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A motivationally-based simulation of performance degradation under pressure

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ABSTRACT

The CLARION cognitive architecture has been shown to be capable of simulating and explaining a wide range of psychological tasks and data. Currently, two theories exist to explain the psychological phenomenon of performance degradation under pressure: the distraction theory and the explicit-monitoring theory. However, neither provides a detailed mechanistic explanation of the exact processes involved. We propose such a detailed theory within the CLARION cognitive architecture that takes into account motivation and the interaction between explicit and implicit processes. We then use our theory to provide a plausible explanation of some existing data. The data are simulated using the theory within the CLARION cognitive architecture.

1. Introduction

Research on performance in mental as well as physical tasks has shown that accuracy of performance often tends to worsen as anxiety increases (e.g., in high-pressure situations; as we see them in our interpretations of the data of Beilock, Kulp, Holt, and Carr (2004), Lambert et al. (2003)). Whether one refers to this phenomenon as "choking under pressure" or "losing control", anxiety (as in our interpretations of high-pressure situations) often tends to hinder a person's ability to perform optimally. What is anxiety and why does it have such an effect on performance, mechanistically?

Within the theoretical framework of CLARION (Sun, 2002, 2003, 2009), as we see it, experiences of anxiety are the results of elevated levels of anxiety-inducing (avoidance-oriented) motivational drives (as will be elaborated later; see (Sun, 2003, 2007, 2009)). When these drives are elevated by high-pressure situations to a certain point, they tend to hinder performance. It has been well documented that attention and control are a finite resource (Navon, 1984; Shiffrin & Schneider, 1977). It has also been shown that there are internal factors that can reduce levels of attention and control (Lambert et al., 2003; Payne, 2001). Anxiety-inducing motivational drives (Sun, 2007, 2009) can cause a reduction of attention and control, and therefore performance degradation on tasks when they are present in conjunction with the execution of the tasks (Lambert et al., 2003).

Attempts at explaining the phenomenon have led to competing theories. One view is that normally people tend to prefer executing tasks in a somewhat controlled (somewhat explicit) fashion, which requires a certain level of attention but may also result in higher accuracy (Sun, 2002). Anxiety (or other distracting factors) may reduce attention and control (Eastbrook, 1959), thus limiting a person's ability to use explicit (controlled) processing, forcing them to rely more on their implicit processes (Cohen, 1978), thereby reducing performance (unless in very highly practiced situations). This theory is commonly known as "the distraction theory" (Lewis & Linder, 1997).

Another view is that tasks become implicitly encoded during practice in a "top-down" fashion (Shiffrin & Schneider, 1977; Sun, 2002) and after a certain period of time, people rely more on the well-rehearsed implicit processes than explicit processes. Under this view, anxiety (or other distracting factors) may affect a person's ability to rely on their well-rehearsed implicit processes causing them to become more explicit and engage in step-by-step monitoring (thus affecting both performance and response time). This theory is referred to as "the explicit monitoring theory" (Beilock & Carr, 2001; Langer & Imber, 1979; Lewis & Linder, 1997; Masters, 1992).

The following section will detail the explicit monitoring theory and the distraction theory. We will then develop an alternative mechanistic, process-based explanation of the phenomenon of performance degradation under pressure, within the framework of CLARION. This new CLARION based theory will be applied to the simulation of the golf-putting task using the CLARION cognitive architecture and the results will be matched to some data from Beilock and Carr (2001).

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2. Some existing theories

Let us look into the golf-putting task from Beilock and Carr (2001, experiment 3). In their experiment 3, participants were asked to hit a golf ball at a red square from 9 different positions. Participants were put in several different types of context. Then, following training, they were presented with a high-pressure scenario (aimed at causing presumably elevated levels of anxiety). The results indicated that participants who were trained in a distraction-free (single-task) condition experienced the performance degradation phenomenon in a high-pressure (presumably high anxiety) post-test while those participants who were trained in a self-conscious condition during training did not suffer performance degradation.

Beilock and Carr's (2001) results might be explained by the explicit monitoring theory. It might be postulated that when performance degradation occurred, it resulted from explicit monitoring (e.g., in response to performance anxiety). Performance pressure appeared to elicit maladaptive efforts to impose step-by-step explicit control/monitoring over complex, well-rehearsed, implicit procedures that would be more automatic had such efforts not intervened. Practice under the self-conscious condition served to mitigate this tendency.

