Unconscious Processing of Information in Dynamic Decision-Making – An Experimental Approach

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Abstract

The purpose of the paper is to investigate the effects of unconscious versus conscious ways of making decisions in a dynamic decision-making task. An experimental setting is used to study this question; three experimental groups are distinguished: immediate decision-making (only limited time for cognitive processing), considered decision-making (time for conscious processing), and distracted decision-making (time for unconscious processing). As experimental stimulus, a simulator based on the Kaibab Plateau model is employed. Although more than 100 subjects have been tested so far, group differences are not significant for most data examined. Implications comprise the improvement of the experiment in order to derive at more substantial results. The value of the paper lies in the fact that it connects to a recent discussion in psychology and transfers it into a domain in the core interest of the system dynamics community: decision-making in situations with dynamic complexity.

Keywords: dynamic decision-making, unconscious information processing, dynamic complexity, experiment

The motivation for this paper came from the question, what we—as researchers of decision-making—would recommend managers: deciding “straight from the gut” (Welch and Byrne, 2003) or “don’t trust your gut” (Bonabeau, 2003)? Thus, the purpose of the paper is to investigate the effects of unconscious versus conscious ways of making decisions in a dynamic decision-making task. More specifically, we want to research the question if humans perform better when they have time to think about a dynamic problem, or when time for deliberate consideration is limited, either because decisions have to be made immediately or because persons are distracted during their preparation time.

In the light of some recent findings in psychology but also according to some anecdotal evidence, it seems that unconscious forms of decision-making are more effective than conscious forms, more often than expected by proponents of rational problem solving. However, these findings were often achieved when static and single tasks had been involved. So, in accordance with a common interest in the system dynamics community, we want to transfer experiments on the effectiveness of conscious versus unconscious processing of information to decision-making into a dynamic context.

To this end, the paper is divided in five sections. In the first section, we review the status of the (mostly psychological) literature on conscious versus unconscious processing in decision-making. In the section after that, characteristics of dynamic tasks are briefly explained; it is proposed that most experiments on the conscious/unconscious difference employ static and single decision tasks. In the third section, the design of an experiment is presented that should help to evaluate the effects of unconscious information processing in environments, where dynamic complexity is high. The results of this experiment are shown and discussed in the fourth section. The paper closes with a section that discusses implications for research and the management of dynamically complex systems; issues for further research are identified.

Evidence in favor of unconscious deliberation when making decisions

Recently 'unconscious processing' of information and subsequent decision-making has received substantial attention in psychological research (Mandler 1984; Oatley, 1992; Damasio, 1994; Wilson, 2002; Dijksterhuis et al., 2006). While authors use different terminology ('unconscious', 'recognition-primed', 'deliberation without attention', 'thinking without thinking'), they basically describe the same phenomenon: making decisions without conscious consideration of what the best decision would be. In this paper, we use the term "unconscious information processing in decision-making" to refer to this phenomenon. Thus, not the act of making a decision itself is unconscious, but the preceding cognitive processes are not consciously related to the decision that has to be made.

Wilson (2002: 19) illustrates the crucial part unconscious cognitive processes play with an example of a man who loses his sense of proprioception (i.e. the sense of the relative position of body parts). With a great deal of effort, the patient had to replace unconscious proprioception with conscious control of his body. Whenever his concentration was lost he would loose control over his body and end up 'in a heap of tangled limbs on the floor'.

On the basis of experimental as well as real world purchase decisions, Dijksterhuis et al. (2006) conclude that unconscious thinkers are better able to make the best choice among complex products. Conscious thinkers are better able to make the best choice among simple products. Popular books such as *Blink* (Gladwell, 2005) maintain that expert decision-making is often instantaneous, difficult to access by conscious processes and in specific circumstances leads to high quality decisions.

