Psychology Research, ISSN 2159-5542
May 2013, Vol. 3, No. 5, 276-289

# The Role of Memory Templates in Experts' Strategic Thinking*

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There is ample evidence that experts' performance is mostly due to domain specific knowledge. Some complex memory structures, termed templates, have been theorised to underpin strategic thinking in expert chess players. A behavioural study and computer simulations have been used to test this hypothesis. The behavioural study is the first to show that experts identify strategic systems with more accuracy than novices do. A new artificial neural network model is introduced to implement visuospatial templates. The simulations indicate that templates adequately model identification of strategies in novice and expert players. Both results support the view that templates underpin strategic thinking. The findings constitute a demonstration of the dependence of strategic thinking on memory processes and open the door for a new theoretical approach to understand high-level cognition.

*Keywords*: memory, expertise, artificial neural network, template, strategy

## Introduction

Templates are sophisticated memory units that materialize only in the later stages of expertise development (Gobet & Simon, 1996b). The use of memory templates by experts has been documented in several domains such as language acquisition (Freudenthal, Pine, & Gobet, 2009), computer programming (Gobet et al., 2001), and physics (Lane, Cheng, & Gobet, 2000). Templates underpin experts' performance in many tasks such as perception (Chase & Simon, 1973; De Groot & Gobet, 1996; Ferrari, Didierjean, & Marmèche, 2006), memory (Gobet & Simon, 1996b; 2000), imagery (Campitelli & Gobet, 2005; Saariluoma, 1991), and problem-solving (Bilalic, McLeod, & Gobet, 2008; Campitelli & Gobet, 2004). In chess, a template typically codes the position of a dozen chessmen and includes optional slots for which the values are determined during recognition. In addition to perceptual flexibility, templates provide access to a rich database of knowledge such as tactical manoeuvres, attacking procedures, and strategic knowledge. Since visuospatial templates are thought to lie at the core of strategic thinking, they would provide an invaluable insight into how experts in different fields make correct decisions in complex situations. This paper uses chess, a key domain for research in expertise (Charness, 1992), to show that experts identify strategic systems accurately and that memory templates adequately account for such performance.

Gobet and Simon (1996b) have put forward the hypothesis that frequently-occurring openings are stored as templates. In the chess jargon, the term "opening" has two meanings. On the one hand, opening refers to the first stage of the game. On the other hand, the term refers to the strategic system used by the player (Chassy & Anic, 2012). The template theory refers to the second meaning. To avoid such semantic ambiguity, the author will use the phrase strategic system in this paper. When playing a given strategic system, pieces are developed

***Acknowledgments:** The author would like to thank Prof. Fernand Gobet, Dr. Cathal O'Siochru and two anonymous reviewers for their constructive observations.
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according to a set of system-dependent principles. As a result, the position of those pieces creates a typical pattern that varies slightly as a function of the opponent's strategy. Templates are memory units that are suitable to encode such flexible, visuospatial patterns. Scholars and world-class professionals agree that the mastery of strategic systems plays a central role in experts' performance (Alekhine, 1979; Capablanca, 1931; Gobet & Simon, 1996b; Goldin, 1978; Kasparov, 1986). In line with this view, trainers recommend that players spend between 25% and 50% of their training time studying strategic systems (Alburt & Chernin, 2001; Mednis, 2002). If these ratios are applied to the amount of time necessary to reach experts' level, 10,000 hours according to Ericsson, Krampe, and Tesch-Römer (1993), they yield an estimate of 2,500 to 5,000 hours spent in learning strategic systems. Such a colossal investment in time ensures that players have accumulated huge amounts of knowledge; which is precisely what makes strategic systems particularly suitable to be encoded as templates. The consequence of which is that strategic thinking would be underpinned mainly by sophisticated memory structures.

The second part of the paper reports a human experiment where novice and expert chess players were to identify strategic systems; a demonstration that strategic thinking in experts is quick and efficient. The third part reports a neural network model of templates that simulates both novices' and experts' performance; hence showing that the ability of expert is adequately accounted for by memory processes. The discussion highlights the impact of the findings on the interaction between memory and high-level cognition.

## Experiment

### Rationale

The proposal of Gobet and Simon (1996b) that strategic systems are encoded as templates calls for an empirical test. That strategic systems are a central feature of chess performance has been emphasized by both scientists (Charness, 1976, 1981; Gobet & Simon, 1996b; Goldin, 1978; Holding, 1989; McGregor & Howes, 2002; Saariluoma, 1991, 1995), world chess champions (Alekhine, 1979; Kasparov, 1986), and chess trainers (Alburt & Chernin, 2001; Chassy & Anic, 2012; Mednis, 2002). Even though the importance of strategic systems is fully acknowledged, at the best of the author's knowledge there is no study designed to contrast novices' and experts' ability in identifying strategic systems. Since template formation is thought to occur at an advanced stage of expertise acquisition, novices should not have formed templates. By contrast, experts have templates at their disposal to identify strategic systems. As a result, novices' performance in recognizing strategic systems should be weaker than that of experts. The purpose of the experiment is twofold: (1) to show that experts can identify strategic systems with high levels of accuracy; and (2) to yield data for the modelling of templates.

