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Challenges and insights of transferring animal maze studies principles to human spatial learning research

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Maze tasks, originally developed in animal research, have become a popular method for studying human cognition, particularly with the advent of virtual reality. However, these experiments frequently rely on simplified environments and tasks, which may not accurately reflect the complexity of real-world situations. Our pilot study aims to transfer a multi-alternative maze with a complex task structure, previously demonstrated to be useful in studying animal cognition, to studying human spatial cognition. The challenges to be resolved at this stage included developing a virtual maze and selecting an appropriate instruction that will elicit processes similar to those observed in animal models. A virtual maze was developed, and two types of instructions were provided to the participants: (1) to collect coins; (2) to interact with the maze in order to draw its structure after the game. The results indicate that a more structured instruction with a clear attainable goal ("collect") prompted more in-depth exploration and engagement with the key elements of the maze, eliciting processes similar to those of animals. While the maze demonstrates promise as a tool for comparative studies, it also has the potential to uncover different aspects of human cognition.

Keywords Virtual maze, Spatial navigation, Spatial cognition, Animal research

The ability to identify locations, landmarks, and goals belongs to the fundamental cognitive processes enabling the mobile organisms to navigate their environment with precision[1,2]. Cognitive mechanisms involved in storing, processing, and retrieving spatial information are complex and multifaceted. To comprehend this complexity, spatial cognition has been reduced to its various aspects, each studied through specific testing procedures. Maze-type experiments have been employed as a means of assessing spatial abilities in animals for a long period of time. A number of studies have since employed a variety of maze types, including the Morris Water Maze, T-maze, and radial arm maze, in order to gain insights into the processes underlying spatial navigation[3–6].

The advent of virtual reality (VR) has revolutionized the field of cognitive research, with maze tasks becoming a prevalent tool for studying human spatial cognition[7,8]. VR offers the possibility to create immersive and controlled experimental environments[9–12]. Thus, in the past few decades, there has been a growing interest in transferring the experimental settings originally designed for animals into those with humans using VR technology[13,14].

The tasks, such as the "open field" maze, the "T-maze", the "8-arm maze" and other mazes, are popular due to their simplicity[15–17]. However, the experiments often rely on simplified behavioral models, which may not accurately reflect the complexity of real-world situations. They yield a quick final result and do not require subjects to form a comprehensive representation of the problem or the environment. While effective in modeling particular elements of intelligence, the behavioral responses in these tests are typically limited to simple reactions (e.g., running to the target, running to the feeder). As a result, these tasks do not require the formation of a stable and purposeful sequence of actions, which limits the complexity and richness of the phenomena that can be studied[16,18].

In animal studies there are mazes that are more challenging to navigate and reach the goal compared to those mentioned earlier. One example of this kind is the Lashley maze[19,20]. In these mazes, the task difficulty

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is increased by incorporating numerous dead ends, which increases the number of erroneous paths. However, despite their increased difficulty, there is still only a single correct solution to the problem. While subjects can explore freely, the experimental design ensures that only one route leads to success. Therefore, cognitive activity is also not fully modeled in these tasks, no matter how difficult they appear. Thus, it is crucial to elaborate an approach to creating a task that does not reduce the participants' response to a single action but requires a sequence of actions with more than one equally correct way to solve it. Based on these principles, it might be possible to evaluate the solution not only in terms of its speed and accuracy, but also to reconstruct the process of finding that solution, in other words, to reconstruct the learning process.

These challenges were effectively addressed in animal (hedgehogs, rodents, non-human primates, etc.) studies that investigated their ability to solve problems in tasks related to foraging using a system-information (SI) approach[21]. This approach relies on two important aspects: system and information. The systemic aspect refers to the ability to evaluate various aspects of cognitive activity within a single task. Within the context of animal behavior, this includes assessing the locomotor activity, the spectrum of unconditional reactions (freezing, grooming, etc.), conditional reactions (trials, rewards, errors), cognitive activity in dynamics. The purpose of this evaluation is to determine how these aspects, including analytical and synthetic activity, and unconditional reflex, are conjugated as parts of a complex activity within a single task. The information aspect refers to implementing certain principles of information theory[22], with the core being the quantification of spatial complexity in the experimental environment by measuring the amount of uncertainty in the choice of route implementation. A cyclic foraging task combined with multialternative (refers to the presence of multiple equally viable solutions to a given problem) environments, symbolic recording of behavior and a multilevel system of behavioral analysis allowed the researchers to describe the mechanisms of animals' cognitive activity under normal conditions and under conditions involving local and systemic impacts on the central nervous system[23–30]. The approach enabled researchers to identify the required and optimal conditions for cognitive activity in situations involving strict conditioning and free choice, depending on the complexity of the environmental structure, the degree of food deprivation, the duration of information exposure, and the inter-experimental interval. The system-information approach has demonstrated sensitivity in studying spatial learning in animals. Specifically, research on BALB/c and F1 (C57BL6/DBA/2) mice has shown that an animal's first interaction with its environment influences the development of later stereotyped behavior in that environment[31,32].

The results of this line of research are rich and varied. However, our pilot study aims to specifically examine the behavioral patterns of humans in multialternative situations previously observed in animal models. In particular, maze exploration in animals that succeeded in solving the task (or "learning") began with circular routes with minimal or no reinforcement. This was followed by routes that satisfied the principle of maximum reinforcement (collecting two reinforcements per trial) but not the principle of minimum action. The final stage of learning consisted of committing fewer errors and optimizing behavior to a solution that satisfies both the principle of maximum reinforcement and the principle of minimum action[32].