A classic example of expert decision-making, reported by Simon as early as 1957, already has many of these features. Simon studies a chess player who tries to decide on the next move in a game, an activity which is thought to involve a highly analytical approach. Expert chess players indicate that good moves usually come to mind after a few seconds of looking at the board, after which considerable time is spent on verifying that the move does not have hidden weaknesses (Simon, 1987: 59). So although a decision comes to mind almost immediately, a more analytical and time-consuming process is used to check this first option. This analysis may reveal that the first option is biased. Simon (1987) describes how in a situation of stress, for example, intuitive decisions may be based on 'primitive urges' such as the need to reduce embarrassment or guilt. Research in biases and heuristics (e.g. Tversky and Kahneman, 1971; 1974; Sterman, 1989; Gilovich et al., 2002) shows convincingly that human judgment is biased in systematic ways.

Gigerenzer and colleagues argue that the same simplifying heuristics that are responsible for cognitive biases are the cognitive mechanisms "that make us smart" (Gigerenzer and Todd, 2001). Only because they allow us to make fast decisions that are frugal in the sense that they do not require much information as input, we are able to survive in a complex world. Thus, Gigerenzer assumes that unconscious processing is a basic characteristic and success factor of human beings.

In summary we can conclude that—despite all the biases and heuristics related to human decision-making and all claims by proponents of rational decision-making—there is some evidence that unconscious processing of information for decision-making is effective in many occasions. This paper tries to shed some additional light in the context of dynamic tasks, which differ from the static, single tasks mostly used in experiments of decision-making.

Decision-making in dynamic environments

Individual decision-making in dynamic systems differs from the static tasks which are mostly used when unconscious processing before decisions is studied. We define dynamic decision-making as characterized by three features:

1. not one, but a series of decisions have to be made (repeated decision-making),
2. the system's state changes over time based on past decisions, and
3. there is some element of time pressure involved, although not all persons experience it at the same level.

Thus, the current state of a dynamic decision-making environment depends on the past system states and the decisions that have been made in the past.

The distinction between static and dynamic decision-making is related to the different types of complexity people in decision situations experience. Here, detail complexity and dynamic complexity are to be differentiated (Senge, 1990; Sterman, 2000). Detail complexity can be divided further into three sub-components: number of elements in a system, number of connections between elements, and types of functional relations between elements (Milling, 2002). The dynamic component of complexity comprise the variability of a system's behavior over time and the variability of a system's structure (assuming that a system can stay the same when its structure changes as long as its underlying goal set is not substantially modified; cf. Größler et al., 2006). An important proposition for this study is that in dynamic decision-making, effects of dynamic complexity are prevalent that do not occur in static decision-making. Thus, static and dynamic decision-making might have different characteristics and success strategies, due to the existence of dynamic complexity in the latter.

In several fields of expertise, decision makers confronted with time pressure and uncertainty typically carried out the first course of action that came to mind. This idea is similar to Simon's assertion that '*intuition and judgment – at least good judgment – are simply analyses frozen into habit*' (1987: 63). This process, termed 'recognition-primed' decision making, actually consists of a range of strategies. In its simplest form, the strategy comes down to seizing up the situation and responding with the initial option identified. If the situation is not clear, the decision maker may supplement this strategy by mentally simulating the events leading up to the situation. In a situation that is changing continuously, a different kind of simulation may be applied as well. Here, the proposed plan of action is mentally simulated to see if unintended consequences arise that are unacceptable. In a review of these studies, Klein (1998) considers the conditions under which recognition-primed decision making applies: when the decision maker has considerable expertise relevant to the situation at hand, is under time-pressure, and when there is uncertainty and/ or ill-defined goals. Recognition-primed decision making is less likely to be used with highly combinatorial problems, when a justification for the decision is required, and when the views of different stakeholders have to be taken into account.

From our previous description it is clear that dynamic decision-making falls into the former category: since only individual decision-making is studied, no stakeholders exist and there is no need to explain (or justify) decisions. By definition, dynamic tasks involve a degree of time pressure and uncertainty about the system's future, which are based on the dynamic complexity of the situation and the difficulties people have with estimating developments over time (Dörner, 1980). Thus, it seems likely that for individuals confronted with dynamic problems, unconscious processing or recognition-primed decision-making is the most used approach.

