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Original Research Article

The Effect of Speed and Scale on Movement Behaviors in Virtual Environments

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Abstract

Problem statement: Success in designing virtual environments requires maximizing the quality of users' experience within these digital spaces. Such environments also allow for the adjustment of fundamental environmental properties, including avatar speed and spatial scale. Therefore, understanding the effects of altering these basic variables on user behavior, particularly movement behaviors, is essential.

Research objective: In this regard, the present research investigates the effect of avatar speed, environmental structure scale, and environmental information density on users' movement strategies. It is hoped that this study will provide useful results for various applications, from game design to assistive virtual environments.

Research method: The paradigm of this research is post-positivist, and in terms of objective, it falls under applied research. The research data were obtained by observing the behavior of users -including 18 participants experienced in computer games - during search activities in a virtual environment, and then extracting their behavioral patterns by 9 other users. The findings from this part were validated through a Delphi method. The collected data were analyzed using regression tests for each dependent variable separately.

Conclusion: The results indicate that speed, scale, and environmental information density influence the movement behaviors adopted by users in the virtual environment. Speed and environmental information density particularly affect motion-strategy-based behaviors, such as the distance traveled in straight paths, whereas scale primarily influences behaviors related to spatial structure, such as the preferred distance from walls and edges. An individual's search efficiency is also affected by environmental information density.

Keywords: *Avatar movement speed, Spatial structure scale, Environmental information density, Movement behaviors, Virtual environment*

Introduction and Problem Statement

In Virtual reality (VR) is currently recognized as one of the most promising technological platforms of the future. The daily growth of the digital world and the emergence of more advanced hardware elements, such as higher quality and lighter VR headsets, haptic feedback in VR controllers, wireless VR solutions, and other technological advancements, increasingly present the digital world to us in a more realistic form and bring the emergence of integrated digital worlds -the Metaverse- closer to reality. To take this virtual world seriously, it suffices to note that it is estimated that private equity firms and venture capitalists collectively invested $120 billion in metaverse-related ventures in the first six months of 2023, which is 24 times Iran's oil sales in the same period.

Currently, most virtual spaces built by computer

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specialists are experimental. However, it is evident that as this technology matures, it is environmental designers and particularly architects who must take on the design of these environments and create spaces suitable for human experience. On the other hand, when a designer faces designing these environments, they realize that many of the limitations of the real world do not exist in these spaces, and thus the designer can design space and spatial experience with great freedom. However, these extensive possibilities raise new questions for the designer. Two very important and intertwined variables that a virtual environment designer must decide on are the speed of individual movement in the environment and the scale of spatial elements. Generally, virtual environments, in many cases, do not simulate the real speed and scale of the individual in the environment and, aiming to create more attractive environments and faster access to environmental diversity, significantly alter these variables.

This article aims to examine how these two factors affect users' movement strategies in virtual environments and investigates:

- How can changes in speed and scale in virtual space affect user behavior and decision-making?
- Based on what criteria and needs can the optimal speed and scale for a virtual environment be determined?

The conceptual framework of this research is based on the foundations of Perception Action Theory. Based on this paradigm, virtual environments are not considered as a set of neutral data, but as a field of "affordances" that directly guide the user's motor behavior. In this regard, the independent variables of the research, including avatar speed, environmental structure scale, and environmental information density, are considered as fundamental and adjustable factors by the designer that transform the user's spatial perception and movement possibilities in the virtual environment. It is assumed that changes in these parameters systematically affect the user's movement strategies as dependent variables, including path-based strategies (such as distance traveled in a straight path) and spatial structure-based strategies (such as preferred distance when passing edges).

The present framework explains these relationships in the form of a causal-descriptive model in which the quality of human experience, as the ultimate goal of design, is influenced by the efficiency of these movement strategies. This model predicts that speed and information density mainly affect dynamic and linear aspects of navigation, while environmental scale primarily affects the user's interaction with the geometry and boundaries of space.

This research possesses methodological and conceptual innovation, because for the first time, it systematically and simultaneously examines the effects of three fundamental design variables of virtual environments -avatar speed, spatial scale, and environmental information density- on user movement strategies. While previous studies have mostly examined these factors separately, this research, by presenting an integrated framework, explores the complex interaction of these variables and the distinct impact of each on specific types of motor behaviors. This approach provides a more precise understanding of how wayfinding behavior is formed in the user's mind in response to changes specific to the virtual environment and offers valuable empirical insights for optimizing user experience in applied fields such as video games and assistive VR environments.

Background and Theoretical Foundations

The differences and similarities between real and virtual environments have been extensively studied. A study titled "Similarities and Differences Between Immersive Virtual Reality, the Real World, and Computer Screen" by screening 1083 articles and selecting 56 for qualitative analysis, summarized this topic and showed that human behaviors in VR environments created with Head-Mounted Displays (HMD) closely resemble behaviors in the real world. These findings indicate that behavioral results obtained in these environments are significantly generalizable to the real world and can serve as an effective tool for replicating real-world scenarios in psychological research (Hepperle & Wölfel, 2009; Nolé et al.,2024).

Despite fundamental similarities, it should be noted that in the real world, there are physical limitations that shape many environmental characteristics and spatial experience. However, designers of virtual worlds have great freedom in arbitrarily designing many of these variables. They can adjust everything from fundamental avatar properties like speed, dimensions, and height to the most basic environmental variables like gravity and the speed of phenomena as they wish. The impact of changing these variables on the spatial experience of the environment has been the subject of much research. For example, studies by van Nes & Yamu (2021) show that participants in a VR club perceived time as passing faster and estimated longer durations. These results indicate that the speed of avatar movement and environmental elements alter the subjective experience of time by increasing temporal stimulation.

