values of the direction angles showed that it was mostly placed southwest of its actual location, which mutually supports the underestimations of distance from Csobánc.

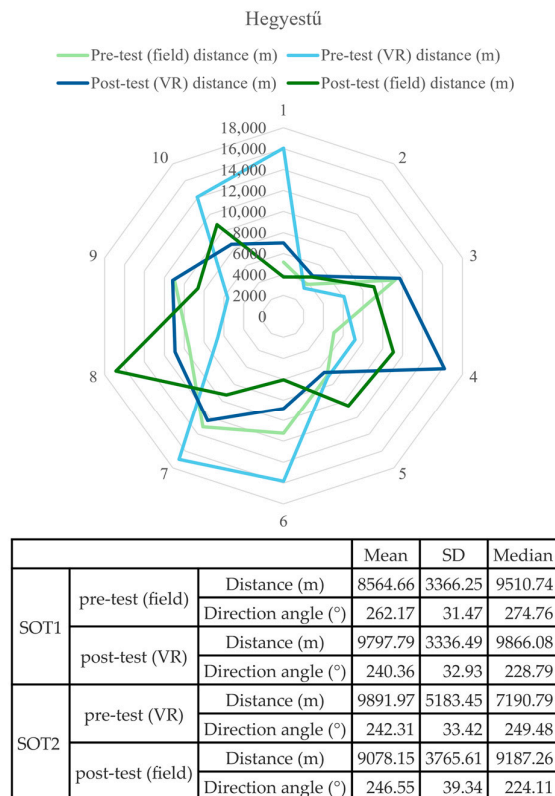


Figure 16. Spatial distribution of individual student responses (radar chart) and corresponding descriptive statistics for distance and direction angle estimations regarding Hegyestű (SOT1: Group 1, Field–VR; SOT2: Group 2, VR–Field).

In the post-VR test, the average distances increased, and the standard deviation and median values remained relatively unchanged compared to the pre-test, thus slightly increasing the distance between the spatial markings of the points. The variation in the values associated with the direction angles showed that the students were consistent in their marking, with a standard deviation similar to that of the pre-test.

A comparison of the VR pre-test and field post-test, in Group 2, confirmed the pattern seen previously. The mean distance values for the VR and field tests showed slight improvement, while the direction angle values remained roughly the same, meaning that the estimation of direction angles remained stable, while the distance error persisted.

4.2. Analysis of Point-to-Point Distances

The distances between the points marked by the students in the pre- and post-tests (point-to-point) showed significant differences in the case of the reference mountains. The

average differences ranged between 3186 and 7433 m, reflecting both the accuracy of spatial orientation and individual differences. The smallest differences were observed in the case of Badacsony, indicating consistent spatial identification on the part of the students, while the largest differences were observed in the case of Hegyestű. This suggests that the recognition and spatial location of Hegyestű caused greater uncertainty at the greatest distance from the viewpoint (Table 8).

Table 8. Summary of descriptive statistics for distance estimation errors across all examined landmarks.

		Mean	SD	Median	Min	Max
Badacsony	Distance (m)	3186.47	2257.72	2984.51	310.98	9363.09
Szigliget		4563.28	3396.97	4010.20	632.38	14,831.37
Haláp		6453.91	4532.04	5171.19	963.55	14,112.41
Mt. Szent György		4753.77	3210.20	3746.95	589.15	12,030.22
Gulács		4431.85	3105.03	3872.80	168.06	9294.36
Hegyestű		7433.80	3621.91	7797.67	2820.55	12,491.82

Based on the median values, the markings were given with an accuracy of between 3000 and 5000 m, but in several cases, such as Haláp and Hegyestű, deviations of more than 10,000 m occurred, which also supports the dispersion of the estimates. The differences between the minimum and maximum values (the most extreme difference being Szigliget) clearly indicate the extreme variations in spatial orientation and the limitations of perception of the designated objects, which can be attributed to the accuracy and detail of the maps created by the students (Figure 17).

The analysis between the points showed that the precise location of the reference points greatly influenced the students' results and spatial accuracy, as did their knowledge of the reference points and their dominance in the landscape.

