# Can computers help overcome limitations in human decision making?

**A John Maule**
Leeds University Business School
University of Leeds
Leeds LS2 9JT
UK

**ABSTRACT**

**Motivation**: The article evaluates computer assisted decision support in the context of contemporary research on decisional thinking, outlines the potential that computers have for overcoming known limitations in this thinking and the problems that occur when some aspects of thinking are overlooked. **Research approach**: The article is derived from a selective review of the literature on thinking and decision making. **Findings/design**: The review identifies aspects of thinking that limit the effectiveness of computer-based decision support and considers ways of overcoming these limitations. **Research limitations/implications**: The review is selective and does not consider all thinking processes nor all possible implications for decision support. **Originality/value**: The work uses contemporary theory on system 1 and system 2 thinking to recommend ways of improving computer decision support. **Take away message**: The full potential of computer-based decision support can only be realised if developed and evaluated with a broad understanding of how decision makers think.

## INTRODUCTION

Decision Making is a vital activity; it determines the actions that people take and the appropriateness of these actions is important for both individuals and organisations. Despite its obvious importance it was not until the mid nineteen fifties that social scientists became interested in investigating how people actually make decisions. Ward Edwards is often credited with providing the foundations for much of the research that followed (e.g. Edwards 1954). He began by testing long held assumptions of philosophers and economists that people are rational decision makers. These assumptions were based on normative theories specifying that people should always choose the best option, having first evaluated all those on offer. At the time the best option had been shown to be the one that maximised utility in riskless situations and subjective expected utility in risky situations, at least for individuals who accepted the axioms of the theory (see French, Maule & Papamichail, 2009 Chapter3). These axioms were simple, plausible and generally accepted by people when they were presented to them (MacCrimmon, 1968).

Since the mid 1950s research has been dominated by studies showing that limited processing and memory capacity make it impossible for people to carry out the mental activities underpinning rational decision making. Instead they rely on short-cuts in thinking that make complicated problems tractable, but lead to error and bias. These short cuts, often described as System 1 thinking, may be contrasted with rational rule-based approaches which provide correct solutions and optimal behaviour, often described as System 2 thinking (Kahneman & Frederick 2002). Research on System 1 thinking has generated a large body of work explaining how people actually make decisions and why these are often subject to error and bias. Such findings have led to the development of prescriptive theories specifying structured procedures that help individuals and organisations make decision that are more akin to System 2 thinking, often founded on normative theories.

The period since the mid 1950s also saw the rise of computers with ever increasing computational power. Given that many of the problems in human decision making were attributed to limitations in storing and processing information it was inevitable that computers were recognised as having the potential to overcome these limitations. However, the primary argument in this article is that many of these systems have been developed without a full understanding of the broad range of System 1 thinking used by decision makers and because of this, have not addressed some aspects that limit decision effectiveness. Indeed, in some cases these applications have changed the decisions context in ways that may have unintentionally increased the usage of some forms of System 1 thinking and in doing so, decreased decision effectiveness. Thus the primary purpose of this article is to consider the extent to which computer aided decision support has addressed all aspects of System 1 thinking when designing procedures to overcome cognitive constraints on decision makers concerned with information processing capacity and memory.

## LIMITED CAPACITY PROCESSING

Miller (1956) showed that people were severely limited in terms of the amount of information they could process at any particular moment in time. Simon (1960) suggested that these processing limitations meant that people were unable to carry out the mental operations necessary to make decisions according to the rational model. He suggested that, instead, people adopt a simpler strategy, satisficing, which involves choosing the first alternative that is acceptable rather than the best. This strategy is sub-optimal in that it involves rejecting an alternative as soon as some negative aspect is revealed (even if all the other aspects are brilliant) and evaluation stops as soon as an acceptable alternative is found, even if there are still many other alternatives left unevaluated (including potentially better alternatives than the chosen one). However, the virtue of this strategy is that it makes the problem tractable and ensures that a chosen alternative is reasonably fit for purpose.

Since this pioneering work, many other simplifying strategies have been discovered, some of which are even easier to execute (e.g. disjunctive rule where people choose the first alternative that has just one reasonable aspect; recognition rule where people choose an option if they recognise it, but reject it if they don't). These simpler strategies allow complex problems to be resolved but often at the expense of making a sub-optimal choice.

