The role of mental rotation in Tetris^{TM} gameplay: an ACT-R computational cognitive model

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NOTE: Paper accepted in Cognitive Systems Research. Post-print version.

Abstract

The mental rotation ability is an essential spatial reasoning skill in human cognition and has proven to be an essential predictor of mathematical and STEM skills, critical and computational thinking. Despite its importance, little is known about when and how mental rotation processes are activated in games explicitly targeting spatial reasoning tasks. In particular, the relationship between spatial abilities and Tetris^{TM} has been analysed several times in the literature. However, these analyses have shown contrasting results between the effectiveness of Tetris-based training activities to improve mental rotation skills. In this work, we studied whether, and under what conditions, such ability is used in the Tetris^{TM} game by explicitly modelling mental rotation via an ACT-R based cognitive model controlling a virtual agent. The obtained results show meaningful insights into the activation of mental rotation during game dynamics. The study suggests the necessity to adapt game dynamics in order to force the activation of this process and, therefore, can be of inspiration to design learning activities based on Tetris^{TM} or re-design the game itself to improve its educational effectiveness.

Keywords: cognitive architectures, ACT-R, mental rotation, Tetris^{TM}, serious

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1. Introduction

In the introduction to the topic "Game XP: Action Games as Experimental Paradigms for Cognitive Science", Gray (2017) lays the foundations for a research program to exploit the possibilities offered by games in the field of cognitive science. Games represent an opportunity for computational cognitive science as they can provide an environment equipped with the necessary level of control to carry out cognitive experiments. Furthermore, they can simultaneously mimic reality, thus mitigating all the limitations of "transferability" of the results typical of controlled environments.

Among the various approaches with which cognitive sciences can exploit the field offered by games, the realization of computational cognitive models designed to explain the mental processes employed by the player during game activities deserves special attention (on this aspect see Lieto (2021)).

The use of games for a better understanding of cognitive phenomena is widely present in the literature. Among others, the classic game of Tetris$^{\text{TM}}$ has repeatedly attracted the interest of researchers from various research fields.

Tetris$^{\text{TM}}$ is a puzzle game in which the primary game mechanics is the positioning of figures called *zoids* in a rectangular space. The user must position these figures by moving and rotating them in a rectangular board divided into blocks (Figure 1).

The game objective is to get the blocks to fill all the empty boxes in a line at the bottom of the screen; once a row is complete, the blocks vanish, freeing up space for positioning other *zoids*, and the player gets awarded some points. The *zoids* appear in the game scene one at a time, descending at a specific rate. The descending rate increases progressively as the game progresses. The original Tetris$^{\text{TM}}$ has seven different types of *zoids* (Figure 2) and takes place on a board of 20x10 blocks. Each *zoid* consists of 4-connected blocks, that is, each block of the *zoid* is connected to at least one other block in one of the four

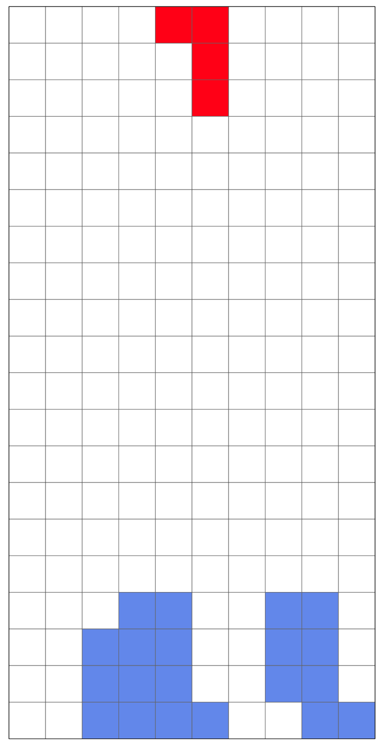


Figure 1: A configuration of the Tetris$^{\text{TM}}$ game and of its board

main directions.

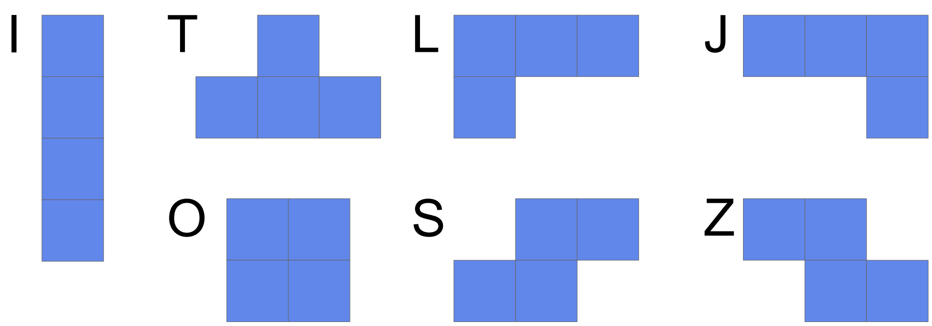


Figure 2: Type of *zoids*

Tetris$^{\text{TM}}$ has been used for several objectives, like training of spatial skills (Milani et al., 2019), analysis of cognitive abilities like cognitive workload (Trithart, 2000), as an investigation tool to investigate mental processes linked to pragmatic actions and epistemic action (Kirsh & Maglio, 1994), or as a work-space in which to train and test neural models or other AI algorithms able to compete or reproduce human performance (Schrum, 2018; Lora Ariza et al., 2017).

It is now common knowledge that spatial abilities, such as mental rotation, spatial visualization, perceptual speed, useful field of view, and visuospatial working memory, play a role during the Tetris$^{\text{TM}}$ game activity (Pilegard & Mayer, 2018). In particular, the mental rotation ability appears to be the primary cognitive process involved, and, in addition, it is an essential cognitive ability possessed and used by humans for spatial reasoning tasks. Such an ability has been studied extensively in humans since the original experiment of Shepard & Metzler (1971). However, despite this widespread interest, "no formal cognitive task analysis of Tetris$^{\text{TM}}$ playing has been completed" (Pilegard & Mayer, 2018).

In particular, despite the relationship between mental rotation skill and Tetris$^{\text{TM}}$ — either as a proxy for players' efficacy in the game or on the contrary as a skill to be trained — has been investigated several times, to the best of our knowledge, there is no computation model able to explain the role of mental rotation in Tetris$^{\text{TM}}$ gameplay.

In this paper, we present an agent explicitly embedding such ability to verify whether, and under what conditions, mental rotation ability is used in Tetris$^{\text{TM}}$ gaming activities.

We modelled the mental rotation ability of the agent by using the ACT-R[1]. The underlying hypothesis is that a cognitively constrained ACT-R agent embedding such an ability could provide insights into the strategy used by human players and the activation of mental rotation abilities in particular game configurations.

[1]ACT-R has been already tested in a variety of games, from backgammon to social ones (Lebiere & West, 2020; Lebiere et al., 2000; Kim & Taber, 2004; Moon & Anderson, 2012; Spiliopoulos, 2013; Augello et al., 2022)

According to the approach proposed by Gentile et al. (2019), a better understanding of the phenomenon could provide an interpretation of the conflicting results concerning the effectiveness of Tetris^{TM} as a spatial skills training tool (Pilegard & Mayer, 2018) and give insights on how to re-design the gameplay to improve the educational effectiveness.

The paper is organized as follows: the section 2 gives an overview of the research conducted concerning mental rotation ability. In section 3, after introducing ACT-R and the principal modules used in this work, we provide a high-level description of the cognitive model proposed in this paper and the theoretical references at the basis of its definition. Section 4 shows the research design, the instruments used for the collection of experimental data and the statistical analysis conducted to verify the validity of the model. In section 5 we present the results of the conducted analyses, while in section 6 we report a critical comment of the results. Finally, section 7 concludes the paper and provides a prospect for future works.

2. Mental Rotation

Metzler and Shepard have coined the expression "mental rotation" in 1971 Shepard & Metzler (1971) by referring to a process based on a particular visuospatial ability through which a cognizer can represent how 2D or 3D objects look like when they are rotated (Shepard & Metzler, 1971; Metzler & Shepard, 1974). The visuospatial ability working in mental rotation processes has been described as the capacity to conceive a rotation of objects in a 2D/3D space (Burnett & Lane, 1980) through a mental manipulation of these objects. The mental manipulation could be performed piece-by-piece (as regards the different elements composing a certain object) or in a holistic fashion (Battista et al., 1989; Clements & Battista, 1992; Olkun, 2003).

The mental rotation process is usually described as shape-matching activities where an agent has to decide whether two elements (e.g. two objects, two pictures), simultaneously or consecutively exhibited and from various angular orientations, are equivalent or different (Shepard & Metzler, 1971).