### Participants

Players were all male with a mean age of 32.37 (*SD* (standard deviation) = 5.60). The data were collected in various chess clubs of France and Spain. The Elo rating is the system used by the World Chess Federation to classify chess players (Elo, 2008). The cut point for expertise is 2,000 Elo. Forty chess players participated on a voluntary basis. The expert group consisted of 20 players with an average rating of 2,028.50 Elo (*SD* = 134.10 Elo). Twenty other players were novices. The novice players were not club players and as such did not have Elo ratings. The experimenter, a chess expert (2,172 Elo), screened the novice players to ensure that they had a correct mastery of chess rules. All players were informed of the purpose of the study and of their right to withdraw at any time. They were also provided with the contact details of the experimenter should they wish to have their data erased from the sample at any time.

**Material & Procedure**

Two sets of material were prepared. One set was designed to assess whether the players could recognize basic chess manoeuvres. Six positions that include basic piece manoeuvres were selected from a chess book for beginners (Fischer, 1966). These positions were selected to ensure that the players, both novices and experts, had mastered the fundamentals of chess. The second set was used to test the ability of the players to identify strategic systems. Seven systems[1] were selected based upon experts' classification of strategic systems (Matanović, Molorović, & Božić, 1971). For each strategic system, four different positions were randomly selected in a commercial database (Chessbase 9, 2006). In addition, four positions were selected among rarely used strategic systems. For all positions, the criterion for selection was that the positions arose between ply 10 and ply 30 (where white and black have played between five and 15 times each). This is a typical measure to determine if a position belongs to the phase of the game wherein armies develop according to the principles underpinning strategic systems (Mednis, 2002). To ensure ecological validity, all positions were selected among games played by experts.

To ensure that the positions were correctly assigned to one category only, they were classified by three different computer programs (Meyer-Kahlen, 2010; Morsch & Feist, 2010; Rajlich, 2010). The degree of agreement across software was 100%. The positions were randomly sorted once and put into a questionnaire. Next to each position, the list of possible defences was presented. Figure 1 shows one position and the choice offered to the player (translated from French).

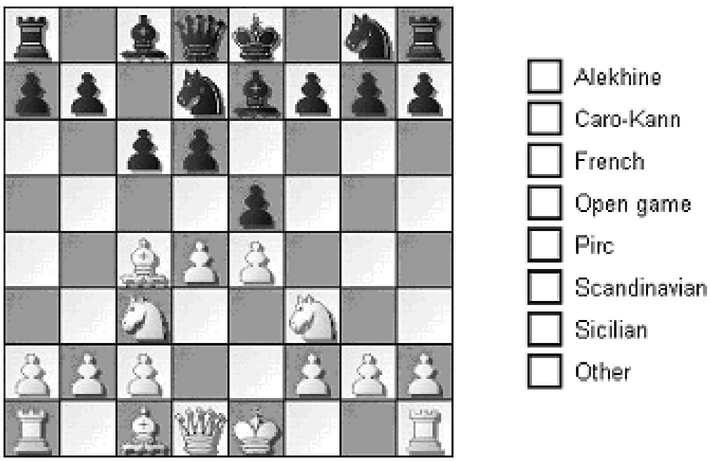


*Figure 1*. Example of a position to be classified.

The experimental procedure consisted of two phases. In the first phase, the chess players were screened for their basic knowledge. The method consisted of presenting the player with the six basic positions and asking for a solution. Both novice and expert players completed this phase with perfect performance. In the second phase, chess players were handed the questionnaire containing the 32 positions and were asked to point out, for each position, which strategic system was used. The players were instructed to tick one box only and were given as much time as they needed to complete the task. Considering that participants had the choice of between eight responses, chance performance is defined as a performance of 12.5% (i.e., 1/8).

[1] The seven systems considered in this paper account for 98.9% (390, 846/395, 198) of experts' games in reply to 1.e4 that were played between 2000 and 2006.

**Behavioural Results**

For each player, the total number of correct classifications (hits) was divided by the total number of positions (i.e., 32) so as to yield a hit ratio, reflecting the average performance of the player. Group performance was then calculated for novices and experts. The group of experts ($M$ = 92.03%, $SD$ = 1.17%) performed better than chance ($t_{(19)} = 68.18$, $p < 0.01$). Novices were less efficient in recognizing positions ($M$ = 11.72%, $SD$ = 1.20%) and their performance did not depart from chance distribution ($t_{(19)} = -0.65$, $p < 0.52$). As predicted, the difference in performance between the two groups was significant ($t_{(38)} = 48.05$, $p < 0.01$).