Given that limited capacity processing is seen as a primary constraint some have argued that computers should be used to support decision making, since they can provide the extra computational power needed to retain all the information about every available alternative and to undertake the complex calculations that underpin the rational model. Over the last 30 years there has been a raft of computer decision support systems designed to help decision makers overcome these limitations (see French et al 2009). For those interested in computer decision support the issue often seems straight forward – to develop more effective ways of supporting the computations necessary to make decisions according to the rational model. However, there are some recent trends in decision research that challenge these assumptions.

## IS IT ALWAYS BETTER TO INDUCE MORE COMPLEX, 'RATIONAL' THOUGHT?

Until comparatively recently researchers and practitioners alike have assumed that known limitations in human decision making can be overcome by encouraging people to adopt more elaborate, System 2 forms of thinking. For example, pioneering work on framing (Kahneman & Tversky, 1984) showed that decision makers build mental models of decision problems that are partial and subject to cognitive distortions. In particular, people model potential outcomes as either gains or losses from a neutral reference point. This gives rise to the framing effect that leads people to be risk seeking when a decision problem is presented in ways that highlight outcomes as losses but risk averse when the same problem is presented in ways that highlight these same outcomes as gains (Maule & Villejoubert, 2007). This inconsistency in risk preferences across different versions of the same problem, called the framing bias, has been shown to occur in important strategic situations with experienced decision makers (see for example Hodgkinson et al 1999). Maule (1989) showed that the framing bias occurs when people adopt shallow frames (i.e. outcomes modelled either as gains or losses) but not when they adopt elaborated frames (i.e. outcomes modelled both as gains and losses). In the Maule study there was no attempt to encourage or support framing elaboration. However, Hodgkinson et al (1999) showed that when participants used cognitive mapping, a decision aid thought to elaborate decision makers' mental models of a problem, the framing bias disappeared and that this occurred in both novices and experienced professionals alike. This is one among a number of streams of work suggesting more elaborate, System 2 thinking leads to better decision making (Arkes, 1991) and suggest that computer-based systems should support this kind of thinking. However, there is some recent research on human decision making that challenges this view. Two examples of this work are reviewed next.

### Fast and Frugal Heuristics

Gigerenzer and his colleagues (see for example Gigerenzer, Todd and ABC Research Group, 1999) have challenged the idea that people perform better when using simple rather than complex decision rules. For example, Hertwig and Todd (2003) describe one example of simple thinking, the recognition heuristic, often used in situations where one choice alternative is recognised, the other is not. In this situation decision makers infer that the one that is recognised has a higher value so choose it. People tend to use this heuristic when they have limited knowledge of an area - if you recognise everything the rule is useless. Despite its simplicity it can lead to better performance than complex forms of thinking that take account of all the available information. For example, when US students were asked which one from a pair of German cities is larger, their performance was better than when they had to complete a similar task involving US cities. Lack of knowledge of German cities allowed them to use this simple recognition rule to good effect and perform better than they did in a comparable situation where they had and used more information. This is one of many studies emerging over the last few years that show simple rules, referred to as fast and frugal heuristics, outperform more complex System 2 forms of thinking that involve processing large quantities of information in a complex way (Gigerenzer and Goldstein, 1999; Schwartz, 2004). Taken at face value, this work not only challenges generally held beliefs that decision making is better if underpinned by elaborate rather than superficial thinking, but also calls into question traditional decision support procedures that use complex models to process relatively large quantities of decision-relevant information. However, before reaching this conclusion it is important to consider more recent evidence showing that the use of these heuristics is not quite as common as first thought (Broder and Schiffer, 2003). Also, much of the evidence comes from relatively simple decision tasks with known correct solutions that can be predicted to some extent from one or two simple aspects of the available information (e.g. bigger towns tend to be better known than smaller ones). These tasks are not representative of the more complex strategic decision problems that are usually the focus for decision support. Nevertheless, the findings challenge the assumption that complex decision rules are necessarily better and suggest those developing computer decision support should evaluate several rules differing in complexity and amount of information used, rather than simply assuming that greater complexity leads to better decision making. Also, these findings suggest that there are different types of decision and that each may need to be supported in different ways (see French et all 2009 Chapter 1); relatively simple decisions that can be executed by taking account of small amounts of information need to be supported in a different way from one-off strategic decisions that may profit from support that encourages more extensive and elaborate thinking.