- **Movement and Avatar speed in the virtual environment**

The theoretical underpinning of the relationship between movement speed and spatial perception goes beyond direct studies in VR environments and has deeper roots in perceptual psychology and neuroscience. From Gibson's theory of perception, movement is the primary tool for discovering "affordances" in the environment, and movement speed determines the rate of this discovery. This idea is reinforced by neuroscience findings regarding place and grid cells, which show our brain relies on motor signals for spatial encoding.

Avatar movement speed in the virtual environment is one of the adjustable variables with broad effects on an individual's spatial experience. Bozgeyikli et al. (2016) conducted a comparative analysis of teleportation, joystick-based movement, and redirected walking[1] , showing that movement speed significantly affects user performance and comfort in VR. Their findings indicate that unnatural avatar speed may lead to user confusion or reduced efficiency in performing activities. Similarly, Langbehn et al. (2017) examined the role of walking speed in maintaining a sense of presence (immersion) and showed that a discrepancy between real and virtual movement speed can disrupt the sense of presence in space.

Ruddle & Lessels (2009) demonstrated that faster movement (e.g., flying or fast walking) reduces spatial learning because users rely on exploratory navigation instead of encoding and memorizing environmental cues. Further research by Xie et al. (2018) revealed a trade-off between speed and accuracy: while higher speeds reduce traversal time, they increase collision rates with obstacles. Their experiments showed that users moving at 1.5 times real-world walking speed in VR showed 30% more errors in complex environments compared to baseline speeds. Conversely, speeds less than 0.7 times real-world equivalents lead to psychological stress and increased cognitive load. More recent research has examined adaptive speed systems to balance efficiency and travel speed. For example, Singh et al. (2021) studied dynamic speed scaling where avatar speed adjusts based on environmental complexity (e.g., slowing down in crowded spaces). Their results showed a 22% improvement in task completion time without loss of spatial awareness. However, it should be noted that the hardware required for variable speed is currently complex and expensive, and most users do not have access to it.

All this research indicates the fact that human perceptual capacity is limited, and when movement speed exceeds the natural range, as cognitive load theory predicts, our perceptual system faces information overload, and critical processes like spatial learning are disrupted.

- **Effect of environmental scale**

Virtual reality, by disregarding real-world constraints, also allows unprecedented manipulation of spatial scale, which can have a profound impact on human cognition, motor behavior, and affective states. According to studies, the best realism is achieved at a 1:1 scale (Slater et al., 2010). Individuals can experience full body ownership over virtual bodies significantly different in size from their physical bodies, highlighting the malleability of self-perception in virtual environments (Piryankova et al., 2014). Nevertheless, many virtual environments utilize the specific emotional possibilities that changing scale offers to the designer.

Expansive scales create a sense of awe and perceived vastness and activate prefrontal cortex regions associated with transcendent experiences (Chirico et al., 2018). Immense virtual spaces (e.g., 50-meter-high ceilings) cause a 40% increase in Electrodermal Activity (EDA) and a decrease in heart rate (-8 beats per minute), consistent with the physiology of awe and wonder experiences (Carbone et al., 2024). Overly scaled virtual spaces (e.g., 10 times real-world ratios) reduce wayfinding and positioning accuracy by 23 to 41% due to distorted depth cues (Ruddle & Lessels, 2009).

On the other hand, in compressed scales, when virtual environment boundaries violate personal space boundaries, claustrophobic responses intensify and increase cognitive load for collision avoidance (Francová et al., 2023). Conversely, space compression, as demonstrated by the global scaling bias in memory representations, impairs perception and disrupts spatial memory encoding (Lhuillier et al., 2024).

In addition to the emotional impacts scale creates independently, this variable also has a direct relationship with "Environmental Information Density." When the scale increases, the environment can accommodate a higher volume of information. On the other hand, in environments where information is fundamental to spatial structure, individual movement creates fewer changes in their visible area (isovist), and the rate of "Environmental Information Density" can decrease. In practice, the environmental space designer must adjust and design all three variables -scale, speed, and "Environmental Information Density"- in a coordinated and simultaneous manner for a better virtual space experience.

- **Environmental information density**

A new and growing set of theories considers the surrounding environment as a rich source of data, and human movement (especially walking) as a means of collecting and accessing this data. In this paradigm, the rate of receiving this information depends on human speed in the environment, and higher speed leads to faster access to information. Humans have evolved to be able to move at their maximum physical speed in the environment while simultaneously analyzing the information they receive from the environment, predominantly visually. However, the virtual environment makes it possible to increase movement speed beyond this, and therefore the rate of information an individual receives per unit time can be greater than what the brain has evolved to analyze (Saelens & Handy, 2008; Christman et al., 2020; Zhang et al., 2024).

In fact, this research indicates the existence of an environmental variable known in recent research as "information entropy rate" or "environmental information density." This variable expresses how quickly new and useful data become available to the individual while moving through the environment (Carlson et al., 2012; Rondinel-Oviedo, & Keena. 2023; Netto et al., 2025). At high speeds, the individual quickly sees new perspectives of the environment and encounters a new set of environmental information, thus "Environmental Information Density" is higher. However, at lower speeds or in larger environments with fewer details, this process of accessing information slows down, and the individual has more time to perceive and remember the totality and details of the environment. "Environmental Information Density" is lower. Note that this "Environmental Information Density" is not the information accessible per unit location, but the information accessible per unit time during movement.