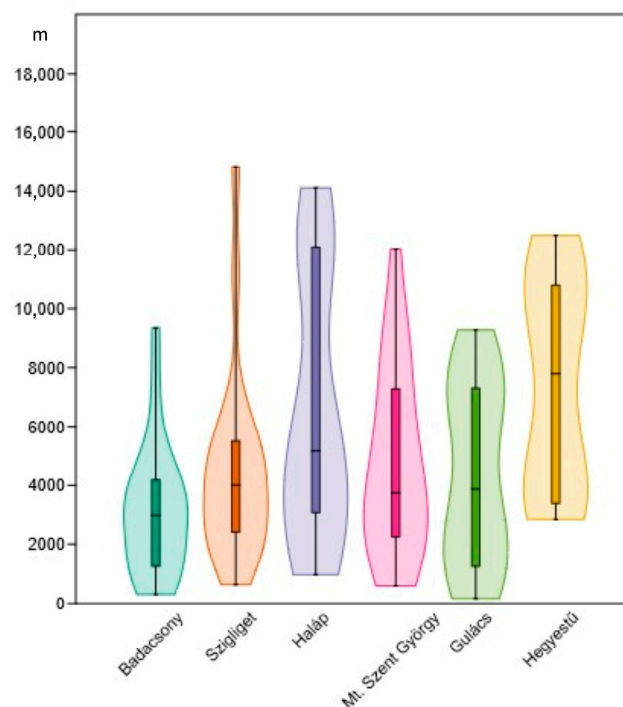


Figure 17. Violin plots illustrating the spatial distribution and density of point-to-point distance deviations for the six examined remnant hills (m).

5. Discussion

The findings of our study provide a significant contribution to the field of geography education in two ways. First, it addresses longitudinal knowledge retention using a three-month delay. While the existing literature on VFTs and spatial orientation typically focuses on immediate post-test performance or short-term retention cycles of one month or less [30,31,43–45], our results offer insights into the “durability” of spatial mental models over a three-month interval. This temporal delay is essential for isolating the long-term cognitive transfer of navigational skills from the temporary novelty effect often associated with immersive VR technologies.

The counterbalanced crossover design further elucidates the bidirectional relationship between physical and virtual environments. By comparing the Field-First and VR-First sequences, the study highlights how initial in situ experiences provide a “kinesthetic anchor” that enhances the interpretation of digital spatial data months later. Conversely, the success of the VR-First cohort suggests that immersive simulations can effectively scaffold the cognitive frameworks required for real-world map-and-compass navigation. Building on this longitudinal framework, our analysis of mental mapping tasks revealed significant insights into the nature of retained spatial models.

Based on the average distances and direction angles calculated from the distance matrix data from Csobánc, we reconstructed how the students arranged the remnant hills in space during the test pairs. The resulting arrangement shows significant differences compared to the actual topographical location of the remnant hills, which is how we created the cognitive map of the landscape. The results generally show that spatial representations are highly distorted. The underestimation and overestimation of distances between points marked on the blank map, as well as the shift in direction angles, depended largely on the visual dominance of the mountains in the landscape and the environment in which the task was performed (field or VR). Due to their striking morphological appearance and spatial position, landmark mountains often served as visual reference points (e.g., Gulács), while in the case of Hegyestű, the error rate was higher due to the large spatial distance and the resolution limitations of the panoramic image used in the VR environment (Figure 18). This finding corroborates the technological and methodological limitations highlighted by Czimre et al. [1], suggesting that the physical constraints of current mobile VR hardware—specifically regarding image clarity and depth perception at distance—can directly impact the accuracy of spatial information gathering.

