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A COGNITIVE DSS FOR INVESTMENT DECISION MAKING: CHALLENGES & OPPORTUNITIES

By

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ABSTRACT

Recent findings from behavioral finance indicate that cognitive support is critical to investors as their psychological biases strongly influence their investment decisions. This paper proposes a conceptual model of investor misjudgment based on the three-stage human information-processing model. The importance of such a model is that it classifies investment-related biases as being long-term or short-tem and consequently, provides a way to implement debiasing mechanisms in DSS. The paper then suggests an architecture for building such a cognitive investment DSS using recent computational technologies for human attitudes modeling. This research work fills a gap in the current IS literature related to behavioral finance and offers a novel approach for integrating findings from that domain into a cognitive investment DSS.

KEYWORDS

Investment Decision Making, Cognitive DSS, Psychological Biases, Behavioral Finance

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1. INTRODUCTION

Due to recent innovations in the financial industry, the advent of the Web and the proliferation of inexpensive personal computers, individuals are getting unparalleled opportunities for investment. However, they face two critical problems: (i) a difficulty in finding the right investment instruments due to the enormous complexity of financial markets; and (ii) an increasing vulnerability to a vast amount of potentially biased and unsubstantiated information from the web. Individuals often make wrong investment decisions due to these problems (Barber and Odean 2001, 2002; Rashes 2001).

Besides short-term investors, retirement plan participants are also facing difficulty in making right investment decisions. As the world is moving from the defined benefit (DB) pension plans to defined contribution (DC) pension plans, the burden of making right investment decisions has now shifted to employees (Mitchell and Utkus 2003). In DB plans, employers pay fixed benefit amounts to their employees by taking the investment risk themselves whereas in DC plans, employees decide where and how much to invest. Research in retirement investment has found that plan participants jeopardize their investments as they are subject to several behavioral and psychological biases (Bailey et al. 2003; Bernatzi 2001; Bernatzi and Thaler 2001).

From their early days, decision support systems (DSS), "which are computerized aids designed to enhance the outcomes of an individual's decision-making activities" (Singh 1998) were used in several financial sectors such as banking, financial analysis and investment (e.g. Bouwman 1983; Sprague and Watson 1976). The focus of these DSS was primarily on providing quantitative support such as computation of fundamentals, risks, and economic trends. More recently, in investment decision making researchers have proposed and developed many DSS tools by making innovative use of such technologies as neural network (e.g. Trippi and Turban 1993), genetic algorithms (e.g. Goldberg 1994) and their combinations (e.g. Leigh et al. 2002). However, none of them assists investors in overcoming the influence of their psychological biases. Although technical analysis-based DSS use some indicators of market psychology such as *relative strength index, oscillators, candlestick patterns* to predict stock price movements (Williams 1988), they do not help individuals in overcoming the influence of their psychological biases.

The remainder of this paper is organized as follows. We first provide an overview of the role of psychology in investment decision making and previous research efforts in cognitive DSS. A conceptual model that explains investors' biases from a human information processing perspective is then proposed. We then propose an architecture for developing a cognitive investment DSS. The paper concludes with a discussion of the proposed architecture and implications for future research.

2. PSYCHOLOGY OF INVESTMENT DECISION MAKING

The finding that financial markets are influenced by human psychology is not new. The *Tulipmani*a, which started with the speculative trading of tulip bulbs and ended with the spectacular market crash in Holland and England, occurred in the late 1630s. MacKay (1980) presented a timeline of several panics and crashes in his book *Extraordinary Popular Delusions and the Madness of Crowds* first published in 1841. Seldon (1996) discussed the role of psychology in stock markets in his book *Psychology of the Stock Market* first published in 1912. Slovic (1972) outlined several implications of human psychology for investment decision making. However, his study with a few exceptions was done in non-financial settings.