In the original Shepard & Metzler (1971) experiment, participants were presented with pairs of 3D objects; the first one is the target, while the second one is a similar version of the target object. Usually, this second object is rotated around its centre (Figure 2 provide an example task from the original experiment on mental rotation for human subjects by Shepard & Metzler (1971)). In the adapted version for children (Vandenberg & Kuse, 1978), two flat images of animals are compared by the participants. In addition to being rotated in two-dimensional space, the control version can be presented in standard or mirrored form. Finally, in both the 2D/3D versions, the control object/image is presented from time to time through different disparities in orientation, varying the degree of rotation.

Cooper & Shepard (1973) describe this complexity utilizing four sub-processes composing mental rotation:

- realizing a visual encoding of the stimuli;
- rotating an object (referring to another);
- comparing two objects (similar or different);
- responding [Wright et al. (2008)]

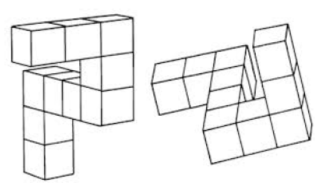


Figure 3: An example of the stimuli used by Shepard & Metzler (1971)

Several investigations have demonstrated that the mental rotation skill is a good predictor of mathematical skills and achievements in mathematics (Kozhevnikov et al., 2005; Holmes et al., 2008; Cheng & Mix, 2013; Verdine et al., 2013). Mental rotation is also considered a proxy of spatial reasoning ability (Carpenter et al., 1999) that is considered necessary in STEM disciplines and critical thinking tasks. Città et al. (2019) have also described a relationship between mental rotation ability and high-order cognitive processes related to computational thinking.

The mental rotation process has also been the subject of study in computational cognitive science. Peebles (2019) recently compared the piece-by-piece and holistic strategies by realising two computational models using the ACT-R cognitive architecture Peebles (2019). The results show the consistency of the models concerning the rotation times collected through an experiment conducted on human participants[2].

Despite the importance of this phenomenon, little is known about when and how mental rotation processes are activated in the context of an explicitly targeting spatial reasoning tasks game like Tetris™. The only relevant insight coming from the literature analysing the distinction between epistemic and pragmatic actions shows that players do not always use mental processes but often use pragmatic actions as a shortcut to simplify the decision-making process (the distinction between these different types of actions is outlined in the next section).

3. An ACT-R based mental-rotation model of Tetris gameplay

This paper aims to assess whether and under what conditions mental rotation ability is employed in Tetris™ gaming activities. For this purpose, we have defined an ACT-R computational model of a Tetris player that exploits mental rotation as a fundamental step in positioning a *Zoid* according to the classical information-processing approach. In this section, after introducing ACT-R, we present the theoretical basis that guided the definition of the computational

[2] In a nutshell, the holistic strategy suggests that mental images are rotated as whereas the piece-by-piece strategy assumes the decomposition of the mental image into pieces and their individual rotation. See Peebles (2019) for details.

model, and provide a high-level description of its ACT-R implementation for the sake of completeness.

3.1. ACT-R: Adaptive Control of Thought—Rational

ACT-R is a general cognitive architecture explicitly inspired by theories and experimental results coming from human cognition (Anderson et al., 1997). The ACT-R architecture consists of a set of modules (i.e., goal, imaginal, perceptual and motor modules), each devoted to processing a different kind of information. In the ACT-R architecture, the intelligent behaviour of computational agents emerges from the interaction of two types of knowledge: declarative and procedural knowledge (see Lieto et al. (2018) for a knowledge level analysis of these components). The former encodes explicit facts that the system knows in terms of schema-like structures called chunks, whit an *isa* slot specifying their category and some number of additional slots encoding their contents. A specific module named "declarative module" is in charge of storing and managing declarative knowledge. Procedural knowledge encodes rules for retrieving and processing declarative knowledge and is managed by a production system, which is also responsible for coordinating the behaviour of all the different modules. The production system interacts with the different modules through specific buffers associated with each module. The current task state of a model and relevant information for the current task are typically managed by the goal module.

The perceptual and motor modules (i.e., audio, visual, motor and speech) provide the primary interfaces between the ACT-R architecture and the external world. The interaction with perceptual and motor modules prescribe the possible action requests and information chunks each module can manage. For an updated and complete overview of ACT-R, we remind at Ritter et al. (2019).

In the context of this work, it is helpful to deepen how the ACT-R higher-level processes interact with a visual interface. Since version 5.0, ACT-R integrates the visual module to model how visual attention and perception concur in defining high-level representations that can be managed according to the ACT-R theory of cognition. Firstly, the ACT-R visual module provides an iconic memory that maintains a feature-based representation of the environment[3]. According to a theory of visual attention[4] implemented in ACT-R, the visual model allow to move the attention to a specific region of the screen and sequentially create a representation of the focused object in term of a chunk. The ACT-R vision module system has been successfully applied in the literature to model several classic perceptual phenomena, like the Sperling and visual-search tasks.

Nevertheless, as reported by Peebles (2019) neither the ACT-R visual module nor the proposed extensions available in the literature (e.g., the ACTR/E project (Trafton et al., 2013)) provide mechanisms to cope with spatial-imaginary problems. Thereby, for the aim of this work, we employ the ACT-R extensions provided by Peebles (2019) both in terms of chunk-types for the representation of visual objects and in terms of imagery operations available on those chunks (e.g., translation, scanning, scaling, zooming, reflection, rotation and composition functions such as intersection, union and subtraction).

In addition to the visual module, another key module in the context of this work is the imaginal module, whose main buffer correspond to the dorsolateral prefrontal cortex (DLPFC) area of the brain (Oh et al., 2021). In particular: while the visual module allows ACT-R to perceive the Zoid and to store its representation in an appropriate chunk, the imaginal module functions as a working memory in which information related to the mentally transformed object is represented and manipulated during the task (Borst et al., 2010).

The involvement of these two modules is consistent with recent discoveries in neuroscience related to the study of mental rotation processes. Recent studies (Albers et al., 2013; Christophel et al., 2015) have shown that the processes of

[3]In the ACT-R context, the term environment usually refers to a 2D system cause the primary goal of the ACT-R models is to interact with the computer screen where the cognitive tasks under examination are performed.

[4]As reported in (Anderson et al., 1997), the visual attention theory used in ACT-R is a synthesis of Posner's (1980) spotlight metaphor, Treisman & Gelade's (1980) feature-synthesis model, and the Wolfe's (1994) attentional model.

perception of external input and internal generation of the transformed representation, processes included in mental rotation, are simultaneously mediated by the primary visual cortex. Furthermore, in a recent study, Iamshchinina et al. (2021) demonstrated that cortical depth separation allows for concurrent representation of both perceived and mentally rotated content. This distinction of neural representations explains why the two representations are not confused and suggest the view of primary visual cortex as a dynamic blackboard.

3.2. Model assumptions

The developed ACT-R computational model is based on a number of assumptions. The first one concerns the attention process. We hypothesize that the player focuses on a portion of the board while searching for the position to place the *zoid*. The board portion focused by the player during the first part of the task will be referenced as *attention area* in the rest of this paper.

The second one is that the player generates, via an internal simulation mechanism, one or more imaginary *zoids* in the empty squares of the *attention area* according to the shape of descending zoid, also known as *target zoid*.

Finally, in our model, these imaginary *zoids*, which we will call *solutions*, are generated by the user according to the main features of the *target zoid* through a sort of subitizing process (third hypothesis); that is, the ability of humans to fast and accurately enumerate small groups of four or fewer objects (Mandler & Shebo, 1982).

In line with this hypothesis, all *zoids* are composed of four cells arranged according to the following configurations:

- I: 4 linear blocks;
- O: a 2x2 blocks square;
- T: 3 consecutive positions and one at the middle of the configuration;
- S or Z: 2 offset lines made by two consecutive blocks;

- J or L: 3 consecutive blocks with one at the beginning or the end of the configuration.

The characteristic element of the latter hypothesis is that generating solutions is not without an error process. In other words, we hypothesise that for some zoid types, the generated solutions may not coincide with the *target zoid*.

From the entire list of the *zoids* available in Tetris™ (shown in Figure 4), suppose an attempt to position one of the following 4 *zoids* (L, J, S, Z). In that case, the solutions generated may lead to a *zoid* that is compatible with the features but not identical to the starting *zoid*.