The chance performance of the novices, together with the significantly higher performance of the experts, converges towards the same conclusion: namely, those experts can recognize strategic systems by merely considering the distribution of pieces in a position. This result is consistent with the idea that templates are sophisticated memory units. The data collected were used to assess the performance of the computer model of templates.

**Computer Model**

ANNs (artificial neural networks) have demonstrated a high ability to detect and classify patterns (Behrman, Linder, Assadi, Stacey, & Backonja, 2007; Geetha, Pratibha, Ashok, & Ravindra, 2000; Gupta, Molfese, & Tammana, 1995; Stevens, Ikeda, Casillas, Palacio-Cayetano, & Clyman, 1999; Werbos, 1974). These techniques also proved to be highly efficient when applied to various fields of psychology (Geetha, Pratibha, Ashok, & Ravindra, 2000; Hill, Marquez, O'Connor, & Remus, 1994; Quek & Moskowitz, 2007; Read, Monroe, Brownstein, Yang, Chopra, & Miller, 2010; Schyns, 1991). Within cognitive psychology, ANN architectures are particularly suited to model perceptual and memory phenomena (Botvinick & Plaut, 2006; Carpenter, 1989; Chartier, Renaud, & Boukadoum, 2008; Kawamoto & Anderson, 1985; McClelland & Rumelhart, 1981; Norman, Neman, & Detre, 2007). In spite of its successes as a theory of expertise development, there have been surprisingly few attempts to provide a computer implementation of the template theory (Gobet et al., 2001). At the best of the author's knowledge, there were no ANN architectures. Consequently, the model will be the first to model templates utilising an ANN architecture to simulate novices' and experts' ability to identify strategic systems. The purpose of the model is to demonstrate that: (1) Templates can be implemented in an ANN; and (2) This architecture adequately accounts for identification of strategies. Before moving onto the description of the model, the author would like to indicate the key findings in cognitive neuroscience that were used as criteria to constrain the model's design.

Two processes determine the percept that will access conscious recollection: template activation and attentional filtering. Template activation results from bottom-up processing of perceptual signals along neural structures that encode long-term memories; that is, recognition takes place at the actual site where information is stored (Chassy & Gobet, 2011a). Functional neuroimaging has shown that such recognition activates knowledge in the ventral path of the visual cortex (Spiridon & Kanwisher, 2002; Squire, 2004). This region has subparts that are particularly responsive to specific types of visual stimuli, such as faces (Kanwisher, McDermott, & Chun, 1997), words (Cohen & Dehaene, 2004), or cats (Haxby, Gobbini, Furey, Ishai, Schouten, & Pietrini, 2001). Since templates are perceptual units (Gobet et al., 2001), they are also stored in visual-related areas (Amidzic, Riehle, & Elbert, 2006; Campitelli, Gobet, Head, Buckley, & Parker, 2007; Guida, Gobet, Tardieu, & Nicolas, 2012). Learning at the neural level is mediated by neural plasticity (Kandel, 2001) ; a process whereby biological neural networks are gradually rewired (Alberini, 2004; Alvarez & Squire, 1994). In line with this literature, one ANN in the current model will be devoted to perform both storage and recognition.

The other process to be implemented is attentional filtering. Top-down processes, such as response selection, are under the control of other brain areas (Barcelo, Suwazono, & Knight, 2000). These TDC (top-down control) systems bias the bottom-up processing of perceptual information to match it with goal-directed requirements. TDC is an attentional bottleneck (Tombu, Asplund, Dux, Godwin, Martin, & Marois, 2011) that is adequately modelled as a filter. In brief, a competition takes place between all perceptual inputs to access consciousness (Desimone & Duncan, 1995); such bottom-up process is biased towards task-relevant information (Beck & Kastner, 2008) by TDC. The successful percept will access working memory and thus conscious recollection (Baddeley, 1986; Gaskell & Marslen-Wilson, 2002). Thus, in line with this literature, a second ANN in the current model will be devoted to implement attentional filtering.

## Architecture

The model is termed the TEKS (templates for expert knowledge simulator). In line with the distinction between memory and attentional processes, TEKS is made of two modules; a long-term memory module and an attentional module. Figure 2 (Panel A) shows the basic structure of TEKS. The VTS (visual template store) plays the role of long-term memory. It will be the target of supervised learning and will also implement recognition by delivering the level of activation of the templates. Perceptual competition is served by the TDC module. The role of TDC is to act as the attentional bottleneck by forwarding to working memory the template that has the higher level of activation. The TDC output represents the active pointer in the frontal lobes that maintains the correct answer active in the posterior regions of the brain (Curtis & D'Esposito, 2003).