According to the explicit-monitoring theory, when a task that is procedural and automated in nature (i.e., implicit) is affected by certain situations (e.g., high pressure and thus high anxiety), execution of the task will become more explicit. This is the "over-thinking" phenomenon that happens sometimes when a person is anxious, which often hampers performance.[1]

On the other hand, the distraction theory assumes that actions chosen with a certain level of explicit processing (control, or attention) should be more exactly arrived at and thus are often more likely to be accurate or correct (Reber, 1989; Sun, Slusarz, & Terry, 2005). Explicit processes are deliberate (controlled, or explicitly attended to), and more cognitively accessible, making thought processes involved behind decisions more traceable. In contrast, implicit processes exist on a subconscious level, are reactive in nature, and are more difficult (at least) to recall. Processes involved in making decisions implicitly are often faster, harder to explain, and are more susceptible to inaccuracies and mistakes (Reber, 1989; Sun, 2002).

It is reasonable to suggest that in usual circumstances, people will tend to prefer acting in a somewhat more precise and more controlled (i.e., somewhat more explicit) fashion than in a purely reactive and uncontrolled (i.e., purely implicit) manner (Curran & Keele, 1993; Sun, 2002; Sun, Merrill, & Peterson, 2001; Sun et al., 2005). However, distracting contexts (e.g., anxiety) may hamper explicit processes (Sun et al., 2005), leading to more implicit processing, which often hurts performance.

Note that the latter theory is perfectly consistent with the basic postulates of the CLARION cognitive architecture as will be discussed later (see also Sun, 2002, 2003), while the former theory may also be incorporated into CLARION.

Within the theoretical framework of CLARION, it may be hypothesized that participants' performance worsened when faced with distracting contexts (including anxiety), maybe because they were prevented from using a sufficient amount of explicit processing as appropriate. In this regard, it might be assumed that performance in the golf-putting task by participants under the afore-mentioned experimental condition was not completely implicit. While putting might be a rather implicit task for beginning novices, it might become less implicit with practice (as explicit rules for performing the task are extracted in a bottom-up fashion; see the discussion of "bottom-up learning", e.g., in Sun et al. (2001, 2005)).

The notion of bottom-up rule extraction learning has been well documented in the literature, and in particular, within the CLARION framework (see Sun, 2002, 2003; Sun et al., 2001, 2005). In the case of the putting task (experiment 3 of Beilock & Carr, 2001), when a novice first begins, he or she is not equipped with any information on how to effectively putt. However, through trial and error, the person begins to learn implicit skills, and in the process acquires simple explicit rules to help to increase accuracy as training continues. The improvement in performance seen during practice is, in part, the result of explicit rules being extracted (in addition to primarily being the result of implicit skill learning). As the number of rules increases and the types of rules become more complex in nature, accuracy continues to improve. Experienced golfers have extracted large sets of explicitly accessible rules (or obtained them from outside sources such as a coach) that can be recalled relatively easily. Ask any avid golfer to describe the process they go through prior to taking a putt and one will undoubtedly get a detailed answer (although there might be an inverted U curve here, i.e., a gradual increase of explicit knowledge as experiences accumulate and then a decrease when one becomes a true expert; Beilock & Carr, 2001; Dreyfus & Dreyfus, 1987). However, admittedly, there is no guarantee that detailed explicit knowledge that one possesses is actually used in action decision making, as opposed to post hoc rationalization. Judging from our own prior work and work by others, there are reasons to believe that at least some of that explicit knowledge is indeed used for actual action decision making (see, e.g., Mathews et al., 1989; Reber, 1989; Sun et al., 2001, 2005; Willingham, Nissen, & Bullemer, 1989). In general, people prefer to perform tasks in a somewhat explicit fashion (i.e., mixing implicit and explicit cognitive processes to a certain extent; Mathews et al., 1989; Reber, 1989; Sun, 2002; Sun et al., 2005). Within the framework of CLARION, a theoretical notion of "synergy" has been proposed in this regard (as a potential explanation): mixing implicit and explicit processes (with appropriate proportions) leads to better performance than using either alone (see Sun et al., 2001, 2005 for data analysis and other evidence). This synergy is the ultimate reason for people to use both implicit and explicit processes in most skill domains (Sun, 2002).

CLARION (the computational cognitive architecture) may be used to provide a process-based, mechanistic (i.e., computational) explanation of the phenomenon (as well as other cognitive phenomena and data), based on motivational processes. In addition, while we refer to processing in terms of explicitness and implicitness based on the CLARION framework (Sun, 2002; Sun & Naveh, 2009), this phenomenon has been referred to with different names by various researchers from different areas of psychology (often with slightly different meanings). We hope that our theoretical framework (CLARION, as will be discussed below) will provide some clarification to these terms. Beyond these relatively simple terminological issues, more importantly, CLARION provides detailed (computational) interpretations that help to shed new light on underlying processes (as will be discussed later).