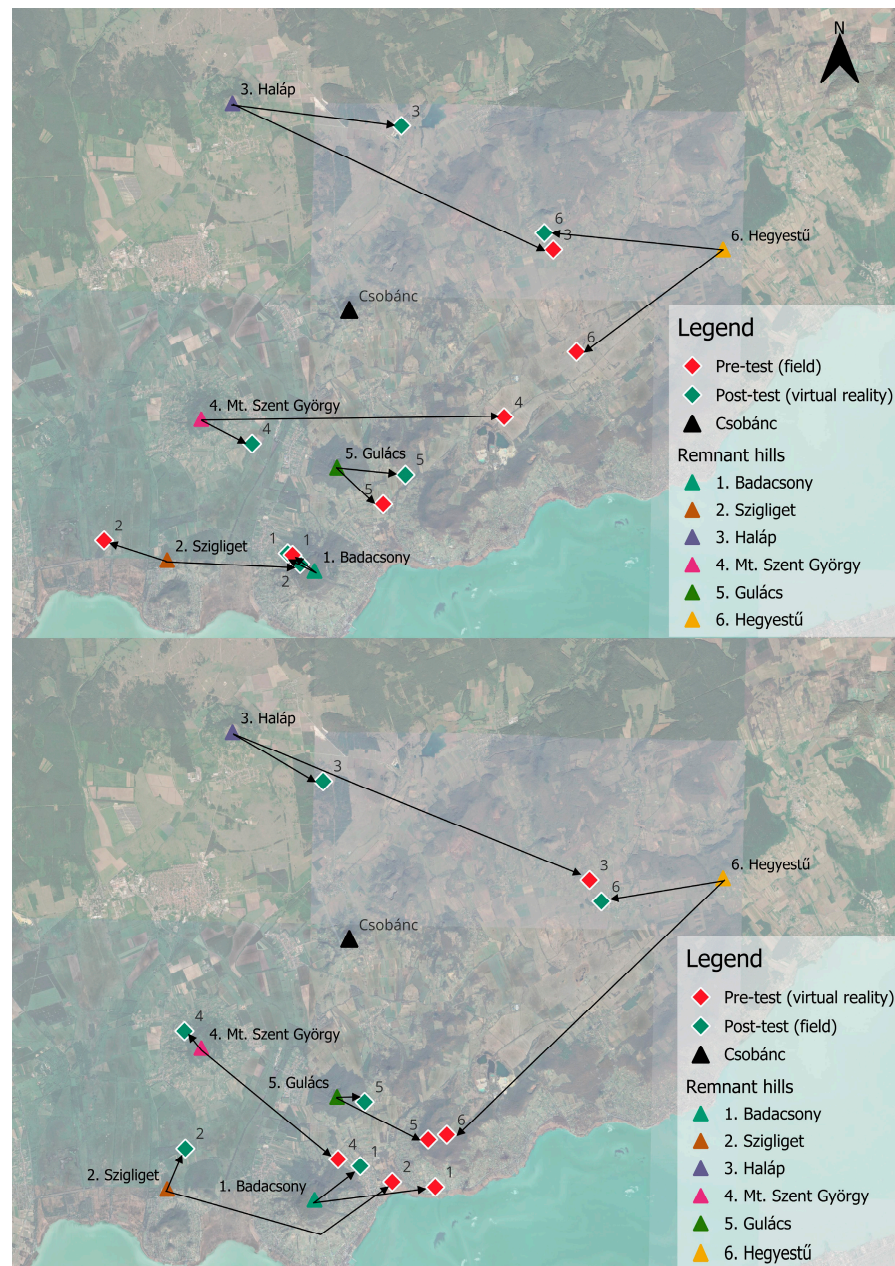


Figure 18. Reconstructed cognitive map of the remnant hills. The diagram illustrates the spatial shift between the actual geographical locations and the students' perceptions. Displacement vectors indicate the direction and magnitude of the systematic spatial distortions. Color coding of the remnant hills is consistent with Figure 17.

In summary, students based their responses during mental mapping mainly on visual connections; thus, our cognitive map better reflects the perception of the landscape than its actual geometric and spatial structure. Consequently, the VR environment did not eliminate spatial distortions, but rather reinforced the spatial patterns previously used by students, which in turn clearly demonstrates the role of visual stimuli in spatial orientation and may justify the use of virtual reality environments in geography education.

Limitations and Future Research

Despite the robust crossover design, this study has certain limitations that should be addressed in future investigations. First, the use of smartphone-based Cardboard VR—