To better understand "Environmental Information Density," understanding the concept of the isovist can be helpful. An isovist is the area an individual can see in space at any given moment. The isovist is essentially the area from which the individual can receive environmental information (Daneshjo et al., 2022). Changing this area means accessing new environmental information, and when information about spatial structure is considered, Environmental Information Density can be considered as the acceleration of change in this area (isovist) over time, resulting from individual movement.

- **Search in the environment**

Since the emergence of early humans, the ability to find food sources, identify dangers, and navigate complex environments effectively has been a determining factor in evolutionary success, driving humans to explore their environment. Search behavior in human evolution involves sequential decision-making in which the individual must balance between moving in different directions to explore new areas and exploiting known areas (Moura & Menezes, 2021). Recent studies show that human movement during search is shaped by multiple constraints, including physiological, cognitive, and environmental constraints. Search strategies are under homeostatic control in the brain and are linked to various factors, including the need to move, available energy, and environmental characteristics (Stults-Kolehmainen, 2023).

Search in the environment begins with perceiving the surroundings. Then, the human brain begins to build a cognitive map of the environment; this map is a combination of new environmental information, previous experiences, and available visual evidence (Epstein et al., 2017). In familiar environments, each entry or passage through different parts improves and completes this mental map, and individuals familiar with the environment reach the goal faster and with fewer errors (Dijkstra, 2014). Spatial memory plays a vital role in human search behavior (New et al., 2011; Kerster et al., 2016). The "cognitive map" hypothesis suggests that the brain builds an integrated representation of the spatial environment that supports memory and guides future action (Maguire et al., 2017; Zhou & Yu, 2021). Cognitive maps are instantiated by place cells, grid cells, border cells, and head direction cells in the hippocampus and related structures, with grid cells in the entorhinal cortex providing a metric map of space (Hafting et al., 2005). These spatial neurons work together to create a comprehensive cognitive representation of the environment that facilitates effective search (Moser et al., 2008). In this process, short-term memory is activated for recalling details of the current path, and long-term memory for identifying general features of the building (Epstein et al., 2017).

- **Movement strategies in environmental search**

As mentioned, evolution has led to strategies for human activities, including search. Human movement strategies during search can be classified into two main categories: goal-directed movement (global search) and predictive movement (local search). Goal-directed movement often involves moving directly towards areas expected to be rewarding, while predictive movement involves strategic displacement based on information that emerges while moving through the environment and efforts to gain better access to this information (Moura & Menezes, 2021).

Studies on Hadza hunter-gatherers from northern Tanzania showed that they use mathematical patterns from nature known as Lévy walks when searching for food resources. Lévy walks describe a set of random movement patterns in which step lengths follow a power-law distribution. These patterns are recognized as optimal search strategies for sparse and heterogeneous targets (Viswanathan et al., 1999; Humphries et al., 2014). These findings indicate that Lévy walks are an important movement pattern for humans as the most complex searchers on Earth (Raichlen et al., 2014).

Area-Restricted Search (ARS) is a fundamental search strategy where searchers confine their search to a focused area to find resources (Benhamou & Collet, 2015). This pattern involves slowing down movement and increasing turning after encountering a resource or cues that increase the probability of finding additional resources nearby (Hills et al., 2013; Benhamou & Collet, 2015).

Laboratory studies on humans have shown that they typically adopt the Area-Restricted Search strategy in virtual environments. However, when targets are distributed sparsely and the environment is vast, humans also tend towards Lévy-like patterns. This indicates that humans can flexibly adjust their search strategy based on target distribution (Hills et al., 2013).

In built environments, due to the presence of numerous cues, human search strategies change. In complex or unfamiliar environments (like airports or hospitals), individuals first choose a path that provides more visibility or is equipped with more signs, and if unsuccessful, choose an alternative route based on new information (Iftikhar et al., 2021). During movement, environmental data (such as new signs, path changes, or corridor nodes) are updated, and the individual revises their route by reviewing the mental map. In crowded or multi-story spaces, repeated experience improves movement strategies and reduces search time (Epstein et al., 2017; Dijkstra, 2014).

- **Micro-behaviors of the individual in the virtual environment**

Some micro-behaviors of the individual in the built environment have been examined in research. For example, the straight-line distance an individual travels without changing direction depends on several key factors. The most important are architectural design and the presence of physical obstacles. Visual information is also very important; if a person has a direct line of sight to the goal or a prominent landmark, they are more likely to travel a longer distance in a straight line. On the other hand, uncertainty about the goal's location, lack of guiding signs, or limited visibility usually causes the individual to stop sooner, correct their direction, or change the path. Cognitive confidence, prior familiarity with the environment, and path clarity also increase the average length of straight-path travel (Jansen et al., 2011; Epstein et al., 2017; van der Zee et al., 2024).

The preferred distance of individuals from a wall while walking is influenced by multiple variables. The most important of these include individual, environmental, and neurobiological factors. From an individual aspect, levels of anxiety and neuroticism (Gifford, 2013) and past experiences (such as being a victim of violence) can increase the tendency to maintain a greater distance for a sense of security. From an environmental perspective, corridor width (Passini et al., 1980), the presence of multiple windows or doors as escape options, and lighting level (which affects perception of safety) directly influence this distance. From a neuroscience viewpoint, this behavior is rooted in ancient survival mechanisms, where the wall is perceived as a "shelter" that limits the semi-enclosed space (field of view), removes potential danger from one side, and thus reduces the brain's cognitive load for monitoring threats (LeDoux, 2012). Therefore, this distance is a dynamic adaptive behavior arising from the interaction between the individual's psychological state, the physical design of the environment, and the neural architecture of the mind for survival.

