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Combining Experimental Observations and Modelling in Investigating Feedback and Emotions in Repeated Selection Tasks

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Abstract. People seem to learn tasks even without formal training. This can be modelled as the outcome of a feedback system that accumulates experience. In this paper we investigate such a feedback system, following an iterative research approach. A feedback loop is specified that is detailed using contemporary ideas on human behaviour. The resulting model is investigated in an empirical study. Finally, we consider a computational mechanism to explain the results. This approach is aimed at understanding how a feedback mechanism might work rather than at observing its outcomes. In this paper, we study the approach through adjustments in card selections in a game consisting of repeated card choices. Playing this game, participants do not know what rules determine gains and losses. Therefore there is some tension between exploring the options and achieving immediate profit. To decide in such situations it is argued that often evaluations below the level of conscious awareness, such as affect, play an important role. The results support the hypothesis that participants would draw better cards as the game progressed. There is some evidence that emotions are involved, since the hypothesis that profit and emotions are correlated is confirmed. Further evidence that formal logic is not sufficient follows from the observed effects of music on card selections. In the second part of the paper the aim is to understand the results from a computational point of view. Four possible ways of integrating feedback into a decision criterion are compared. Using one of these mechanisms, a computational model is investigated that might describe the role of music in card selection. Although there are limitations to both the empirical and computational findings, the chosen approach indicates that computational modelling of experiential appraisal, at a preconscious level, and the effect of external factors, such as music, is in principle feasible, and can lead to a research agenda aimed at understanding such phenomena.

Key words. cognitive model, emotions, experience, experiential processing, feedback

1. Introduction

When a complex application such as Microsoft Word is first installed on the computer, most users can probably only operate simple functions, such as typing plain text. After a while, some users discover more about the rationale and functionality of the application, which allows them to make better use of the options of the program.

This example indicates that interaction processes change with experience. These changes can be explained if some kind of guidance system is assumed that optimises user interaction with experience (Carver and Scheier, 1998). Such a guidance system allows users to interact in the best possible way, based on the available knowledge of the interaction process. The guidance system accumulates more information about ongoing interaction as it progresses. With this increased knowledge, future interactions can be improved.

The aim of this paper is to explore how a feedback control system for such improvements can be specified while taking into account contemporary insights into the human mind, and how a sequential approach of modelling and experimentation can generate questions for future research.

1.1. APPROACH TO THE RESEARCH

In this paper an iterative approach to the research question, that of reverse engineering, is adopted (e.g., Dennett, 1994; Marr, 1982). In Section 2 a guidance system for interaction is specified based on the available literature. Following this an empirical study is described that investigates the merits of this conceptual model. Based on the empirical results a more detailed version of the model is proposed, aiming to better understand the results of the study better. Although this final model was not formally confirmed it is meant to give insight into mechanisms leading to the observation. As such it is a stepping stone for future empirical and modelling efforts. So rather than proposing a model and then confirming it by empirical research; the approach chosen in this paper is aimed at increasing our understanding of how the underlying mechanisms might be working.

1.2. CONCEPTUAL MODEL OF THE PRESENT RESEARCH

The first stage is to specify a feedback guidance system for user-system interaction with three commonly defined components (Fischer, 2004): a monitoring module, an evaluation module, and an adjustment module (Figure 1). This bears much resemblance to previously suggested cybernetic feedback loops first introduced in the 1960s (see for example, Miller, Eugene and Pribram, 1960). In this paper, we explore such a feedback system when it has to deal with a task previously unknown to the user. In other words, we investigate how this system can accomplish the discovery of a successful strategy for interaction. When optimising the

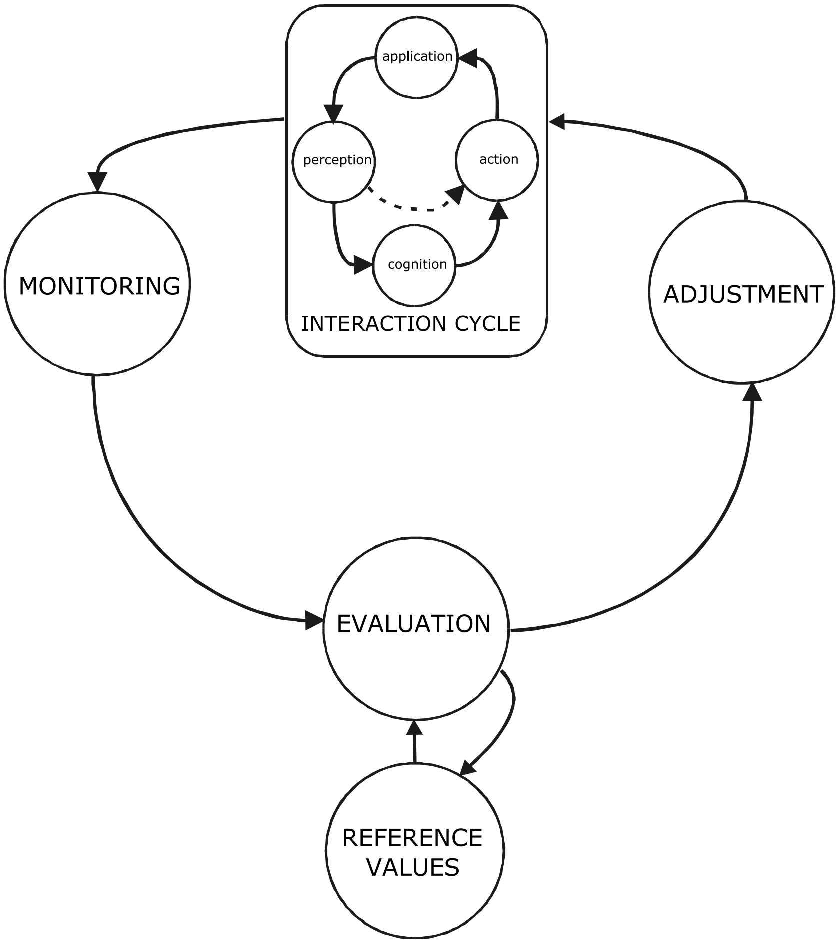

Figure 1. A computational model for regulation of user system-interaction. Besides regulation of the interaction cycle, the reference values for evaluation and the relevant elements for monitoring and adjustments have to be determined.

strategy for a new task, the relevant components of the interaction control system should ‘learn’ what interaction properties to focus on. In this paper, the evaluation mechanism should learn the correct reference values for the interaction process, and the adjustment mechanism should know what elements can be adjusted and what the effects of these adjustments will be on the interaction process. Only when these are known, can the interaction be improved. While applying the impact of previous experience on behaviour control, classical feedback models required massive cognitive effort and assumed a numerical calculation and summation of all involved values. The fact that the mind does not work with such numbers has become increasingly clear since the early 1970s (e.g., Tversky and Kahneman, 1974). By adopting an experiential or affective component to come up with a feeling rather than a value, these problems with the classical feedback approach can be overcome (Vaa, 2001), and it is this idea that is adopted in this paper.

1.2.1. *Specification of the Conceptual Model*

The proposed feedback loop consists of three components that are commonly defined in cybernetic control systems (see, Carver and Scheier, 1998). The first is a monitoring module, which records the ongoing interaction. This is followed by an evaluation module, which determines the quality of the ongoing interaction. Based on the outcome of the evaluation an action is adjusted and executed.

Recent work has shown that not all evaluation follows conventions of formal logic but is conducted by relating the current situations to a reference value in the form of anticipated feeling (e.g., Damasio, 1994). To incorporate this idea, an affective value is introduced as the outcome of the comparison of each element of the interaction process with a reference value (Fischer, Blommaert and Midden, 2004a). If the current situation is better than the reference a positive affect occurs, if it is worse a negative affect occurs. These outcomes of evaluation can be interpreted as hedonic tones (Johnston, 1999) that accumulate to a feeling of pleasure (Cabanac, 1992) that is positive if the ongoing interaction is better than the reference value, and negative if the ongoing interaction is worse than the reference value. Based on the evaluation of different interaction processes, the feedback system chooses the interaction process with the highest anticipated pleasure. In practice this means that the adjustment mechanism will continue the ongoing interaction if it receives positive hedonic tones, but will choose another interaction process if the ongoing interaction results in negative hedonic tones.

1.2.2. *Choosing Strategies*

The way in which successful strategies can be developed through experience is illustrated by looking at the problem of finding the best search strategy in an unknown situation. In an unknown situation a complete structured exploration through all options probably is not sufficient, since it is not certain whether that will result in finding a satisfactory solution within the allowed search time. Therefore, a guidance system for such a search has to put effort into achieving the interaction goal immediately, using whatever information is available (Newell and Simon, 1972). If too much effort is spent in working out the exact properties of the interaction, the benefits of the application may not be high enough to warrant the costs of learning how to use them. On the other hand, major benefits could be missed if too little time is spent understanding an application. Two heuristic search methods are associated with such explorations in an unknown problem space (Winston, 1992). The first type is the breadth-first search, which is the selection of different options leading to the most knowledge about the search space. However, the breadth-first heuristic explores a large proportion of the possibilities, which means that it might take very long to find a good solution. The second way to explore an unknown problem space is through a depth-first search, which is a method to continue the search along the lines of a successful strategy without ever exploring other possibilities. The drawback is that the depth-first heuristic might follow an unsuccessful strategy for some time before abandoning it, and after its discontinuation still little knowledge about alternative solutions has been gathered. When first confronted with an unknown situation, an optimisation system can start by randomly applying one of these heuristics. The feedback system determines the success of the chosen heuristic in optimising the task and, if necessary, can change it (Cohen, 1974). In terms of the present research, the first aim of this paper is to show that, within a feedback loop, a simple decision rule is constantly monitored and with accumulating knowledge is changed if that is necessary, thus reducing the options that have to be explored. For simple homeostatic bodily systems such as blood pressure, it seems obvious such regulation is derived from a simple feedback loop, or self-regulatory adjustment system. However, there are arguments that such an automated regulation system might also play a role in more complex behaviour (Carver and Scheier, 1998), and we will build on these findings in this paper, by defining our decision model as a feedback loop.