More recently, the interest in psychology as a tool for understanding financial market behavior has resurfaced with the emergence of a new field called *behavioral finance.* Using findings from cognitive psychology, behavioral finance has been able to explain many anomalous phenomena in capital markets such as high volatility of stock prices (Shiller 1993) and excessive trading of stocks (Barber and Odean 2000). Behavioral finance through empirical studies demonstrates that individuals do not necessarily make rational choices and that these choices can have significant and persistent impact on financial markets (Barberis and Thaler 2002).

3. COGNITIVE SUPPORT IN DSS

Researchers have been interested in finding ways to eliminate the influence of biases in decision making as soon as they were identified (Fischhoff 1982; Sharp et al. 1988). They found that several features of information systems tools such as graphs, probability maps, and feedback can serve as cognitive support and assist in decision-making process. For example, graphical

presentation has been found more effective than tables in several decision tasks such as forecasting earnings and sales (DeSanctis and Jarvenpaa 1989; Anderson and Reckers 1992) and reducing information overload (Diamond and Lerch 1992; Umanath and Vessey 1994). A problem representation tool called *probability map* has been used as a cognitive aid in solving Bayesian problems (e.g., Cole 1988; Roy and Lerch 1996, Lim and Benbasat 1997). A probability map is a grid of cells (generally 10X10) with some cells shaded or differentiated to represent different characteristics (e.g., prior probability) within the population. Researchers have also observed that feedback often improves the performance of subjects who are making decisions under uncertainty (Alpert and Raiffa 1982; Sharp et al. 1988) and benefits of feedback increase as the decision-making environment becomes more complex (Montazemi et al. 1996). Silver (1991) provides a framework for developing decisional guidance in decision support systems and identifies two broad categories: suggestive guidance, and informative guidance. Suggestive guidance recommends how decision makers can respond to the current decision problem whereas informative guidance enlightens their judgment by furnishing relevant information.

DSS researchers have long identified cognitive support to decision makers as being a requirement of DSS. As early as the 1980s, Sprague (1980) stated, "A very important characteristic of a DSS is that it provide the decision maker with a set of capabilities to apply in a sequence and form that fits each cognitive style". However, Huber (1983) was skeptical about the usefulness of cognitive style as a basis for designing DSS. Robey and Taggart (1982) recommended that DSS should support intuitive processes in the same way as the right hemisphere of the human brain supports them. More recently, Hoch and Schkade (1996) suggested that DSS should capitalize on decision makers' strengths and compensate for their weaknesses including cognitive shortcomings. Todd and Benbasat (1991) designed a DSS for apartment selection by implementing an elimination-by-aspects strategy that reduced the cognitive effort of decision makers. The DSS designed by Roy and Lerch (1996) assisted decision makers in overcoming a bias involving base-rate neglect. George et al. (2000) designed a real-estate DSS to lessen the effects of the anchoring and adjustment bias even though the effects remained persistent. Singh (1998) showed that computerized cognitive aids can be successfully incorporated into DSS and that they can have a positive impact on both decision-

making efficiency and effectiveness. More recently, Chen and Lee (2003) developed a prototype cognitive DSS for strategic decision making which showed some evidence for the usefulness of the cognitive approach.

4. A CONCEPTUAL MODEL OF INVESTOR MISJUDGMENT

The field of behavioral finance emerged to explain investors' misjudgment attributed to their psychological biases. However, it still lacks a theoretical framework to integrate these biases. For example, Shefrin and Statman (1984) propose an investor's model with four elements: prospect theory, mental accounting, regret aversion, and self-control. De Bondt (1998) divides investment anomalies into four categories: perception of price movements, perception of value, management of risk and return, and trading practices. Barberis et al. (1998) explain investor sentiment in terms of underreaction and overreaction to different types of news. In this paper, we propose a conceptual model of investor misjudgment following the human information processing (IP) approach.