3. A CLARION-based theory

CLARION is a well-established cognitive architecture (Sun, 2002, 2003; Sun et al., 2001; Sun & Naveh, 2009; Sun et al., 2005). It consists of a number of subsystems: the action-centered subsystem (the ACS), the non-action-centered subsystem (the NACS), the motivational subsystem (the MS), and the meta-cognitive subsystem (the MCS). Each subsystem is divided into two levels of representation. See Fig. 1.

[1] In Beilock and Carr's (2001) opinion, this was what was occurring when performance degradation under pressure occurred in the putting task.

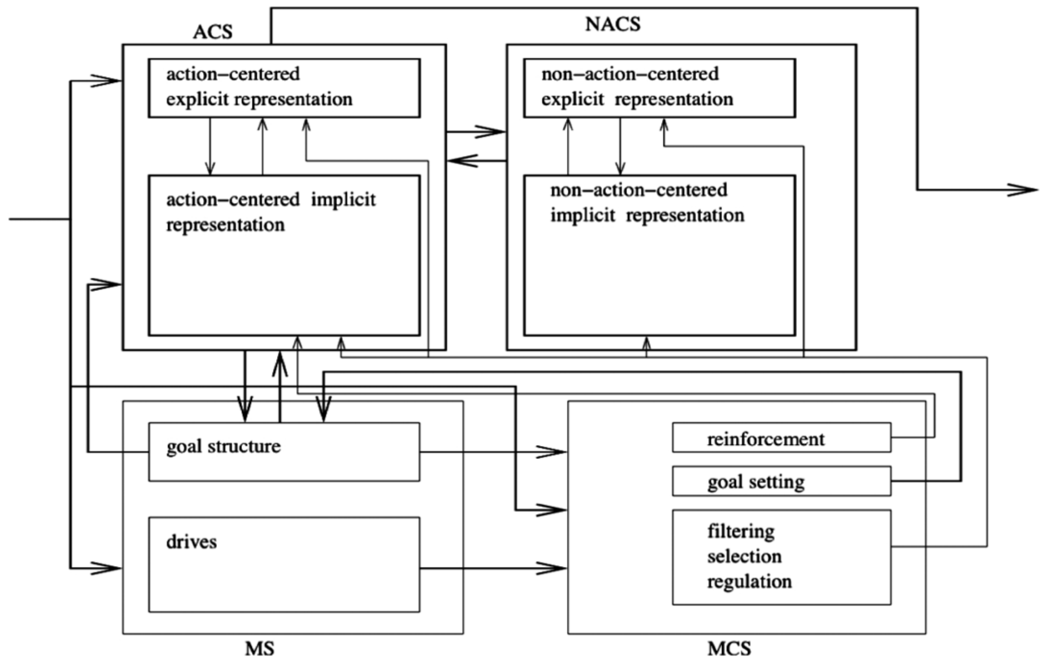

Fig. 1. The subsystems of CLARION. ACS stands for the action-centered subsystem, NACS stands for the non-action-centered subsystem, MS stands for the motivational subsystem, and MCS stands for the meta-cognitive subsystem.

One fundamental assumption in CLARION is the distinction between implicit and explicit processing. What we term explicit processing is also known as "controlled" processing (Lambert et al., 2003) or "working memory intensive" processing (Beilock & Carr, 2001; Beilock et al., 2004). Explicit processes are often rule-based, require more time to obtain results, and sometimes require more than one step to reach a conclusion (Sun, 2002). Similarly, implicit processes are often referred to as "automated" processes. When researchers refer to "a loss in cognitive control", what they are referring to is an inability to use explicit processes in addition to implicit processes. A loss of cognitive control, therefore, is equated to using more implicit processes.

CLARION takes note of the fact that the inaccessible nature of implicit knowledge is best captured by subsymbolic, distributed representations (such as in a backpropagation network). This is so because distributed representational units in (the hidden layers of) a backpropagation network are capable of accomplishing processing but are subsymbolic and generally not individually meaningful (Rumelhart, McClelland, & The PDP Research Group, 1986). This characteristic of distributed representations, which renders the representational form less accessible, accords well with the relative inaccessibility of implicit knowledge (Cleeremans, Destrebecqz, & Boyer, 1998; Reber, 1989).

In contrast, explicit knowledge may be best captured in computational modeling by symbolic or localist representations (Sun, 2002; Sun et al., 2005), in which each unit is more easily interpretable and has a clearer conceptual meaning. This characteristic of symbolic or localist representations captures the characteristic of explicit knowledge being more accessible and more manipulable (Sun, 2002). Accessibility here refers to the direct and immediate availability of mental content for the major operations that are responsible for, or concomitant with, consciousness, such as introspection, forming higher-order thoughts, and verbal reporting, as well as meta-level control and manipulation.