In line with the aim of applying the basic principles of SI approach to study human spatial learning we devised a multialternative virtual maze comprising a task and environmental complexity that was designed to effectively guide participants towards the optimal solutions discovered in animals. The principles behind the methodology adapted from earlier animal studies were as follows[21]:

- Behavioral response should not originate from a single action of simply approaching a goal. Instead, it should be formed through the process of experience and require organization. The task should be designed to promote the development of consistent and coordinated behavior, rather than a single action that exists in the behavioral arsenal until the moment of learning.
- The orientation of the target must not align with the movement vector (i.e. upon entering the maze a subject must not see a target and/or be presented with a linear route to reach it).
- Key elements of the task (e.g., button, doors, coins) should be spaced apart to avoid simultaneous processing.

We preserve the spatial structure of the maze used in animal studies and employ one of the most optimal maze configurations that was successful in gaining insights into animal cognitive processes during maze exploration[21,30]. Transferring this methodology to studying human spatial learning presents significant challenges. One particularly important challenge is ensuring that comparable cognitive phenomena are observed and examined in diverse species. Therefore, the first difficulty we encounter is the necessity to provide a clear instruction to the task to elicit the response similar to animals'. In this study two types of instruction are provided to participants: one explicitly emphasizes spatial aspects of the game to, presumably, guide participants into constructing a spatial representation of the environment i.e. stimulate spatial learning; and the other explicitly focuses on objectives related to rewards. Second, we test how participants draw the structure of the experimental environment with its key elements, expecting that this should serve as a measure of their understanding of the maze layout and problem situation. This should give us some information about how effectively participants are able to translate their navigational experience into a holistic spatial representation, depending on the instruction given. The main objectives of this pilot study are to examine whether the spatial learning process varies depending on the type of instruction and to identify the instruction that yields results comparable to those observed in animal studies. The overarching aim is to gain insight into the process of elaborating optimal solutions in spatial problem-solving in humans. In particular, the study focuses on determining the number of trials required for participants to reach optimal solutions, thereby quantifying the learning process.

Results

First, we analyzed behavioral parameters of in-maze performance under two types of instruction. A Chi-squared test showed a significant association between the instruction type and the learning criterion ($\chi^2(1) = 22.7$,

Learning criterion		Instruction		Total
		Collect	Draw	
Yes	Observed	21	3	24
	% within column	67.7%	9.4%	38.1%
No	Observed	10	29	39
	% within column	19.2%	90.6%	61.9%
Total	Observed	31	32	63
	% within column	100.0%	100.0%	100.0%

Table 1. Contingency table of association between the type of instruction and the ability to reach the learning criterion.

Key variable	Grouping variable	Group	n	Mean	Median	SD	SE	Min	Max	Range
Number of trials	Instruction	Collect	31	11.3	11	1	0.18	10	14	4
		Draw	32	4.34	3.5	3	0.51	1	12	11
	Accuracy	0	14	6.07	6	3.50	0.93	1	12	11
		1	49	8.22	10	4.15	0.59	1	14	13
	Learning criterion	No	39	5.72	4	3.82	0.61	1	13	12
		Yes	24	11.0	11	1.63	0.33	5	14	9
Learning rate	Instruction	Collect	21	6.95	6	2.36	0.47	3	12	9
		Draw	3	3.67	3	1.15	0.48	3	5	2

Table 2. Descriptive statistics of key variables based on instruction type, the accuracy of maze reproduction and the learning criterion.

Accuracy		Learning criterion			Instruction		
		No	Yes	Total	Collect	Draw	Total
0	Observed	14	0	14	3	11	14
	% within column	35.9%	0%	22.2%	9.7%	34.4%	22.2%
1	Observed	25	24	49	28	21	49
	% within column	64.1%	100%	77.8%	90.3%	65.6%	77.8%
Total	Observed	39	24	63	31	32	63
	% within column	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Table 3. Contingency tables of associations between the accuracy of reproducing the structure of the maze and (I) the ability to reach the learning criterion and (II) the type of instruction.

$p < 0.001$), indicating that the number of participants reaching the learning criterion (i.e. using optimal solutions twice in a row) was greater in the collect group (see Table 1). Because of this difference ($n_{collect}$= 21 vs. n_{draw}= 3), we did not compare the learning rates between the groups by instruction. The descriptive statistics of the learning rates by instruction are presented in Table 2. Using the Mann-Whitney U test, we found that there was a significant difference in the number of trials between the groups by instruction (U = 51.50, $p < 0.001$), with the participants in the "collect" group producing a greater number of trials on average. We then compared the number of trials in groups divided by achieving the learning criterion and found a statistically significant difference (U = 137.00, $p < 0.001$) as well, indicating more trials on average among the participants who achieved the criterion. Then, we compared the number of trials between the participants who accurately reproduced the maze structure and those who failed to: no statistically significant difference was revealed (U = 236, $p = 0.076$). Descriptive statistics for the number of trials by instruction type, accuracy of maze reproduction and the learning criterion are presented in Table 2. To investigate the relationship between the number of trials and the learning rate, we computed Spearman's rank correlation, which showed a significant moderate positive correlation ($r(22) = 0.631$, $p < 0.001$).

We then examined the associations between the remaining key variables using the Chi-squared test. There was a significant relation between the accuracy of the maze reproduction and the learning criterion ($\chi^2(1) = 11.1$, $p < 0.001$; see Table 3). Another significant association was observed between the accuracy of reproducing the maze structure and the type of instruction ($\chi^2(1) = 5.56$, $p = 0.018$; see Table 3).

Route preferences in optimal solutions

Participants in the "collect" group that used optimal solutions twice in a row demonstrated clear preferences in their routes.