Based on findings from perceptual psychology, cognitive neuroscience, and ergonomics, the distance an individual prefers when passing a visual obstacle (such as a column, a large vase, or a low wall) results from a dynamic and unconscious assessment of the interaction between "field of view," "personal space domain," and "probability of threat occurrence." The physical characteristics of the obstacle are key variables affecting this preferred distance. The height and width of the obstacle, which determine the degree of "visual occlusion," are very important. A tall obstacle that completely covers the space behind it (like a solid wall) demands a safer and therefore larger passing distance due to creating an unpredictable "blind spot" (Gibson, 1979). The environmental context is another key variable. The presence of escape spaces or alternative paths near the obstacle reduces this distance. Also, crowded or dimly lit environments that make perceptual information processing difficult increase the tendency to maintain a greater distance.

From a neuro-evolutionary perspective, the preferred distance when passing a visual obstacle reflects an ancient monitoring mechanism in which the brain automatically calculates the probability of a predator or threat behind a visual obstacle. Neural circuits related to the amygdala and cortex are activated to create a dynamic "safety margin" to provide sufficient time and space for a potential reaction (such as detouring or sudden stop) in case of unexpected emergence of danger from behind the obstacle (Caminiti et al., 1996). Consequently, this preferred distance is an optimal adaptive strategy to ensure safety and maintain movement efficiency in complex environments.

Research Method

In the research, the relationship of three virtual environment variables -avatar speed, scale of the spatial structure, and environmental information density - which were thought to have a high impact on individual behavior in the environment, were considered as independent variables. For the first variable- avatar movement speed in the environment - three states were considered: baseline speed (equal to an individual's running speed in the real world and commonly used in computer games), twice the baseline speed, and half the baseline speed. The second variable is the scale of the spatial structure of the environment. Scale here refers to the distance and length of walls, while furnishings remain fixed and do not change with scale changes.

Three states were also considered for scale: baseline scale (close to build environment scales with wall heights of 3 meters), twice the baseline scale, and half the baseline scale. It should be noted that in tests with a variable scale, speed is constant and equal to the baseline speed of the above tests.

The third variable is "Environmental Information Density," which was introduced in the theoretical foundations of the research. The rate of new information received per unit time by an individual while moving through the environment is called Environmental Information Density. Essentially, one of the primary goals of movement is access to environmental information. When an individual enters a new part of space, they gain access to new information, which includes the structure of that part of space as well as objects within it. The less time there is between entering new spaces, the faster their access to environmental information occurs. This process is faster at higher speeds and smaller scales, and slower at lower speeds and larger scales.

It should be noted that Environmental Information Density is not an independent variable from scale and speed; it is directly related to these two variables, and an individual's speed and environmental scale are the primary variables shaping Environmental Information Density. Therefore, in the present article, this variable is not considered an independent variable but rather a combination of the two variables speed and scale. Although there is no precise definition for measuring Environmental Information Density based on speed and scale, it was assumed that doubling the speed doubles the Environmental Information Density, and doubling the scale halves the value of this variable, and vice versa.

The paradigm of this research is post-positivist, and in terms of objective, it is applied research. This study is mixed-method and consists of three parts. In the first part, the behavior of users while moving and searching in the virtual environment was categorized into strategies adopted by them. As a result of analyses performed in this part using the Delphi method, six quantitative variables of an individual's qualitative behavior in the environment, which were thought to be potentially related to speed and scale, were extracted. These variables, which include length of movement in a straight path, preferred distance from walls, preferred distance from edges, duration of stops, degree of turning during direction changes, and overall search efficiency, can be considered as dependent variables of the research.

To create the experimental floor plan, initially, a $50x^{50}$ grid area with medium complexity was considered as the overall research domain. It was decided to design a simple environment with open and closed walls like a maze within this grid for simplicity and to control confounding variables, suitable for search. To achieve this goal, architecture students were asked to design a space within this grid, only by adding and removing walls, which would facilitate movement and search while not being immediately fully comprehensible to allow for an exploratory process. After collecting the proposed plans from students (43 total), analysis and review were conducted by experts- a group of architecture professors -and one sample was selected as the main experimental environment. This sample was then virtually constructed in the Unity game engine. The construction of the environment was attempted such that the only influential variable shaping individual behavior would be the spatial structure, to highlight the effect of the two main variables -speed and scale- in the tests, and to minimize the effect of confounding variables like color and light as much as possible.

For the experimental environment of the second part of the research, which recorded individual behavior, a $50x^{50}$ meter grid area was specified. Then, architecture students were asked to design a simple environment with open and closed walls like a maze within this area.

To create the virtual environment in this research, a VR headset (Oculus Development Kit 2) was used. Movement inputs from users were received via a standard XBOX controller. Also, the created environment lacked ambient sound, and the sound element was not used in the tests.

A small initial environment was also built alongside the test environment to provide participants with better familiarity with the hardware used and to better learn movement in the environment. After initial activity and familiarization in this environment, participants were automatically transferred to the main environment and began searching there (Fig. 1). The statistical population of this study included 18 participants selected from a university student population with experience in video games. Participants were aged 18 to 28, with approximately equal distribution between men and women. Participants were asked to search for a recognizable target (a red apple on a pedestal) in the virtual environments presented to them, and their behavior was recorded by software.

A time limit of two minutes was set for each user. After this time or after finding the apple, the participant was transferred to another starting point of a different type of environment (with a different avatar speed or scale), and the test was repeated.