The dichotomous difference in the representations of the two different types of knowledge led to a two-level architecture, whereby each level uses one kind of representation and captures one corresponding type of process, implicit or explicit.

While this two-level structuring is the key foundation of CLARION, additional distinctions, for instance, between action-centered and non-action-centered subsystems (the ACS and the NACS), are also made. The present paper focuses only on the interaction between implicit and explicit processing within the action-centered subsystem (the ACS). The ACS consists of implicit processing (in the bottom level of the two-level architecture) in the form of a backpropagation network and explicit processing (in the top level) through explicit rules (Sun, 2002). Explicit knowledge (at the top level of the ACS) may be learned in a bottom-up fashion (i.e., extracted from the implicit knowledge at the bottom level, using, e.g., the RER algorithm of Sun et al. (2001)), or from external sources, while implicit knowledge (at the bottom level of the ACS) may be learned in a trial-and-error fashion through interacting with a task (using, e.g., the Q-learning or simplified Q-learning algorithms), or through assimilating explicit knowledge (from the top level). See Sun (2002, 2003) for full details.[2]

In particular, for learning implicit knowledge at the bottom level of the ACS, Q-learning or simplified Q-learning may be used (as described and justified in Sun (2002, 2003)). Using either of these two algorithms, implicit knowledge may be learned by adjusting numerical weights (which are to be used for action decision making) gradually and incrementally on the basis of reinforcement signals (which indicate whether actions selected and performed are successful or not), within a backpropagation network. The backpropagation learning algorithm is applied for the sake of adjusting the internal weights of the network, based on the reinforcement signals received, in accordance with the Q-learning or simplified Q-learning algorithms (which essentially calculate the amount of adjustments from the reinforcement signals received; Sun, 2002, 2003).

Among other learning algorithms for acquiring explicit knowledge at the top level of the ACS, there is the Rule-Extraction-Refinement algorithm (RER). Using RER, explicit rules are learned at the top level by using information from the bottom level, which

[2] For information about the non-action-centered subsystem (the NACS), and its interactions with the action-centered subsystem, see Sun (2002, 2003).

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captures a bottom-up learning process — an implicit-to-explicit explication process (Sun et al., 2001). The basic idea of the RER algorithm is as follows: If an action decided by the bottom level is successful (i.e., if it satisfies a certain criterion), then the agent constructs a rule (with its action corresponding to that selected by the bottom level and with its condition specifying the current state), and adds the rule to the top level. Then, in subsequent interactions with the world, the agent refines the constructed rule by considering the outcome of applying the rule: If the outcome is successful, the agent may try to generalize the condition of the rule to make it more universal; if the outcome is not successful, then the condition of the rule should be made more specific. These operations above are guided by some statistical criterion (i.e., the "information gain" measure; see Sun et al. (2001) for details).

When both implicit and explicit knowledge is available in the ACS for deciding on an action to be performed, the two types of knowledge are "integrated", for example, through stochastic selection of one type or the other (Sun, 2002, 2003).

In addition to the action-centered and non-action-centered subsystems, there is yet another major component in CLARION: the motivational subsystem (the MS). This subsystem is responsible for motivational states (comprised of "drives" and "goals"; Sun, 2009). In CLARION, drives are fundamental motivational forces behind action decision making (as well as behind non-action-centered processes). Goals are determined from drives, to provide specific and tangible motivation and context for actions. Actions are selected (within the ACS) based on their "values" (i.e., Q-values) with regard to the current goal and the current state (see Sun, 2002 for details). Such "values" (or evaluations of actions) are behind decisions to take specific actions.

CLARION includes generic and essential drive representations in the motivational subsystem (see Sun, 2003, 2009). When the environment causes anxiety, anxiety can be thought of as the biological/physiological consequence of a heightened (avoidance-oriented) drive strength level (see the discussion of drives in Sun, 2003, 2007, 2009). Thus, in simulation, the simulated participant's drive strength levels are set in the MS based on the experimental context.

In conjunction with the motivational subsystem, the meta-cognitive subsystem (the MCS) uses the resulting drive strengths from the motivational subsystem to perform a number of backend actions. One such type of MCS action is goal setting based on drives. Goals are important within the action-centered subsystem (the ACS) as it helps to determine the specific actions chosen. Another type of MCS action is parameter setting within other subsystems. Parameters for reasoning, action competition and selection, various types of learning, etc. may be determined by the MCS based on motivational states.