while highly accessible for geography education—presents hardware constraints regarding image resolution and depth perception. As noted in the case of Hegyestű, the lack of visual clarity at extreme distances can induce spatial distortions that might be mitigated by high-end, standalone VR headsets. Second, while the three-month interval provided valuable insights into longitudinal knowledge retention, the study did not account for students' extracurricular activities (like hiking or GIS use) during the time between the tests, which may have influenced their mental map stability. Third, this study focuses primarily on distance estimation and directional accuracy as quantifiable metrics of spatial orientation. While these provide precise data, they do not account for other critical components of spatial cognition, such as landmark recognition, place-name memorization, or the ability to determine one's position during active navigation. Fourth, although the sample involved 20 participants from geography BSc and geography teacher major programs, the results are primarily representative of a specific university-level demographic. Furthermore, the final sample size was constrained by the rigorous requirements of the longitudinal crossover design. To ensure data integrity, only participants who completed all testing phases over the three-month period were included (complete-case analysis). While this selective approach ensures the reliability of the spatial analysis for the two sequences, the reduction to five participants per group limits the broader statistical representativeness and generalizability of the results. Consequently, the findings should be interpreted as a focused exploration of cognitive sequencing rather than a large-scale demographic assessment.

Future research should explore a broader range of spatial cognitive components, including path integration and landmark identification, as well as the impact of higher-fidelity immersive systems on spatial orientation to determine if increased resolution reduces the perceptual biases observed in this study. Additionally, it would be beneficial to investigate the role of augmented reality (AR) as a bridge between the virtual and physical field, potentially layering cartographic data directly onto the landscape. Finally, future research should aim to involve larger cohorts and utilize automated spatial data collection to minimize participant attrition, and to include diverse age groups to help generalize these findings across all levels of geography education. With an expanded dataset, future studies will also prioritize the application of inferential statistical testing—such as paired comparisons and mixed-model approaches—to provide more robust causal interpretability regarding the effectiveness of VR-based hybrid learning.

6. Conclusions

This research demonstrates that the strategic integration of virtual field trips and in situ field experiences significantly enhances the development of spatial orientation and map-reading skills in geography education. However, it is important to clarify that these findings specifically pertain to the durability of spatial mental models and the accuracy of map-to-terrain alignment within a defined geographical context. By employing a counter-balanced crossover design, the study successfully isolated the effects of learning sequences, revealing that both physical and virtual environments contribute uniquely to the formation of internal spatial models. The three-month longitudinal interval proved to be a critical methodological element, confirming that the navigational competencies acquired—such as bearing calculation and distance estimation—possess a degree of cognitive resilience that transcends immediate short-term recall.

A key finding of the study is that students' cognitive maps are fundamentally driven by visual stimuli and the perception of physiographic landmarks rather than objective geometric accuracy. While both real-world and virtual environments are susceptible to spatial distortions, the VR setting was found to reinforce existing mental patterns while introducing specific perceptual biases, suggesting that high-fidelity simulations are

effective tools for externalizing and practicing spatial reasoning. However, the observed distortions—particularly regarding distant landmarks—confirm that the technical limitations of mobile VR must be considered when interpreting these digital representations.

Ultimately, the synergy between immersive technology and traditional field methods—supported by a constructivist pedagogy—offers a robust framework for modern geographic training. Accordingly, future educational programs for both geographers and geography teacher majors should leverage the scaffolding potential of VR to prepare students for the physical complexities of the landscape. While VR acts as a powerful preparatory or reinforcing tool, in situ fieldwork remains the essential “kinesthetic anchor” for spatial intelligence. These results justify the broader implementation of hybrid experiential learning models to equip future geographers and educators with the flexible spatial competencies required for professional practice.

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Abbreviations

The following abbreviations are used in this manuscript:

3D	Three-Dimensional
AR	Augmented Reality
SD	Standard Deviation
SOT	Spatial Orientation Task
SPT	Spatial Perspective-Taking
STEM	Science, Technology, Engineering, and Mathematics
VALID	Virtual Reality Assisted Learning Device
VFT	Virtual Field Trip
VR	Virtual Reality
VRLE	Virtual Reality Learning Environment