For clarity, we categorized the optimal solutions into three segments: the route from the entrance to the first coin (1), the route between the first and second coins (2), the route from the second coin to the exit door (3).

For segment 1, in 75.6% of cases, participants favored approaching the first coin via the center ("O-Q"): 46.7% approached the coin located near "C2" and 28.9% approached the coin located near "C1". In 24.4% of cases, participants opted for diagonal paths: 14.4% approached via location "B" and 10% approached via location "K" to the nearest coin. For segment 2, among the 21 participants analyzed, 100% consistently selected the direct route between the coins ("G-H or H-G", depending on which coin was collected first). Segment 3: a majority of participants (91.1%) exited using a route adjacent to the wall ("Z-U-T" or "D-S-A"), depending on the position of the second coin. The remaining 8.9% of participants exited via the routes "B-N" or "K-L", depending on the position of the second coin.

In examining the route choices in three participants in the "draw" group that achieved learning criterion we found that all routes in segment 1 were implemented through the center ("O-Q"). Specifically, 57.1% of the cases involved approaching the first coin at point "C2", while 42.9% were directed towards point "C1". For segment 2, all routes were implemented through direct points ("G-H or H-G") between the coins as in the group "collect". For Segment 3, a significant majority of cases (92.9%) implemented a route adjacent to the wall ("Z-U-T" or "D-S-A"). The remaining cases implemented an exit route "K-L".

Additional analyses

First, we compared the overall duration of the game between the "collect" and "draw" groups: significant differences were found ($U = 185$, $p = 0.034$, $r_{rb} = 0.362$), with the "collect" group playing the game longer than the "draw" group. When comparing the amount of time spent in the starting zone before first four trials (we only compared the first four trials as this was the average number of trials completed by the "draw" group; taking the next (5th, 6th etc.) trials would reduce the sample size of the "draw" group, thus making the results of the analysis less reliable) and the duration of the trials themselves, we found that there were differences in the time in the starting zone before the 1st ($U = 149$, $p = 0.004$, $r_{rb} = 0.486$), the 2nd ($U = 165$, $p = 0.036$, $r_{rb} = 0.365$), and the 3rd ($U = 148$, $p = 0.047$, $r_{rb} = 0.356$) trials, with the "draw" group spending more time in there (see Fig. 1); no significant differences were observed in the time in the starting zone before the 4th trial ($p > 0.05$). Also, no statistically significant differences between the "collect" and "draw" groups were found in the time spent in

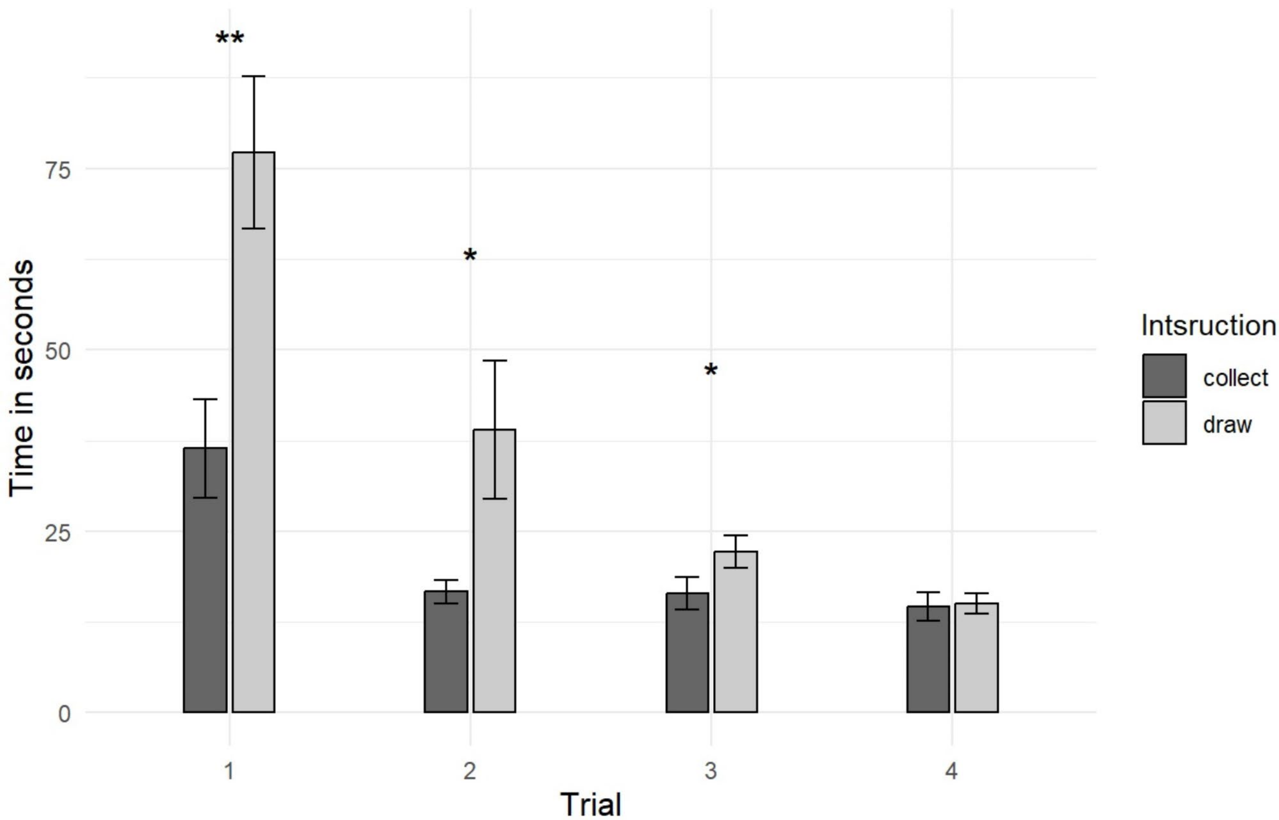


Fig. 1. Comparison of time spent in the starting zone across four trials between the "collect" and "draw" groups. * $P < 0.05$, ** $P < 0.01$.

the multialternative subspace during the first four trials. Please, refer to Supplementary Table 1 for descriptive statistics and the results of the Mann-Whitney analysis.