To record movement behaviors, a C# script was added to the Unity game engine that, at fixed time intervals (0.5 seconds), captured and saved the individual's position and viewing direction. Then, another piece of code was added to the entire program that, after the test, converted the saved positions into a series of vectors and presented the final result of the individual's behavior as an image showing their search method in the environment (Fig. 2). In total, 90 behaviors were extracted from this process, although a few of them were not used due to the individual's search behavior not fully forming.

In the third part of the research, images representing the behavior of searchers from the second stage were prepared and presented to a new set of participants (9 individuals). Also, a text defining the behavioral variables of interest to the article -such as preferred distance when passing near a wall- was provided to these individuals. They were asked to first locate the desired behaviors in the behavioral images and then quantitatively estimate the extent of these behaviors based on their perception. For example, these participants first had to specify the path the searcher moved in a straight line and then measure the length of this path. This provided the ability to quantitatively extract the mentioned dependent variables from the searchers' behavior based on the perception of the analysts in the third part (Fig. 3). The collected data were analyzed quantitatively using SPSS software and regression techniques.

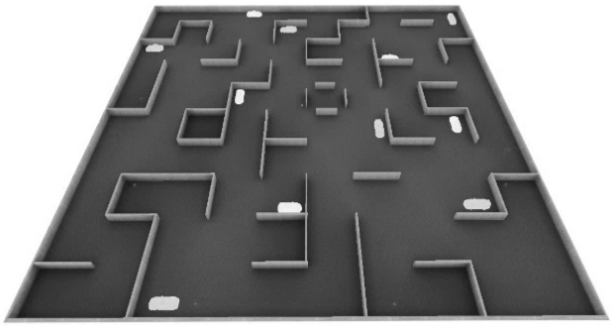

Fig. 1. Design of the virtual environment and testing in the main environment. Source: Authors.

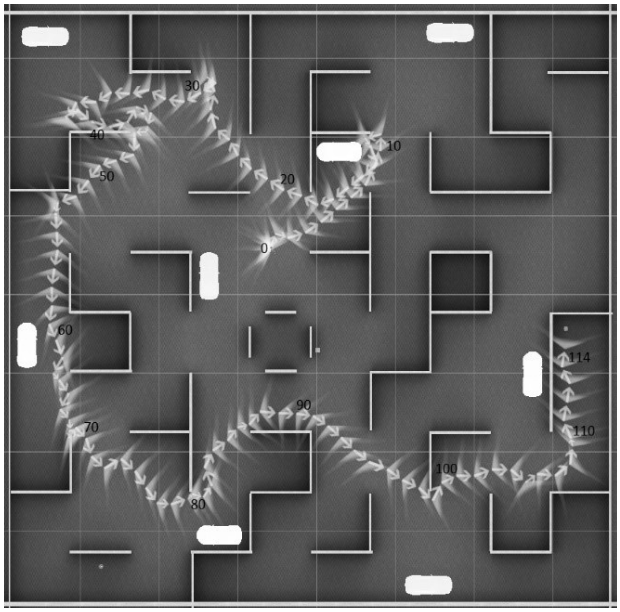

Fig. 2. The individual's behavior in the environment was translated into an image. In this image, vectors show displacement and triangles show the individual's viewing direction at a moment. Source: Authors.

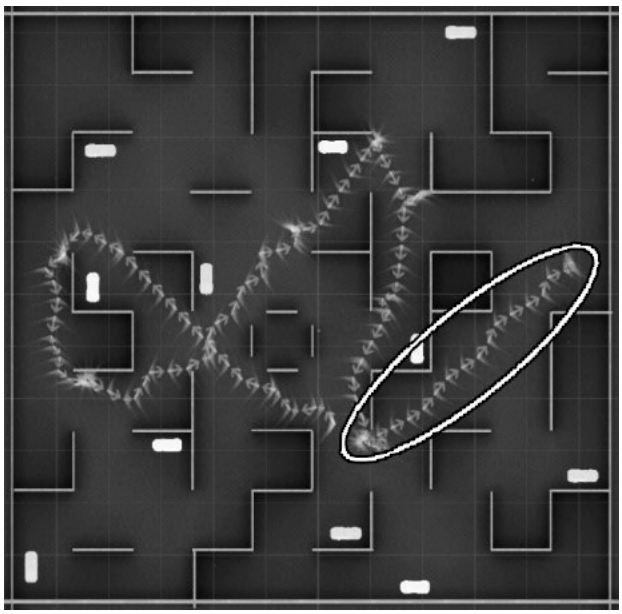

Fig. 3. The length of movement in a straight path is one of the quantitative variables extracted from the searchers' behavior. This length was extracted from images representing behavior based on the number of vectors - indicating the temporal length of the behavior - according to the opinion of the stage three participant. Source: Authors.

Findings

The behavioral characteristics examined in this research as dependent variables include 6 patterns: length of movement in a straight line; distance when passing near a wall; preferred distance from edges; time needed to look around in seconds; time to reach the goal; and degree of turning. The relationship of each of these six patterns with the independent variables of speed and scale changes was examined and is presented below.

- **Length of movement in a straight line**

Variable introduction: In many cases, segments of movement in a straight path can be extracted from an individual's movement in the environment (Fig. 3). The existence of these straight movement segments indicates the existence of momentary goal-setting during environmental search and traversal by individuals (Dijkstra et al., 2014).

The overall variable of movement in a straight line was analyzed in three ways. First, the time moving in a straight line was considered, then the length of this movement was seen as the dependent variable. It should be noted that because avatar speed in the test is variable, movement time and movement length do not have a one-to-one relationship. In the third state, movement length relative to environmental scale (movement length divided by scale) was seen as the independent variable. Given the removal of the scale effect in the third state, this variable has the most connection with spatial structure. Also, in this state, the scale is removed from the independent variables of the regression.