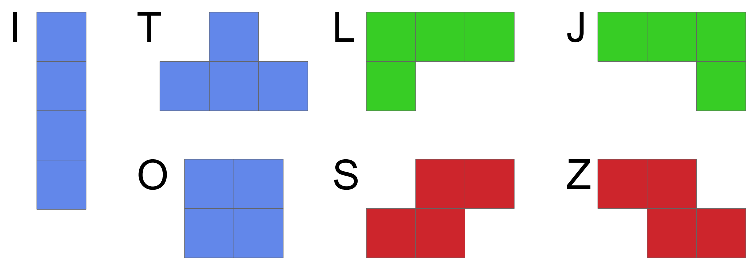


Figure 4: List of *zoids* in Tetris™. Highlighted in red and green the couples of zoid that require the activation of mental rotation process.

To better illustrate the situation, let us assume the appearance of a J *zoid* in a 4x4 area that presents the following configuration (Figure 5). The red *zoid* represents the *zoid* (J) to be placed, while the 4x4 square is the portion of the board where to place it. Not all positions are accessible in this board portion, because some are occupied by previously positioned *zoids* (the part in blue).

According to this configuration, we report some of the possible solutions generated according to the features of the *zoid* J in Figure 6. As we can see, not all the solutions coincide with the original J *zoid*. In b,c, and d configurations, the algorithm generates a *zoid* L that is exactly the reflection of the *zoid* J. Once a possible solution has been selected, it is necessary to verify through the mental rotation process whether or not it coincides with the starting *zoid* unless it is rotated or represents the reflection. This verification represents exactly the

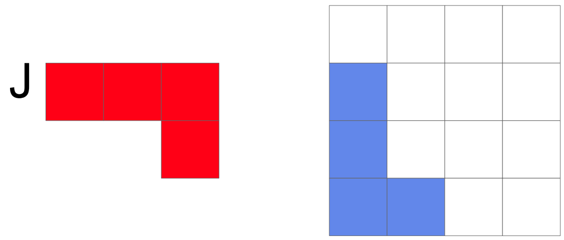


Figure 5: An example task

mental rotation process identified by Shepard & Metzler (1971) in 1971.

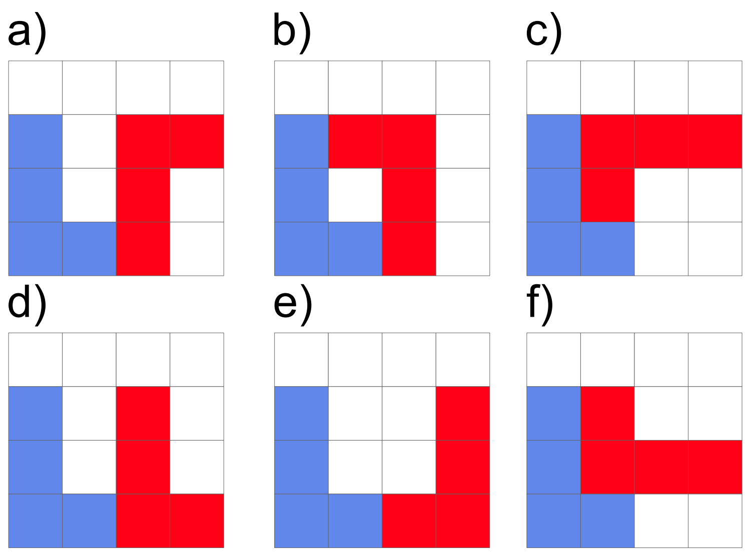


Figure 6: A sample of solutions generated according the *zoid* features

3.3. The computational model

According to the assumptions reported above, the cognitive model described in Figure 7 was formalised.

The model is composed of a first phase in which the zoid target is identified, leading to the creation of a relative imaginal chunk. For this purpose, according to the visual attention and perception models of ACT-R, after adding a set of perceived visicon features representing the zoid to the iconic memory, the model

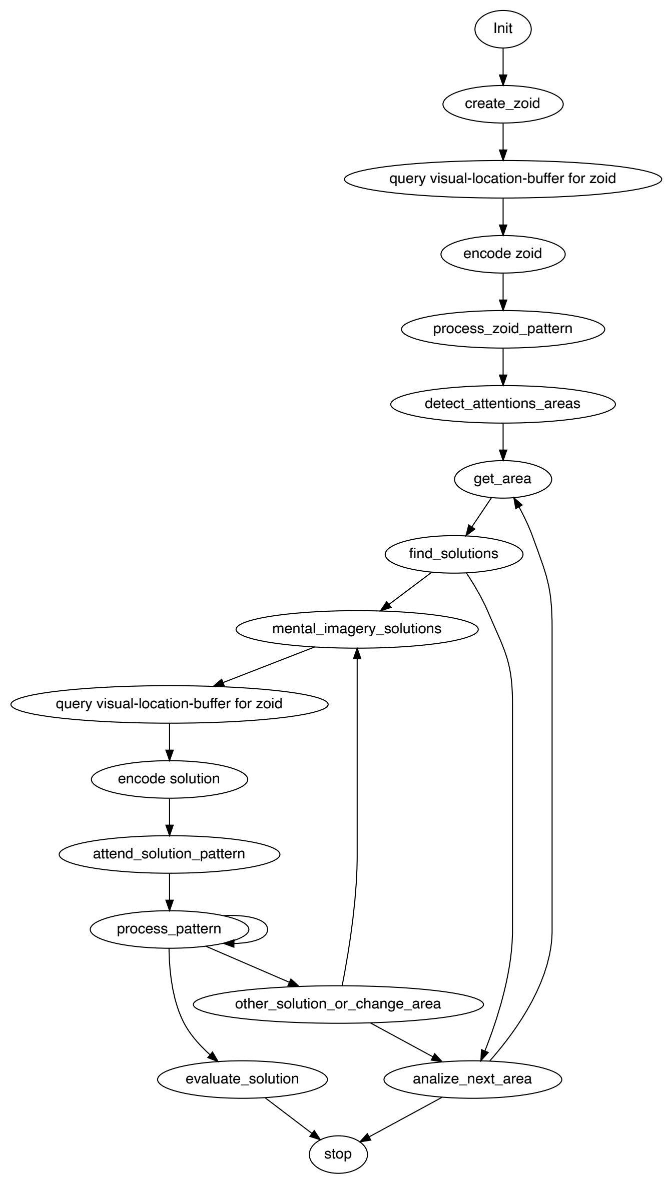


Figure 7: The Tetris$^{\mathrm{TM}}$ cognitive model

starts the search process in the visual location buffer. Then, once identified, we search in the visual buffer the zoid that is then copied in the imaginal buffer.

Subsequently, the model passes to the board's analysis, to extract the possible attention areas. The areas are identified by dividing the upper part of the chessboard into blocks of dimension n x m where n and m represent the number of rows and columns of the attention area, respectively. These dimensions are parametric and allow the exploration of different configurations.

By moving the upper left corner of the area from the first column to the $cols - m$ column — cols represents the number of columns of which the board is composed —, the algorithm searches the n x m blocks that touch the boundary represented either by the last row of the board or by a complete row. Then, the identified areas are sorted according to a specific heuristic. The implemented heuristic sorts the areas according to the percentage of free squares in the attention area, preferring the attentions areas with the freest blocks.

Once an area has been selected, the model moves to the next step for searching all possible solutions in the attention area. As described before, by solution, we mean a possible placement of a mentally generated zoid in the empty spaces of the attention area.

The solution generation process is carried out through a subitization process, which involves firing 4-connected blocks. The generation algorithm generates all possible 4-connected configurations, which are then filtered in such a way that the configuration is compatible with the salient features of the target zoid. Once generated, the solutions are ordered according to a second heuristic. This heuristic analyzes the empty connected components in the attention area and the percentage of occupation of the rows, starting from the lower rows of the attention area.

Once the solution has been identified, the model generates the visual chunk that represents this solution according to the steps already described above for the generation of the chunk of the target zoid. Once the two chunks have been identified, we move on to the mental rotation process that evaluates the disparity angle between the target zoid and the imaginary solution under analysis. If the angle of disparity is greater than a certain threshold, the rotation is carried out.

In particular, the holistic computational model realised by Peebles (2019) was used as a reference for the definition of the mental rotation phase in our model[5].

The rotation process ends if an angular configuration is found for which the two images coincide or if all possible rotations have been tested. In the case of non-coincident figures, if the number of solutions tested in the area is less than the *MAX_solutions* parameter, the algorithm proceeds to evaluate the next solution identified in the area of attention. Otherwise, in the case in which the algorithm has already tested the maximum number of solutions in the area, the algorithm proceeds to analyse the next area of attention. The process is iterated until the maximum number of explorable areas, identified by the parameter *MAX_areas*, has been reached.

On the other hand, if the algorithm identifies a rotation for which the two figures coincide, the algorithm terminates after evaluating the identified solution. Precisely, the distance of the current solution from the solution identified in the same task by the human user is calculated.

