

# Debiasing Decision Makers Through Knowledge Management

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## INTRODUCTION

The need to improve decision making is a longstanding concern in decision support research. As the accelerated technological development and fierce competition coming from global sources are becoming more apparent in the new 21st century, enhanced decision-making capabilities are required more than ever before to enable organisations to meet the new challenges.

Decision making can be viewed as a dynamic and iterative process comprising: (1) identification phase, which involves decision problem recognition and diagnosis activities; (2) development phase, which concerns search and design activities; and (3) selection phase, which comprises screening, evaluation, and authorisation activities (Mintzberg et al., 1976). The quality of the subsequent decisions will depend on the nature of the preceding diagnostic, design, and selection activities.

There is a considerable body of evidence indicating that people systematically deviate from the prescribed decision-making norms. Such deviations are termed *decision biases* and are described as cognitions or mental behaviours that prejudice decision quality (Arnott, 2002). The variety of biases documented in behavioural decision literature include: memory, statistical, confidence, adjustment, presentation, and situation-related biases. Most decision biases tend to cause poor decision outcomes. Therefore they are of concern to designers of decision support systems that aim to facilitate and improve decision makers' task performance.

Of particular interest to this study is to address biases that people experience in combining multiple cues into single judgmental responses. The problem of combination could be due to misperception and/or misaggregation (Lim & O'Connor, 1996). With respect to misperception, the literature shows that people are lacking the ability of correctly assigning the weights to the cues. Both tendencies to overestimate unimportant and underestimate important cues have been identified.

With respect to misaggregation, the literature indicates that people have difficulties in performing mental calculations when combining multiple cues due to cognitive overload.

Knowledge management (KM) offers a promising new approach to reducing or eliminating biases from the cognitive strategies of a decision maker. Assuming that the decision maker is the primary source of the biased judgement (Fischhoff, 1982), our attention is focused on how to better manage the decision maker's knowledge. Two main trends are distinguishable in terms of this support. One is to focus on the use of information and communication technology (ICT) as tools to facilitate management of knowledge processes (e.g., Handzic, 2004). The other trend is the proposition of a set of prescribed social and structural mechanisms to create an enabling environment for knowledge development, transfer, and application (e.g., Holsapple, 2003).

While there is considerable theoretical support for suggesting efficiency and effectiveness benefits of different socio-technical KM initiatives for decision making, there is little empirical evidence regarding the actual impact of these initiatives on decision makers' working knowledge and performance (Alavi & Leidner, 2001). The main objective of this chapter is to fill the existing gap between theory and practice by providing some empirical evidence regarding the potential and limitations of specific technology-based KM initiatives for supporting individual decision makers in the context of judgemental time series forecasting.

Two knowledge management system (KMS) designs are considered that differ in how they attempt to "debias" decision makers' judgment strategies. One system focuses on automating knowledge integration in the attempt to reduce decision makers' cognitive overload and thus eliminate misaggregation bias. The other system focuses on organising and representing knowledge for human consumption in a way that would reduce misperception. It is implicitly assumed that the availability of such systems should lead to better deci-

sion performance. The study based on Handzic (2007) empirically tests this assumption.

## **BACKGROUND ON KNOWLEDGE MANAGEMENT AND DECISION SUPPORT**

Various KMS implementations provide differing levels of support in locating, extracting, and utilising knowledge and impose differing burdens to their users. In this section, we discuss two approaches to KMS development (*automating* versus *informating*) that may help to overcome some of the negative influence of decision biases.

### **Automating**

The artificial intelligence (AI) approach to KMSs focuses on “automating” knowledge processes. It involves the use of “smart” systems that apply knowledge to solve problems for and instead of humans. Typically, such systems can reason in a narrow domain and in relatively mechanistic way (Becerra-Fernandez, Gonzales, & Sabherwal, 2004). Examples of popular systems in this category include those that can facilitate activities of direction and routines. Other well known examples are knowledge-based systems (KBS) in the form of intelligent decision support and expert systems. These were devised as problem solving systems long before the term KM became popular (Hasan, 2003). Neural networks are another significant development by AI researchers. The most important feature of neural networks is their ability to learn from noisy, distorted, or incomplete data (Glorfeld & Hardgrave, 1996).

Of special interest to this study is an automated knowledge aggregation tool that mechanically combines multiple cues into a single judgemental response. It is argued that the provision of such a tool may help alleviate or even completely eliminate negative effects of misaggregation bias. In general, computers are considered to be better than people in making complex calculations and in making calculations rapidly and accurately (Stair & Reynolds, 2003). However, despite benefits offered by these systems they are not free from criticism. Some scholars warn that replacing people with machines may have important ethical implications. Most AI systems are of the “black-box” kind. This means that the tool produces conclusions without any

explanation and justification of the reasons behind such conclusions. Consequently, it may have a detrimental effect on decision makers’ working knowledge. Past empirical studies report general preference for heads over models in judgment (Dalrymple, 1987).

### **Informating**

The previous discussion suggests that an alternative approach to KMS focusing on “informating” and guiding rather than “automating” knowledge work may be more useful to decision makers. Essentially, this approach involves organising and presenting knowledge to users in ways that would enhance their interpretation of the available knowledge and thus enable them to apply it more effectively in solving problems (O’Leary, 2003). Such approach can be considered as a “white box” kind of approach to managing knowledge. Recent empirical studies reported its beneficial effects in initiatives such as competency and procedural knowledge maps (Handzic, 2004).

## **EMPIRICAL STUDY**

The focus of this study is on another white-box type of KMS, a knowledge weighting tool that provides users with a graphical image of task-relevant cues and their relative importance weights. It is argued that the provision of such a tool may help alleviate/eliminate negative effects of misperception bias. In addition, the white-box approach to KMS may help increase people’s “trust” and reliance on helpful decision aids. Empirical evidence from recent knowledge tagging and content rating studies (Poston & Speirer, 2005; Shanks, 2001) also hint that such a tool may enhance users’ working knowledge and performance.

### **Study Objectives**

In view of the prior findings and concerns expressed, the main objective of the current study is to determine the nature of assistance, the extent of assistance, and the limitations of the aforementioned two approaches to KMS in supporting managerial decision making. In particular, the study examines whether and how KMSs of varying knowledge weighting and knowledge aggregation support may assist individual decision makers in enhancing their working knowledge and improving

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