In particular, anxiety levels (as reported by the MS in the form of avoidance-oriented drive strengths) are used to determine the likelihood of performing a task in a more explicit or more implicit way in the ACS, which is decided by the MCS (Sun, 2009). The working hypothesis in this regard is that when anxiety is at a relatively low level, it can help to increase control in the ACS action decision making (i.e., the ACS becomes more explicit); however, when anxiety hits a certain high level, it begins impairing control (because, in such situations, there is an evolutionary advantage to favor faster and more automatic [i.e., implicit] processes; Sun, 2009; Weiner, 1992).

The equation used to represent this phenomenon is an inverted U curve (cf. Hardy & Parfitt, 1991). The curve begins at $x = 0$ at some point before the top of the curve, which represents the level of control when the drive strength is very low. As the drive strength increases (i.e. as anxiety increases), the level of control will follow along what appears approximately as an inverted U (see Fig. 3).

Let us now look into the golf-putting task (Beilock & Carr, 2001) to see how our theoretical and computational framework can be applied to this task.

4. Experiment & simulation

4.1. Experiment

Beilock and Carr's (2001) experiment 3 was (in part) based on a golf-putting task. Participants were undergraduate students with little or no golf experience. Participants were randomly assigned to the single-task condition, the self-conscious condition, or the dual-task condition. 18 participants took part in each condition. Because we were interested in the effects of drives on decision making, we focused on the results of the single-task and the self-conscious condition (and we dealt only with the putting task here).

The experiment examined the accuracy of golf putting over a series of trials. The objective was to putt a golf ball as accurately as possible from nine locations on a carpeted indoor putting green. The locations were 1.2, 1.4, or 1.5 m from the target. The target was a red square, on which the ball was supposed to stop. All participants putted from the nine locations in the same randomly determined order. A standard golf putter and ball were provided.

Participants completed 270 training putts. The 270 training putts were broken into three blocks of 90 putts each. The experimenter recorded the mean distances of the first and last 18 training putts respectively. The training was followed by an 18-putt low-pressure (presumably low-anxiety) post-test and then an 18-putt high-pressure (presumably high-anxiety) post-test.

The factors used to create the self-conscious condition were introduced during the training phase. Participants in the single-task condition performed the task during the training phase exactly as it was just described. Participants in the self-conscious condition, during the introduction of the training task, were informed that they would be filmed using a video camera. They were told that golf coaches were videotaping them for later review in order to gain a better understanding of how individuals learn to putt. The camera was set up on a tripod that stood on a table directly in front of the participants (1.8 m away). The camera was turned on and pointed at the participants during the entire training phase (except during short breaks between blocks of putts). After the training phase, the camera was turned off and pointed away from the participants (where it remained for the remainder of the experiment).

The low-anxiety post-test was the same for all groups. To participants in the single-task condition, the 18 low-anxiety putts following the training seemed like just another block of putts. Participants in the self-conscious condition were not made aware of any changes except the fact that the camera had been turned off and pointed away.

The high-anxiety post-test was identical for all groups. Participants were informed of their mean putting performance for the last 18 putts in the training phase and were provided with a scenario designed to create high pressure (and consequently high anxiety presumably). Specifically, participants were told that if they could improve their accuracy by 20% in the next set of putts, they would receive $5. The monetary award was also a team effort — Each participant was told that he/she had been randomly paired with another participant, and in order to win the money, both had to improve by 20%. In addition, it was revealed that the other participant had already improved by the required 20%. The participants then took an 18-putt (high-anxiety) post-test.

The results from this experiment were as shown in Fig. 4 (Beilock & Carr, 2001). Basically, as predicted and explained earlier, participants' performance worsened during the high-pressure (high-anxiety) post-test for the single-task condition (but not the self-conscious condition). Detailed statistical analysis of the human data (Beilock & Carr, 2001) will be presented below along with the simulation results.

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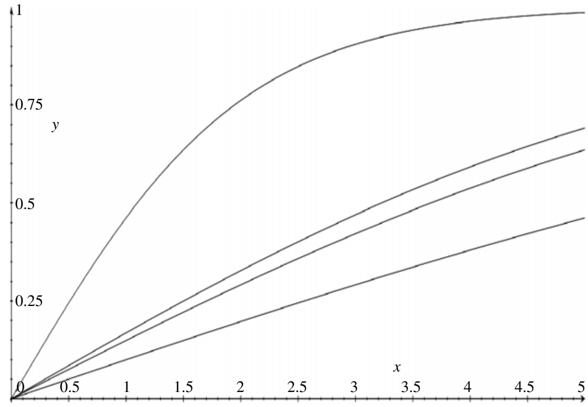

Fig. 2. The x-axis represents pre-existing bias ($0 \leq x \leq 5$); the y-axis represents drive strength ($0 \leq y \leq 1$). The topmost function is for the single-task high-anxiety post-test. The second function is for the self-conscious high-anxiety post-test. The next function is for the self-conscious training phase. The bottommost function is for the single-task training phase, the single-task low-anxiety post-test, as well as the self-conscious low-anxiety post-test.