It should be noted that the model allows for the exploration of various experimental hypotheses. In particular, the model is characterised by two heuristics, the first for ordering the areas of attention and the second for ordering the imagined solutions. Furthermore, the model is characterised by different parameters.

[5]Despite the original inspiration, there are some essential differences between our model and the Peebles's ones. Whereas Peebles' models analyse the mental rotation process, our model models the entire Tetris game process. Furthermore, even concerning the implementation of the mental rotation process, our model highlights some differences in respect to the model presented by Peebles (2019). In particular, our model implements the recognition processes of the two figures to be compared in two different phases. In fact, the target zoid recognition is done just once outside the cycles at the beginning of the process. In contrast, the recognition of the second object is made for each tested solution since the model explores different areas of attention and solutions in each area. Moreover, another difference is the adoption of a 90° degree rotation step, according to the particular case represented by Tetris™.

Two parameters are used to identify the dimensions of the area of attention. The maximum number of testable solutions in the single area of attention and the maximum number of analysable areas represent two other essential parameters of the model.

4. Material and methods

4.1. Research design

In order to evaluate the computational model, we compare the behaviour of human agents engaged in gaming activities with the behaviour of a virtual ACT-R agent that exploits the model presented in section 3.3.

To collect data about the players' behaviours, we implemented a specific application, described in detail in section 4.2.

The unit of analysis (referenced as "task" in the rest of this paper) is the positioning process of the single zoid. The process begins when the zoid appear on the screen and ends with its positioning on the board. Within this time, the player typically performs all the visual, decisional and motor processes related to recognising the zoid, choosing the position, and doing all actions that allow moving the zoid to the chosen position.

For each task, different temporal information was collected, such as the time of the first action ($t_{firstAction}$), the time of the last action ($t_{lastAction}$) and the time of task completion (t_{total}). In addition, data about the number of rotation and translation actions and the drop action have been collected.

A pivotal element in our comparison process is time analysis. In particular, isolating the mental rotation process within the task performed by the human user is not a trivial task. To overcome this problem, we explored whether and to what extent the time used by the model to complete the task (t_{model}) could partially explain the time taken by the human agent in performing the same task.

In particular, the t_{model} covers the time interval between the start of the task and the completion of the first three phases of the classic information processing model (Atkinson & Shiffrin, 1968), namely the creation of a bitmap representation of the current task, its conversion into a symbolic representation, and the search for the best point where to place the Zoid. The current version of the model does not consider the final motor-control phase of defining the trajectory of moves that allows the final positioning of the Zoid.

For this reason, we hypothesise that the t_{model} could help explain the time before the execution of the first action. Moreover, according to Kirsh & Maglio (1994) according to which users often perform the first action almost immediately, we also hypothesise that model time may help explain both the time of the last action and the total time of the task.

Generally, the times related to the focused task performed by the human agent suffer from a high variability due to different factors. For this reason, we have used regression analysis as a technique that allows us to verify the correlation between the (t_{model}) and the human task times net of a set of explanatory variables that allow us to reduce (or explain) the variance of the variables under investigation.

In particular, the timing of the tasks performed by the players was explained from three sets of information:

- the characteristics of the task, like: the level of the game, the progressive number of the task within the game, and the shape of the zoid to be placed;
- the player's characteristics, such as: gender, age and skill level in the mental rotation ability;
- the actions performed by the human user during the task and, in particular: the number of rotations and translations and whether or not the fall of the zoid was forced.

In addition to these three sets of variables, we consider two other central explanatory variables in the analysis. The first is the time taken by the virtual agent to perform the same task following the computational model described in section 3.3.

The second one is the game mode. In fact, within this study, two different game modes have been designed. The first mode is the classical one ($gameMode_{Classical}$) in which the descent speed of the *zoids* and the progression system between levels follow the original version of Tetris ^{TM}. The second mode ($gameMode_{Forced}$) has been designed to force the user to activate the mental rotation process by preventing the player from performing a rotation in the first part of task execution. Rotation actions become possible once the *zoid* approaches the boundary identified by the *zoids* already placed on the board. This distinction relies on the distinction pointed out by the study of Kirsh & Maglio (1994), according to which, in Tetris^{TM}, it is possible to have two types of actions performed by the players: pragmatic actions, aimed at achieving a step towards the goal, and epistemic actions, whose goal is to provide the player with additional information to simplify the cognitive task. Since, in our setting, it is conceivable that epistemic actions — in particular the rotation actions executed on a keyboard — may simplify the mental rotation process (or even inhibit its activation) we introduced the modes mentioned above.

4.2. Mental Jigsaw

Mental Jigsaw is an adapted version of of the classic Tetris^{TM} game, customized according to our research needs, that has been developed as a mobile app and has been distributed through the main official stores (Figure 8 shows a screenshot of the released app).

We implemented the application using the Unity3D game engine. Since it was designed for use on a smartphone, the translation, rotation and drop game mechanics were realised using touch interaction. Dragging the Zoid allows translation, while a tap on the screen to the right or left of the Zoid corresponds to a clockwise or anticlockwise rotation, respectively. Finally, the drop has been realised intercepting a tap at the bottom of the screen.

The application has been designed according to the recommendations indicated by Gray (2017). In particular, the system includes a server-side backend

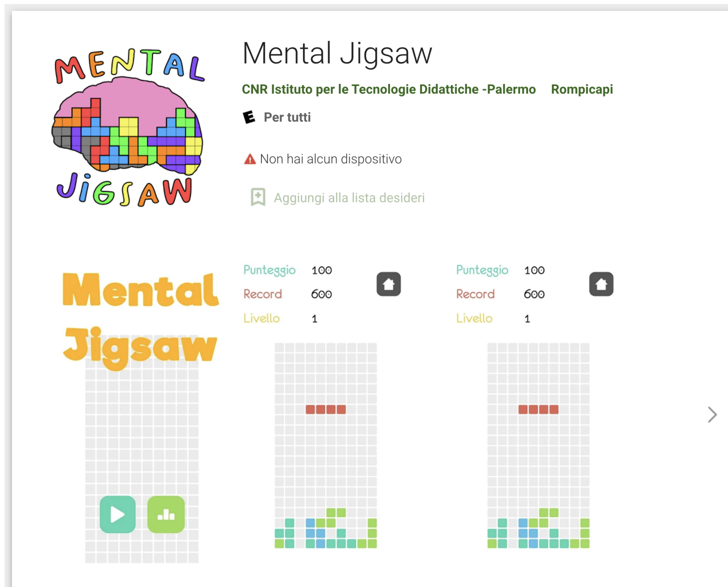


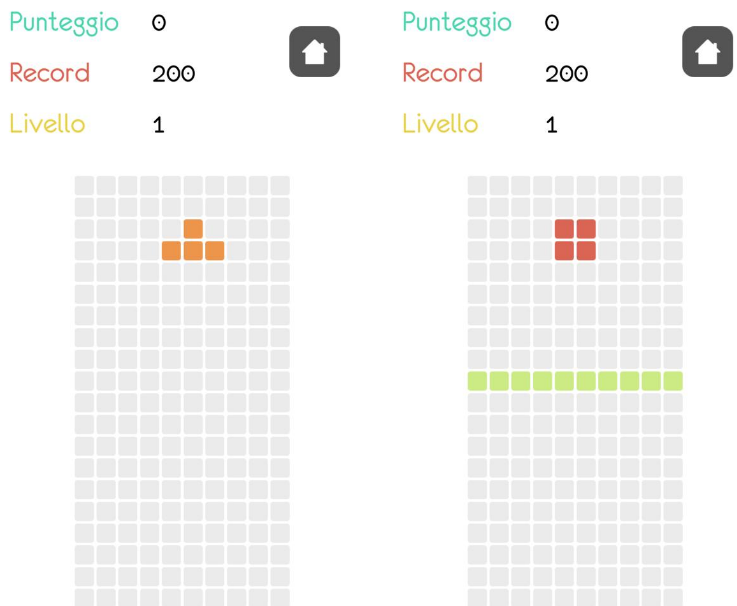
Figure 8: The MentalJigsaw web page on play store (`https://play.google.com/store/apps/details?id=it.cnr.itd.pa.MentalJigsaw&hl=it&gl=US`) MentalJigsaw is also available for iOS device at the following url `https://apps.apple.com/us/app/mental-jigsaw/id1524501681`

that allows the control of the main game parameters (e.g., drop speed, progression rules between levels). In addition, the system collects all the data needed for analysis. All the actions performed by the user during gameplay are stored with the relative timestamp and with an anonymous identifier which allows linking the data relating to the same player.

Another distinguishing aspect of the application is the possibility of dynamically modifying the game dynamics to constrain human behaviour.