1.2.3. *The Functions of Emotions in Behavioural Control*

To be able to control the application of behavioural search heuristics, a feedback mechanism has to be able to determine when the action taken to solve a problem matters. In earlier studies it was shown that in well-practised interaction tasks, a feedback system can rank different interactions on adequacy (Fischer et al., 2004a) even when the ranking criteria are initially unknown (Fischer, Blommaert and Midden, 2004b). One way of learning to rank criteria is when the feedback loop accumulates prior knowledge. So instead of a 'calculated' optimum as an evaluation reference, a shifting evaluation value consisting of prior experiences is introduced (Carver and Scheier, 2000). This kind of experience-based decision making allows comparison of situations where not all the relevant information is available as consciously experienced information. Indeed, even when people do not consciously register certain stimuli, these stimuli are registered at a subconscious level (Zajonc, 1980; Zajonc and Rajecki, 1969). Previously experienced stimuli are liked better than others, while participants are not aware why. This is in line with ideas that experiences have an emotional impact. In saying so, we do not wish to make a strict cognition/emotion division. The appraisal leading to the affective liking of a certain situation probably contains many cognitive elements (Clore and Ortony, 2000), whereas seemingly conscious logical decisions often incorporate emotional elements (Slovic et al., 2004). That differences in prior experiences lead to different evaluations of the same situation, and the fact that feeling is probably important for this was shown by Mellers and colleagues (see e.g., Mellers, 2000). One of the experiments conducted by Mellers showed that order effects of wins and losses in a gambling game, with a predetermined pattern of wins and losses, resulted in differences in the satisfaction of participants although they all achieved the same final outcome (Mellers, Schwartz and Ritov, 1999). This indicates that a continuously updated reference value plays an important role in emotional appraisal. Damasio (1994) argues that there is neurological evidence that the evaluation derived from experience, which is not necessarily appraised emotionally, is integrated into an emotional assessment of the value of a situation. He also argues that in situations where the logical rules cannot yet be derived, these somatic markers result in acceptable problem solving at an earlier stage than can be achieved by following the rules of formal logic. The idea that emotions are important was supported by comparing two kinds of neurological patients and a control group playing a gambling task (Bechara et al., 1994). The neurological patients differed in the type of impairment with regard to emotional capabilities and intellectual capabilities. One group, suffered from prefrontal damage. This group exhibited normal scores on intelligence tests but had low emotional and social capacity. The other control group scored far below average on intelligence tests but had normal emotions. The results of this experiment showed that patients with prefrontal damage achieved significantly lower results in a gambling task, while there were no significant differences between the control groups. The experiment by Bechara et al. (1994) shows that emotional impairment rather than rational impairment negatively influences this gambling task. This experiment provides evidence that emotions play a role in indicating what options are good or bad. Once this is determined, 'bad' options can be avoided and 'good' options selected.

To date, much of the research on the influence of emotional elements on decision making has mainly focussed on the role of emotions strictly as such a signal of good or bad: a valenced signal. However emotions give richer signals than only good-bad (Lerner and Keltner, 2001). Specific emotions also convey qualitative information about how to adjust the ongoing interaction. Each affective experience has its own specific function in the control of interaction (Oatley and Johnson-Laird, 1987). Fear, for example, is a powerful interrupt signal that reprioritises all current goals and frees all resources for immediate survival (Simon, 1967). Anger is a signal that the chosen interaction strategy does not result in the desired outcome and that additional effort has to be invested to overcome obstacles (Oatley and Jenkins, 1996). In decision making it has been shown that happiness for example leads to both creative solution generation but also the tendency to avoid risks, the latter being consistent with the preservation of an optimal state, signalled by happiness (Isen, 2000). It is in such ways that mood or emotions convey information (Gasper and Clore, 2000; Schwarz and Clore, 1983, 2003). These specific functions of emotions can be interpreted as heuristics (Epstein, 1994).

When emotions are considered as the endpoint of a process of appraisal, initial 'good-bad' differences precede specific changes in action readiness or basic emotions (e.g., Frijda, 1986; Lazarus, 1991). Adopting such an approach, the valenced response occurs early on in the appraisal process while the more qualitative 'basic' emotions emerge later on, which gives us a framework for sutdying emotional importance within a single study.

1.3. OPERATIONALISATION OF THE AIMS

In an experimental study we look for confirmation of the above-mentioned ideas. First of all, we want to know if emotions convey a good-bad signal that allow for optimisation. To do this the reference value of Figure 1 is considered to be similar to an anticipated outcome, i.e. a somatic marker. This reference value is constantly updated and at the same time used to determine the quality of the interaction. Furthermore, the idea that specific emotions give specific directions for action adjustment also needs to be investigated. In terms of Figure 1 this means that besides valenced information the evaluation process also generates a qualitative direction for change. Since emotions allow integration of the relevant elements of a task (Cabanac, 1992), we argue that by manipulating the emotions in a manner that is unrelated to the task in hand, these emotions will nevertheless influence the way in which interaction takes place (see for example Isen, 2000).

In the experiment we partially replicate the earlier mentioned study (Bechara et al., 1994) of which it is generally accepted that emotion plays an important role in the regulation of the participant's behaviour. To investigate the potential for the heuristic function of distinct emotions, we decided to study what kinds of effects a potentially mood inducing procedure might have. This will give us an idea of how to understand the control of interaction in the context of emotion-directed control. In the second part of this paper we aim to increase our understanding of user behaviour and adaptation by adopting a computational angle. To achieve this aim we use the results from the experiment to build a simulation of this behaviour. Such a simulation can provide new insights into the structure underlying such choices (Braitenberg, 1984) and might therefore generate directions for future research.

2. Experiment

To test the idea of feedback in optimising a new task, an experiment was conducted in which participants had try to make a profit in a card game following unknown rules. The experiment is a variation on the experiment by Bechara and colleagues (Bechara et al., 1994). Differences between the original and this instance of the experiment are compared in the methods section (see for a summary of differences: Table I). The main goal of the experiment was to investigate in more detail how the accumulation of knowledge in a search task can lead to the improvement of behaviour. Investigating this effect in a new search task, rather than in a practised task, allowed the study of the process of optimisation.

When the game started, every element in the task could be of importance, such as the colour of the drawn card, the deck of the card, the sequence of wins or

Table I. Differences between the original experiment and the study reported in this paper

	Bechara et al. (1994)	The study in this paper
Participants groups	$N = 59$ Adult americans 3 matched groups $n = 6$ prefrontal brain damage $n = 9$ other brain damage $n = 44$ normal control	$N = 48$ Dutch students of a university of technology 3 randomly assigned to 3 music files of 12 min prior to the task. $n = 16$ hardcore $n = 16$ 'summer' pop $n = 16$ melancholic
Interaction	Human experimenter	Computer interface
Instruction[1]	Hint: look at gains and losses	
Card game	Losses and gains handled separately Number of loss gain combinations for each deck A: 5 B: 2 C: 4 D: 2 Starting money 2000 U$. (gross) Gains of 50 or 100 U$ (gross) Losses of 0 up to 1250 U$ Play-money; bills of 50U$	Net losses and gains used Number of loss gain combinations for each deck A: 2 B: 2 C: 4 D: 2 Starting money 2 Euro. (net) Gains of 1 to 10 € cents (net) Losses of 1 up to 115 € cents Electronic bank account and transactions visualised by Euro coins; indicating experimental reward. Monetary reward for participation equals the amount in the bank at the end of the experiment

[1] This difference was only discovered after the experiment was conducted, see discussion of the experimental results.

losses, etc. The only adjustment available was the selection of cards. In addition, because the participants did not know how many cards would be drawn, they had to find a balance between aiming for a profit early in the game or investigating more thoroughly giving them more certainty about winning options. So, the exhibited behaviour should be the result of a trade-off between spending much effort in trying to figure out how the game works, after which informed, profitable choices can be made, and taking gambles from the start. Damasio (1994) argued that the card selections made are based on the feeling whether the outcome of an action is 'good' or 'bad'. Early on no such anticipation exists, meaning that initially very successful, or very unsuccessful, options might be selected. When a participant discovers a successful strategy, is evaluated as being positive and this strategy is continued. The control system should interrupt un-successful interaction sequences.

To explore how emotions can influence these choices in a more qualitative way, the emotions of participants in the experiment were manipulated independently of the context of the task. Emotional experience is assumed to have a regulatory function in interaction (e.g., Oatley and Johnson-Laird, 1987; Sloman, 1999). This would mean that if an emotion is superimposed, the current regulation of the interaction is shifted towards the signal conveyed by that emotion. Therefore, induced emotions could be a way to change the interpretation of interaction goals in a way that is not obvious to participants. Lewis et al. (1995) showed that simply listening to music prior to filling out a mood scale has an influence on measurable effects of the mood of participants. To influence participant emotions, participants listened to different types of music. No control condition without music was included because it can be expected that asking a participant to sit in a silent cabin for 12 min would probably have a probably negative affective influence.

2.1. METHODS AND MATERIALS

2.1.1. *Participants and Design*

Forty-eight participants, all students at Eindhoven University of Technology, took part in the experiment. Sixteen of the participants were female and 32 were male, with an average age of 21.6 ($SD = 2.2$). Mood was manipulated between participants, by exposing three groups of each 16 participants to one of the three music files of 12 min. The music files were meant to induce one of three different moods, i.e. angry, happy, and sad (Lewis et al., 1995). Music was played before the experimental task started. After the music finished, each participant played a game in which maximum profit had to be achieved by successively selecting a card from one of four decks of cards. The total number of cards a participant selected was 100.

2.1.2. *Interface and Rules of the Game*

The experiment reported in this paper is a computerised variation on the experiment by Bechara et al. (1994), in which is shown that intuitive, emotional control plays an essential role in the optimisation of a task. To allow easy comparison between differences in the two instances of the experiment, Table I sums the main differences between the study in this paper and the original study.