Trial-to-trial comparisons of the parameters "trial duration", "time in the starting zone" and "number of turns" were performed within each group and showed that: (1) the "collect" group across seven trials (a mean number of trials needed to elaborate optimal solution) demonstrated a steady decrease in time spent in the starting zone ($\chi^2(6)=42.5$, $p<0.001$) and an uneven decrease in trial duration ($\chi^2(6)=21.4$, $p=0.002$) and number of turns ($\chi^2(6)=25.1$, $p<0.001$) within each trial (the parameters that are inherently related, as more time spent in a maze implies more active turning to navigate in it); (2) there were no significant changes in trial duration ($\chi^2(3)=2.30$, $p=0.512$), as well as in the number of turns ($\chi^2(3)=2.06$, $p=0.561$) in the "draw" group across four trials (an average number of trials that the participants completed), however, the time spent in the starting zone decreased ($\chi^2(3)=14.7$, $p=0.002$). Please, refer to Supplementary Table 2 for descriptive statistics and the results of Durbin-Conover post hoc comparisons.

Discussion

Comparative studies are of fundamental importance as they help identify universal cognitive mechanisms across species, while also highlighting unique aspects of human cognitive activity[33]. Understanding these similarities and differences can provide deeper insights into the fundamental principles of learning and cognition. To make such comparisons it is essential to transfer efficient methodologies from animal to human studies, necessarily taking into account the specificities of both species. The primary objective of this study was to determine how the spatial learning process initiated in the multialternative maze (originally used to study cognition in animals)[21] is influenced by different instructions and to identify which instruction yields results comparable to those found in animals.

Unlike rodents in which engaging with the maze is conditioned by their inner physiological need to satisfy hunger[34], humans require specific instruction that will elicit this "need" (or "motive") to explore and memorize the maze. This poses a significant challenge in ensuring that comparable cognitive phenomena are studied. The results of our study showed that the participants in the group instructed to collect coins had significantly more trials and longer overall duration of the game, i.e. engaged with the key elements of the maze more than the group instructed to draw it. An interesting finding was that participants in the "draw" group spent more time in the starting area compared to the "collect" group during the first three trials, but this difference disappeared by the fourth trial. This suggests that the type of exploratory activity may differ between the two instructions during the initial trials. The results also indicate that a total of 67.7% of participants in the "collect" group managed to use optimal solutions twice in a row compared to only 9.4% in the "draw" group. Additional analyses showed that, in the "collect" group, the time spent in the starting zone, the duration of exploration within the multialternative subspace, and the number of turns made within it decreased across the seven trials. These patterns reflect the process of learning the environment and gradually developing optimal solutions. These results suggest that the "collect" instruction encouraged more extensive exploration and interaction with the maze, likely because it promoted a greater number of trials. Furthermore, the number of trials was found to be bigger among the participants, who managed to reach the learning criterion. This finding is consistent with the positive correlation observed between the learning rate and the number of trials, showing that more trials are needed to elaborate optimal solutions and to be able to use them repeatedly. These results align with animal studies in which animals progress from exploratory behavior to optimal pathfinding adhering to the principle of minimum action and maximum reinforcement[21]. Humans, however, reached optimal solutions much faster than rodents. Previous studies have shown that, for example, mice required 83.1 ± 8.2 trials to form optimal solutions[32] while human participants that were given the instruction to collect coins needed 6.95 ± 2.36 trials. Thus, it appears reasonable that the cognitive process unfolding in our problem situation is analogous across species and its driving forces are also similar (reducing uncertainty, maximizing reinforcement, optimizing actions). So, we may speculate that, during evolution there was a "cost reduction" in cognitive effort in terms of time spent.

The results obtained also highlight the necessity of addressing the question why the instruction to draw the maze did not yield the processes comparable to those observed in rodents and why this instruction did not encourage a sufficient number of trials for forming optimal solutions in most participants. One potential explanation may lie in the nature of the motivation elicited[35]. The "draw" instruction might have imperatively imposed a "need" to memorize the maze upon the individual without affording them the opportunity to create it themselves. This could have resulted in their behavior being motivated primarily externally. The instruction was also quite vague concerning what the final result had to look like as well as how to engage with the maze to successfully complete the task. The instruction to draw the maze relied on a more subjective set of criteria. Participants needed to determine for themselves what aspects of the environment were most relevant and worth attending to in order to accurately reproduce its layout. This task required them to actively define and structure the problem, which was inherently not so well-defined. This lack of specificity might have introduced an excessive degree of uncertainty and novelty, potentially increasing anxiety[36] and presumably disrupting exploratory activity[37]. Additionally, the feedback, required to maintain targeted exploratory behavior in the maze, was also lacking (the number of collected coins did not serve as a measure of progress under this type of instructions). In contrast, the "collect" instruction presented a clear and achievable task which incorporated the exploration and memorization as inherent components of organized activity[38] of collecting coins. Therefore, we hypothesize, the motive to explore and remember was generated by the participants themselves, making those activities motivated "intrinsically"[39]. As the necessity for action was not externally derived but rather internally generated by the participants, the observed behavioral patterns were more akin to those observed in rodents during their physiologically (internally) driven maze exploration. The insights from the comparative affective neurosciences to a certain degree support this explanation[40]. They suggest that human intrinsic motivation can be traced to ancient mammalian motivations for exploratory behavior. It is therefore essential to give careful consideration to the motivational aspects of human activity when transferring and applying research methodologies devised for animals to the study of human cognition, particularly when adapting methods that require providing an instruction.