When a position is presented to TEKS, processing occurs in two stages. In the first stage, the signal is processed in VTS wherein the input is matched against each template. VTS provides the level of activation of the templates as output. These levels of activation are forwarded to the TDC, the role of which is to filter out the less appropriate answers.

Figure 2 (Panel B) shows the structure of the VTS. Consistent with Gobet and Simon (1996b), who put forward the hypothesis that one strategic system is coded as one template, the eight strategic systems will be coded as eight templates. The VTS is a three-layer feedforward neural network that can store up to eight templates. The VTS is a fully connected network: Each neuron of one layer connects to all neurons of the next layer. The input layer is made of 64 neurons. Each neuron codes the material content of one square of the chessboard. The second, hidden layer is made of 32 tan-sigmoid neurons. The output layer is made of eight linear neurons where each neuron codes the level of activation of one template. For example, the fifth neuron of the layer always codes for the "Pirc" defence. VTS takes 64-element vector as input and outputs an 8-element vector that reflects the degree of activation of the templates.

The architecture of the TDC is presented in Figure 2 (Panel C). The TDC is a probabilistic neural network made of three layers that serve the function of selecting the most active template. There is a one-to-one mapping between the VTS output and the TDC input so that the VTS output vector is used as the TDC input. The hidden layer of the TDC is made of eight neurons with radial basis transfer function. The output layer is made of one single, competitive neuron. It outputs a digit (from one to eight) reflecting which input neuron was the more active. The output neuron represents the active neurons in the frontal lobe that maintain online the active representation in the posterior areas. The TDC simulates access to working memory and thus to conscious recollection. Consequently, the TDC output simulates the participants' responses.

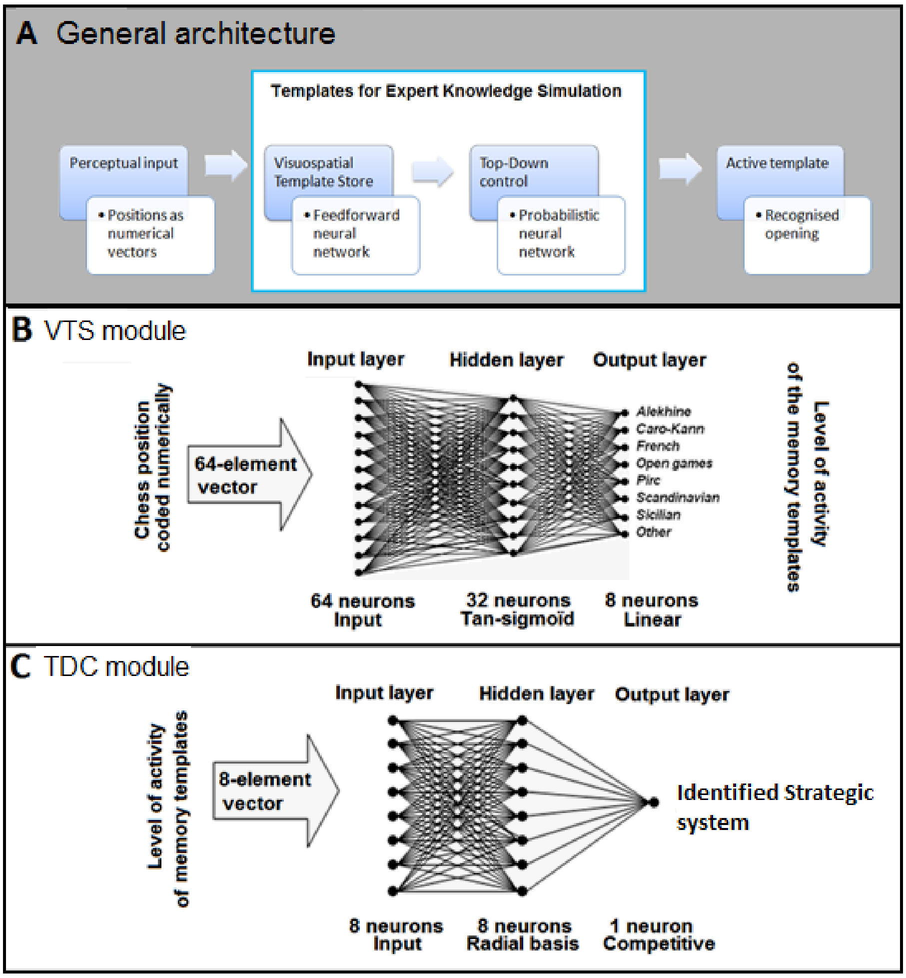


*Figure 2*. Panel A: Architecture of the TEKS model; Panel B and C: Structure of the VTS and TDC modules.