The experiment was fully computerised. Using Visual Basic 6.0, a graphical user interface was built for the card game (Figure 2). The interface consisted of four decks of cards, from now on called decks A, B, C, and D, in relation to their gain–loss statistics. The decks were positioned in a square, the exact locations of each deck were balanced over the participants and conditions. The interface showed a dealer bank and a player bank, the latter was visualised simultaneously by a pile of Euro coins and a numerical account. Furthermore, the interface had a dialogue box at the top of the screen, in which the relevant next action was prompted.

The card game started with an animated card shuffle, after which all decks showed the blank side of a card. The dialogue box instructed the participants to select a card. After the participant had selected a card by clicking it, the card was revealed to show either a black or a red face. The dialogue box told the

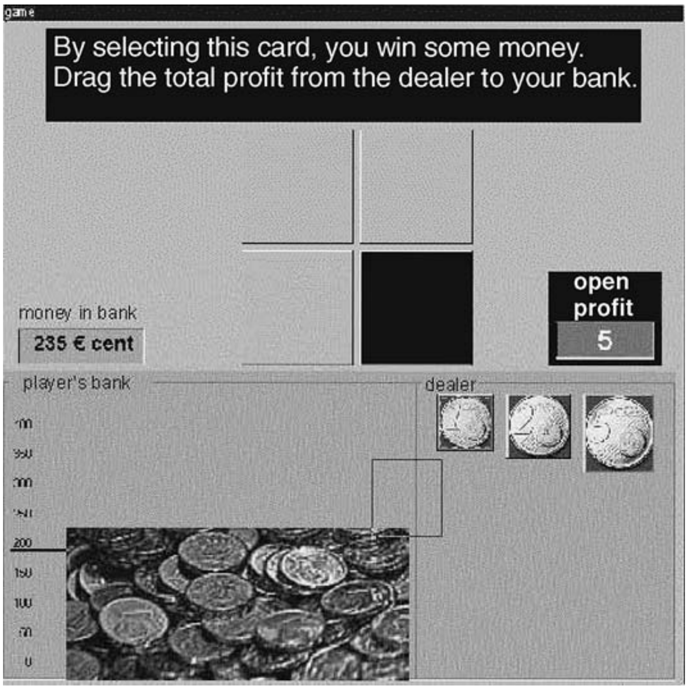

Figure 2. User-interface of the card game (texts are translations from original Dutch). On top there is a dialogue box, and under it there are four decks of cards. Left a numerical bank account and the bank area with a pile of coins indicates the current bank account. At the bottom right is the bank of the dealer. Above this an indicator shows as yet unpaid wins/losses.

participants whether a profit or loss was made. The participants then had to move all profit from the dealer's account to their bank by dragging the images of Euro coins. Losses had to be dragged from the participant's bank to the dealer's account. After dragging all of the required coins, the chosen card face once again became blank and the participant was asked to draw a new card. A completed card game consisted of a total of 100 drawn cards.

In short, the rules of the game came down to: decks A and B being 'losing' decks that resulted in a net loss of 25 Euro cents per 10 cards; decks C and D being 'winning' decks that resulted in a net profit of 25 Euro cents per 10 cards.

More specifically, the participants were given an initial balance of €2. The wins and losses depended on the selection of a deck was selected, and were randomly distributed within blocks of ten cards. Table II shows the different yields of the four decks. As the participants were paid according to the outcome of the game, the monetary values were lowered compared to the original experiment, in which (non-paid) yields were between 50U$ and 100U$ (Bechara et al., 1994).
In the original experiment participants always received some money for a card, but sometimes had to pay a loss as well. This rule was modified so that, instead of separately paying winnings and asking for losses if applicable, a net outcome was generated. The reason for this was related to computerisation of the experiment.

Table II. Deck pay-offs per block of 10 cards

A	B	C	D
5 × 10€ cents 5 × −15€ cents	9 × 10€ cents 1 × −115€ cents	5 × 5€ cents 1 × 2€ cents 1 × 1€ cent 3 × −1€ cent	9 × 5€ cents 1 × −20€ cents
Net −25€ cents	Net −25€ cents	Net +25€ cents	Net +25€ cents

In a pilot study it became clear that participants developed a dislike of the decks with frequent small losses (A and C) compared to the decks with incidental large losses (B and D). From observation and debriefing we gathered that one of the elements that was important in this dislike was the larger number of mouse operations to separately pay the losses and gains. Since drop-drag movements can be tedious, avoiding these operations would be a sign of optimising the process, but not one that was the focus of this study. For the same reason the net gains and losses of option C were adjusted to prevent the occurrence of net yields of 0 € cents, that would not result in any drag-drop operations. This made up for one of the differences in experimental design. However, since the original experiment contained similar differences in payback over the decks, no large effects were expected.

2.1.3. *Procedure*

Participants were recruited by approaching students during breaks, asking them to participate in the experiment and by advertising in the hallways, so that they could join the experiment whenever time and computers were available. The participants were welcomed into a cognitive laboratory, where they were assigned one of eight cabins with a PC, a 15 In. display, a standard Microsoft mouse, and stereo headphones. Participants were assigned to one of the three conditions, based on entrance to the lab; the 1st, 4th, 7th, etc. were assigned condition 1, the 2nd, 5th, etc. condition 2 and the 3rd, 6th, etc. condition 3. Participants were played about 12 min of music to induce different moods prior to the task (Lewis et al., 1995). The conditions differentiated the music between three types of modern music that can be classified as hardcore, 'summer' pop and melancholic rock.[1] The experimenter gave a short verbal introduction, in which participants were told that they would receive a reward of €2 for filling out a questionnaire on their music experience, which would be increased by however much money was in the bank at the end of a subsequent card game. The participants listened to the assigned music and then filled out a Dutch translation (Fischer, 2004) of the PANAS mood scale (Watson, Clark and Tellegen, 1988) on the computer. After the participants had filled out the scales, they were given on-screen instructions for the card game. The

[1]see Appendix A for the titles and performing artists of the songs

instructions told the participants that they had to draw cards from four decks, that the cards were randomly shuffled before the experiment, that each card could generate either a profit or a loss, that the game had strict rules, and that they could make a profit if they could work out these rules. No further information was given. The participants were not told how many cards were available. After these instructions the user interface was displayed and the game began. The order of the decks on the screen was balanced between the participants so that each deck occurred equally often at each position in each condition. After drawing the hundredth card, the participants were asked to fill in the PANAS mood scale once more, after which they were thanked, debriefed, and paid an amount dependent on the outcome of the game, in practice an amount between €3 and 6. The entire experiment lasted about 35 min. The actual time spent on the game was on average 6 min 48 s ($M = 408$ s; $SD = 184$ s), there was no difference between the time needed to complete the experimental task for the different music conditions $F(2, 45) = 0.2$; $p = 0.8$.

2.1.4. *Recorded Variables and Experimental Hypothesis*

The items of the PANAS scale (pa1..10, na1..10) were recorded for each participant, both after the music and at the end of the card game. The overall measures of the scales (PA, NA) were calculated. The deck and rank number of each card was also recorded. These variables were used to determine the length of the series, defined as the number of consecutive cards drawn from the same deck.

The main task of the proposed feedback mechanism is to optimise interaction. Although music may play a role in the detailed way in which this optimisation occurs, it should play a secondary role to this optimisation aim. Therefore, to determine to what amount the participants in this study managed to fulfil this optimisation aim, a first series of analyses will be conducted using the aggregated data of all 48 participants. Only once overall applicability of feedback in this task is established the specific effects of music are investigated.

For optimisation to occur, it should be able to determine the success of the current interaction, which in this case is simply the monetary reward. Pleasure can be seen as the outcome of the evaluation of the interaction (Cabanac, 1992), therefore affective experience should be more positive if the interaction is more adequate.

Hypothesis 1: The direction of mood change during the experiment is positively correlated with profit.

Hypothesis 1 states that participants determine the success of the game by relating profit to pleasure. In the specification of the evaluation mechanism, a hedonic tone is the outcome of the evaluation of each element of the interaction process (Fischer et al., 2004a). In this experiment this would mean that each deck of cards generates its own hedonic tones that are integrated in the hypothesised anticipation for that deck (called ‘somatic marker’ by Damasio, 1994). Cards are assumed to be selected based on this anticipation. In other words, as long as the experience with a certain deck of cards is better than the anticipated result of the other decks, the feedback system should ensure that the current deck is selected again. The more obviously profitable the selected deck is, compared to the other decks, the more stable the selections from that deck are assumed to become.

Hypothesis 2: Choices from profitable decks are continued, even when the rules of the game are unknown.

Additionally, the combination of hypotheses 1 and 2 means that if both the length of series and change of mood are positively correlated with profit then the length of series should also be positively correlated with mood change. This co-occurrence of a stable action pattern and positive mood agrees with the cognitive function of happiness: signalling and stabilising adequate interaction (Oatley and Jenkins, 1996).

However, there is a chance that a losing action sequence occurs when it is based on initial positive experiences. The outcome of the evaluation mechanism should decrease the anticipated profit of the losing deck as the losses accumulate. At a certain stage the feedback system should interrupt any ongoing series from a losing deck and re-initiate a broader search phase among the options.

Hypothesis 3: Series of losing decks are discontinued.

There are several ways by which the control mechanism can learn to improve the interaction, either through a lasting period of trial and error, by choosing a good action sequence and sticking to it (hypothesis 2), or by choosing a bad action sequence first and abandoning it (hypothesis 3). The accumulated information increases during the course of the experiment, which means that later card choices should be more profitable.

Hypothesis 4: There is a positive relationship between the rank number of the card drawn and the proportion of profitable cards.

The idea that emotions play a role in behaviour adjustment is investigated by following the idea that basic emotions generate typical action adjustments (Oatley and Johnson-Laird, 1987). Therefore by triggering different emotions, we anticipate that the related type of action adjustment is initiated. An aggressive mood should initiate forceful strategies to overcome obstacles (Oatley and Johnson-Laird, 1987). Or in other words, aggression is a heuristic to overcome frustration by applying force, while at the same time going for short-term benefits and being insensitive to losses (Evans, 2002). The function of aggression is to open up interactions sequences that have become stuck in a dead-end street. Therefore during aggression past experience is disregarded. There is some evidence that hardcore music invokes aggression (see, for example, Anderson, Carnagey and Eubanks, 2003). To induce aggression we therefore asked participants to listen to several hardcore songs.