Different instructions can promote distinct types of interaction with the environment and influence how people learn from that interaction. The study by Lhuillier et al.[41] shows that the nature of learning — active or passive — can influence spatial cognition. Our results, in conjunction with previous research, demonstrate the need to carefully define the problem and tailor instructions, as the type of interaction significantly impacts the type of spatial knowledge acquired.

We also observed a relationship between the accurate representation of key elements of the maze, its overall structure, and the formation of optimal solutions. The map drawing served as a considerable source of information about the integration of the space the participants never saw as a whole. To perform that task, they had to combine different views of the space into one representation. The creation of a spatial map appears to be a critical step in problem solving[18,42]. But it raises important questions: can a sequence of actions or strategies for solving the task be developed without first forming a spatial map, or is the creation of such a map a necessary intermediate step? These issues warrant further investigation in complex problem-solving tasks. Future studies should ensure that solutions have multiple equally possible outcomes, and include larger samples with more advanced methods for assessing drawing accuracy and spatial representation formation.

A distinctive feature of our method is a large set of equally possible options to solve the task. For example, the optimal tactic has 24 route realizations that differ in the order of passing through the compartments (refer to Table 4). This fundamentally distinguishes this approach from other situations where complexity is determined by the number of dead ends[19,20]. Although multiple optimal solutions were available for implementation, participants demonstrated a clear preference for specific routes. In the majority of cases, participants who utilized optimal solutions in consecutive trials commonly reached the first coin by navigating through the center of the maze, moved between the first and second coins via the direct route, and exited using routes adjacent to the walls. These findings suggest that certain routes may be perceived as more efficient, highlighting consistent spatial navigation strategies despite the availability of multiple choices. In further studies, it is also important to compare the complexity of maze structures, as the current structure may have been relatively simple for humans. Increasing the complexity may provide more insight into the cognitive strategies used.

This is a pilot study, and while the maze holds promise for studying behavior and cognition in complex environments, it has two major limitations. The first is that the assessment of spatial representation requires the use of more objective methods. Specifically, our future studies will incorporate the drawing of the maze structure on a tablet, which will enable us to track different patterns of the drawing process (e.g. trace the order of recalling the features of the environment), or such characteristics as speed of drawing and the number of perpetrated and corrected errors. The second limitation is that the study did not focus on the intermediate stages leading to the formation of optimal solutions. Future research should analyze in detail the tactical repertoire of humans during the spatial problem-solving in maze and describe the stages involved in forming optimal solutions. This analysis will provide a more comprehensive understanding of the cognitive mechanisms involved and the progression from initial exploration to optimal pathfinding. By developing further metrics to measure these factors accurately, we can advance our understanding of the cognitive processes underlying problem-solving and spatial representation in more complex and uncertain environments.

Tactic	Sequence of key elements	Possible route corresponding to algorithmic structure	Number of equally possible routes to implement the solution
Optimal	Entrance-Coin+-Coin+-Exit	**En**-O-Q-H-**Coin1+**-H-G-**Coin2+**-Z-U-T-**Ex2** **En**-O-Q-H-**Coin1+**-K-I-M-B-**Coin2+**-Z-U-T-**Ex2** **En**-O-Q-H-**Coin1+**-K-I-Q-G-**Coin2+**-Z-U-T-**Ex2** **En**-O-Q-H-**Coin1+**-H-G-**Coin2+**-B-N-P-**Ex2** **En**-O-Q-H-**Coin1+**-K-I-M-B-**Coin2+**-B-N-P-**Ex2** **En**-O-Q-H-**Coin1+**-K-I-Q-G-**Coin2+**-B-N-P-**Ex2** **En**-O-I-K-**Coin1+**-H-G-**Coin2+**-Z-U-T-**Ex2** **En**-O-I-K-**Coin1+**-K-I-M-B-**Coin2+**-Z-U-T-**Ex2** **En**-O-I-K-**Coin1+**-K-I-Q-G-**Coin2+**-Z-U-T-**Ex2** **En**-O-I-K-**Coin1+**-H-G-**Coin2+**-B-N-P-**Ex2** **En**-O-I-K-**Coin1+**-K-I-M-B-**Coin2+**-B-N-P-**Ex2** **En**-O-I-K-**Coin1+**-K-I-Q-G-**Coin2+**-B-N-P-**Ex2** **En**-O-Q-G-**Coin2+**-G-H-**Coin1+**-D-S-A-**Ex1** **En**-O-Q-G-**Coin2+**-B-M-I-K-**Coin1+**-D-S-A-**Ex1** **En**-O-Q-G-**Coin2+**-B-M-Q-H-**Coin1+**-D-S-A-**Ex1** **En**-O-Q-G-**Coin2+**-G-H-**Coin1+**-K-L-R-**Ex1** **En**-O-Q-G-**Coin2+**-B-M-I-K-**Coin1+**-K-L-R-**Ex1** **En**-O-Q-G-**Coin2+**-B-M-Q-H-**Coin1+**-K-L-R-**Ex1** **En**-O-M-B-**Coin2+**-G-H-**Coin1+**-D-S-A-**Ex1** **En**-O-M-B-**Coin2+**-B-M-I-K-**Coin1+**-D-S-A-**Ex1** **En**-O-M-B-**Coin2+**-B-M-Q-H-**Coin1+**-D-S-A-**Ex1** **En**-O-M-B-**Coin2+**-G-H-**Coin1+**-K-L-R-**Ex1** **En**-O-M-B-**Coin2+**-B-M-I-K-**Coin1+**-K-L-R-**Ex1** **En**-O-M-B-**Coin2+**-B-M-Q-H-**Coin1+**-K-L-R-**Ex1**	24

Table 4. Variety of equally possible ways to execute an optimal solution.