In fact, as described in section 4.1, Mental Jigsaw provides two different game modalities: the classical Tetris™ and an ad-hoc modality, called *forced* designed to avoid epistemic actions and force users to activate the mental rotation cognitive process (see Figure 9).

Finally, Mental Jigsaw allows us to assess players' mental rotation ability through the administration of mental rotation test in the classic version defined



(a) Classic (b) Forced

Figure 9: A screenshot of the two Mental Jigsaw game modes

by Shepard & Metzler (1971). After completing a couple of matches, the application asks the players if they are willing to complete the mental rotation test and contribute to the research.

For the implementation of the test in Mental Jigsaw, we used the mental rotation stimuli proposed by Ganis & Kievit (2015). Starting from a set of 48 three-dimensional objects, Ganis & Kievit (2015) generated 384 stimuli with different angular disparities minimizing the self-occlusion at all views used. Figure 10 shows a screenshot of a stimulus presented to the user. As in Shepard & Metzler (1971), stimuli are typically composed of a pair of three-dimensional objects: the baseline object on the left, and a target object on the right.

In this way, we were able to record and cross-compare the data coming from the classical mental rotation test with the ones coming from the Tetris$^{\mathrm{TM}}$ game.

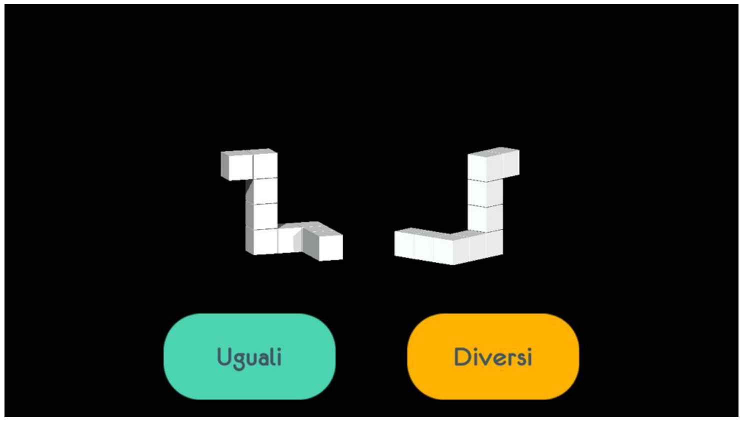


Figure 10: The mental rotation test in Mental Jigsaw

4.3. Participants

We recruited the participants through the snowball sampling method. The recruitment process started by publishing the invitation to participate on the main social networks and sending the same message on different mailing lists.

4.4. Statistical Analysis

In order to evaluate the computational model, we compare the behaviour of human agents engaged in gaming activities with the behaviour of a virtual ACT-R agent that exploits the model presented in section 3.3.

To collect data about the players' behaviours, we implemented a specific application, described in detail in section 4.2.

The first step of the investigation was to explore the tasks performed by human users in terms of times and actions performed (Table 1). Within the analysis, all the analyzed times are reported in milliseconds. Moreover, we performed a descriptive evaluation to investigate if and how the different zoids shapes impacted those data (see Table 2).

The validation of the cognitive model presented in section 3.3 was carried out through the comparison of our model with the human data collected via Mental Jigsaw. In particular, it was obtained through the fitting of five linear models constructed to explain the execution times recorded during human tasks. We used as predictors the following sets of parameters:

- The characteristic of the task: type of zoid ($zoid$), the level of the game ($level$) and progressive number of the task in the game ($task_{index}$));
- users' variables like age (age), gender ($gender$) and mental rotation skill level (mr);
- Variables describing users' actions like the number of rotation and translation actions ($rotationsActs$ and $translationActs$) and the drop action ($dropAct$);
- the game modality ($gameMode$).

We considered the variables of the third group as predictors just in the case of the time of the last action ($t_{lastAction}$) and the total time of the task (t_{total}).

In the first three models, we analyzed the time of the $t_{lastAction}$. Model 1 (Equation 1) includes all the variables reported before as predictors of the $t_{lastAction}$. Model 2 (Equation 2) introduces the time spent by proposed cognitive model on the same task performed by the user (t_{model}) as an explanatory variable of $t_{lastAction}$. Finally, model 3 (Equation 3) adds the effect of the interaction between t_{model} and the game mode variable. The goal of model 3 is to test whether or not the forced game mode ($gameMode_F$) forces the player to activate a mental rotation process following the design hypothesis.

The research hypothesis is to test under what conditions model time succeeds in contributing to the variance explained. We also performed an ANOVA between models to test which of the three models could explain a significantly more significant percentage of the variance.

In addition, we also analyzed the impact of game mode and model time on the first action time ($t_{firstAction}$) and total task time (t_{total}) to check if the game mode and t_{model} have the same effect on all recorded times.

The linear models were estimated using the Ordinary least squares (OLS) method.

$$
\begin{aligned}
t_{lastAction} = {} & 1 + gender + age + mr + level + task_{index} + zoid + \\
& translationActs + rotationsActs + dropAct + gameMode
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
t_{lastAction} = {} & 1 + gender + age + mr + level + task_{index} + zoid + \\
& translationActs + rotationsActs + dropAct + \\
& gameMode + t_{model}
\end{aligned} \tag{2}
$$

$$
\begin{aligned}
t_{lastAction} = {} & 1 + gender + age + mr + level + task_{index} task_{index} + zoid + \\
& translationActs + rotationsActs + dropAct + \\
& gameMode * t_{model}
\end{aligned} \tag{3}
$$

$$
\begin{aligned}
t_{firstAction} = {} & 1 + gender + age + mr + level + task_{index} task_{index} + zoid + \\
& gameMode * t_{model}
\end{aligned} \tag{4}
$$

$$
\begin{aligned}
t_{total} = {} & 1 + gender + age + mr + level + task_{index} task_{index} + zoid + \\
& translationActs + rotationsActs + dropAct + \\
& gameMode * t_{model}
\end{aligned} \tag{5}
$$

All the analysis was performed using the open-source software R (R Core Team, 2018).

5. Results

Nineteen users (10 men, nine women) with an average age of 41.6 years ($sd = 8.31$) participated in the experiment. On average, each user played 5.84 games ($sd = 6.51$), corresponding to an average task score of 405.47 ($sd = 701.96$). In total, participants completed 7704 tasks. Thirteen users additionally completed the mental rotation test through the Mental Jigsaw app. Those users achieved an average score of 0.85 ($sd = 0.07$), corresponding to the percentage of mental rotation tasks for which the user provided a correct answer.

The following two tables provide a descriptive aAnalysis of the timing of the tasks conducted by human players collected through the Mental Jigsaw app. Specifically, Table 1 shows the descriptive analysis of the times of the tasks performed by the players. Table 2 report the human tasks times by zoid type. It shows a different distribution of times ($t_{firstAction}$, $t_{lastAction}$, and t_{total}) for the different zoid types; in particular, for the zoid pairs S/Z and J/L the times are on average longer than for the other zoids. This result is in line with the basic assumptions of the proposed cognitive model that hypothesize the activation of the mental rotation process just for those zoids for which their reflected version exist.

Table 1: Descriptive statistics of players' tasks times

Variable	Mean	SD	Skewness	Kurtosis	% Missing
$t_{firstAction}$	1594	1351	2.95	12.42	0.675
$t_{lastAction}$	3788	2513	1.48	2.04	0.675
t_{total}	5081	3166	1.89	11.43	0.000

Table 2: Means and sd of tasks' times by zoid type

zoid	n	$\overline{t_{firstAction}}$	$\sigma(t_{firstAction})$	$\overline{t_{lastAction}}$	$\sigma(t_{lastAction})$	$\overline{t_{total}}$	$\sigma(t_{total})$
O	1144	1505.03	1052.66	2782.07	1811.70	4071.40	2430.40
I	1123	1261.70	1227.47	3221.34	2367.63	4542.95	3111.66
T	1119	1659.05	1425.73	4154.55	2554.88	5432.29	3533.88
S	1110	1682.99	1395.60	3850.42	2556.27	5087.80	3198.52
Z	1085	1714.55	1433.59	4034.08	2685.35	5332.39	3250.04
J	1041	1714.45	1420.65	4423.36	2654.76	5793.15	3259.42
L	1082	1639.77	1411.86	4139.84	2472.54	5395.80	2961.09

The validation experiment was conducted by testing the cognitive model (see section 3.3) on the same 7704 tasks completed by the users. The specific configuration of the board and the type of zoid to place define the task. The experiment was conducted considering an *attention area* of 4x4 blocks ($n = 4, m = 4$), a maximum number of 2 *attention areas* to be explored ($MAX\_areas = 2$) and a maximum number of 2 solutions for each area to be verified ($MAX\_solutions = 2$). In 6473 out of 7704 tasks (i.e., 84.02% of the cases), the cognitive model was able to find a solution within the constraints imposed by the model.