In summary, in dynamic situations decision-makers experience the effects of not only detail complexity like in many static tasks. Also, dynamic complexity plays an important role and might hamper effective decision-making. The hypothesis of this research is the advantage of unconscious processing of information in decision-making for dynamic tasks. Thus, we want to find out whether the superiority of unconscious decision-making holds for dynamic tasks or whether dynamics requires a thorough consideration of the situation proves to be more useful.

An experiment to investigate the effects of unconscious information processing in dynamic decision-making

We investigate whether unconscious deliberation of the situation is superior to conscious deliberation in dynamic decision-making with the help of a laboratory experiment with three experimental groups. In group 1, subjects have to start making decisions right after the task has been introduced to them ("immediate condition"). Group 2 is the experimental group that represents conscious decision-making ("consideration condition"). Subjects in this group are given three minutes to contemplate about the task before they are allowed to start with actually using the simulator. In experimental group 3, unconscious decision-making is tested ("distracted condition"). Subjects in this group are also not allowed to start using the simulator immediately but have to wait for three minutes. However, in contrast to the consideration condition, they are occupied by another cognitive task during this time (in our case, solving simple Sudoku puzzles). A timetable of the experiment is depicted in Table 1, which is the result of two trial runs of the experiment with colleagues and students.

Table 1: Timetable of experiment

Time [min]	**Immediate condition [Exp. group 1]**	**Consideration condition [Exp. group 2]**	**Distraction condition [Exp. group 3]**
0	Welcome	Welcome	Welcome
2	Instruction	Instruction	Instruction
10	X1	Y1	Z1
20	Break		
23		break	break
25	X2	Y2	Z2
35	Break		
38		break	break
40	KnowledgeT	KnowledgeT	KnowledgeT
50	Bio	Bio	Bio
55	Debrief	Debrief	Debrief
60	End	end	end

Instruction: explain task to subjects, clarify how to use the simulator
X1, X2: two game runs, 50 decisions each, with limited decision time (“immediate condition”)
Y1, Y2: two game runs, 50 decisions each, with time to consider task before round 1 (“consideration condition”)
Z1, Z2: two game runs, 50 decisions each, with time in which subjects are distracted before round 1 (“distraction condition”)
KnowledgeT: test of knowledge about the system
Bio: Biographical data (sex, age, studies, experience, etc.)
Debrief: short explanation of experiment to subjects

As dynamic task in the experiment we use a simulator (Rouwette et al., 2004) which is based on the Kaibab Plateau model. This model is well documented in the literature (Senge, 1980) – Figure 1 depicts the overshoot and collapse behavior of a deer population which is represented in the model (for overshoot and collapse cf. Senge, 1990). The model is based on real events, happening in the Kaibab national park in Arizona between 1900 and 1950. Thus, in the figure estimated historical data is shown as well; differences to the simulation outcomes are due to estimations (in the model as well as in the real data) and factors not considered in the model, for instance weather conditions. This model has been used in a variety of educational settings, for example to explain dynamic complexity resulting from feedback loops (Goodman, 1974; Roberts et al., 1983; Sterman, 1984; Sterman, 1994) or unintended consequences of human policies in ecological systems (Ford, 1999; the human interference with nature was the quasi extinction of predators of deer in the years between 1907 and 1920: cougars, wolves, and coyotes).