### Recoding of Chess Positions as Input Vectors

The chess positions used for training and simulation were coded numerically. The process aimed to code both the type of piece and its location on the board. The coding of pieces was done by a numerical equivalence between the nature of a piece and an integer. The numerical code used to transcribe chess positions into numerical matrices is presented in Table 1. For example, a black rook was coded -4 and a white bishop was coded 3.

Table 1

*Numerical Code Used to Code Pieces as Integers*

| Type | Color | |
|---|---|---|
| | White | Black |
| King | 6 | -6 |
| Queen | 5 | -5 |
| Rook | 4 | -4 |
| Bishop | 3 | -3 |
| Knight | 2 | -2 |
| Pawn | 1 | -1 |
| Empty | 0 | |

*Note*. An empty square was coded as zero.

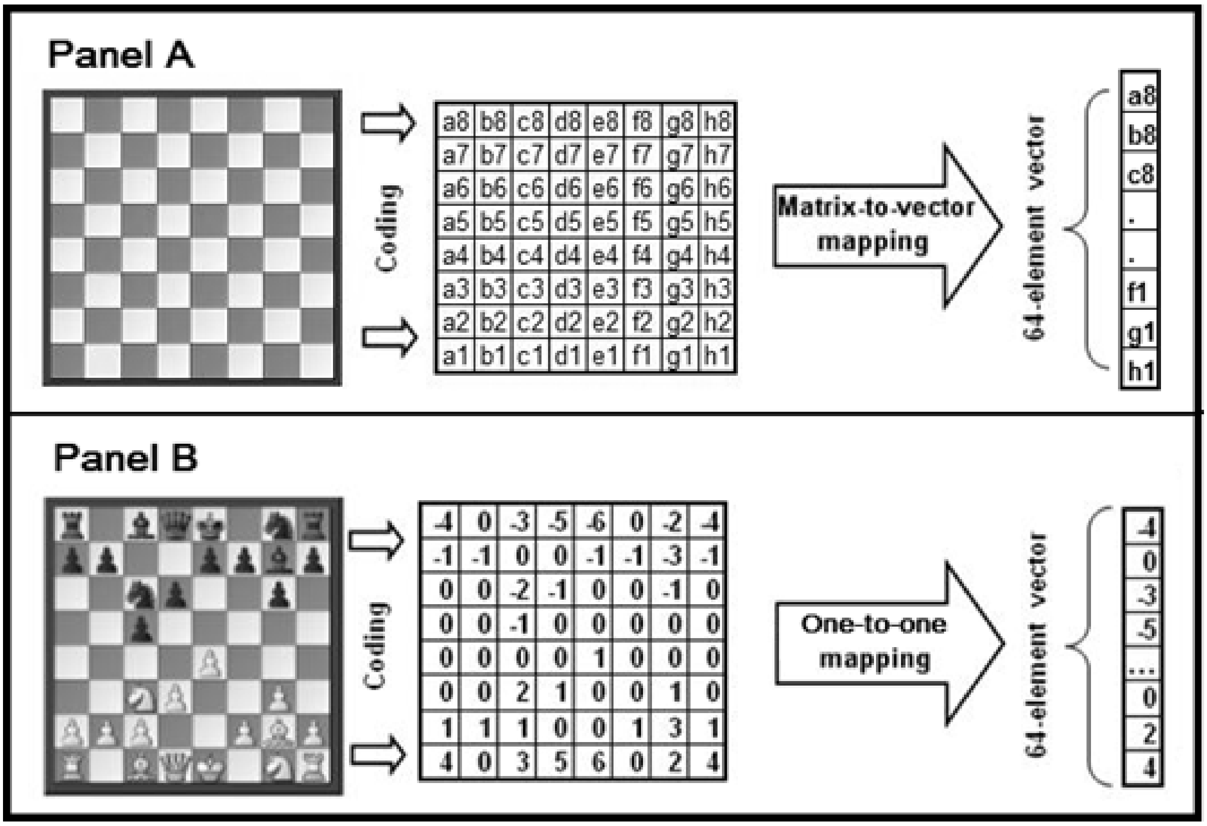


*Figure 3*. Numerical code used to code positions as numerical vectors.

Figure 3 (Panel A) shows the spatial mapping used to code a chess position (i.e., 8×8 matrix) as a TEKS-compatible input vector (i.e., 64 values in a one-dimensional vector). A one-to-one mapping between each chessboard square and a position in the input vector was used to ensure that any given slot of the one-dimensional vector always coded for the content of the same square across positions. Squares were processed one after another from left to right. Rows of the position were processed one after another from top to bottom. Panel B shows an example of the coding procedure. In the first phase, the 64 squares had their content recoded in an 8×8 matrix. Consider for instance the black bishop in square c8 (top row, third square), which was coded as -3 (see the matrix), or the white knight standing in g1 (bottom row, seventh square), which was coded as 2. In the second phase, the matrix was rearranged as a 64-element vector. This mapping technique was used because it enabled encoding chess positions numerically while maintaining the topological relationships between the pieces.