**The deliberation without attention effect**

In a series of studies Dijksterhuis and his colleagues (see for example Dijksterhuis, Bos, Nordgren & van Baaren, 2006) present evidence to show that thorough conscious System 2 deliberation of the kind that underpins the rational model can lead to worse decision making than unconscious less deliberative System 1 thinking. For example, in one study participants read information about apartments and chose their favourite in one of three ways: immediately, after a period of conscious thought/evaluation, after an equivalent period during which time they completed another activity that prevented them from deliberating on the choice task. The latter group made better decisions than the other two (better determined from a normative perspective). In response to these and similar findings the authors developed Unconscious Thought Theory that suggests that conscious thought is rule based and subject to extreme capacity limitations, whereas unconscious thought is not constrained in this way. Because of this, conscious thought should be better than unconscious thought in simple situations (where there is enough capacity to engage conscious thought effectively) but become progressively worse as the complexity of the situation increases and it becomes increasingly difficult to process the information in a conscious rule based way. The theory is supported by findings from laboratory studies and field studies comparing the two forms of thinking when people buy simple and relatively complex goods in shops.

These findings have important implications for computer assisted decision support systems. In particular, they challenge the view that these systems should always seek to promote rational elaborative thinking. Perhaps an even more intriguing possibility is that, in complex situations, the outputs of particular activities underpinning decision support might be more accurate if undertaken using unconscious rather than conscious thought. However, the most important aspect of these findings is that they show that 'intuitive' System 1 thinking can lead to different and sometimes better outcomes than those that evolve from more complex forms of System 2 thinking. This suggests that decision makers should not simply accept the outputs and recommendations from computer modelling, but should review these in the light of their own intuitive preferences for different options. From this standpoint the modelling process should be seen as creative, dynamic and cyclical, with decision makers exploring the outputs of computer based solutions in the context of their own intuitions until such point that no new insights are found. This process, called 'requisite decision modelling' (Phillips, 1984), is critical if we are to gain the advantages and insights that accrue from both thinking systems.

**Preference Reversals and Constructive Preferences**

A primary assumption underpinning the rational model is that decision makers are perfectly informed, including knowledge about their own values and preferences. However, research shows that this is often not the case and this finding has far reaching implications for computer decision support. The early studies (e.g. Lichtenstein & Slovic, 1971) showed that when research participants were given gambles to *evaluate* one at a time (e.g. by indicating the maximum amount they were willing to pay to buy and play the gamble) they could readily give a higher value to one gamble rather than another; but later when these two gambles were paired together and participants asked to *choose* which they wanted to play, they often chose the one that they had previously given a lower value when evaluating them. This paradoxical finding, referred to as a preference reversal, has been explained in terms of the compatibility hypothesis (Slovic, Griffin and Tversky, 1990) - people focus on those aspects of the presented information that are compatible with the mode used to reveal their preference. Thus, people focus more on the value of the outcomes of gambles when setting a price (because valuation and price are 'compatible'), but focus more on probability of winning when making a choice, since this is more salient when choosing between uncertain alternatives (Wedell and Bockenholt, 1998). In discussing these and similar paradoxical findings Slovic (1995) argued that decision makers do not have a set of stable internalised values that they draw on when determining their preferences. Instead, they construct their values 'on the spot' and that the method used to elicit these (e.g. choice or evaluation) crucially affects how these preferences are expressed by temporarily raising the salience of some aspects of information over others. This raises important issues about how best to elicit decision makers' preferences in a consistent and accurate way.

In discussing these issues French et al (2009) suggest that decision makers construct their values and preferences as they deliberate during the decision process. Thus the method used to support deliberation influences the final outcomes of the process. No matter how intuitive or user friendly the interface between computer and decision maker, the method used will affect the values and preferences elicited and may lead to inconsistencies similar to those described above. This can lead to poor decision making if the values and preferences that are elicited at the point of choice are different from those in operation when outcomes are realised later when decision makers have to live with the consequences of their choices.

In discussing this issue, French et al (2009) argue that it is important that a decision support system provides a supportive framework that guides the evolution of decision makers' values and preferences towards consistency by considering different ways of capturing them. This involves asking decision makers to consider different resolutions and resolve inconsistencies such that the final values embody the rationality that they wish their judgements to embody. Typically this process is supported by an experienced decision analyst interacting with decision makers. Whether such an informed and dynamic procedure can be run by a computer system remains a moot point – if not, then this provides an important limitation for computer assisted decision making and suggests that the role of an experienced analysts may need to be an integral part of the support system. If so, then this suggests the need to develop a flexible and interactive interface between the decision maker and the computer.