References

1. Czimre, K.; Teperics, K.; Molnár, E.; Kapusi, J.; Saidi, I.; Gusman, D.; Bujdosó, G. Potentials in Using VR for Facilitating Geography Teaching in Classrooms: A Systematic Review. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 332. <https://doi.org/10.3390/ijgi13090332>.
2. Shatokhin, O.; Dzedzickis, A.; Pečiulienė, M.; Bučinskas, V. Extended Reality: Types and Applications. *Appl. Sci.* **2025**, *15*, 3282. <https://doi.org/10.3390/app15063282>.
3. Maroukgas, A.; Troussas, C.; Krouska, A.; Sgouropoulou, C. Virtual Reality in Education: A Review of Learning Theories, Approaches and Methodologies for the Last Decade. *Electronics* **2023**, *12*, 2832. <https://doi.org/10.3390/electronics12132832>.
4. Cho, Y.; Park, K.S. Designing Immersive Virtual Reality Simulation for Environmental Science Education. *Electronics* **2023**, *12*, 315. <https://doi.org/10.3390/electronics12020315>.
5. Chen, C.H.; Yang, J.C.; Shen, S.; Jeng, M.C. A Desktop Virtual Reality Earth Motion System in Astronomy Education. *J. Educ. Technol. Soc.* **2007**, *10*, 289–304.
6. Kozhevnikov, M.; Gurlitt, J.; Kozhevnikov, M. Learning Relative Motion Concepts in Immersive and Non-Immersive Virtual Environments. *J. Sci. Educ. Technol.* **2013**, *22*, 952–962. <https://doi.org/10.1007/s10956-013-9441-0>.
7. Muhanna, M.A. Virtual Reality and the CAVE: Taxonomy, Interaction Challenges and Research Directions. *J. King Saud Univ. - Comput. Inf. Sci.* **2015**, *27*, 344–361. <https://doi.org/10.1016/j.jksuci.2014.03.023>.
8. Chang, S.-C.; Hsu, T.-C.; Jong, M.S.-Y. Integration of the Peer Assessment Approach with a Virtual Reality Design System for Learning Earth Science. *Comput. Educ.* **2020**, *146*, 103758. <https://doi.org/10.1016/j.compedu.2019.103758>.
9. Ou, K.-L.; Chu, S.-T.; Tarng, W. Development of a Virtual Wetland Ecological System Using VR 360° Panoramic Technology for Environmental Education. *Land* **2021**, *10*, 829. <https://doi.org/10.3390/land10080829>.
10. Sedlák, M.; Šašinka, Č.; Stachoň, Z.; Chmelík, J.; Doležal, M. Collaborative and Individual Learning of Geography in Immersive Virtual Reality: An Effectiveness Study. *PLoS ONE* **2022**, *17*, e0276267. <https://doi.org/10.1371/journal.pone.0276267>.
11. Vert, S.; Andone, D. Virtual Reality Authoring Tools for Educators. *ITM Web Conf.* **2019**, *29*, 03008. <https://doi.org/10.1051/itmconf/20192903008>.
12. Huang, H.-M.; Rauch, U.; Liaw, S.-S. Investigating Learners' Attitudes toward Virtual Reality Learning Environments: Based on a Constructivist Approach. *Comput. Educ.* **2010**, *55*, 1171–1182. <https://doi.org/10.1016/j.compedu.2010.05.014>.
13. Mohring, K.; Brendel, N. Producing Virtual Reality (VR) Field Trips—A Concept for a Sense-Based and Mindful Geographic Education. *Geogr. Helv.* **2021**, *76*, 369–380. <https://doi.org/10.5194/gh-76-369-2021>.
14. Roelofsen, M.; Carter-White, R. Virtual Reality as a Spatial Prompt in Geography Learning and Teaching. *Geogr. Res.* **2022**, *60*, 625–636. <https://doi.org/10.1111/1745-5871.12551>.
15. Edler, D.; Wiktorin, D.; Becker, G.; Schweins, U.; Reichert, K.; Keil, J.; Dickmann, F. The Potential of Immersive Virtual Reality for Teaching Geography in Schools. *KN J. Cartogr. Geogr. Inf.* **2025**, *75*, 205–217. <https://doi.org/10.1007/s42489-025-00204-1>.
16. Johanesen, K.E.; Jones, J.A.; Poole, T.; Ryker, K.; Green, C. VR Geoscience Education: Building Spatial Reasoning Skills. In Proceedings of the 2024 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW), Orlando, FL, USA, 16 March 2024; pp. 167–172.
17. Cheng, K.-H.; Tsai, C.-C. A Case Study of Immersive Virtual Field Trips in an Elementary Classroom: Students' Learning Experience and Teacher-Student Interaction Behaviors. *Comput. Educ.* **2019**, *140*, 103600. <https://doi.org/10.1016/j.compedu.2019.103600>.
18. Hurrell, E.R.; Hutchinson, S.M.; Yorke, L.; Batty, L.C.; Bunting, M.J.; Swanton, D.; McDougall, D.A.; Parsons, D.R. The Role of Virtual Field Trips in Geography Higher Education: A Perspective Paper. *Area* **2025**, *57*, e70011. <https://doi.org/10.1111/area.70011>.
19. Carbonell-Carrera, C.; Saorin, J.L.; Jaeger, A.J. Navigation Tasks in Desktop VR Environments to Improve the Spatial Orientation Skill of Building Engineers. *Buildings* **2021**, *11*, 492. <https://doi.org/10.3390/buildings11100492>.
20. Carbonell-Carrera, C.; Saorin, J.L. Virtual Learning Environments to Enhance Spatial Orientation. *Eurasia J. Math. Sci. Tech. Ed.* **2017**, *14*, 709–719. <https://doi.org/10.12973/ejmste/79171>.
21. Waller, D.; Hunt, E.; Knapp, D. The Transfer of Spatial Knowledge in Virtual Environment Training. *Presence Teleoper. Virtual Environ.* **1998**, *7*, 129–143. <https://doi.org/10.1162/105474698565631>.
22. Lim, K. Augmenting Spatial Intelligence in the Geography Classroom. *Int. Res. Geogr. Environ. Educ.* **2006**, *14*, 187–199. <https://doi.org/10.1080/10382040508668350>.
23. Patel, K.K.; Vij, S.K. Spatial navigation in virtual world. In *Advanced Knowledge Based Systems: Models, Applications & Research*; Sajja, P.S., Akerkar, R., Eds.; TMRF e-Book: Kolhapur, India, 2010; Volume 1, pp.101–125.