Table 1 shows the regression results between time moving in a straight path and the independent variables. The regression results show that the overall model explains very little variance in the dependent variable (R^2 = 4.2%), and other important variables have likely been omitted. Among the stated independent variables, only "Speed" and "Environmental Information Density" are statistically significant predictor variables, while "Scale" has no significant effect ($p = 0.4$).

Table 2 shows regression results between the length of a straight path and independent variables. Based on the results, this model explains 44% of the variance, which is a relatively good result. "Speed" is the dominant influential variable with a large positive effect (Beta= 0.81), and "Environmental Information Density" has a smaller but significant negative effect (Beta= -0.23). "Scale" appears insignificant in this model ($p=0.57$) and can be removed.

Results obtained from regression between length of movement in a straight path relative to scale (length divided by scale) and independent variables (Table 3) indicate a strong relationship between independent and dependent variables ($R=0.69$). Also, the model explains 48% of the variance of the dependent variable, which is considered strong explanatory power in many research fields. The adjusted R^2 (0.48) is very close to R^2, indicating that all independent variables are significantly

Table 1. Regression results between time moving in a straight path and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	1.04	0.42	0.25	2.48	0.01	0.205	0.042	0.035	1.904
Scale	-0.38	-0.40	-0.09	-0.96	-0.34				
Environmental Information Density	-1.16	0.39	-0.39	-2.97	0.00				

Table 2. Regression results between the length of movement in a straight path and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	5.04	0.48	0.81	10.41	0.00	0.66	0.44	0.44	2.19
Scale	-0.26	0.46	-0.04	-0.57	0.57				
Environmental Information Density	-1.03	0.45	-0.23	-2.31	0.02				

Table 3. Regression results between length of movement in a straight path relative to scale (length divided by scale) and independent variables except scale. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	1.72	0.32	0.26	5.39	0.00	0.69	0.48	0.48	2.25
Environmental Information Density	2.32	0.23	0.49	10.09	0.00				

related to the dependent variable. "Environmental Information Density" has the strongest positive effect (Beta=0.49), followed by "Speed" (Beta=0.26). Both variables also have clear directional effects, and an increase in either variable increases the result.

Preferred distance when passing near a wall

Variable introduction: In both real and virtual environments, walls are a common and familiar element. It often happens that individuals move along walls. The distance from the wall that an individual chooses for their movement can be influenced by a set of variables (Fig. 4).

Preferred distance, like movement in a straight path, was considered from two angles in the present research. This variable was first obtained in raw form with real dimensions (meters) and then examined as a ratio of the environment (divided by scale).

Results of examining the variable of preferred distance from walls are presented in Table 4. Based on these results, this model explains only 18% of the variance, indicating weak predictive power, although the small standard error (1.20) shows precise estimates. Among the three independent variables, only "Scale" is statistically significant and has a moderate positive effect (Beta=0.32). The effects of "Speed" and "Environmental Information Density" in the model are negligible and not significant ($p > 0.05$).

Dividing the preferred distance from walls by scale is meaningful in that it shows the distance taken from the wall relative to the total width of the passage. Defining the variable this way yields the regression results in Table 5. Based on the results, the overall model explains limited variance (16%). While both independent variables are highly significant ($p<0.001$). These two variables have opposing directional effects. Speed decreases the result (β=-0.48) while Environmental Information Density increases it (β=0.54). Environmental density also has a slightly stronger effect.

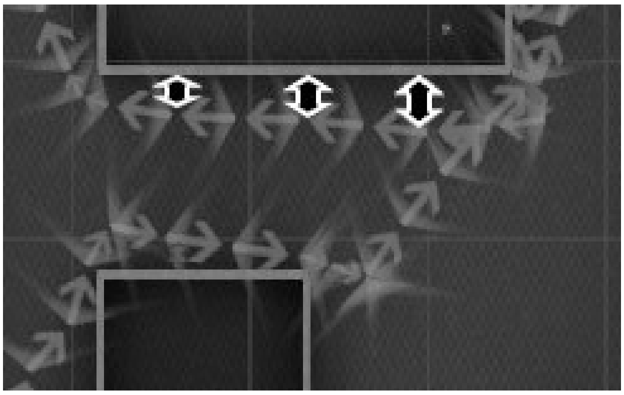

Fig. 4. Preferred distance when passing near a wall. Source: Authors.

- **Preferred distance from edges when passing**

Variable introduction: It often happens that an individual passes by an obstacle in their path in the environment. In the real world, the distance from this obstacle when passing is often chosen unconsciously based on human experience. In the virtual world, this distance is also chosen unconsciously (Fig. 5). The variable of preferred distance from edges was also considered in two ways: raw and divided by scale.

Regression results for the variable of preferred distance from edges in raw form are presented in Table 6. Analyzing the table shows a moderate correlation between independent and dependent variables (r=0.45), and the model has moderate explanatory power (R^2=0.20). Scale is the strongest predictor variable (Beta=0.64, $p<0.001$), Environmental Information Density has a moderate effect (Beta=0.34, p=0.03), and Speed shows no significant effect (p=0.35).

If the preferred distance from edges is defined relatively and divided by scale, the results of Table 7 are obtained. Based on these results, the model explains only 12% of the variance of the result, indicating its weakness. Environmental Information Density is the strongest predictor variable (Beta=0.45, $p<0.000$), and Speed also shows a negative effect (Beta=-0.23, $p<0.00$).