In the context of this game this meant that the participants who listened to hardcore music had to draw from the decks with the highest gains. These are the losing decks. However, losing deck A only generates a gain five out of ten times, and results in high losses in the other five cases. This deck is soon identified as a losing deck. Deck B, on the other hand, exhibits frequent high gains and only sporadic losses. Therefore participants that listened to hardcore music were expected to favour deck B.

Hypothesis 5: The participants who listened to hardcore music initially prefer deck B, although this is a losing deck.

As a control, two other types of music were introduced. 'Summer' pop music, which might induce happiness. In problem solving, happiness leads to careful, risk-evasive behaviour in cases where there is a chance that the interaction will decrease the current feeling of happiness (Isen, 2000). 'Summer' pop should therefore lead participants to draw cards from the 'low risk-low gain' decks, which is the most profitable interaction since these are the winning decks.

Hypothesis 6: The participants who listened to 'summer' pop music will prefer low risk-low gain decks, and will therefore make the most profit.

Finally, to control for differences between negative emotions (Lerner and Keltner, 2001), melancholic music was played to a third group of participants. Melancholy is most closely related to sadness, an emotion that signals that the interaction is frustrated, but that no solution is readily available; the current goal hierarchy would have to be reconsidered and a new approach to goals and strategies would have to be initiated (Oatley and Johnson-Laird, 1987). This would suggest that melancholic music leads to two types of behaviour, i.e. a low-intensity goal reprioritisation, or an aggressive search for a new strategy.

Since asking participants to sit for 12 min probably influences physiological variables such as heartbeat, and asking participants to sit still without any music prior to the task probably is too boring and thus in itself influence mood and emotions; no condition without music was included as a control.

2.2. RESULTS

We will first present aggregated data, to find evidence for an overall functionality of feedback in improving this task. The more subtle differences between music conditions are studied in Section 2.2.1.

On average participants lost some of the base reward of €2 in the game, ($M =$ 12 Euro cents loss; $SD = 102$ Euro cents). The greatest loss was €1.86; the highest profit was €2.44. Only a few participants expressed knowledge of the correct rules during debriefing.

A MANOVA shows that the mood of participants changes significantly during the experiment, $F(2, 44) = 4.9$, $p = 0.01$. The overall mood-change is negative, but

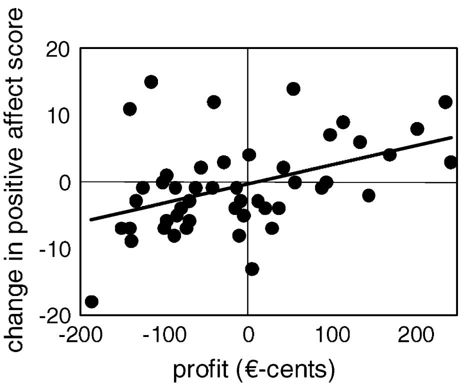

Figure 3. Relation between profit and change of positive affect.

this effect is mitigated by a positive correlation between the final bank balance and the change in the PA scale, $r = 0.44$, $p < 0.01$ (Figure 3). Although the NA scale slightly decreased, this was not significant. The participants who develop winning strategies apparently evaluate this as positive, thus confirming the first hypothesis.

Since profits strictly depended on the choice of deck, the numbers of cards from the different decks are compared. There was a difference between the number of cards drawn from each deck, $\chi^2(3, N = 4800) = 339$, $p < 0.01$. For each deck it was tested whether the number of cards drawn from that deck differed from a random selection (25 out 100). The losing deck A was chosen significantly below chance level, $M = 14.9$, $t(47) = 10.1$, $p < 0.01$. The losing deck B was chosen more often than the chance level, $M = 33.1$, $t(47) = 3.6$, $p < 0.01$. The winning decks C, $M = 28.1$, $t(47) = 1.0$, $p = 0.30$, and D, $M = 24.0$, $t(47) = 0.5$, $p = 0.65$, did not significantly deviate from the chance level. The participants appeared to notice that they should stay away from deck A, but were attracted to deck B, although this deck should have been identified as a losing deck.

The development of choice is investigated by looking at blocks of 20 cards (Figure 4). This showed an overall decrease in the losing decks A, $F(1, 45) = 9.6$, $p < 0.01$, and B, $F(1, 45) = 4.6$, $p = 0.04$, as well as an increase of the winning deck D, $F(1, 45) = 6.9$, $p = 0.01$. A trend towards an increase of cards drawn from deck C was found, $F(1, 45) = 3.0$, $p = 0.09$. All these changes led to more profitable card selections. This confirms hypothesis 4 that, on average, the participants develop more profitable selections during the course of the experiment.

To determine whether a successful strategy has been discovered, we investigated the length of the series of consecutive cards drawn from the same deck. The average length of a series per participant varied between 1 and 33. On average, the participants changed decks 57 times, $SD = 30$. Two participants changed decks 99 times, which meant that no two consecutive cards were drawn from a single deck throughout the entire experiment. Most participants changed decks less frequently. One participant only changed decks for the first two cards and then started drawing from one (profitable) deck, which he continued doing for the remaining 98

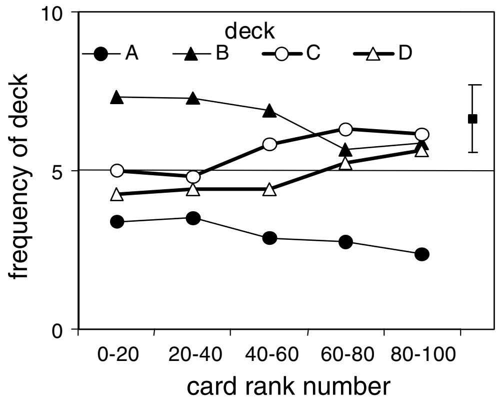

Figure 4. Selected decks for blocks of 20 cards. The closed markers indicate the losing decks. The error bar indicates the significant difference between observations at the 0.05 level.

cards of the game. There was a significant positive correlation between the average length of a series and the profit at the end of the game, $r = 0.56$, $p < 0.01$. This correlation was slightly higher if the last card in the series was also the last of all of the cards, $r = 0.65$, $p < 0.01$. Although these correlations are mostly due to the extreme values, these findings confirm hypothesis 2 that long series generally only occur if they are profitable. The higher correlation towards the end indicates that more profitable series are drawn later in the experiment. When comparing the rank number of the card at the end of a series with the length of that series, we found that the length of series increased during the course of the experiment, Kruskal–Wallis $H(99) = 181$, $p < 0.01$. This, together with an increase in profitable cards, indicates that participants were starting to converge on a profitable strategy.

The typical properties of longer series were studied in more detail by only considering series of 10 cards or more. Series with at least 10 cards are considerably longer than average ($M = 1.8$ cards). The series of at least 10 cards are singled out because they span a complete combination of losses and wins for a deck. There were 34 series of at least 10 cards. Nineteen of these series were drawn from the losing deck B, and 15 were either from winning deck C or D. When comparing the actual length of the series containing at least 10 cards, long series from the winning decks were significantly longer, $M = 41$, than those from the losing deck $M = 16$, Mann–Whitney $U(n = 34) = 47.5$, $p < 0.01$ (Figure 5).

This confirms hypothesis 2, that winning series are continued, and hypothesis 3 that losing series are discontinued. Further evidence for this statement is found by investigating the rank-number at which these series ended. Of the series from the losing deck B, only 5 out of 19 ended after card 50, which was significantly lower than the 12 series out of 15 that ended after card 50 for the winning decks C and D, $\chi^2(1) = 4.8$, $p < 0.05$. The 6 longest series ended at card 100; each of these series was drawn from one of the winning decks. This confirms that although the participants occasionally generate long series of cards from the losing deck B, they

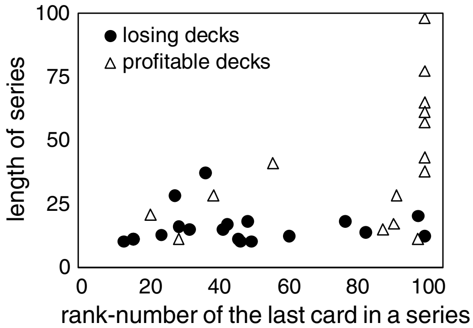

Figure 5. Rank-number of the last cards of series. Only series of at least 10 consecutive cards from the same deck were considered. Most losing series ended early in the experiment; profitable series continued.

Table III. Summary of the main findings for the total sample

N	48			
Profit $M(SD)$	$-12^{ns}(102)$			
Correlation mood change and profit	$r = 0.44^{**}$			
Correlation series length and profit	$r = 0.56^{**}$			
Changes of deck $M(SD)$	57 (30)			
	Total	Ending after card 50	Ending at card 100	average length
Losing series >10 cards	19	5	1	16
Profitable series >10 cards	15	12	8	40
	A	B	C	D
% cards from deck[1]	14.9^{**}	33.1^{**}	28.1^{ns}	24.0^{ns}
Change in deck choice[2]	D^{**}	D^{*}	I^{+}	I^{**}

[1]Significance levels indicate whether the number of cards selected deviates from chance (i.e. 25 cards)

[2]D indicates Decrease; I indicates Increase of that deck per block when determined per group of 20 cards

^{ns}not significant $^{+}$significant at .10, *significant at .05, **significant at .01

discover that drawing long series from losing decks was not a successful strategy, while drawing long series from winning decks was. The main findings are summarised in Table III.

2.2.1. *Music Conditions*

In the music condition the negative correlation between change in NA score and profit was not significant for any condition. Only the positive correlation between profit and the change in PA of participants in the ‘summer’ pop condition was significant ($p < 0.01$; $R^2 = 0.55$). In both the hardcore and melancholic condition this (positive) correlation was not significant.