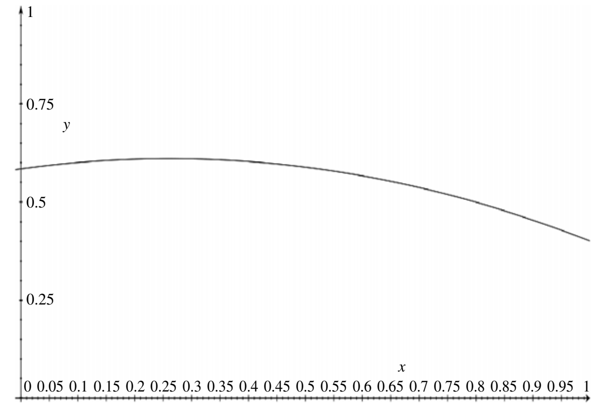

Fig. 3. The x-axis represents the drive strength from the MS ($0 \leq x \leq 1$); the y-axis represents the degree of control (explicit processing) determined for the ACS ($0 \leq y \leq 1$).

4.2. Simulation setup

For this simulation, in the motivational subsystem, only one drive is relevant: "honor", which is roughly related to the need to avoid blame in this case (Sun, 2003, 2007, 2009). The drive strength was obtained using a pre-trained backpropagation network with 6 inputs, 10 hidden nodes, and 1 output, with the default parameter settings (learning rate $= .01$, momentum $= 0$). The first 5 nodes of the inputs were used to specify the experimental conditions (including type of training, type of post-test, and training versus test). The final input node specified the individual difference variable that indicated an agent's predisposition toward becoming anxious.

During the training phase of the single-task condition, drive strengths of the agents were determined using: $\tanh(.1x)$ (where x is the individual difference variable; $0 \leq x \leq 5$). This function was also used for the low-anxiety post-test of both the single-task and the self-conscious condition (because the situations were essentially the same as the training phase of the single-task condition). During the training phase of the self-conscious condition, drive strengths of the agents were determined using: $\tanh(.15x)$, because of the (presumably) higher anxiety levels of the self-conscious training condition. During the high-pressure (high-anxiety) post-test, for those agents trained in the self-conscious condition, the function changed to: $\tanh(.17x)$, in response to the anxiety inducing cues (presumably). For those agents trained in the single-task condition, during the high-pressure (high-anxiety) post-test, the function changed to: $\tanh(.5x)$, in response to the anxiety inducing cues (presumably). Note that the function used by the self-conscious group during the high-anxiety post-test increased to be only slightly higher than the function used during the training phase. This is because the agents in the self-conscious condition were exposed to an anxiety-inducing situation during training for an extended period of time, and therefore, as we have previously discussed, the effect that the high-anxiety post-test had was presumably mitigated. (Within CLARION, this can be explained by the depletion of an internal "deficit" variable related to the drive in question, as a result of prolonged exposure to anxiety-inducing situations; see Sun (2009) for further details.) These agents were certainly affected; however, the effect was not nearly as strong as for those agents trained in the single-task condition where no mitigating factor was present during training. A graphical representation of the drive strengths, as assumed within the CLARION based model, can be seen in Fig. 2.

The MCS of CLARION was used to determine the proportion of explicit versus implicit processing in the ACS (i.e., the degree of cognitive control). Specifically, the MCS was pre-trained mapping drive strengths to explicitness of processing using an inverted U curve (as discussed earlier). The MCS determines, using the inverted U curve, the probability that the agent would use the top level of the ACS (i.e., explicit processing) when performing the task. The probability output was obtained using a backpropagation network with 1 input, 4 hidden, and 1 output nodes, using the default parameter settings (learning rate $= .01$, momentum $= 0$), with the input to the network being the drive strength from the MS. Fig. 3 shows a graphical representation of this basic assumption of CLARION (where the MCS was pre-trained to select probabilities between 0 and 1 based on the parabolic equation: $-0.38x^2 + 0.20x + 0.58$, where x is drive strength).

The ACS was set up the same way for all agents. The bottom level of the ACS was set up with a backpropagation network with 12 inputs (representing information concerning the putting positions and their distances to the target), 5 hidden nodes, and 3 outputs, with the default parameter settings (learning rate $= .01$, momentum $= 0$). The 3 outputs represent three possible putting actions: swing easy, swing medium, swing hard. The network started with no knowledge of the proper input-output mapping, and was trained through interacting with the task (using simplified Q-learning as explained earlier; Sun et al., 2001); eventually, implicit knowledge of putting was captured by the structure and weights of the network.