Methods
Participants
A total of 64 young adults (38 female, 26 male; M_{age}=22.20, $SD = 3.35$) were enrolled in this study. We used convenience sampling to recruit participants primarily from the researchers' immediate social circles and easily accessible groups, including students at a nearby university. All participants voluntarily agreed to participate without any financial compensation. Inclusion criterion was normal or corrected-to-normal vision. Exclusion criteria were the current use of pharmacological medication, psychiatric or neurological disorders. Participants were provided with detailed instructions on the experimental procedure and gave written informed consent. Each participant was paired with another participant of a similar age and gender. Then, the pairs were randomly assigned to one of two experimental groups: Group 1 ("draw": $n = 32$, M_{age}=22.3, $SD = 3.43$, 59.4% female) was instructed to interact with the virtual environment in order to draw a 2D map of the maze and Group 2 ("collect": $n = 32$, M_{age}=22.0, $SD = 3.33$, 59.4% female) was initially instructed to only collect 20 coins. Data from one participant in the "collect" group were excluded from the analysis because the participant was unable to complete the task due to cybersickness. This study was performed in concordance with the principles of the Declaration of Helsinki. The study was approved by the Ethics Committee of the Institute of Medicine of RUDN University. All participants provided informed consent.

The structure of the maze
The maze was developed using Unity3D 2021.3[43] with original scripts written in C#. The game used a standard first-person controller and was displayed on a 17-inch monitor. Moving in various directions was facilitated by employing the keyboard inputs, encompassing both arrow keys and the key combinations "W", "A", "S", and "D". Pressing the "Shift" key allowed users to move faster and pressing the "Space" key allowed them to perform "jump" action. The player's viewing angle was 90º, the horizon included 2–3 compartments. The computer mouse was used to change the viewpoint orientation.

The playing area comprised two sections: a starting zone and a coin area (Fig. 2). These two sections were connected via three doors that allowed movement in only one direction - one for entering the maze and two for exits towards the starting zone. A button was available in the starting zone, which the participants had to push to open the entrance door to the maze. Coin area also included columns that divided it into separate compartments and two dead ends, each with and without gold coins.

The structure of the task
Prior to the start of the game, participants were presented with one of two instructions.

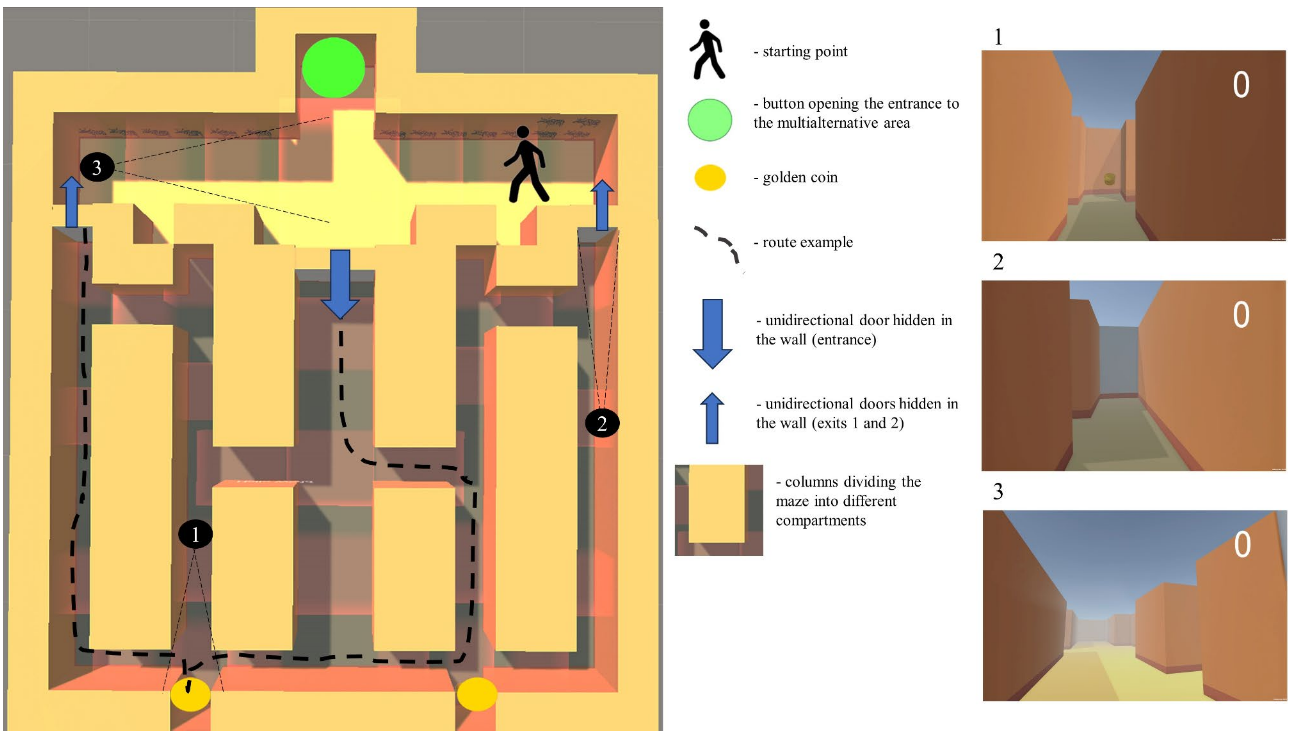


Fig. 2. The structure of the maze. Left: two-dimensional overhead view (2D map) of the virtual environment and its essential components (left). Right: first-person view of the main elements of the maze: viewpoint 1 - Coin 1, viewpoint 2 - Exit 2, viewpoint 3 - start area; upper right corner - number of collected coins.