24. Chikha, A.B.; Khacharem, A.; Trabelsi, K.; Bragazzi, N.L. The Effect of Spatial Ability in Learning from Static and Dynamic Visualizations: A Moderation Analysis in 6-Year-Old Children. *Front. Psychol.* **2021**, *12*, 583968. <https://doi.org/10.3389/fpsyg.2021.583968>.
25. Macken, C. What in the World Do Second Graders Know about Geography? Using Picture Books to Teach Geography. *Soc. Stud.* **2003**, *94*, 63–68. <https://doi.org/10.1080/00377990309600184>.
26. Hilman, M.; Mainaki, R. Advantage of map as geography learning media to enhance students' spatial intelligence. *GEOMATE J.* **2021**, *18*, 225–232. <https://doi.org/10.21660/2020.68.ICGeo3>.
27. Fiantika, F.R.; Setyawati, S.P. Representation, Representational Transformation and Spatial Reasoning Hierarchical in Spatial Thinking. *J. Phys. Conf. Ser.* **2019**, *1321*, 022056. <https://doi.org/10.1088/1742-6596/1321/2/022056>.
28. González, C.R.; Martín-Gutiérrez, J.; Domínguez, M.G.; HernanPérez, A.S.; Carrodegua, C.M. Improving Spatial Skills: An Orienteering Experience in Real and Virtual Environments with First Year Engineering Students. *Procedia Comput. Sci.* **2013**, *25*, 428–435. <https://doi.org/10.1016/j.procs.2013.11.054>.
29. Demetriou, Y.; Parikh, M.; Eskandari, S.; Weimer, W.; Endres, M. Training Spatial Ability in Virtual Reality. *arXiv* **2025**, arXiv:2508.10195. <https://doi.org/10.48550/arXiv.2508.10195>.
30. Putra, A.K.; Khalidy, D.A.; Handoyo, B.; Thang, H.V. Construction of Immersive Experiences: Development of Virtual Reality Technology to Facilitate Physical Geography Learning. *Int. J. Emerg. Technol. Learn. (iJET)* **2023**, *18*, 47–60. <https://doi.org/10.3991/ijet.v18i19.40859>.
31. Carbonell-Carrera, C.; Hess Medler, S. Spatial Orientation Skill Improvement with Geospatial Applications: Report of a Multi-Year Study. *ISPRS Int. J. Geo-Inf.* **2017**, *6*, 278. <https://doi.org/10.3390/ijgi6090278>.
32. Klatzky, R.L. Allocentric and Egocentric Spatial Representations: Definitions, Distinctions, and Interconnections. In *Spatial Cognition: An Interdisciplinary Approach to Representing and Processing Spatial Knowledge*; Freksa, C., Habel, C., Wender, K.F., Eds.; Springer: Berlin, Heidelberg, 1998; pp. 1–17, ISBN 978-3-540-69342-0.
33. Guo, H.; Yang, N.; Wang, Z.; Fang, H. Effects of Spatial Reference Frames, Map Dimensionality, and Navigation Modes on Spatial Orientation Efficiency. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 476. <https://doi.org/10.3390/ijgi12120476>.
34. Hegarty, M.; Waller, D. A Dissociation between Mental Rotation and Perspective-Taking Spatial Abilities. *Intelligence* **2004**, *32*, 175–191. <https://doi.org/10.1016/j.intell.2003.12.001>.