## NATURALISTIC DECISION MAKING

The last few years has seen the emergence of a different approach to understanding human decision making that focuses on what expert decision makers actually do rather than experimental investigations of how and why less experienced decision makers depart from predictions made by the rational theory (Pliske & Klein, 2002). This approach, called Naturalistic Decision Making (NDM), provides a rather different account of how decision makers overcome limitations in processing capacity based on the suggestion that, through expertise and experience, they learn to recognise situations and implement actions that are known to be effective in those situations. If the current situation matches strongly with previous situation then the decision maker executes the usual action; if the match is not so strong they simulate how the usual action might play out in the new situation and make the necessary modifications. This way of making decisions is both computationally simpler and effective, and has the added advantage that decisions are taken quickly (vitally important for the kinds of emergency situations that have been the focus of attention for this approach), in ways that place less demand on limited capacity processing.

This approach raises important issues for computer decision support. First, RPD is underpinned by a different decision logic founded on assessing situations, matching them to those already experienced, knowing what actions to take in each situation and being able to simulate actions to deal with small differences between the current and previous situations. Thus, traditional support systems underpinned by the rational model are not appropriate and should be replaced by systems that support key RPD processes such as recognition and simulation. Second, those developing such systems face a difficult dilemma. While the RPD model captures what experts do, it does not specify how we can determine whether or not decision makers are expert. Some have argued that it takes 10,000 hour practice and that most of this needs to be narrowly focused on a specific and relatively well understood domain that has actions that are universally accepted as appropriate. These conditions may be in place for some groups such as doctors and fire-chiefs, but not for others such as managers who make a broader range of decisions across domains where there is no agreement about what the appropriate action should be. These latter groups may be using an RPD type process (e.g. do what I did last time if it worked) and may request this type of support even though the domain knowledge and the decision makers' own experience may be too limited. There is an urgent need for research clarifying when each of these different approaches to decision support should be used.

## LIMITATIONS IN HUMAN MEMORY

Limitations in memory are a second crucial aspect of human cognition that impinges on decision making (see Baddeley 2004 for a review of memory research). When discussing this topic, psychologists make a distinction between short-term or working memory and long term memory. Working memory holds the information that is the focus of our attention, sustains this information by rehearsal and is the workspace where ideas and concepts are registered, transformed and manipulated. The most important feature of this memory is that it has limited capacity for processing and storing information that leads to the issues and problems discussed in the previous section. In this section we focus on the second type of memory, long term memory (LTM) that retains large quantities of information over relatively long periods of time.

There are some key limitations in long term memory that are particularly critical for decision making. First, the amount of knowledge that can be acquired by any single individual is necessarily limited and so, for any particular decision domain, what can be retrieved from memory is very likely to be less than the total sum available. Second, even if domain relevant information is acquired, people forget, further reducing the amount of knowledge that a particular decision makers may have. Together these two limitations reduce the amount of relevant information used to inform a decision, thereby reducing its effectiveness. Third, and in many ways more important, there is strong evidence that human memory works by association and reconstruction rather than simple recall. Thus people remember associations between features of an event or fact and then, when they recall it, do so by reconstructing it from these associations. However, they may not use all the associations nor in the same order (Hogarth, 1980; Klein and Methlie, 1995) so their memories are often distorted. In addition, when they retrieve a memory, aspects of the current context is often incorporated into that memory thereby changing it further. People rarely appreciate these biases nor consider the implication they have for their decision making Fourth, human memory is subject to priming – when particular memories are accessed related memories become temporarily more accessible increasing the chances that they will also be recalled, so biasing the retrieval of decision relevant information. For example, when assessing whether we should embark on a new business venture we might begin by thinking about a past example that was successful. This will make all other successes temporarily more accessible and failures relatively less accessible thereby biasing our experienced-based judgements of the likelihood of success of the new venture. These four examples show how the information we draw on when making decisions may be distorted or even wrong.

In contrast to this, computers can acquire and hold more information about a particular decision domain than most experts. In addition, computers recall precisely what they store in terms of both the data themselves and their format so are not subject to the human memory biases outlined above. Thus, it is not surprising that computers have been used extensively to provide decision relevant information in the form of different types of information systems.