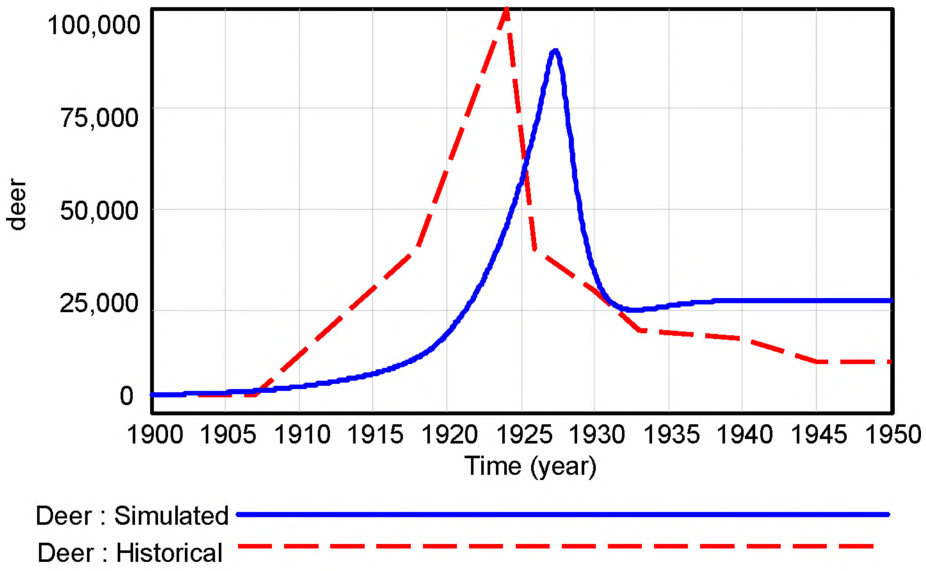

Figure 1: Overshoot and collapse of deer population in the Kaibab model and reality

In the simulator, the model is used with one extension: now users can decide—for each simulated year—on a harvest rate of deer (meaning either the hunting of deer or the transfer of deer to other regions). By sensibly controlling the number of deer, it is possible to avoid the enormous increase of deer and the subsequent collapse of the population due to too little food available. The deer harvest rate is the only decision users have to make. The user interface of the simulator is depicted in Figure 2. The model is developed using Vensim; the user interface is programmed in Sable (for another version of a Kaibab simulator see Ford, 1997, and McCormack and Ford, 1998; in their simulator the number of predators can be controlled by subjects as well). The goal for subjects is to stabilize the deer population on the highest level possible over the total simulation run.