35. Shelton, A.L.; McNamara, T.P. Systems of Spatial Reference in Human Memory. *Cogn. Psychol.* **2001**, *43*, 274–310. <https://doi.org/10.1006/cogp.2001.0758>.
36. Moysey, S.M.J.; Lazar, K.B. Using Virtual Reality as a Tool for Field-Based Learning in the Earth Sciences. In *Interdisciplinary Perspectives on Virtual Place-Based Learning*; Lansiquot, R.D., MacDonald, S.P., Eds.; Springer International Publishing: Cham, Switzerland, 2019; pp. 99–126, ISBN 978-3-030-32471-1.
37. Garcia, M.B.; Nadelson, L.S.; Yeh, A. “We’re Going on a Virtual Trip!”: A Switching-Replications Experiment of 360-Degree Videos as a Physical Field Trip Alternative in Primary Education. *Int. J. Child Care Educ. Policy* **2023**, *17*, 4. <https://doi.org/10.1186/s40723-023-00110-x>.
38. Li, J.; Wu, K.W.; Zhou, Q. Enhancing Students' Field Experience in Physical Geography Courses Using Virtual Reality Technology. In *Teaching with Technology in the Social Sciences*; Moorhouse, B.L., Li, S.S.C., Pahs, S., Eds.; Springer Nature: Singapore, 2024; pp. 81–87, ISBN 978-981-99-8418-3.
39. Chen, C.-C.; Chen, L.-Y. Exploring the Effect of Spatial Ability and Learning Achievement on Learning Effect in VR Assisted Learning Environment. *Educ. Technol. Soc.* **2022**, *25*, 74–90.
40. Parkinson, A.; Kitchen, R.; Tudor, A.-D.; Minocha, S.; Tilling, S. Role of Smartphone-Driven Virtual Reality Field Trips in Inquiry-Based Learning. University of Surrey, Guildford, UK, 21 April 2017.
41. Di, X.; Zheng, X. A Meta-Analysis of the Impact of Virtual Technologies on Students' Spatial Ability. *Educ. Tech Res. Dev* **2022**, *70*, 73–98. <https://doi.org/10.1007/s11423-022-10082-3>.
42. Tapolca Basin. Available online: <https://www.bfnp.hu/en/tajegyseg/tapolca-basin-en> (accessed on 27 March 2026).
43. Merchant, Z.; Goetz, E.T.; Cifuentes, L.; Keeney-Kennicutt, W.; Davis, T.J. Effectiveness of Virtual Reality-Based Instruction on Students' Learning Outcomes in K-12 and Higher Education: A Meta-Analysis. *Comput. Educ.* **2014**, *70*, 29–40. <https://doi.org/10.1016/j.compedu.2013.07.033>.

44. Meyer, O.A.; Omdahl, M.K.; Makransky, G. Investigating the Effect of Pre-Training When Learning through Immersive Virtual Reality and Video: A Media and Methods Experiment. *Comput. Educ.* **2019**, *140*, 103603. <https://doi.org/10.1016/j.compedu.2019.103603>.
45. Petersen, G.B.; Stenberdt, V.; Mayer, R.E.; Makransky, G. Collaborative Generative Learning Activities in Immersive Virtual Reality Increase Learning. *Comput. Educ.* **2023**, *207*, 104931. <https://doi.org/10.1016/j.compedu.2023.104931>.

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