Although there were indications that the music used did indeed influence mood (Fischer, 2004), we did not find the anticipated emotion induction in detail. Therefore the effects will be treated as that of music alone. Taking the limitations about the manipulation into account, there were some small effects of the music on the game. The differences in the final loss and profit varied slightly between the conditions: hardcore ($M = 57$ cents loss, $SD = 77$), 'summer' pop ($M = 24$ cents profit, $SD = 116$) and melancholic ($M = 2$ cents loss, $SD = 109$), $F(2, 45) = 2.6$, $p = 0.09$. Hypotheses 5 and 6 were confirmed at a significance level of 0.1, i.e. that 'summer' pop music leads to the highest and aggressive hardcore music leads to the lowest gain.

If the bank balance of participants is studied throughout the experiment, this effect becomes clearer, as it is found that on average, the participants in the hardcore condition had a lower bank account for most of the 100 cards of the experiment, (repeated measure ANOVA) $F(2, 45) = 5.0$, $p = 0.01$. This means that the participants who listened to hardcore music were initially worse off than the participants who listened to the other music types. Later on in the experiment, they partly recovered from their earlier losses, possibly because their initial losses were sufficient to develop a dislike to the losing deck B (see the development of deck choices as depicted in Figure 6a).

To study the difference between music more explicitly, the number of cards from the different decks is compared between the conditions. The number of cards drawn from deck B was significantly higher for the hardcore condition, $\chi^2(2, n = 1585) = 49$, $p < 0.01$. The participants in the hardcore condition also encountered more losses in deck B ($M = 4.4$), than those in either the 'summer' pop, $M = 2.8$ or the melancholic music condition, $M = 3.4$, $\chi^2(2, n = 170) = 6.2$, $p < 0.05$. This difference mainly occurred in the first 20 cards (Figure 6). The participants who had listened to hardcore music chose deck B more often in the early stages of the game, but in doing so better learnt to avoid this deck. This confirms hypothesis 5, listening to aggressive music results in high-gain, high-risk choices even if those are loosing. There were no significant differences between the selections of decks A, C, or D between the conditions.

On the whole in all conditions there was a change for the better, although not always significant. More specifically, in all but one deck in a single condition, the deck changes were in the expected direction (see Table IV).

There were differences in frequencies of drawn cards from the profitable decks C ($\chi^2(2, n = 1349) = 22$, $p < 0.01$) and D ($\chi^2(2, n = 1150) = 22$, $p < 0.01$) over the conditions. In the hardcore music group decks C and D were drawn about equally often; $\chi^2(1, n = 705) = 1.7$, *ns*, which was also the case for the 'summer' pop group $\chi^2(1, n = 705) = 0.4$, *ns*. Participants who listened to melancholic music preferred cards from deck C to cards from deck D, $\chi^2(1, n = 858) = 24$, $p < 0.01$. So there is apparently only a difference between deck C and D after listening to melancholic music. This issue is discussed later on.

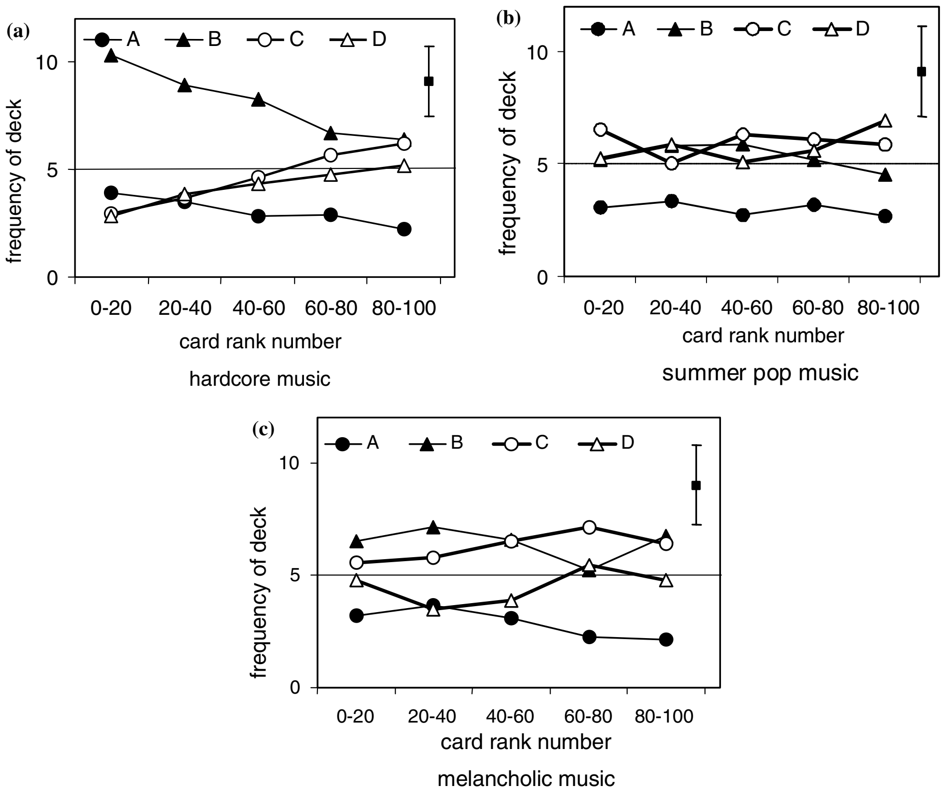

Figure 6. Deck selection for blocks of 20 cards for (a) hardcore music, (b) 'summer' pop music, (c) melancholic music. The legends indicate the marker for each of the decks. Closed markers are used for the losing decks. The error bars indicate the significant difference between observations at the 0.05 level.

Table IV. Summary of the main findings for the music

	Hardcore				'Summer' pop				Melancholic			
n	16				16				16			
Profit $M(SD)^+$	−57 (77)				24 (116)				−2 (109)			
	A	B^{**2}	C	D	A	B	C	D	A	B	C	D
% cards from deck	15.4	40.6	23.1	20.9	15.0	26.5	29.8	28.7	14.3	32.1	31.3	22.3
Change in deck choice[1]	D**	D*	I^+	I**	D^{ns}	D^{ns}	D^{ns3}	I^{ns}	D^{ns}	D^{ns}	I^{ns}	I^{ns}

[1]D indicates Decrease; I indicates Increase of that deck per block when determined per group of 20 cards

[2]Compared between conditions

[3]Deviates from the hypothesised direction. This effect was four times smaller than the next smallest effect

^{ns}not significant $^+$ significant at .10, *significant at .05, ** significant at .01

2.3. DISCUSSION OF THE EXPERIMENTAL RESULTS

2.3.1. *Interpretation of the Results in Comparison with the Hypotheses*

To optimise behaviour, participants have to be able to determine what the adequacy of the undertaken interaction is. The positive correlation between profit, an indicator for interaction adequacy and change in the mood scores, confirms hypothesis 1, participants can evaluate their strategy. The fact that this change could be measured on a mood scale is an indication that the evaluation is at least partially affective. Apparently, there is information available to participants about the adequacy of their interaction. However, it is not clear how wins and losses are evaluated exactly. This evaluation is probably not linear, and negative outcomes are probably evaluated as larger than similar positive outcomes (Shafir and Tversky, 1995). There were indications that participants used the information they gathered during the game to immediately improve interaction. The participants that won the most did so by making the correct choice almost at once, which means they could have had very little information about the rules of the game. Even without being able to figure out the possibilities, the accumulation of profit proved to be enough information to stay with the chosen strategy, confirming hypothesis 2 that profitable series are continued. On the other hand, participants that made an early choice for a losing deck figured out that ongoing selections from a single deck generate a consistent loss and stopped drawing from that deck (hypothesis 3). The feedback-mechanism apparently selects a strategy of drawing continuing series of cards from a single deck only when this strategy results in long-term profit. If losses accumulate the selection is expanded to the other options. Over the whole group, a positive correlation between the rank number of the drawn card and series length was found. When interpreting the co-occurrence of these findings, it becomes apparent that longer and more profitable series emerge, which is the start of convergence towards the more stable and profitable strategy of selecting long series from the profitable decks (hypothesis 4).

However, not many participants found the correct strategy to make a profit in the card game. This was mainly because the losing deck B was favoured. A possible explanation is the make-up of deck B, which gives high profit and it does so frequently (90% of the cards). On average participants encountered only 3.5 losses in deck B compared to 29.5 wins. Apparently participants needed a lot of information before discarding deck B.

The music did influence the number of cards drawn from the different decks. According to hypothesis 5, aggression, should lead to exploring new strategies. This would mean the control system should go for easy profits and not be stopped by initial losses. Hypothesis 5 was confirmed by the results that participants who listened to the hardcore music, which was used to evoke aggression, had a clear initial preference for the deck that yielded the most frequent high wins (deck B). Participants that listened to the 'summer' pop music exhibited careful risk-evasive actions, by either sticking with proven profitable decks or by staying with the low-risk strategy of randomly drawing cards as was predicted by hypothesis 6. These results, however, have to be taken with some reservations because we did not test the whether the effect of music was indeed that of an induced emotion. It might also be the case for example that the differences found are related to a completely other property of the music, such as its speed. To substantiate the claims about the interpretation of the effect of music in relation to emotions, we must carefully research whether different types of high-arousal music have different influences on the mood of participants.

Another effect is found for participants that were exposed to melancholic music. It was found that participants that had listened to this type of music chose significantly more often from the winning deck C than from the winning deck D. The difference between the decks is that only low yields (5, 2, or 1€ cents) and very low losses (1€ cent) occurred in deck C. A possible explanation is that participants in this condition preferred low-intensity experiences while changing their goal priority (Oatley and Johnson-Laird, 1987) and maintaining a low mental activity (Izard and Ackerman, 2000). On the other hand, participants that listened to melancholic music also favoured deck B. A possible explanation is that the invoked sadness leads to the search for new goals, which can result in a period of aggression (Blumberg and Izard, 1986) to overcome initial obstacles. This explanation indicates that the effect of sadness on behaviour is complex, and warrants critical examination in future research, both with regard to the effect of sadness on decision making and to the fundamental aspects of sadness as a basic emotion (see for example, Barr-Zisowitz, 2000)

2.3.2. *Comparison of the Results with the Original Study*

A limitation for the interpretations of the behavioural measures recorded in this experiment, is that less clear results were found than in an earlier version of the same experiment (Bechara et al., 1994). Especially the preference for deck B in this version of the experiment, led to a large number of losing cards. This difference cannot be attributed to the number of participants (48) alone or to the music manipulation since at least the pattern should have emerged. Particularly since the originally reported study found effects within the 'normal' control group of 44 participants and the 'IQ-impaired' control group of nine participants (Bechara et al., 1994).