Table 4. Regression results between distance when passing near a wall and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	0.16	0.41	0.06	0.38	0.70	0.42	0.18	0.16	1.20
Scale	1.00	0.49	0.32	2.05	0.04				
Environmental Information Density	-0.30	0.43	-0.15	-0.70	0.49				

Table 5. Regression results between preferred distance when passing near a wall relative to scale and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	-0.46	0.15	-0.23	-3.04	0.00	0.34	0.12	0.11	0.98
Environmental Information Density	0.70	0.12	0.45	5.95	0.00				

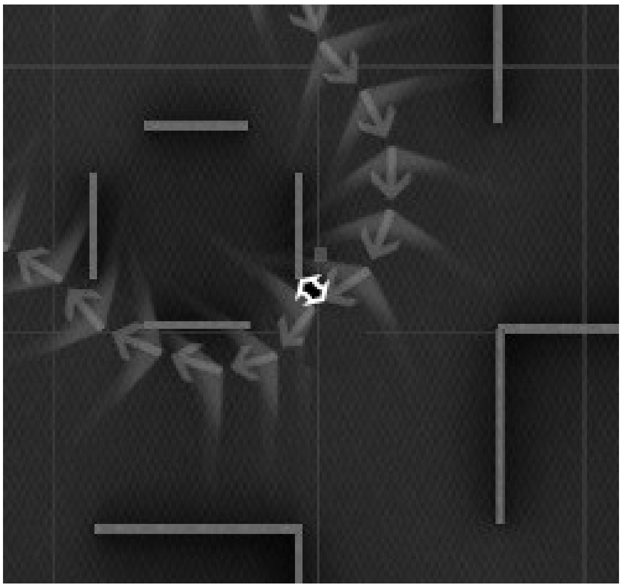

Fig. 5. Preferred distance from edges. Source: Authors.

- **Duration of looking around**

Variable introduction: During environmental search, it sometimes happens that an individual feels the need to stop and look around before continuing. It was thought that the time an individual spends studying the environment might be related to the scale of the environment. Unlike previous variables, this variable has no significant relationship with scale and spatial structure and was therefore considered in its primary form based on time.

Regression results for this variable (Table 8) show that the model explains only 7% of the variance and is very weak. No significant predictor variables were found (all p-values > 0.05), while Environmental Information Density shows the largest (but non-significant) effect (Beta=0.27).

Table 6. Regression results between preferred distance from edges when passing and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	-0.21	0.23	-0.11	-0.93	0.35	0.45	0.20	0.19	0.90
Scale	1.45	0.27	0.64	5.41	0.00				
Environmental Information Density	0.52	0.24	0.34	2.18	0.03				

Table 7. Regression results between preferred distance from edges when passing relative to scale and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	-0.46	0.15	-0.23	-3.04	0.00	0.34	0.12	0.11	0.98
Environmental Information Density	0.70	0.12	0.45	5.95	0.00				

Table 8. Regression results for time spent looking around and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	-0.03	0.47	-0.02	-0.07	0.95	0.27	0.07	0.03	0.96
Scale	-0.04	0.51	-0.02	-0.09	0.93				
Environmental Information Density	0.38	0.48	0.27	0.79	0.43				

Besides the duration of each look around, which seems unable to be significantly affected by the research's independent variables, the number of occurrences of these looks in each search process was also considered. The results obtained are seen in Table 9. Given that values are summarized in this way, regression was not used for its analysis. Free analysis of these results shows no significant relationship between the number of looks around and the independent variables. It seems speed has the highest relationship with the number of stops and looks around.

Table 9. Average number of looks around in different conditions. Source: Authors.

Average number of head turns	Environmental Information Density	Scale	Speed
5	2	1	2
2.7	0.5	1	0.5
3	1	1	1
3.1	0.5	2	1
2.1	2	0.5	1

- **Degree of turning in direction change**

Variable introduction: It often happens that during environmental search, after traveling a path that is generally straight, an individual decides to change their direction of movement and move on a new path (Fig. 6). Typically, the new path has an angle with the previous path. The amount of this angle can also be considered the degree of turning when changing direction. In the present research, the relationship between the degree of turning when changing direction and the independent variables of the research was examined.

Results examining this variable (Table 10) show: Based on these results, the relationship between independent and dependent variables is meaningless ($p > 0.05$), and standard errors are very high. These results indicate the model is overall useless and meaningless.

Regression results for the model in this variable are also very weak (adjusted $R^2 = 0.01$ vs. $R^2 = 0.12$), and the model has weak explanatory power (Table 11). Also, there are no significant predictor variables, and standard errors are close to the size of coefficients, indicating unstable results ($p > 0.05$).

- **Time to reach goal (Search behavior efficiency level)**

Variable introduction: Efficiency refers to the degree of success in finding the goal within the given time and is a general concept. In the present test, since efficiency was not the only dependent variable, the test was designed such that goals appeared after a while from the start of the search, and the search ended even if the participant was unsuccessful within 2 minutes. Considering this, efficiency was considered as the success rate in each condition, which is observable in Table 12.