Instruction 1
One group was given the following instructions: "Your task is to draw a 2D map of the maze. You can move around the maze, interact with its elements. You will have to draw the map when the game is over. When you are ready to draw the maze, you can finish the game".

At the end of the game, the participants drew the walls of the maze with a black marker, the key elements - doors, coins and the button that opened the entrance door - with colored markers. The purpose of giving this type of instruction was to assess the ability to compile the 3D spatial experience and present it in the form of a 2D map (scheme) in a condition where the players were explicitly instructed to draw a 2D map of the space. Therefore, the instruction was hypothesized to encourage increased attention to the spatial features and details of the game.

Instruction 2
The second group received the following instruction: "Your task is to collect 20 coins in the shortest time you can". At the end of the game, participants were asked to draw a map of the maze, just like the players in Group 1. The instruction did not contain any information about memorizing the spatial layout. The purpose of giving this type of instruction was to assess learning and representation of spatial characteristics in a condition when the attention and focus of the players was deliberately directed towards other objectives of the game.

Basic rules of the game
Regardless of the type of instruction the participants received before starting, the gameplay remained the same for both groups and the game contained several basic rules.

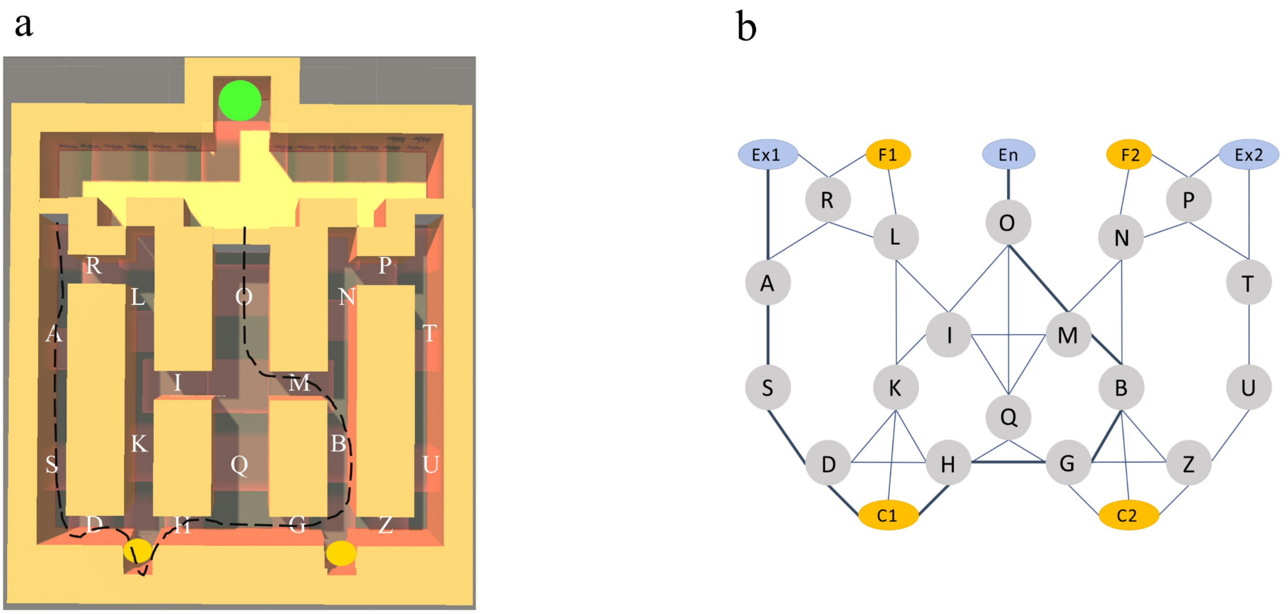
The participants started the task in an open area (starting zone). The button allowed them to open a secret entrance door to the multialternative subspace (coin area) for 10 s. At the same time, the color of the button would change from red to green, and the secret door would make a specific sound. The difficulty for the players was that the button and the door were in different places: the door was behind the participants when they were in front of the button. Therefore, the players never saw the button and the open door at the same time, so they had to figure out the first rule: if they approached the button, the door would automatically open for 10 s, and they would be able to enter the maze area with coins. Thus, to enter the coin area, the player had to establish a connection between the button and the door, approach the button, turn around, and cross the starting zone. If the players performed these operations slowly, they would not be able to enter the multialternative subspace. In our sample all participants managed to quickly approach the button in the starting zone and enter the coin area.

When the hidden door opened, the participants entered the coin area, which was divided into sections by columns. In this area, there were two dead ends with gold coins for the players to collect and two dead ends with no coins. The second rule the participants had to figure out was that for new coins to appear in the same locations, it is necessary to return to the starting zone. The starting zone and the coin area were connected by three hidden doors. The doors only opened in one direction. The central door only allowed access from the starting zone to the coin area, and the two side doors (left and right) only lead from the coin area to the starting zone. Thus, there were the following basic rules that participant could figure out:

- The entrance door is opened after approaching the button.
- Through the entrance door one can enter the coin area but cannot leave it.
- There are two dead ends with the coins.
- For new coins to appear in the dead end it is necessary to exit from the coin area and reenter.
- One can enter the starting zone only through the side doors but cannot get back into multialternative space with coins through them.