There are several more conceptual factors that may have contributed to this difference. One explanation for this observed difference is that the participants in our experiment were students from a university of technology. The technological environment places a heavy emphasis on rational and logical reasoning, accompanied by a distrust of intuition and emotion, while it was argued that intuitive deciding is faster in this type of task (Bechara et al., 1997). The logical stance of participants might have been increased by the fact that the experiment was fully computerised, since a computer could give an additional logical frame for the experiment. This interpretation of an too large emphasis on logic is supported by remarks of some of the participants during debriefing, who were looking for complex combinations of the number of consecutive wins, combined with cards of the same colour and their relation to the size of loss and profit.

A second explanation for the differences could be a motivational issue. Where a human experimenter conducted the original experiment, our experiment was fully computerised. This could result in a lower level of social compliance to achieve the aims of the experiment and therefore lower motivation of participants. Lower motivation can result in less clear relations between the available information and behaviour (Petty and Cacioppo, 1981). To try to motivate participants, they were actually paid according to the outcome of the game. However, for this reason the monetary amount of the reward was adjusted. This might have had a negative side effect by influencing the experience of wins and losses. Another adjustment to the game might also have played a role. Yields and losses were not handled separately but as a net value, which might have caused a vaguer interpretation of the independent yield and loss systems of the decks.

A third point is that in our instructions no indication was given on which elements of the game participants should focus. Schmitt, Brinkley and Newman (1999), who also used a computerised version of the gambling task, encountered similar problems and found that the final instructions of an earlier instance of the experiment (Bechara et al., 1997) included unreported hints to specifically look at wins and losses. Furthermore, in both Schmitt's and the currently reported study, the main difference in the procedure was that of replacing the human experimenter by a fully computerised version of the experiment. One of the possible differences is that the computer did not give any information on how well the participant was playing the game other than monetary ones, where the human experimenter might have given implicit signals about the success in the game to the participant, for example via facial expressions. To work this out, it is highly recommended that in future work a comparison is made between possible computerised versions (e.g., with and without implicit feedback) and a face-to-face version of the same experiment.

2.3.3. *Remaining Limitations*

Although the music files did result in the expected change in the selection of cards, there are some issues that should be resolved in future research. First and most important there is little explicit data about the effect of the music on emotions in the reported study. If in future work the effects of mood on this task are further explored, attention should be paid to devise emotion manipulations that can be measured, for example by using more discriminating self-report scales or other measurement methods (e.g., galvanic skin resistance) to distinguish between the different emotions. The fact that the effects that we found agree with existing theories on basic emotions suggests that the approach to distinguish basic emotions beyond the good-bad dimension alone is probably a good idea. A second issue in relation to the induced mood is that the music was played and finished prior to the task. This would mean that differences in behaviour between conditions for the first part of the experiment are likely to be induced by the music, but that differences at the end might not be because the effect of the manipulation had faded. On the other hand, playing the music during the task may have an influence on the interpretation of gains and losses besides its effect on strategy selection. In future research it might be interesting to compare effects of mood induction that finishes before the task, and those that continue throughout the task. In the latter case a no-music control group could be included more easily. A third issue is that it might well be that personality traits and musical preference play an important role in the effect of music on the participants. Although we tried to eliminate this by using randomly sampled participant groups, this effect cannot be disregarded. For future research it is advisable to include personality and musical preference information in the data to compensate for this kind of effect.

2.3.4. *Conclusion of the Experiment*

In spite of these limitations the data supported all of the hypotheses. The mechanism of card selections was well on its way to discover more profitable strategies, although it was not there yet. Furthermore, anticipated effects of anger, leading to high-risk choices, and happiness, resulting in risk avoidance, were found. This supports the idea that heuristics of an emotional type are involved.

3. Computational Mechanisms

In the discussion of the experimental results we argued that participants in an ill-defined situation such as a card gambling game begin to learn the more profitable strategy, even if they do not have the information required to work out the exact rules of the game. Relating to Figure 1 this would mean that the feedback loop influencing the experience results in an improved evaluation of the interaction. To gain a better understanding of how such a system of experience-based optimisation works, we will explore to what extent the selection of cards can be described by a simple computational mechanism in the following section of this paper. This approach allows us to identify potential aims for future research, which are oriented towards underlying processes than can be derived from empirical studies alone. To achieve this aim a computational model is introduced that emulates parts of the observed behaviour. More explicitly, we start with investigating ways to aggregate knowledge about the different options in the experimental gambling task. At the end of this section, the results of the experimental study are compared to the outcome of the selection mechanism developed, and we discuss the similarities and differences between the simulation and the experiment.

3.1.1. *Accumulating Experience*

To achieve effective strategy selection, all mechanisms should generate some kind of anticipation of the outcome of the next card from each deck. Following the idea of feedback, this anticipation is constantly updated. We adopt the recent notion of Carver and Scheier (2000) in referring to this anticipation value as 'recalibration' of reference values in the affect system. In future work such notions might be further developed to link these computational ideas to neurological evidence for similar ideas such as the 'somatic markers' (Damasio, 1994). As argued before, these evaluation values require emotions in decision making. For computational or artificial intelligence purposes emotions have been described as control and alarm systems that hierarchically control interaction (Sloman, 1999). In a more specific network of perceptions, actions, drives and behaviours, emotions are considered to control the different nodes (Velásquez, 1998). The model presented in this paper describes a more hierarchical structure than that of Velásquez but adopts a similar adjustment function of the separate elements of an ongoing interaction system (see Figure 1). By placing the adjustment system outside the interaction cycle, it combines with the hierarchic structure of Aaron Sloman (1999).

The proposed computational mechanism aggregates experience into 'reference values', which is a valenced value attached to each of the options. The decision which action to take is subsequently based on the most positive reference value. In this case this decision is the selection of the deck from which a card is drawn. The way in which reference values are updated and maintained is essential in the selection of cards. Three demands must be met for this updating. First, they should be cheap in relation to cognitive resources, which is an important issue in implicitly regulated tasks as we argued in the introduction. Second, to be successful in an unknown situation the reference values should be able to adapt. This may seem trivial, but it is not since, thirdly, such an integrator should be insensitive to random fluctuation and should therefore be as stable as possible. The balance between the second and the third determines in particular the potential of the different integrators.

With these demands, we can readily think of several ways in which the reference values can be updated. The first of these is to simply adopt the last occurrence of a card as the expectation of that deck. This makes it a recency effect fully determining the content of the reference value. This mechanism requires hardly any cognitive effort and is highly flexible, but is also very sensitive to random fluctuations, and therefore probably not a good predictor. The reference value formed in this way is given by Equation 1, in which the reference value (*RV*) for a deck at card i of that deck is completely determined by the experience (*E*) of the previous card $(i-1)$ drawn from that deck.

$$RV_i = E_{(i-1)} \tag{1}$$

A second function aggregates experience by averaging all previous experience for a deck to form a reference value (Equation 2a). In itself this is a straightforward way of finding the expected value of a certain option. There is, however, a problem with this approach: in the proposed model we would like to minimise the need for cognitive resources. By using Equation 2a to calculate the average interaction as a reference value, the system needs to store all previous experiences (E), which results in a high cognitive load (e.g., by storing all these values in some kind of working memory). An alternative notation that does not have this requirement is given in Equation 2b. This notation only requires the storage of the last occurrence and the number of occurrences. This only partially fulfils the demand to minimise cognitive effort since the reduction in stored values requires a calculation that is rather elaborate, which in turn increases cognitive effort.

$$RV_i = \frac{\sum_{n=1}^{i} E_n}{i} \tag{2a}$$

$$RV_i = \frac{(i-1) \cdot RV_{(i-1)} + E_i}{i} \tag{2b}$$

If we want to limit the resources spent on calculation and storing past occurrences, a third way of calculating the anticipated interaction comes to mind. Following this method the reference value for interaction is determined by the aggregated past experience (the present reference value). This is partially changed towards the last interaction that occurred, through a fixed relation between these two. This can be easily modelled as an iterative Equation 3a by introducing a stability index (S, $0 \leq S \leq 1$) that determines the extent to which the reference value depends on the past. Note that when S equals 0, equation 1 results and that when S equals 1 the system becomes completely non-responsive to new experience. This equation results in a reference value for the interaction that is sensitive to structural changes but not hampered by incidental noise signals; it requires limited calculations and it requires a storage of only a single constant (S) and the reference value. This formula can be restated analytically (Equation 3b) in which some kind of exponential smoothing function is found. By comparing Equations 2 and 3, it immediately becomes clear that the analytic function is more easily calculated in Equation 2, whereas in Equation 3 the iterative function is more easily calculated. Therefore, we argue that Equation 3 is probably a better way to describe the development of reference values for the evaluation of interaction than Equation 2.

$$RV_i = S \cdot RV_{(i-1)} + (1-S) \cdot E_i \tag{3a}$$

$$RV_i = \sum_{n=1}^{i} S^{(i-n)} \cdot (1-S) \cdot E_n \tag{3b}$$

Equation 4 is a final option that is mentioned just to make clear that more elaboration on these type of functions is possible is. In this equation the stability gradually increases as a function of the number of occurrences. Setting the parameter of this additional function at 0, Equation 4 reverts to Equation 3. For our current simulation, estimating an initial value for S as well as the increase of this parameter would require more parameter estimations than can be derived from our evidence. Therefore, we will use Equation 3 for the remainder of this paper. In future research it might be valuable to compare these functions with performance of neural networks or with neurological findings. This might generate additional ideas for such integrators, or might support the choice of one of them.

$$RV_i = S_i \cdot RV_{(i-1)} + (1 - S_i)\, E_i \quad S_i = f\,(i) \text{ e.g., } S_i = i/\,(i+1) \tag{4}$$

We apply these equations to a noisy signal with an average value of -3. Note here that this is only an example to show that these functions adjust to an arbitrary signal. All the mechanisms started off with a neutral anticipated value of 0. Each mechanism managed to find the average value (Figure 7). Only three of the four introduced mechanisms reduce random noise and generate a stable, but still flexible, anticipation for subsequent occurrences. To obtain a first evaluation of this approach, we selected one formula that we related to the empirical results. As discussed above, Equation 2, although integrating prior experience, requires too much cognitive effort for the type of mechanism we have assumed, while Equation 4 is too complex for the aim of this paper.