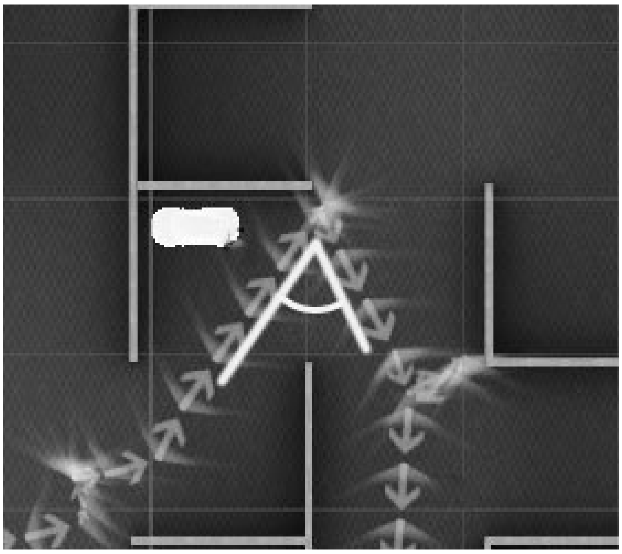

Fig. 6. "Degree of turning in direction change" is the average angle the searcher chooses between their previous and new path. Source: Authors.

Due to the small number of values, regression was not used to analyze this table. However, the table values indicate a positive relationship between Environmental Information Density and individual search efficiency.

Table 10. Regression results for turning in direction change and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	-0.03	0.47	-0.02	-0.07	0.95	0.27	0.07	0.03	0.96
Scale	-0.04	0.51	-0.02	-0.09	0.93				
Environmental Information Density	0.38	0.48	0.27	0.79	0.43				

Table 11. Regression results for the number of turns in direction change and independent variables. Source: Authors.

	Coefficients					Model Abstract			
	B	Std. Error	Beta	t	Sig.	R	R Square	Adjusted R-Square	Std. Error of the Estimate
Speed	1.82	1.82	0.44	1.00	0.33	0.35	0.12	0.01	2.13
Scale	-1.09	1.76	-0.24	-0.62	0.54				
Environmental Information Density	-0.56	1.76	-0.18	-0.32	0.75				

Table 12. Success rate of participants in different conditions. Source: Authors.

Speed	Scale	Environmental Information Density	Success rate
2	1	2	71
0.5	1	0.5	49
1	1	1	57
1	0.5	2	69
1	2	0.5	16

Conclusion

Results show that avatar speed and environmental scale influence a set of movement behaviors, and by adjusting these two variables, the spatial experience can be brought closer to what the designer intends.

Avatar speed correlates with the length of individual movement in a straight path (both in its pure form and its relative form), and the higher the avatar speed, the longer the movement in a straight path. On the other hand, "Environmental Information Density" has a significant negative relationship with the time moving in a straight path and also the length of movement in a straight path. While this variable has a positive and direct relationship with the relative length of this movement. These results together indicate that the searcher abandons movement in a straight path when they have obtained a certain amount of information along this path or have spent time on it. Therefore, complicating the environment and reducing avatar speed can reduce the path the searcher travels directly, and vice versa.

Avatar speed shows a significant, weak negative relationship with the preferred and relative distance from walls, and also a strong negative relationship with the preferred and relative distance from edges. The negative relationship of speed with these two variables indicates that at higher speeds, the individual tends to get closer to the edges and walls of the environment. Proximity to edges and walls effectively reduces the individual's visible area (isovist) from one side and creates a somewhat tunnel vision. "Environmental Information Density" also shows a strong direct relationship with preferred distance from edges, and the searcher in environments with high "Environmental Information Density" takes distance when passing edges. To understand this phenomenon, it should be noted that passing close to edges at high speed suddenly changes the individual's visible area (isovist), and the individual suddenly enters a new environment. These two phenomena indicate that in environments with high avatar speed and "Environmental Information Density," the searcher tries to control the rate of changes in the visible area (isovist) and consequently access to environmental information by reducing distance from walls and increasing distance from edges.

On the other hand, scale has a significant and positive relationship with preferred distance when passing near walls and also edges. This clearly shows that preferred distance from walls and distance from edges follow the overall scale and spatial structure of the environment, and humans generally consider a proportion of the environmental scale in choosing these values. Attention to the effects of the stated variables helps designers estimate at what distance an individual will pass by walls and edges of the environment, and enhance the spatial experience based on this.

Considering the results obtained from this research and comparing them with existing literature, it can be understood that while previous studies have mainly examined the independent impact of various factors on navigation in virtual environments, the findings of this research, by simultaneously exploring three fundamental variables, provide a more comprehensive and systematic understanding. For example, confirming the relationship between avatar speed and increased traversal of straight paths aligns with classic findings in perceptual-motor psychology, but the main innovation becomes apparent here: this research shows that this effect can be moderated by other variables like “Environmental Information Density.” This finding goes beyond studies that have only considered single-variable effects and ignored the complex interaction of these factors.

Furthermore, the key finding of this research regarding “preferred distance from walls and edges” distinguishes it from many studies. Although the concept of isovist (visible area) itself is known in spatial design literature, this research quantitatively shows how users actively try to control the rate of isovist change and manage information load by adjusting their distance from spatial boundaries. This adaptive strategy explains why users take a greater distance from walls in larger -scale environments- a phenomenon less addressed by previous research. Overall, these results not only confirm past findings but also, by showing the dynamic interaction of variables and the causal mechanisms behind movement behaviors, provide a more advanced and practical framework for the informed design of virtual environments.

For future research, it is suggested that studies specifically and independently on Environmental Information Density be conducted, independent of speed and scale, by creating environments that are visually crowded or sparse, and the relationship of this variable to movement behaviors be examined. On the other hand, efforts to define standard and meaningful variables for individual behavior in the environment can pave the way for much research in environmental psychology.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Endnotes

1. Redirected Walking is a VR navigation technique that enables users to explore a virtual world that is significantly larger than the tracked workspace. With this approach, the user is guided through manipulations applied to the displayed scene, causing users to unconsciously compensate for the motion of the scene by changing their position and/or reorienting themselves.

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