**Simulation Cycle**

TEKS has two operational modes: learning and simulation. The simulation cycle corresponds to the total of operations that are carried out by TEKS from the input in VTS to the output of TDC. Figure 4 shows the detailed structure of the VTS module. The input vector (considered as the perceptual signal) is processed four times within the VTS module. Firstly, it is weighted between the input and hidden layers. Secondly, hidden neurons process the signal by applying the tan-sigmoid transfer function. The signal is then weighted between the hidden and output layers. Finally, the signal is linearly processed by the output neurons. As a result, the VTS module has determined to which level the input signal activates each memory template.

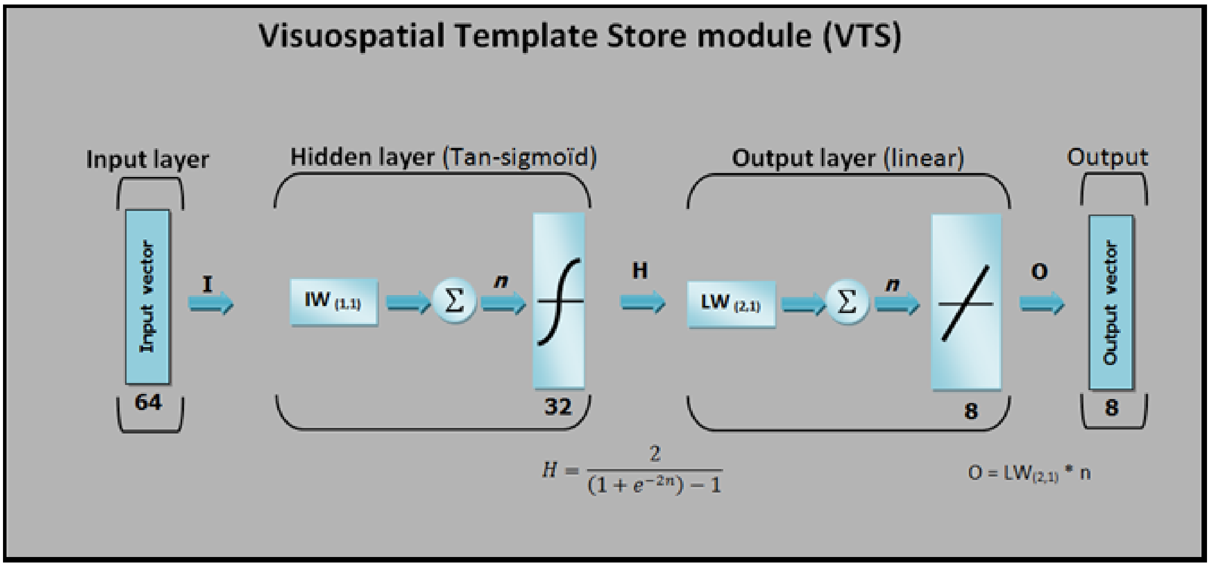


*Figure 4*. Detailed architecture of the VTS module.

The levels of activity serve as input to the TDC module. It will process the signal in three steps (See Figure 5 for the detailed structure of TDC): weighting, radial basis transformation (hidden layer), and competition. The output of the competitive neuron represents the template that accesses consciousness. If the identified template is the correct one then TEKS scores a hit (1); if it is incorrect TEKS scores a fail (0). To compare with human performance, TEKS was simulated with the 32 test positions used in the behavioural experiment. The 32 responses from TEKS were recorded and the hit ratio was calculated.