Data analysis
Moving from continuity to discreteness with graphs: behavior encoding principles
We placed invisible "triggers" in each part of the maze that had turns, as it was considered as a decision-making point. Each trigger was assigned a unique symbol, and each symbol was considered as one compartment of the maze. When a player crossed a trigger, the corresponding symbol was recorded into a file. This process enabled us to convert the continuous trajectory of the player through the maze into a string of symbols representing their route (see Fig. 3). Each section of the route from the entrance to the exit was defined as a single trial. As a result, the movement of the subject through the maze will be represented as a 'text'. This text can then be analyzed to identify stable sequences or congruent patterns. This analysis is of particular importance for identifying the number of optimal solutions used during problem solving. An optimal solution is defined as one that adheres to the principle of minimum action and maximum reinforcement. This involves visiting both compartments with the coins before returning to the starting zone (Entrance-Coin1-Coin2-Exit2 or Entrance-Coin2-Coin1-Exit1) without visiting unnecessary compartments.

Measuring behavior in virtual maze and assessment of drawing accuracy
To measure behavior in the virtual maze we evaluated several parameters. One key parameter was the number of trials, defined as the route section from entrance to exit. In the group that received the "draw" instruction, participants decided when to stop playing. In the second group, the game ended when 20 coins were collected. Thus, in the second group, participants needed at least 10 trials to collect 20 coins, as the maximum number of coins that could be collected during a trial was 2. Performance in the maze was further evaluated by measuring the learning rate, defined as the number of a trial from which the optimal solution was used twice in a row, and the learning criterion ("yes" or "no"), which assessed whether the participant used optimal solutions twice in row. Additionally, time parameters, namely, overall game duration, time spent in the starting zone and time



c

Entrance-O-M-B-G-H-Coin1-D-S-A-Exit1

Fig. 3. Sequence of behavior encoding stages: (**a**) each compartment of the maze contains an invisible 3D trigger; when players cross the trigger zone, the program writes the name of the trigger in the line, so the routes are recoded to the text – the sequence of the characters; (**b**) graph-like representation of the maze; (**c**) an example of a path recoded to the text. En - entrance, C1 - coin 1, C2 - coin 2, F1 – dead end 1 with no coin, F2 – dead end 2 with no coin, Ex1 - exit 1, Ex2 - exit 2.

spent in the multialternative subspace during each trial were registered. The analysis of these parameters is described in the Additional analyses subsection in the Results.

We also assessed drawing accuracy by asking participants to draw a 2D map of the maze ("bird's eye view") after the game, marking key elements such as doors, coins, and columns. The "draw" group knew from the beginning that they would be drawing the maze, but the "collect" group was asked to draw the maze only after completing the game. This task was challenging because participants never saw the entire maze and had to integrate different parts of the virtual experience into a single holistic unit. We assigned the scores of the drawing accuracy as follows: a score of 0 was assigned if no elements were placed correctly in pairs, or if the elements were placed correctly in pairs but the axes of the coins and doors were incorrect; a score of 1 was assigned if the elements were placed correctly but the pattern of the columns was inaccurate, or if both the elements and the pattern of the columns were placed correctly. Examples of accurate and inaccurate integrations are shown in Fig. 4. Thus, accuracy was defined by how well participants represented the vector relationships between the key elements and the structural layout of the maze.

Statistical analyses

Statistical analyses were conducted in Jamovi version 2.3.18[44]. The main analyses included three major steps. First, we analyzed the characteristics of in-maze performance (the number of trials, the ability to achieve the learning criterion and the learning rate) in the "collect" and "draw" groups. Second, the relationships between the characteristics of in-maze performance, type of instruction and the accuracy of maze reproduction were analyzed. Third, we analyzed which routes were most frequently used to implement optimal solutions. Additionally, we compared the time characteristics of the groups with different instructions. This was excluded from the main analyses, since the time data (overall game duration, time in the starting zone before entering the multialternative subspace, and trail duration) of fourteen participants (22% of the sample) were lost due to a technical error. Here, we also examined trial-to-trial changes in the time spent in the starting zone and in multialternative area as well as in the number of turns participants made. For between-groups comparisons of in-maze performance parameters and the accuracy of maze reproduction, either the Mann-Whitney for continuous variables or the Chi-squared test for categorical data were used. Spearman's rank correlation was calculated to examine the relationship among the variables of interest. For trial-to-trial comparisons within each instruction group a non-parametric Friedman test for repeated measures and a Durbin-Conover test for post-hoc comparisons were utilized.

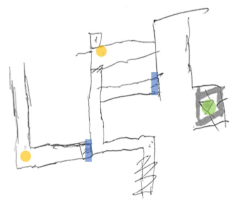
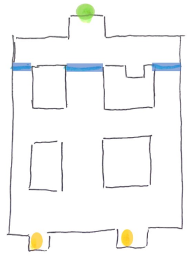
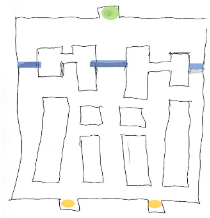
	Inaccurate		Accurate	
2D maze reproduction				
Integration type	Incorrect integration	The integration of the pairs of elements is accurate, but the axes of the coins and doors are not parallel	The vector model is accurate, and the elements are correctly positioned relative to each other. However, there is an inaccuracy in the display of columns	The vector model is accurate, and the columns are displayed correctly

Fig. 4. Principles of assessing the accuracy of maze structure reproduction based on the degree of integration of maze fragments into a unified scheme.

Data availability

All the data are available upon reasonable request to the corresponding author Elizaveta Romanova.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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