3.1.2. *Action Selection*

In this section, the results of the experimental study are interpreted as the outcome of a selection mechanism that enabled us to investigate to which extent the selection of cards can be described by a proposed user model (Figure 8). The aim of introducing this action-selection mechanism is to investigate the potential of designing computational mechanisms that can describe successful decision processes that follow another rationale than that of formal logic. The mechanism selects an action, which in this case is the picking of the deck to draw a card. The mechanism needs some knowledge of the game to select the most profitable card. To do this, the mechanism stores the anticipated outcomes of each of the decks in what we call a reference value. This anticipation is based on previous experiences as specified in Equation 3. The difference in anticipation is modified by a first parameter, called the influence of reference values on card selection. If this parameter becomes 1, the selection is completely determined by prior experience. If this parameter becomes 0, the selection is completely random. Based on the differences in anticipation between the decks, and the parameter for influence, the probability that each deck will be selected is calculated, with the condition that the overall chance should be 1 (see Table V). Decks with a better reference value have a higher chance of being selected; the better the reference value, the higher the chance. To prevent early deadlocking in a successful strategy, or early rejection based on a chance loss of a successful strategy, a certain level of noise is

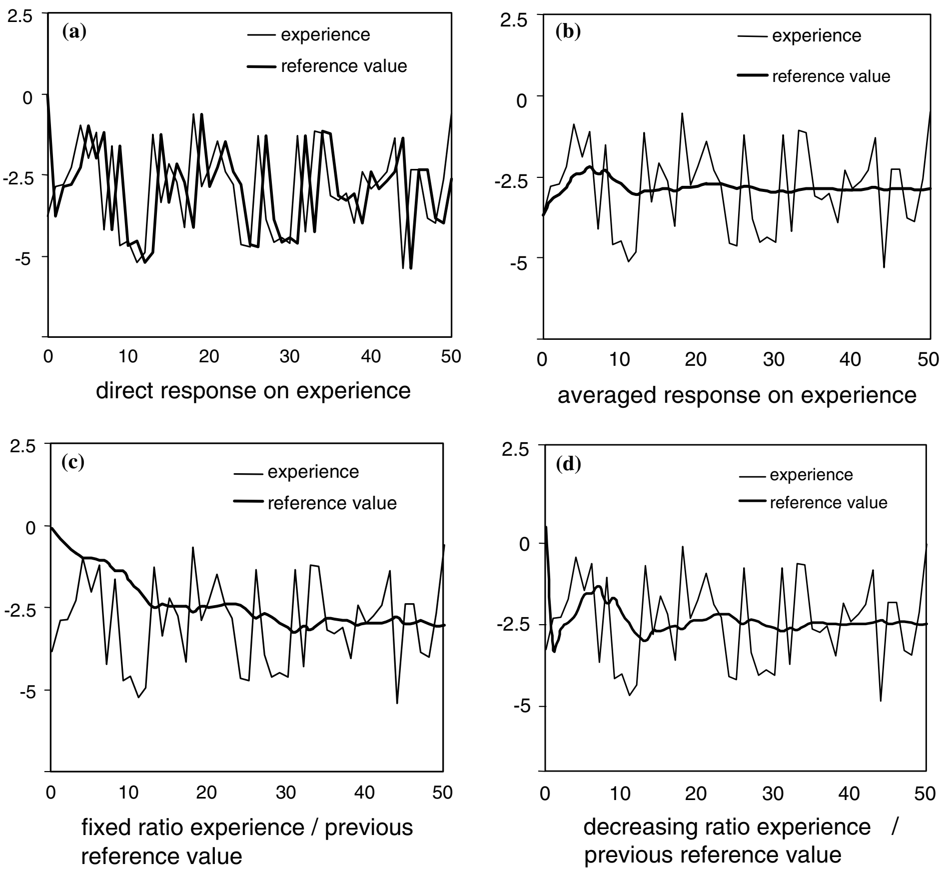

Figure 7. The development of a reference value over 50 consecutive interactions. (a) The development of the reference value is modelled by Equation 1: direct response. (b) Modelled by Equation 2: averaged experience. (c) Modelled by Equation 3: fixed influence of the previous reference value. d) Modelled by Equation 4: increasing influence of the previous reference value.

added to the decision. A computer generated random number provides this noise level. The selected deck generates an outcome similar to the one in the experimental task (see Table I). The outcome is integrated into the new reference value of that deck. A second parameter, the stability parameter (S) of Equation 3, models how strong the effect of past occurrences is compared to a new experience. If this parameter is small, past occurrences are readily forgotten. If the outcome of the deck is better than expected, the reference value for that deck increases. A positive experience, therefore, means that the deck has a higher chance of being selected in the next selection. A negative experience, on the other hand, results in a smaller chance of the same deck being chosen again. The process starts over again with the new anticipation values, so a new selection can be made. The two parameters that were specified are correlated: both indicate that reference values play an important role. The rationale for defining two parameters lies in the role of the

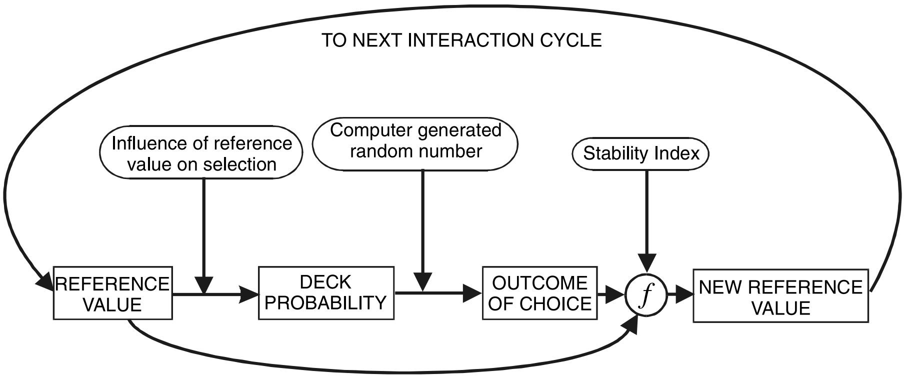

Figure 8. The simulated mechanism with two parameters to describe the influence of experience.

Table V. Example computation of a single card selection, and the subsequent updating of anticipation. The mechanism in this table is specified according to Equation 3a

Initial Reference VALUE ($RV_{(i-1)}$)	$RV_{A(i-1)} = 5$; $RV_{B(i-1)} = 0$; $RV_{C(i-1)} = -5$; $RV_{D(i-1)} = 0$
Influence (I) of reference value on selection	$I = \mathbf{0.5}$; $(1 - I) = \mathbf{0.5}$
Raw deck probability for four decks	$P = (1 - I)^*25 + I^*RV$
RAW deck probability	$A = \mathbf{0.5}^*25 + \mathbf{0.5} * 5 = 15$; $B = \mathbf{0.5}^*25 + \mathbf{0.5}^*5 = 12.5$; $C = \mathbf{0.5}^*25 + \mathbf{0.5}^* - 5 = 10$; $D = \mathbf{0.5}^*25 + \mathbf{0.5}^*5 = 12.5$
Over all chance correction	Overall chance $= A + B + C + D = 50$. This should be 100(%) therefore multiply all chances by factor 100/50=2
Deck probability (%)	$A = 30$; $B = 25$; $C = 20$; $D = 25$
Random number (0..100)	$= 42 \Rightarrow$ **Deck B selected**
Experience (E); outcome of choice	$E_{\mathrm{B}_i} = 10$; $E_{(\mathrm{A,C,D})_i} = 0$
Stability index (S) - integration of previous reference value	$S = \mathbf{0.8}$; $(1 - S) = \mathbf{0.2}$
Use equation 3a to calculate new reference value	$RV_{(\mathrm{A,B,C,D})_I} = S \cdot RV_{(\mathrm{A,B,C,D})_I} + (1 - S) \cdot E_{(\mathrm{A,B,C,D})_i}$
New reference value	$RV_{\mathrm{A}_i} = (\mathbf{0.8}^*5 + \mathbf{0.2}^*0) = 4$; $RV_{\mathrm{B}_i} = (\mathbf{0.8}^*0 + \mathbf{0.2}^*10) = 2$; $RV_{\mathrm{C}_i} = (\mathbf{0.8}^*- 5 + \mathbf{0.2}^*0) = -4$; $RV_{\mathrm{D}_i} = (\mathbf{0.8}^*0 + \mathbf{0.2}^*0) = 0$

card selection procedure. This stage occurs between application of the two parameters. Therefore, it is not possible to reduce the model to a single parameter model.

An example of the selection of a single card and the integration of this experience into the anticipation for the next draw is computed in Table V.

So far, we have specified a mechanism that keeps track of a single interaction object. When several decks of cards have to be kept track of simultaneously, the mechanism has to store more reference values (4 in this case). It is likely that some sort of decay will occur for values that were not accessed recently; participants are expected to forget. The simplest way to model this decay is by assuming a neutral (0) experience for each deck that is not chosen. This leads to a system in which non-selected negative experiences slowly revert to the neutral and once more become eligible for subsequent selections. This could however be too stringent a model for 'forgetting', since every turn in which a deck is not selected is modelled as an effective zero result. More specific modelling of the storage system would require even more parameters, which cannot be justified at this stage, but might be interesting for future development. The alternative (i.e. not modelling decay of reference values at all) would generate a model that would very rapidly learn to discard decks for the remainder of the simulation. The experimental data with regard to the number of losses taken in deck B, suggests that this cannot have been the case in the experiment. Therefore, for this simulation, this solution was selected. With more experimental data more elegant solutions can probably be found.