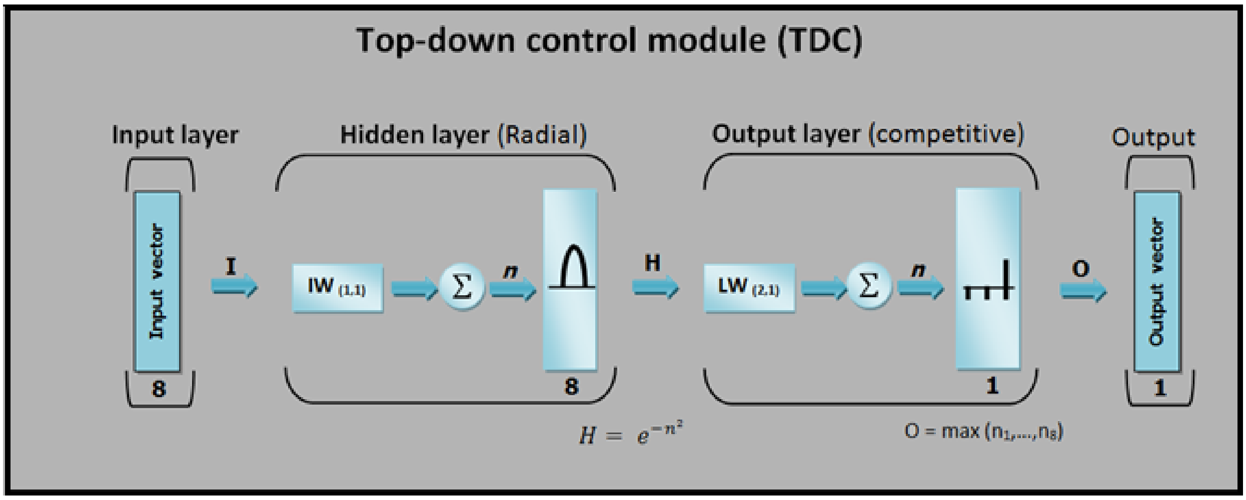


*Figure 5*. Detailed architecture of the TDC module.

**Training Cycle**

The learning mode refers to the storage of the templates in long-term memory. In TEKS, learning takes place in the VTS module. To learn, an ANN modifies the weights until it is able to provide an output vector that matches the training values. This objective is attained by gradually reducing the difference between the actual and expected outputs. In this paper, supervised learning was performed with the Levenberg-Marquardt algorithm (Levenberg, 1944; Marquardt, 1963), which had been successful in training feedforward networks in various fields of research (Adeloye & Munari, 2006; Fun & Hagan, 1996; Kermani, Schiffman, & Nagle, 2005;

Übeyli, 2009). The mathematical details of the algorithm might not always be consistent with neurobiological findings of mechanisms occurring at the molecular level (Kandel, 2001). However, its use in a network makes sense at the brain map level since real networks storing memories are also restructured progressively (Broadbent, Squire, & Clark, 2004; Squire, 2004; Squire & Zola-Morgan, 1991). The cycle of presenting an input vector, calculating the output and adjusting the weight matrix, is termed an epoch. The correction of the weights is gradual and so learning requires several epochs. It is essential to note that the set of positions used to train TEKS was different from the set used to test its performance.

**Procedure**

To simulate a novice player the network was initialized by assigning random values to the weight matrix of VTS. Then the novice TEKS was simulated with the 32 test positions from the experiment and the hit ratio was computed. To simulate 20 novices the procedure was repeated 20 times.

The procedure for the simulation of an expert consisted in three phases. In the initialization phase, the matrix weight of VTS was randomized. In the training phase, VTS was trained with a set of 128 positions (made of 16 positions per strategic system). All the training positions differed from the 32 test positions used in the behavioural experiment. Two hundred epochs were run for the training phase and only the networks scoring more than 80% with the training set were retained. In the last phase, TEKS was simulated with the 32 test positions and the hit ratio was calculated. The procedure was repeated to simulate 20 experts.

All of the simulations were run using the MATLAB® (Mathworks Inc.) environment supplemented with the Neural Network Toolbox (Demuth, Beale, & Hagan, 2009).

## Results

Figure 6 shows the performance for the participants and for TEKS. The performance of TEKS ($M$ = 12.19%, $SD$ = 4.85%) when simulating novices did not differ significantly from human novices' performance ($t_{(38)} = 0.29$, $p = 0.77$). Similarly, after training, TEKS performance ($M$ = 93.13%, $SD$ = 1.92%) did not differ significantly from the performance of human experts ($t_{(38)} = 0.88$, $p = 0.38$). Furthermore, the simulated experts classified the positions significantly better than the simulated novices ($t_{(38)} = 69.36$, $p < 0.01$), thereby replicating the results of experts and novices in the first study.

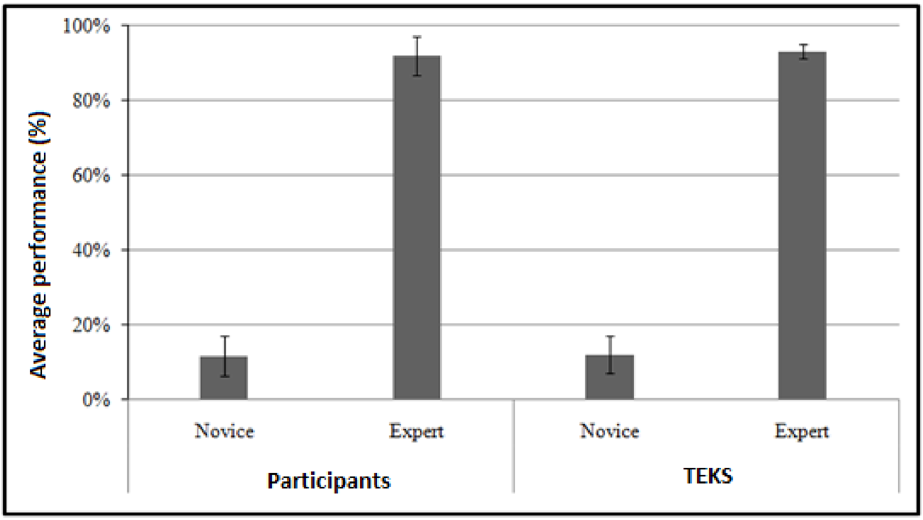


*Figure 6*. Performance of participants and of TEKS at identifying strategies. Error bars represent *SD*s ($n$ = 40).