Linear models were estimated on 6949 tasks, corresponding to the tasks completed by users who completed the mental rotation test for which the player performed at least one action.

The model 1 (Eq. 1) explains a significant and substantial proportion of variance ($R^2 = 0.51$, $F(15, 6933) = 473.45$,$p < .001$, $adj.R^2 = 0.50$). The model's intercept, corresponding to $gender = female$, $age = 0$, $mr = 0$, $task_{index} = 0$, $level = 0$, $zoid = O$, $translationActs = 0$, $rotationActs = 0$, $dropAct = FALSE$ and $gameMode = NORMAL$, is at -1512.10 ($t(6933) = -4.76$, $p < .001$).

The model 2 (Eq. 2) explains a significant and substantial proportion of variance ($R^2 = 0.51$,$F(16, 6932) = 444.74$, $p < .001$, $adj.R^2 = 0.51$). Within the model 2, the effect of t_{model} is significantly positive ($\beta = 0.03$, $t(6932) = 2.74$, $p < .01$)

Also model 3 (Eq. 3) explains a significant and substantial proportion of variance ($R^2 = 0.51$, $F(17, 6931) = 420.42$, $p < .001$, $adj.R^2 = 0.51$). Within the model 3, the effect of t_{model} is no longer significantly ($beta = 0.01$, $t(6931) = 1.09$, $p = 0.275$). On the contrary, the interaction effect of t_{model} on $gameMode_F$ is significantly positive ($beta = 0.12$, $t(6931) = 3.99$, $p < .001$).

The ANOVA between the models evidences a significant $\Delta R^2 = 0.00053$ between model 1 and model 2 $F(1, 6932) = 7.54$, $p < .01$. Furthermore, a significant $\Delta R^2 = 0.00113$ is also shown between model 2 and model 3 $F(1, 6931) = 15.95$, $p < .001$. Table 3 reports the values of the linear model estimates.

Table 4 shows the comparison between the estimates of models 3, 4 (Eq.

Table 3: Fits of linear models

	Dependent variable:		
	$t_{lastAction}$		
	(1)	(2)	(3)
$gender_{male}$	$-1{,}123.40^{***}$ (83.08)	$-1{,}124.98^{***}$ (83.04)	$-1{,}127.61^{***}$ (82.96)
age	17.78^{***} (3.66)	17.63^{***} (3.66)	17.62^{***} (3.65)
mr	$3{,}555.83^{***}$ (450.58)	$3{,}548.34^{***}$ (450.37)	$3{,}567.25^{***}$ (449.91)
$task_{index}$	-1.72^{***} (0.25)	-1.73^{***} (0.25)	-1.72^{***} (0.25)
$level$	-87.79^{***} (17.30)	-86.76^{***} (17.30)	-87.95^{***} (17.28)
$zoid_I$	-229.02^{***} (78.12)	-233.54^{***} (78.10)	-238.02^{***} (78.02)
$zoid_T$	46.73 (82.05)	25.37 (82.38)	15.72 (82.33)
$zoid_S$	518.54^{***} (78.53)	486.32^{***} (79.37)	479.63^{***} (79.30)
$zoid_Z$	625.39^{***} (79.27)	594.91^{***} (80.01)	589.78^{***} (79.93)
$zoid_J$	226.11^{***} (84.27)	156.98^{*} (87.92)	152.86^{*} (87.83)
$zoid_L$	-29.70 (82.91)	-106.63 (87.49)	-107.00 (87.40)
$translationActs$	171.05^{***} (7.35)	171.45^{***} (7.34)	171.02^{***} (7.34)
$rotationActs$	737.30^{***} (14.82)	736.11^{***} (14.82)	737.88^{***} (14.81)
$dropAct$	-565.88^{***} (52.25)	-565.30^{***} (52.22)	-561.44^{***} (52.17)
$gameModeF$	$2{,}751.28^{***}$ (66.80)	$2{,}754.27^{***}$ (66.78)	$2{,}513.46^{***}$ (89.93)
t_{model}		0.03^{***} (0.01)	0.01 (0.01)
$gameModeF : t_{model}$			0.12^{***} (0.03)
Constant	$-1{,}512.10^{***}$ (317.51)	$-1{,}539.08^{***}$ (317.51)	$-1{,}512.16^{***}$ (317.24)
Observations	6,949	6,949	6,949
R^2	0.51	0.51	0.51
Adjusted R^2	0.50	0.51	0.51
Residual Std. Error	1,745.65 (df = 6933)	1,744.83 (df = 6932)	1,742.95 (df = 6931)
F Statistic	473.45^{***} (df = 15; 6933)	444.74^{***} (df = 16; 6932)	420.42^{***} (df = 17; 6931)

Note: *p<0.1; **p<0.05; ***p<0.01

4) and 5 (Eq. 5). The comparison allows us to verify the effect of t_{model} on all three recorded times. Specifically, the model 4 explains a significant and moderate proportion of variance ($R^2 = 0.19$, $F(14, 6934) = 114.79$, $p < .001$, $adj.R^2 = 0.19$). The model's intercept, corresponding to $gender = female$, $age = 0$, $mr = 0$, $task_{index} = 0$, $level = 0$, $zoid = O$, $gameMode = N$ and $time = 0$, is at -1540.81 ($t(6934) = -7.09$, $p < .001$). Whithin this model, the effect of t_{model} is significantly positive ($\beta = 0.02$, $t() = 2.07$, $p < .05$), while the interaction effect of t_{model} on $gameMode_F$ is significantly positive ($\beta = 0.07$, $t() = 3.36$, $p < .001$).

Finally, model 5 explains a significant and substantial proportion of variance ($R^2 = 0.56$, $F(17, 6970) = 514.04$, $p < .001$, $adj.R^2 = 0.56$). The effect of t_{model} is non-significantly positive, while the interaction effect of t_{model} on $gameMode_F$ is significantly positive ($\beta = 0.10$, $t() = 2.91$, $p < .01$)

6. Discussion

Statistical analysis was conducted to verify to what extent the proposed cognitive model was able to help to explain the behaviours of human players engaged in the same tasks.

The data show the model strength in finding an adequate solution (84.02% of the cases).

For what concerns the role of mental rotation within the Tetris™ game, the correlation analysis of the times recorded on human tasks and times generated by the cognitive model showed represented the central element of analysis of the present work. For this reason, we tried to reduce as much as possible the extreme heterogeneity of the data. This goal was accomplished using linear models in which the times of tasks performed by human players were explained as a function of certain variables. This operation also has an explanatory value of the process itself. These explanatory variables were used in all five linear models, with consistent results across all models. To explain the role of each explanatory variable, we refer to the results of the first model (Eq. 1).

Table 4: Fits of linear models on first action and total times

	Dependent variable:	
	timeFirstAction	timeSpan
	(4)	(5)
$gender_{male}$	-805.86^{***} (56.86)	$-1{,}192.93^{***}$ (93.86)
age	25.09^{***} (2.51)	43.54^{***} (4.14)
mr	$2{,}186.01^{***}$ (311.51)	173.09 (509.59)
$task_{index}$	-0.84^{***} (0.18)	-2.63^{***} (0.29)
$level$	-3.06 (11.89)	-103.65^{***} (19.63)
$zoid_I$	-182.83^{***} (53.56)	-134.33 (88.50)
$zoid_T$	213.64^{***} (53.94)	44.15 (93.39)
$zoid_S$	217.77^{***} (54.36)	403.65^{***} (89.89)
$zoid_Z$	237.05^{***} (54.71)	516.42^{***} (90.68)
$zoid_J$	219.95^{***} (57.62)	194.46^{*} (99.62)
$zoid_L$	139.62^{**} (57.87)	-218.94^{**} (98.98)
$translationActs$		135.85^{***} (8.29)
$rotationActs$		621.37^{***} (16.80)
$dropAct$		$-3{,}038.79^{***}$ (58.85)
$gameMode_F$	$1{,}078.23^{***}$ (61.73)	$2{,}299.23^{***}$ (101.82)
t_{model}	0.02^{**} (0.01)	0.02 (0.01)
$gameMode_F$:t_{model}	0.07^{***} (0.02)	0.10^{***} (0.03)
Constant	$-1{,}540.81^{***}$ (217.25)	$3{,}952.73^{***}$ (358.56)
Observations	6,949	6,988
R^2	0.19	0.56
Adjusted R^2	0.19	0.56
Residual Std. Error	1,214.48 (df = 6934)	1,983.74 (df = 6970)
F Statistic	114.79^{***} (df = 14; 6934)	514.04^{***} (df = 17; 6970)

Note: *p<0.1; **p<0.05; ***p<0.01

It allows us to explain some general qualities of the process. In particular, concerning the player's characteristics, in our group of participants, a significant effect of gender is highlighted. Male players take, on average, less time to complete the task ($\beta = -1,123.40$, $p < .001$).