At the beginning of the task, no explicit rules existed at the top level of the ACS, because participants in Beilock and Carr's (2001) experiment 3 had no prior golfing experience or knowledge. Rules were extracted from the bottom level of the ACS during the course of learning the task (basically, a rule was extracted when an action caused a putt to land within 5 centimeters of the target; see the brief explanation of the RER algorithm earlier; see the full description of the RER algorithm in Sun et al. (2001), Sun (2003)). The ACS attempted to generalize the rules after they were extracted (with the RER algorithm; see Sun et al. (2001, 2005) for details). The rules were encoded as "condition → action" pairs (for example, "if the distance is 1.4 m, then swing medium").

The accuracy (the distance of the ball from the target) was calculated (based on a pre-specified function) and reported back to the ACS, which used that score as the reinforcement signal for reinforcement learning in the bottom level (using the simplified Q-learning algorithm; see Sun, 2003; Sun et al., 2001), as well

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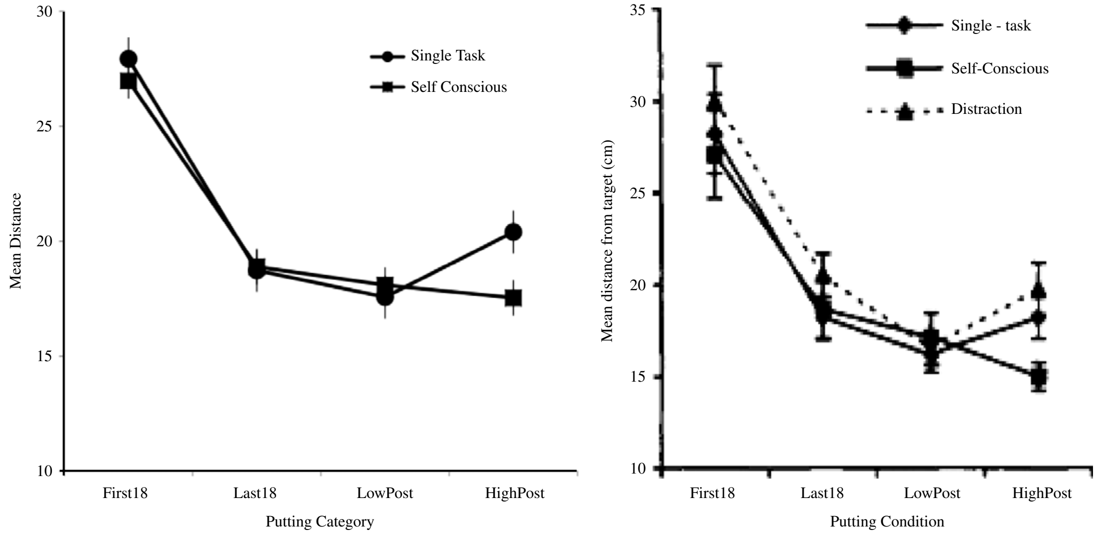

Fig. 4. The graph on the left shows the results from the simulation. The graph on the right is the human data from Beilock and Carr (2001).

as indirectly for rule learning in the top level (using the RER algorithm; see Sun et al. (2001)).[3]

Approximately the same number of simulated participants (agents) was used for each condition during the simulation as the original human experiment (25 simulated participants for each condition).

4.3. Simulation results & comparison

During the simulation, the accuracy of the first 18 and the last 18 putts of the training phase was recorded along with the 18 putts for each of the two post-tests. The simulated participants of both the single-task and the self-conscious condition improved with practice as evidenced by a 2 (single-task vs. self-conscious) $\times 2$ (mean distance from target for the first vs. the last 18 putts of the training phase) ANOVA, revealing a highly significant main effect of practice ($F = 297.097, p < .001$) and no training condition/practice interaction ($p = .27$), which is consistent with Beilock and Carr's (2001) results ($F = 85.03, p < .001$ for the effect of practice).

In the simulation, accuracy in the low-anxiety post-test was essentially the same between the single-task and the self-conscious condition ($M = 17.57$ and $M = 18.09$ respectively, $p = .493$), the same as in the human data (Beilock & Carr, 2001). In the high-anxiety post-test, a significant difference existed between the two conditions, as evidenced by a one-way ANOVA ($F = 9.169, P = .004$), the same as in the human data ($F = 4.57, p < .015$ in Beilock and Carr (2001)). In addition, a 2 (training condition) $\times 2$ (post-test) ANOVA revealed a significant interaction of training condition and post-test ($F = 7.656, p = .008$). This finding matched that found by Beilock and Carr (2001) ($F = 7.37, p < .002$).