## Discussion

The present paper aimed to evaluate the theoretical foundations of Gobet and Simon's (1996b) assumption that memory templates underpin strategic thinking. The behavioural experiment has brought conclusive evidence that experts perform strategy identification better than novices do. The simulations have shown that novices' and experts' performance are both accounted for by the recognition of flexible memory templates. The results are thus supporting Gobet and Simon's (1996b) hypothesis.

Though it may appear trivial that novices do not perform better than chance, it has several implications. First, the assumption that novices cannot recognise strategic systems, although it is an assumption of the template theory, has never been tested and finds here its first empirical supportive evidence. Second, the fact that novices with knowledge of the rules of the game and of basic tactical procedures do not recognise strategic systems is in line with the idea that templates evolve in advanced stages of expertise acquisition. Finally, the baseline level of performance that is to be reached by a psychologically valid model is chance performance (i.e., novices' average performance). By contrast, experts have performed with high accuracy, supporting the view that they have reorganized chess knowledge into complex templates. The results are in line with previous findings regarding the template theory (Campitelli, Gobet, Head, Buckley, & Parker, 2007; De Groot & Gobet, 1996; Gobet, 2003; Gobet & Simon, 1996a, 1996b, 2000; Lane, Cheng, & Gobet, 2000). In addition, the fact that variability in piece distribution within a given strategic system does not impair performance suggests that templates help experts to overcome visual complexity.

The new, modular neural network architecture termed TEKS successfully models the storage of templates and simulates both novices' and experts' ability to identify strategic systems. TEKS simulations suggest that novices' lack of knowledge can be conceptualized as a network with random connections. Also, the fact that TEKS was able to simulate experts' performance shows that experts' responses in a complex task (i.e., identifying strategic systems) are adequately accounted for by an artificial neural network model of memory. The performance of TEKS and human agents in the identification task provides the strongest evidence to date that experts' strategic knowledge is encoded in memory templates.

The findings have also opened the door for new empirical and computational avenues. Since strategic thinking is an essential aspect of experts' performance both in chess (Alekhine, 1979; Capablanca, 1931; Chassy & Anic, 2012; Hellsten, 2010; Pachman, 1972) and in other domains (e.g., Liao, 2008), the recognition of strategic systems, or of strategic features, provides a basis to link memory mechanisms to high-level cognition. Hence, the findings of the present experiment bridge a gap between the research on expertise concerned with low-level processes (*e.g.*, perceptual, Ferrari, Didierjean, & Marmèche, 2006; Simon & Chase, 1973; counting, Saariluoma, 1995; and memory, Gobet, 2003; Gobet & Waters, 2003; Saariluoma & Laine, 2001) and the research concerned with high-level processes such as forward planning (Holding & Pfau, 1985), decision-making (Campitelli & Gobet, 2004), judgment (Holding, 1979), and intuition (Chassy & Gobet, 2011a; De Groot, 1986).

The strength of the results is moderated by the fact that a restricted sample of positions was used for the classification. Unlike machines, human experts accumulate fatigue over trials. To limit the cognitive demand, the amount of material was limited to 32 positions. Research is required to further examine the discriminative capacity of experts with a wider range of strategic systems. The second limitation relates to the definition of expertise. Chassy (2009) had shown that chess experts display some variability in the quality of their decisions and had suggested to distinguish several subclasses of experts; a view that received further support by research on rote memory of sequences (Chassy & Gobet, 2011b). Considering that the experts that were recruited were not of the highest possible standard (world-class players) the performance attained in the present experiment might not reflect the maximum performance that experts can attain. Future research might address these limitations by testing players that span several classes of expertise and by including more strategic systems.

The main findings of this study shed a new light on the role of memory in experts' performance. As the behavioural data indicate, expert chess players are able to identify chess strategies by merely attending to a position. This finding supports the template view of strategic thinking. The first neural network model of the template theory has adequately modelled novices' and experts' behaviour in a strategic identification task. That human data could be accounted for by a neural network model-based architecture lends credence to the notion that memory lies at the core of strategic thinking. The next objective is to show how this system supports intuitive judgment.

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