Table V gives an example of how the calculation of the new reference values for the four decks is implemented when we adopt this idea. The reference value of deck B is adjusted to the last outcome, while the reference values of the other 3 decks move towards 0.

The task of the feedback mechanism is to direct the selections towards the most profitable. To do so, the feedback system sets the two parameters in the simulation. The first parameter that can be adjusted is the influence that the reference value has on the selection of decks. The more important the ongoing tasks is for the current well being of the person, the higher the value of this parameter should be. A second parameter is the stability index, modelling the influence of past experiences on the anticipation of future actions. If this parameter is high, the past occurrences are strongly taken into account, resulting in a stable, but not so flexible interaction control.

In different situations, induced by mood differences in this case, the feedback system should set different parameters. To test the specified card selection simulation, the two parameters are estimated that fit the different induced moods the closest. It was argued that affect could be interpreted as a heuristic (Epstein, 1994) that determines adjustments of action (Oatley and Johnson-Laird, 1987). Therefore, mood induction should result in different parameters, set by the feedback system and based on the interpretation of the induced mood. If the function of anger is considered, this would mean that past experience should not be taken into account in defining a new anticipation of the task. This means that the parameter for integration of past occurrences should be lowest in fitting the parameters to the participants that listened to hardcore music.

Table VI. Fit parameters and variance of the experimental data that is explained by the parameters compared to random card selections

Data	Explained variance (%)	Influence of reference value (I)	Stability index (S)
All experimental	94%	0.15	0.74
Hardcore music	96%	0.11	0.52
'Summer' pop music	97%	0.17	0.84
Melancholic music	75%	0.14	0.83

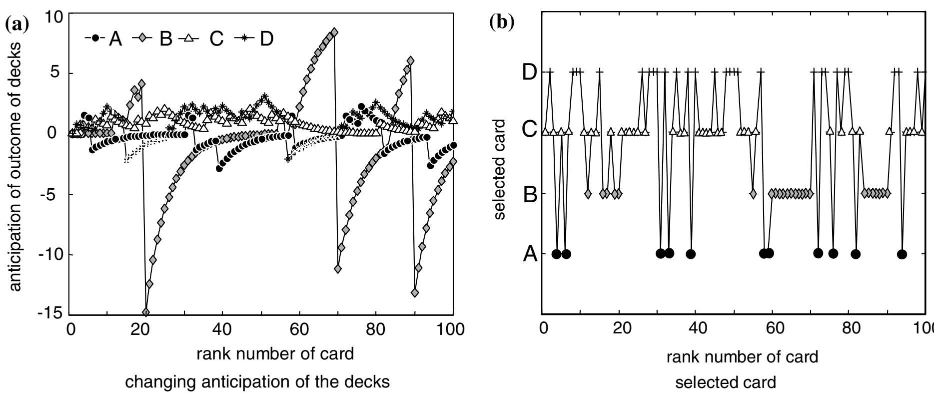

Figure 9. Example of the simulation. (a) The anticipation for each of the decks. (b) Selected card. The parameters were those found for the 'summer' pop music condition.

3.2. OUTCOME AND DISCUSSION OF THE SIMULATION

The simulated mechanism had to select 100 cards; this was repeated 48 times. This resulted in a number of cards drawn from each deck. The outcome of the simulation was compared with the number of cards drawn from each deck as recorded in the experiment. By iteratively minimising the squared difference between the empirical and the simulated data, the parameters were estimated. The simulation rendered overall results that fit the overall outcome of the data fairly well (Table VI), although the data remained inherently noisy.

An idea of how the simulated selection mechanism chooses cards is given in Figure 9. In Figure 9a the anticipated outcome is plotted for each deck at any moment. The decay of stored reference values is clearly visible in the change of the negative values towards the neutral over time. The experimental data with regard to the number of losses taken in deck B suggests that some 'forgetting' occurs in the experiment. Therefore this first order solution was selected for this simulation. With more experimental data more elegant solutions can probably be found.

Participants that listened to hardcore music had the lowest parameter for integration of the past. The stability index was also lowest. This outcome could be interpreted as an indication that accumulating experience has little predictive value for the behaviour of aggressive people, which agrees with the functional idea of aggression, ignoring past experience helps us to generate behaviour that is needed to break through barriers (Evans, 2002). The evidence presented in the current paper, however, is too weak too provide definitive support for this claim. This would be an interesting direction for future research in which the relation between aggression and past experience in decision-making tasks is further investigated.

Although the simulation could be used to predict the fraction of card selections made by the aggregated card selection of the groups of participants, there were limitations to the simulation with regard to predicting individual behaviour of participants. First, in the simulation, no long series were generated, while they were observed in the experiment. This is probably because the simulation did not distinguish between gambling early and going into a prolonged period of trial and error. The problem is probably that in reality two distinct modes of selection alternate (Sloman, 1996), whereas the simulation only had one parameter set. To overcome this problem, the simulator can be nested in a secondary control system that qualitatively determines how the different heuristic or deliberate selections should be made. This adjustment was postponed for future work because a secondary control system would further complicate the simulation and rapidly lead to more complex strategy generation (Dennett, 1995), which goes beyond the scope of this study. Another limitation of the simulation was that it could not distinguish between the two objectively equally good options C and D, which received different scores for the melancholic music (32% versus 22%). The effect of sadness on choices was argued to be a combination of two different strategies: preference for low intensity stimuli or generating anger to start a new sequence. This problem can probably be solved by adding a secondary control system too, which determines whether low intensity or aggressive solutions are favoured.

A final limitation is related to the evaluation of the outcome of the game. In this simulation it was assumed that the monetary yields were evaluated straightforwardly. There is, however, evidence that negative outcomes are perceived as being larger than corresponding positive outcomes and that extreme values are basically perceived as ‘very big’ (Shafir and Tversky, 1995), which complicates the generation of the anticipation of the next action. If these problems are dealt with a more complete mechanism for strategy selections might be designed.

4. General Discussion

People executing an ill-defined problem-solving task optimise behaviour in a way that can be explained by a feedback system that sets parameters, determining how the problem-solving task should be executed. To do so, the feedback system selects strategies for the interaction. For example: “try to make profit as soon as possible”, or alternatively “figure out the rules of a game to be able to make profit later on”. Participants indeed show high-risk early choices and more informed choices later on. This indicates that the underlying psychological mechanism probably acts on a mix of heuristic and more deliberate solutions. This can be interpreted as a dual process, which allows the system to select reasonable actions at every moment (Sloman, 1996). The ongoing control ensures that heuristics resulting in bad choices are abandoned, while those that result in successful guesses are confirmed. This means that good interactions are enforced by positive feedback, while bad interactions are interrupted by negative feedback. With increasing information about the task, a more stable action selection emerges.

Emotions as information probably play a role in the feedback system. Although it was not completely clear how the music influenced the mood of participants, the induced change in mood resulted in different strategies, which indicates that the outcome of the evaluation is at least partially affective and that mood inductions influence strategic decisions. This idea should be substantiated through future research on the influence of music on self-reported mood and the exact measurement of this influence. The decreasing effect of the mood manipulation in the experimental results indicates that mood induction is most important at the start of the experimental task, when the simple emotion as a heuristic is the only available cue and therefore is apparently used as a start for the search process. Later, as more information has been gathered, the effect of mood induction diminishes and the chosen actions are based on strategies that have been generated by the feedback system with accumulating experience. We cannot exclude, however, that part of this effect is due to the dissipation of the initially induced mood.

To achieve a better understanding of the regularities involved in such an intuitive interaction optimisation task, we presented four ways to integrate experience in an anticipated outcome for an interaction. We compared the iterative and analytic functions. By rearranging the equations, the functions are shown to be identical, although simple analytic ones were not always simple iterative functions and vice versa. Under the assumption that a simple function is better than a complex one, we chose a function that was simple when iterative. We chose for an iterative function because it is most likely to be related to the emergence of associations in neural networks or indeed the brain, although this should be confirmed by future and neurological research. Using one of these iterative functions to produce reference values, we simulated the card choices of participants. This simulation generated similar fractions of cards from the decks as those found in the experiment. However, the simulation did not generate the same gaming strategies (e.g., length of series or frequency of changes) as the individual participants. This is attributed to a limitation of the simulated mechanism, which only uses one mode of processing, whereas participants possibly use intuitive, heuristic and rational processes (Bechara et al., 1997; Sloman, 1996).

The approach of sequential modelling and experimenting gives a first hint on how accumulating experience can be modelled in the prediction of the discovery of successful interaction strategies. If this understanding is implemented in the design and development of interactive systems, it might be possible to build applications that allow the users to learn to operate the application with less effort spent on the actual learning process. To fully understand this way of adopting new interaction, we recommend further research (see also the discussion of the experiment and the discussion of the computational simulation) in which the combination between cognitive science (for example, Newell, 1990) and contemporary insights from intuitive action control as suggested in neurological research (for example, Damasio, 1994) and psychology (for example, Oatley and Johnson-Laird, 1987; Sloman, 1996) are combined to determine a more specific description of this type of adaptations. Once this effort has been undertaken, applications designed according to these ideas might lead to more efficient and effective learning as well as higher user satisfaction.

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Appendix A: Music files

Three music files were compiled to induce different moods. The amplitudes of loudness of the different tracks were equalised so all tracks were of approximately equal loudness.

Music tracks that were used to manipulate participant mood

	Condition	Length	Tracks	Band	Year
1	Hardcore	12.42	Bombtrack	Rage against the Machine	1992
			The Future of War	Atari Teenage Riot	1997
			Killing in the Name	Rage against the Machine	1992
2	‘Summer’ pop	13.17	Surfin’ U.S.A.	Beach Boys	1963
			I shot the Sheriff	Bob Marley	1973
			Night Boat to Cairo	Madness	1982
			Brazilian Love Song	Steelbands of the Caribbean	1996
3	Melancholic	12.48	Fatal Wound	A Minor Forest	1999
			The Eternal	Joy Division	1980

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