The player's age seems to play also a significant role; in particular, the data show a positive effect ($\beta = 17.78$, $p < .001$), i.e. as the age increases, the players seem to spend more time solving the task.

Of great interest is the result on mental rotation ($\beta = 3,555.83$, $p < .001$) that at a first interpretation could seem counterintuitive. Results show that players with a higher mental rotation ability take longer to complete the task. A possible interpretation could be given by what has already emerged in the literature concerning mental rotation ability to predict effectiveness in gaming activity (Pilegard & Mayer, 2018). According to this interpretation, more skilled players use all the time at their disposal to evaluate alternative solutions and, therefore, complete the task in a significantly longer time.

Results confirm expectations regarding the task's characteristic variables, i.e. the time of the last action decreases as the level advances ($\beta = -87.79$, $p < .001$) and in general as the game progresses ($task_{index}$) ($\beta = -1.72$, $p < .001$). Moreover, as widely demonstrated in previous studies, the zoid type is essential in explaining the task's times. In detail, some shapes such as the zoid S, Z, and J significantly increase task execution times.

The group of explanatory variables related to the actions performed by the user (number of rotations, number of translations and pressing the drop button) were included to increase the variance explained by the model and to allow a cleaner reading of the possible effect of the two main variables: the game mode and the time taken by the model (t_{model}).

The results of model 1 show that the forced mode contributes significantly to increasing the task resolution time ($\beta = 2,751.28$, $p < 0.001$) as expected.

Models 2 and 3 highlight the contribution of model time in explaining human user execution time. In particular, in model 2, the model time was included as an additional explanatory variable highlighting a significant contribution to the explanation of the time of the last action ($\beta = 0.03$,$p < 0.001$).

The inclusion of the interaction term in model 3 and its results highlight a significant effect of the model within the forced mode ($\beta = 0.12$, $p < 0.001$) at the expense of a global effect that is no longer significant. This result is coherent with design expectations, as it confirms that the user is forced to activate the mental rotation process when engaged with the forced game mode. Therefore, it seems confirmed that the mental rotation process is not always activated by the human user, who often simplify the task and bypass the activation of the mental rotation process by adopting epistemic rotational actions.

Finally, the results of models 4 and 5, conducted respectively on the time of the first action and on the total time, confirm the results obtained concerning the time of the last action.

Even with respect to first action and total task times, model time contributes to their explanation, especially in the forced game mode condition where $\beta = 0.07$ ($p < 0.001$) for model 4 and $\beta = 0.10$ ($p < 0.001$) for model 5. Of note, in the case of first action time (model 4), model time is significant regardless of game mode ($\beta = 0.02(p < 0.01)$).

7. Conclusion

In this paper, we present the first version of a cognitive model that exploits mental rotation as a fundamental process in the Tetris$^{\text{TM}}$ game.

Although the experiment was carried out on a relevant number of tasks (7704), it represents a preliminary step in the formal definition of an agent model able to explain the cognitive processes underlying the game activity in the TetrisTM.

Defining a cognitive model about the Tetris$^{\text{TM}}$ allows us to investigate whether and under what conditions mental rotation ability is employed in gaming activities.

Moreover, a better understanding of the phenomenon allows us to interpret the conflicting results in the literature concerning the effectiveness of Tetris$^{\text{TM}}$

as a spatial skills training tool (Pilegard & Mayer, 2018).

Considerations that may be essential for the eventual re-design of play activities to maximize the educational effectiveness of this tool.

To this end, the game data collected through a specific game app were compared with the results obtained by the virtual agent engaged in the same game tasks.

As extensively described throughout this paper, a central aspect of the model validation process is the analysis of game times.

Generally, the results seem to prove the cognitive model's validity in explaining the users' activities and then confirming the main hypothesis underlying its implementation.

The main idea behind the model is that the mental rotation process is cognitively activated only for those Zoids forms for which the game involves two versions, one reflecting the other. Specifically, in our model, mental rotation plays a role exclusively for the S/Z and J/L pairs, where mental rotation is necessary to avoid errors.

The results confirm what has already been observed by Kirsh & Maglio (1994). Under specific conditions, human players tend to use rotation as an epistemic action to reduce the cognitive load required to solve the task. In our study, the significance of the model in the forced game condition confirms this hypothesis.

This finding opens exciting perspectives about the possibility of rethinking game activities to improve the educational effectiveness of these tools.

In particular, the introduction of the forced rotation mode by preventing the player from using rotations as epistemic actions would seem to succeed in forcing the mental rotation process in the player. It appears urgent the need to verify if this game mode, or other modes designed with the same intent, can improve the effectiveness of Tetris™ in the training of visuospatial skills.

Finally, the significance of the model's time in explaining the timing of the first action regardless of the mode of play suggests the need to analyse the stages preceding the first action in greater detail. To this end, it seems clear that such an analysis requires different observational techniques than the analysis of logs recorded from the game. Mixed approaches based on the techniques of thinking aloud and on the biophysical analysis of signals such as those coming from EEG instruments or related to the eye-tracking of users could provide interesting information to improve the validity of the proposed cognitive model.

This work represents a first case study in which computational cognitive models are applied to get hints on game design and to maximize their educational effectiveness as training tools.

References

Albers, A. M., Kok, P., Toni, I., Dijkerman, H. C., & de Lange, F. P. (2013). Shared representations for working memory and mental imagery in early visual cortex. *Current Biology*, *23*, 1427–1431. URL: `https://doi.org/10.1016/j.cub.2013.05.065`. doi:`10.1016/j.cub.2013.05.065`.

Anderson, J. R., Matessa, M., & Lebiere, C. (1997). ACT-r: A theory of higher level cognition and its relation to visual attention. *Human–Computer Interaction*, *12*, 439–462. URL: `https://doi.org/10.1207/s15327051hci1204_5`. doi:`10.1207/s15327051hci1204_5`.

Atkinson, R., & Shiffrin, R. (1968). Human memory: A proposed system and its control processes. (pp. 89–195). Academic Press volume 2 of *Psychology of Learning and Motivation*.

Augello, A., Città, G., Gentile, M., & Lieto, A. (2022). A storytelling robot managing persuasive and ethical stances via act-r: an exploratory study. *International Journal of Social Robotics, arXiv:2107.12845*, .

Battista, M. T. et al. (1989). Spatial visualization, formal reasoning, and geometric problem-solving strategies of preservice elementary teachers. *Focus on Learning Problems in Mathematics*, *11*, 17–30.

Borst, J. P., Taatgen, N. A., & van Rijn, H. (2010). The problem state: A cognitive bottleneck in multitasking. *Journal of Experimental Psychology:*

Learning, Memory, and Cognition, *36*, 363–382. URL: https://doi.org/10.1037/a0018106. doi:10.1037/a0018106.

Burnett, S. A., & Lane, D. M. (1980). Effects of academic instruction on spatial visualization. *Intelligence*, *4*, 233–242.

Carpenter, P., Just, M., Keller, T., Eddy, W., & Thulborn, K. (1999). Graded functional activation in the visuospatial system with the amount of task demand. *Journal of Cognitive Neuroscience*, *11*, 9–24. doi:10.1162/089892999563210. Cited By 250.

Cheng, Y.-L., & Mix, K. S. (2013). Spatial training improves children's mathematics ability. *Journal of Cognition and Development*, *15*, 2–11. URL: https://doi.org/10.1080/15248372.2012.725186. doi:10.1080/15248372.2012.725186.

Christophel, T. B., Cichy, R. M., Hebart, M. N., & Haynes, J.-D. (2015). Parietal and early visual cortices encode working memory content across mental transformations. *NeuroImage*, *106*, 198–206. URL: https://doi.org/10.1016/j.neuroimage.2014.11.018. doi:10.1016/j.neuroimage.2014.11.018.

Città, G., Gentile, M., Allegra, M., Arrigo, M., Conti, D., Ottaviano, S., Reale, F., & Sciortino, M. (2019). The effects of mental rotation on computational thinking. *Computers & Education*, *141*, 103613. URL: https://www.sciencedirect.com/science/article/pii/S0360131519301666. doi:https://doi.org/10.1016/j.compedu.2019.103613.