Direct analysis of putting performance within each condition showed that the accuracy of the simulated single-task group significantly declined from the low-anxiety to the high-anxiety post-test ($t = -2.618, p = .015$), as was demonstrated by Beilock and Carr (2001) in the human data ($t = -2.21, p < .04$). The accuracy of the simulated self-conscious group did not change significantly between the two post-tests ($t = .969, p = .342$), similar to the human data ($t = 1.81, p < .09$ in Beilock and Carr (2001)), although, consistent with Beilock and Carr (2001), the direction of the change suggested a slight improvement.

A graphical representation of the simulation results can be seen in Fig. 4, along with the corresponding graph of the human performance from Beilock and Carr (2001). Looking at the figure, it should be fairly clear that the results from the simulation match the human results from Beilock and Carr (2001) very closely. This suggests that the specific, detailed, and process-based interpretation of the human results presented in the present paper has merit.

While the explicit-monitoring theory seems like an intuitive conclusion for explaining performance degradation in low-level tasks like putting, our simulation has shown that explicit monitoring is not necessarily the only viable explanation. Explicit processing requires higher levels of control than implicit processing. When a person is distracted or anxious, the amount of control he or she has may be negatively impacted. This may reduce a person's ability to rely on more intensive, more effortful explicit processes. The core of the explicit-monitoring theory as it relates to performance degradation under pressure points to "over-thinking" as the main culprit of performance degradation. However, what is occurring may not be "over-thinking" but instead an inability to engage explicit processes to an appropriate and sufficient extent.

As has been pointed out earlier, there may be a processing difference between relative novices (using a mixture of implicit and explicit processes) and true experts (being equally proficient in either a somewhat explicit or a completely implicit mode, or even performing the best when completely implicit/automated). In this regard, in the literature, highly practiced, automated expert skills sometimes show some negative effects of explicit monitoring under some circumstances (Lewis & Linder, 1997; Masters, 1992), while less rehearsed tasks or skills may often show the effects of distraction in the sense of the distraction theory (Ashcraft & Kirk, 2001; Lewis & Linder, 1997; Tohill & Holyoak, 2000). There is no sufficient evidence in this case to conclude that those human participants in this experiment (i.e., experiment 3 of Beilock & Carr, 2001) had reached that expert level (because, e.g., what might appear to be asymptotic performance may turn out to be a temporary performance plateau that, with much further training, may lead to still better performance), and therefore there is no sufficient evidence to conclude that "over-thinking" in actuality hurt their performance. These simulation results above seem to suggest that our theory based on CLARION (more akin to the

[3] In general, reinforcement signals are determined by the MCS based on motivational states in the MS. In this case, the most relevant drive in the MS is "achievement and recognition" (see Sun, 2009 for details).

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distraction theory) might be properly used to interpret at least some performance degradation phenomena seen in experiments involving sensorimotor tasks, as well as in other types of tasks.[4]

In addition, we have looked into some other data sets, experiments, and tasks relevant to this phenomenon, and our theory and model (based on CLARION) appear to be able to account for all of them (details omitted due to length limits; see Wilson, Sun, and Mathews (in preparation)). Note that even in some arithmetic tasks, the effects of anxiety/distraction have been observed (Beilock et al., 2004). The CLARION based model has successfully captured such data (details omitted; Sun, Zhang, & Mathews, 2009; Wilson et al., in preparation).

5. Conclusions

CLARION provides a computational explanation of the phenomenon of performance degradation under pressure on the basis of motivation (i.e., drive levels). While the suggestion that motivations (e.g., drives) affect performance is not novel, the present work has taken a step toward explaining exactly how and in what way performance is affected by motivational and environmental contexts (see Sun, 2009 for more details). Within the framework of CLARION, we conjecture that the effects of distractions/anxiety act upon implicit and explicit processes in ways that can be described as a function of the context.

CLARION, in relation to this work, focuses on the interaction between motivation (drives) and cognition (Carver & Scheier, 1998; Sun, 2009; Weiner, 1992). In this way, it embodies, explains, and substantiates some previous theories naturally (and this does not rule out other possible motivation-cognition interactions in this or other circumstances).

In relation to the point above, the present paper provides a peek into how drives and motivations act upon a cognitive system, and it does so in a quantitative, process-based, and mechanistic (i.e., computational) way (see Sun, 2003, 2007, 2009 for more details). Therefore, it provides a detailed, process-based explanation. In this regard, CLARION may eventually provide a more general and yet detailed picture of self-monitoring and self-regulation (in a generalized sense) in cognitive agents (see, e.g., Sun, 2003, 2009; Zimmerman, 2000).

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[4] On the other hand, for true beginning novices, reduction of explicit processing may not hurt their performance, because they may not have much explicit knowledge.