French et al (2009) discuss the use a variety of computer based techniques for delivering information to decision makers. They argue that that decision makers exist in the flow of time from past to present and present to future with the past setting the context for their current decisions; making decisions and solving problems in the present; and planning and developing strategies for what they think will happen in the future. They argue that these three functions correspond loosely to three different types of information system: Databases that hold historical data that can be queried and analysed in a variety of ways; Knowledge Management Systems (KMS) that deploy what has been learnt from the past to address the problems of the present; Decision Support Systems (DSS) that help DMs anticipate and shape the future. While these systems have considerable potential to help decision makers (see French et al 2009) there are other facets of human cognition that, if not recognised by developers and decision makers alike, may considerably reduce their effectiveness. Some examples of these factors are presented next, though it should be recognised that this is not a comprehensive list (see for example Bazerman & Moore 2009).

## CONFIRMATION THINKING

There is strong evidence to suggest that when people seek out decision relevant information they adopt a form of System 1 thinking, confirmation, that biases them to focus on those aspects that confirm their existing beliefs, often discounting or ignoring any that disconfirm these beliefs (Klayman & Ha, 1987). Given that people, including experts, are initially likely to be exposed to biased samples of information from the world (Dawes et al, 1989), there is a very strong danger that these biases become reinforced and exacerbated by confirmation thinking. For example, Koriat et al (1980) show that confirmation thinking leads people to become increasingly confident about their judgements even when these are wrong. They asked people to answer general knowledge questions and to express their degrees of confidence that their answers were correct. They showed that people are generally overconfident and only right about 85% of those occasions when they indicated they were 100% sure they were correct. Koriat et al showed that participants asked to list reasons why their chosen answer might be wrong, prior to giving their confidence estimates (i.e. anti-confirmation thinking), were better calibrated than control participants who, by default looked for confirming evidence for why they were right. Thus, confirmation thinking leads people to hold confident beliefs about the world that are often wrong and so leads them to take inappropriate actions.

These findings have important implications for computer based decision support systems, particularly Databases and KMS, since these provide more information than would normally be held by human memory so provide even more opportunities for confirmation thinking. As such they may actually lead to larger errors and biases. One way of addressing this problem is to encourage people routinely to ask themselves how they could disconfirm what they believe to be true – often referred to as 'consider the opposite thinking' (see for example Larrick, 2004; Mussweiler and Pfeiffer, 2000; Soll and Klayman 2004). Such thinking is usually developed through training, though a more innovative solution might be to design interfaces to computer systems that encourage this form of thinking. Other ways of addressing this problem are by: periodically including 'outsiders' in the process who often have different starting positions; routinely involving devil's advocates who challenge all assumptions; developing decision protocols that require people to record alternative interpretations of the problem. Again, these procedures might readily be incorporated in decision support interfaces.

## PLANNING FALLACY

Individuals and organisations are generally bad at predicting the timing and costs of planned projects. Buehler, Griffin and Ross (2002) argue that this is due to an over reliance on 'inside thinking' that focuses on the specific and unique qualities of the current project. This thinking involves sketching out a scenario that indicates how the project will reach a successful conclusion. In doing so, people overlook the large number of other possible scenarios that may involve less successful conclusions so tend to be overly optimistic. Indeed the act of scenario construction itself makes the optimistic outcomes seem even more likely (Koehler, 1991). Providing decision makers with databases and KMS may simply increase the potential for more elaborated inside thinking thereby exacerbating the planning fallacy. One way of reducing this bias is to encourage people to use 'outside thinking' that focuses on the outcomes of similar problems that have been completed in the past, considering where the current problem sits in terms of the distribution of these previous cases and derives predictions from what might be expected given its position in this distribution (Lovallo & Kahneman, 2003). Lovallo & Kahneman outline a five step procedure for facilitating outside thinking which can be taught as a blue-print to follow when making planning decisions. However, it is again interesting to speculate whether computer interfaces may be designed that facilitate this form of thinking.

## GENERAL DISCUSSION

The major conclusion to be drawn from this brief review is that the full potential of computer-based decision support can only be realised if it is developed and evaluated in the context of a broad understanding of how decision makers think. While limits in information processing can be overcome by drawing on the computational power of computers, there is also a need to recognise that: there are occasions when simple rather than complex rules are appropriate; beliefs and values are constructed during the process of deliberation making them highly sensitive to the interfaces supporting this process; intuitive thinking provides important insights and should be used alongside the outputs of formal computer modelling to evolve a requisite decision model; the support mechanism should complement existing forms of decisional thinking, particularly if these are known to be functional. Similarly limitations in memory can be very usefully overcome by computer support, but these must be developed to ensure that they do not exacerbate other thinking biases such as confirmation and inside thinking. This may be achieved through training decision makers to think smarter, the use of decision analysts or through the development of appropriate interfaces between computer and decision maker.

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