Clements, D. H., & Battista, M. T. (1992). Geometry and spatial reasoning. In *Handbook of research on mathematics teaching and learning: A project of the National Council of Teachers of Mathematics* (pp. 420–464). Macmillan Publishing Co, Inc. URL: http://psycnet.apa.org/psycinfo/1992-97586-018.

Cooper, L. a., & Shepard, R. N. (1973). Chronometric studies of the rotation of mental images. *Visual Information Processing: Proceedings*, *Vi*, 555. doi:10.1111/j.1467-9280.1993.tb00468.x.

Ganis, G., & Kievit, R. (2015). A new set of three-dimensional shapes for investigating mental rotation processes: Validation data and stimulus set. *Journal of Open Psychology Data*, *3*. URL: https://doi.org/10.5334/jopd.ai. doi:10.5334/jopd.ai.

Gentile, M., Città, G., Lieto, A., & Allegra, M. (2019). Some notes on the possibile role of cognitive architectures in serious games. In A. Liapis, G. N. Yannakakis, M. Gentile, & M. Ninaus (Eds.), *Games and Learning Alliance* (pp. 231–241). Cham: Springer International Publishing.

Gray, W. D. (2017). Game-XP: Action games as experimental paradigms for cognitive science. *Topics in Cognitive Science*, *9*, 289–307. URL: https://doi.org/10.1111/tops.12260. doi:10.1111/tops.12260.

Holmes, J., Adams, J. W., & Hamilton, C. J. (2008). The relationship between visuospatial sketchpad capacity and children's mathematical skills. *European Journal of Cognitive Psychology*, *20*, 272–289. URL: https://doi.org/10.1080/09541440701612702. doi:10.1080/09541440701612702.

Iamshchinina, P., Kaiser, D., Yakupov, R., Haenelt, D., Sciarra, A., Mattern, H., Luesebrink, F., Duezel, E., Speck, O., Weiskopf, N., & Cichy, R. M. (2021). Perceived and mentally rotated contents are differentially represented in cortical depth of v1. *Communications Biology*, *4*. URL: https://doi.org/10.1038/s42003-021-02582-4. doi:10.1038/s42003-021-02582-4.

Kim, S.-y., & Taber, C. (2004). A cognitive/affective model of strategic behavior-2-person repeated prisoner's dilemma game. In *ICCM* (pp. 360–361).

Kirsh, D., & Maglio, P. (1994). On distinguishing epistemic from pragmatic action. *Cognitive Science*, *18*, 513–549.

Kozhevnikov, M., Kosslyn, S., & Shephard, J. (2005). Spatial versus object visualizers: A new characterization of visual cognitive style. *Memory & Cognition*, *33*, 710–726. URL: https://doi.org/10.3758/bf03195337. doi:10.3758/bf03195337.

Lebiere, C., Wallach, D., & West, R. (2000). A memory-based account of the prisoner's dilemma and other 2x2 games. In *Proceedings of international conference on cognitive modeling* (pp. 185–193). Universal Press Gronigen, NL.

Lebiere, C., & West, R. L. (2020). A dynamic act-r model of simple games. In *Proceedings of the Twenty First Annual Conference of the Cognitive Science Society* (pp. 296–301). Psychology Press.

Lieto, A. (2021). *Cognitive design for artificial minds*. Routledge (Taylor & Francis).

Lieto, A., Lebiere, C., & Oltramari, A. (2018). The knowledge level in cognitive architectures: Current limitations and possible developments. *Cognitive Systems Research*, *48*, 39–55.

Lora Ariza, D. S., Sánchez-Ruiz, A. A., & González-Calero, P. A. (2017). Time series and case-based reasoning for an intelligent tetris game. In D. W. Aha, & J. Lieber (Eds.), *Case-Based Reasoning Research and Development* (pp. 185–199). Cham: Springer International Publishing.

Mandler, G., & Shebo, B. J. (1982). Subitizing: An analysis of its component processes., . *111*, 1–22. URL: https://doi.org/10.1037/0096-3445.111.1.1. doi:10.1037/0096-3445.111.1.1.

Metzler, J., & Shepard, R. N. (1974). Transformational studies of the internal representation of three-dimensional objects., .

Milani, L., Grumi, S., & Blasio, P. D. (2019). Positive effects of videogame use on visuospatial competencies: The impact of visualization style in preadolescents and adolescents. *Frontiers in Psychology*, *10*. URL: https://doi.org/10.3389/fpsyg.2019.01226. doi:10.3389/fpsyg.2019.01226.

Moon, J., & Anderson, J. (2012). Modeling millisecond time interval estimation in space fortress game. In *Proceedings of the Annual Meeting of the Cognitive Science Society*. volume 34.

Oh, H., Yun, Y., & Myung, R. (2021). Cognitive modeling of task switching in discretionary multitasking based on the ACT-r cognitive architecture. *Applied Sciences*, *11*, 3967. URL: https://doi.org/10.3390/app11093967. doi:10.3390/app11093967.

Olkun, S. (2003). Making connections: Improving spatial abilities with engineering drawing activities. *International Journal of Mathematics Teaching and Learning*, *3*, 1–10.

Peebles, D. (2019). Modelling alternative strategies for mental rotation. In T. Stewart (Ed.), *Proceedings of the ICCM 2019*. United States: Applied Cognitive Science Lab. URL: http://iccm-conference.org/ 17th International Conference on Cognitive Modelling, ICCM2019 ; Conference date: 19-07-2019 Through 22-07-2019.

Pilegard, C., & Mayer, R. E. (2018). Game over for tetris as a platform for cognitive skill training. *Contemporary Educational Psychology*, *54*, 29–41. URL: https://www.sciencedirect.com/science/article/pii/S0361476X17304988.

Posner, M. I. (1980). Orienting of attention. *Quarterly Journal of Experimental Psychology*, *32*, 3–25. URL: https://doi.org/10.1080/00335558008248231. doi:10.1080/00335558008248231.

R Core Team (2018). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing Vienna, Austria. URL: https://www.R-project.org/.

Ritter, F. E., Tehranchi, F., & Oury, J. D. (2019). Act-r: A cognitive architecture for modeling cognition. *Wiley Interdisciplinary Reviews: Cognitive Science*, *10*, e1488.

Schrum, J. (2018). Evolving indirectly encoded convolutional neural networks to play tetris with low-level features. In *Proceedings of the Genetic and Evolutionary Computation Conference*. ACM. URL: `https://doi.org/10.1145/3205455.3205459`. doi:`10.1145/3205455.3205459`.

Shepard, R. N., & Metzler, J. (1971). Mental rotation of three-dimensional objects. *Science*, *171*, 701–703. URL: `https://doi.org/10.1126/science.171.3972.701`. doi:`10.1126/science.171.3972.701`.

Spiliopoulos, L. (2013). Strategic adaptation of humans playing computer algorithms in a repeated constant-sum game. *Autonomous agents and multi-agent systems*, *27*, 131–160.

Trafton, G., Hiatt, L., Harrison, A., Tanborello, F., Khemlani, S., & Schultz, A. (2013). ACT-r/e: An embodied cognitive architecture for human-robot interaction. *Journal of Human-Robot Interaction*, *2*, 30–55. URL: `https://doi.org/10.5898/jhri.2.1.trafton`. doi:`10.5898/jhri.2.1.trafton`.

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*, 97–136. URL: `https://doi.org/10.1016/0010-0285(80)90005-5`. doi:`10.1016/0010-0285(80)90005-5`.

Trithart, S. (2000). A preliminary investigation of individual differences in mental workload: An information processing based approach. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *44*, 121–124. URL: `https://doi.org/10.1177/154193120004401701`. doi:`10.1177/154193120004401701`.

Vandenberg, S. G., & Kuse, A. R. (1978). Mental rotations, a group test of three-dimensional spatial visualization. *Perceptual and Motor Skills*, *47*, 599–

604. URL: https://doi.org/10.2466/pms.1978.47.2.599. doi:10.2466/pms.1978.47.2.599.

Verdine, B. N., Golinkoff, R. M., Hirsh-Pasek, K., Newcombe, N. S., Filipowicz, A. T., & Chang, A. (2013). Deconstructing building blocks: Preschoolers' spatial assembly performance relates to early mathematical skills. *Child Development*, *85*, 1062–1076. URL: https://doi.org/10.1111/cdev.12165. doi:10.1111/cdev.12165.

Wolfe, J. M. (1994). Guided search 2.0 a revised model of visual search. *Psychonomic Bulletin & Review*, *1*, 202–238. URL: https://doi.org/10.3758/bf03200774. doi:10.3758/bf03200774.

Wright, R., Thompson, W. L., Ganis, G., Newcombe, N. S., & Kosslyn, S. M. (2008). Training generalized spatial skills. *Psychonomic bulletin and review*, *15 4*, 763–71.