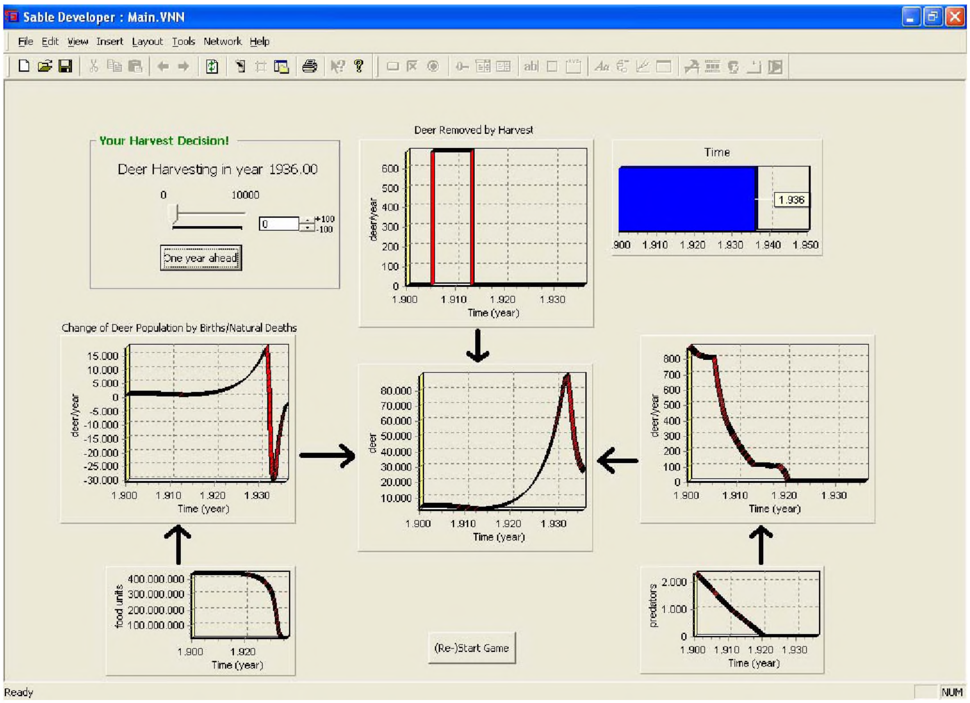

Figure 2: Screenshot of Kaibab simulator

Subjects are participants of a course in the business administration bachelor program at Radboud University. They were told that participating in the experiment is part of the course; however, it was clear that performance in the experiment would not influence grading. Subjects' performance is assessed based on a score that combines the stability of the population with the populations' height, aggregated over all 50 simulated years. Thus, performance is the average number of deer divided by the standard deviation of the population from the average.

Due to the nature of dynamic tasks (which by definition take a while because several decisions have to be made and effects only occur after some time), we assume our results to be affected in two ways:

1. Differences between the experimental groups will be rather low because—during the 50 simulation rounds that the subjects play per experimental run—even in the immediate condition there is some time for at least unconscious processing of information; similarly, subjects in the distraction condition will not be distracted during this time. Thus, differences between groups result from the initial differences in the experimental groups that might have only a weak effect on their performance.
2. Following the reasoning in 1., we assume that differences between groups will become smaller in the course of the experiment. In particular, differences in experimental run 2 should be much smaller (or even non-existent) compared to experimental run 1.

Results of group comparisons

In the experiment, which was conducted on June 12–14, 2008, 120 subjects took part. After eliminating 18 cases due to missing or incomplete data, the following group sizes were achieved: Immediate condition n=41, consideration condition n=30, distraction condition n=31. In total, 58 subjects are male, 44 are female; the age of subjects ranges from 19 to 30, with the average at about 21. No subject reported to have known the Kaibab Plateau task before. Since subjects were randomly assigned to a time slot and time slots were randomly allocated to an experimental condition, we assume that experimental groups are randomly composed. At the end of the experiment, subjects were asked about the degree of difficulty of the task, the time pressure they experienced and their estimation of the realism of the task. None of these items showed significant differences between experimental groups.

Results of subjects in terms of average deer population are far from optimal. As Sterman (1981) indicates, a deer population of 32,000 can be sustained without substantial fluctuations. In comparison to this, the average population size over all subjects in the experiment is 9,433 for the first run and 11,505 for the second run. While one can find a significant increase of the average size of the deer population from run one to run 2, it goes along with a significantly larger standard deviation. In other words, while subjects manage to increase the average population size, fluctuations around the mean increase as well, an indication for the common overshoot-and-collapse behavior of the system. Accordingly, the performance score (mean / standard deviation) is not significantly different between the first and the second run over all subjects.

Table 2 and Table 3 show the results of an analysis of variance for the first and the second run, respectively. We tested the between group differences for the three experimental groups for the performance score. For both runs, within group differences are much bigger than between group differences. There are no statistically significant differences between the three experimental groups concerning performance score (in both simulator runs).

Table 2: ANOVA results for performance score in first simulation run

summary

groups	*count*	*sum*	*mean*	*variance*
immediate	41	232.133	5.661	85.836
consideration	30	207.248	6.908	139.573
distraction	31	200.411	6.464	109.087

ANOVA

differences	*square sums*	*df*	*mean square sum*	*F*	*p*	*critical F*
between groups	28.564	2	14.282	0.131	0.876	3.088
within groups	10753.692	99	108.623			
total	10782.257	101				

Table 3: ANOVA results for performance score in second simulation run

summary

groups	count	sum	mean	variance
immediate	41	290.228	7.078	193.708
consideration	30	163.887	5.462	50.942
distraction	31	177.168	5.715	48.492

ANOVA

differences	square sums	df	mean square sum	F	p	critical F
between groups	55.235	2	27.617	0.255	0.774	3.088
within groups	10680.439	99	107.883			
total	10735.675	101				

In the knowledge test conducted at the end of the experiment, subjects had to answer twelve questions concerning their understanding and recollection of the task. Each correct answer was coded as one point, leading to a maximum of twelve points in the knowledge test. An analysis of variances between groups for results in the test indicates group differences. In order to find out, which groups differed from each other and what the direction of the differences is, we ran T-tests that are summarized in Table 4.

Table 4: T-test results for knowledge test

	distraction	consideration	distraction	immediate	consideration	immediate
mean	7.806	7.467	7.806	8.634	7.467	8.634
variance	3.428	2.051	3.428	2.088	2.051	2.088
n	31	30	31	41	30	41
pooled variance	2.751		2.662		2.072	
df	59		70		69	
t value	0.800		-2.131		-3.376	
P(T<=t) double-sided	0.427		0.037		0.001	
critical t-value (double sided)	2.001		1.994		1.995	

Between the distraction and the consideration group, no statistical differences can be found. However, there are significant differences between the immediate and the distraction group, and between the immediate and the consideration group. In both cases, subjects in the immediate group scored better in the knowledge test than subjects in the other group.

Implications and further research

The results of our experiment are rather disappointing, since none of the initially hypothesized differences between groups could be found. Although this result might simply represent a fact (i.e., there are no differences between conscious or unconscious decision-making for dynamic tasks), we assume that it is more likely an artifact of the experimental design and the task that we used. Therefore, this section discusses explanations for our results and possible changes in experimental set-up.

Before concentrating on the results concerning simulation performance, the one significant difference between groups is discussed—which is the difference for the knowledge test. The direction of the difference (the immediate group scored better than both, the consideration and the distraction group) is counter-intuitive. The group that had the least possibility to cognitively process information about the tasks (either consciously or unconsciously) scored best. We can only explain this in terms of a shorter over-all assessment time (subjects being more concentrated and motivated) and with a shorter time from reading the instruction until filling-out the test questionnaire. Since some of the questions are just testing the recollection of facts, a shorter time span might help recalling these facts.

Since subjects' performance does not significantly increase from run 1 to run 2, no learning seems to have taken place. While subjects achieve a higher average deer population in the second run, the standard deviation increases as well. We hypothesize that subjects are not able to comprehend the structure of the system and they cannot deduct the corresponding behavior mode (overshoot-and-collapse).

Concerning the not existing group differences for task performance, our assumption is that the experimental setting was not differentiating enough between groups. First, the three minutes time span for consideration or distraction might simply be too short, compared to the total duration of the experiment and the complexity of the task. Second, the nature of dynamic tasks makes it difficult to prevent all subjects from consciously or unconsciously processing task information during the game run, since a dynamic task takes a while by definition (and during this time, experimental groups are not treated differently any more). One suggestion to mitigate this effect would be that subjects in the consideration group have to verbally explain all their decisions and that subjects in the distraction group must solve a brief, not-related "distraction puzzle" before their decisions.

Another point to consider is the complexity of the task. While structurally not too simple (consisting of more than a dozen feedback loops, two integration structures—deer and food—, and some non-linear relationships—for instance, the food regeneration time), participants in two pre-tests considered the task to be understandable. However, obviously there is a substantial gap between knowing what one should do in principle, and actually doing it by controlling a dynamic system that is not open for detailed inspection (only behavior graphs and the principle system structure is shown). Although we assume that making the simulation more transparent might help subjects achieving a better result, we question whether this would be more realistic and it would interfere with the experimental setting because then subjects would need a lot of time to explore the system.

The last improvement point concerns the performance score that we used. We gave subjects a verbal goal to achieve ("stabilize the deer population on the highest possible level"), however we did not explain in detail how their performance score is calculated and did not display it during simulation. Furthermore, there is the principle question whether this performance score is appropriate, or whether another (simpler?)

score should be used. This new score could also be a qualitative assessment of the behavior mode of the deer population that the subjects achieved.

In summary, we believe we address a relevant question. Extending the existing research about unconscious decision-making to dynamic tasks is worthwhile, since most decision settings in reality are dynamic and research shows that individuals can deal insufficiently with dynamics. However, further attempts have to be made to investigate the effects of conscious versus unconscious decision-making with an experimental research design.

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