While human information processing (IP) is essentially a complex process (Simon 1979), its architecture, however, can be depicted as a linear flow diagram since "The basic notion of IP is that one must trace the progression of information through the system from stimuli to responses" (Massaro and Cowan 1993). According to Simon (1979), human cognitive processes can be understood at three levels: neural level, elementary level, and higher mental level. Neural level processes may not be appropriate to study investment decision making although recent advances in neuroscience have opened this possibility as well (Adler 2004). Higher mental processes such as problem solving and conceptualization may explain some complex aspects of investment decision making. Elementary level processes are perhaps the most appropriate of all since elementary cognitive processes such as memory retrieval and pattern recognition are often involved in investment decision making.

A general architecture of the human information-processing system in the elementary level uses the three-stage information processing model (Atkinson and Shiffrin 1968). Atkinson and Shiffrin (1968) proposed that humans have three kinds of memory stores: sensory registers, short-term store, and long-term store. While the three-stage information processing model is still

used due to its simplicity, researchers (e.g. Hitch and Baddely 1976) realized that the model has limited usefulness and suggested that the concept of short-term memory should be replaced with working memory. The working memory is like an attentional system through which an individual engages in cognitively demanding tasks (Baddeley 1981). In order to understand the nature and structure of knowledge stored in human memory, Tulving (1972) proposed two types of memory systems: episodic memory, and semantic memory. Episodic memory refers to the storage of specific personal events or episodes and thus has an autobiographical flavour to it. On the other hand, semantic memory stores the knowledge derived from specific events or episodes. Information that is part of an episodic memory gets into semantic memory due to reinforcement of such information. Eysenck (1984) illustrates this with an example," I know that two inverted V's on the front of a car indicate that the car is a Citroen, and this information forms part of my semantic memory. However, my daughter Fleur only discovered this fascinating and useful piece of information when I told her about it very recently, and it is presumably stored in her episodic memory." Using the concept of episodic memory and semantic memory, we now propose a model of investor misjudgment adapted from the human information processing architecture proposed by Reed (1992).

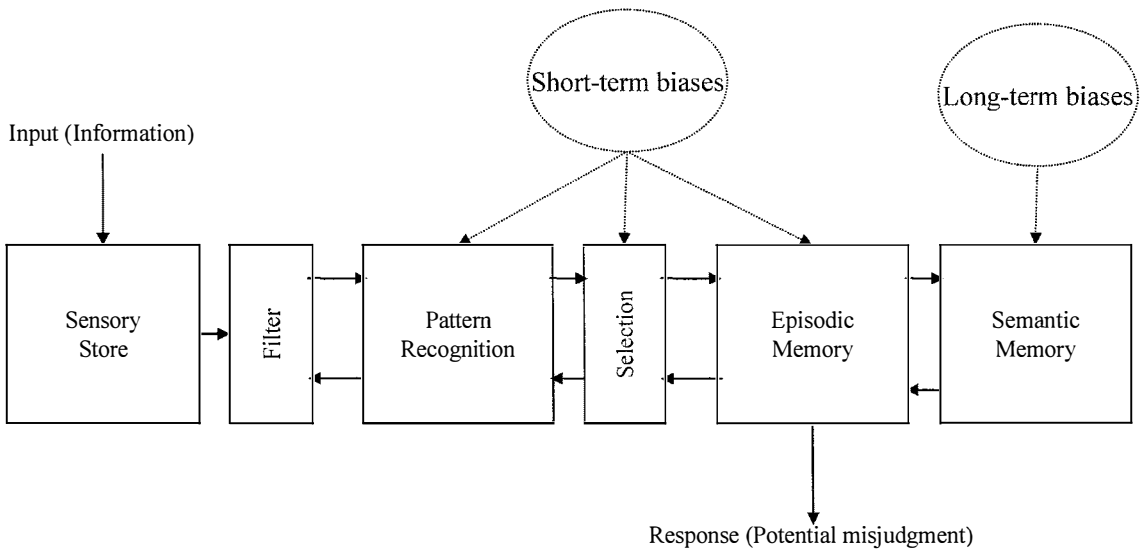

Figure 1. Conceptual Model of Investor Misjudgment

According to the model in Figure 1, the arrival of an incoming stimulus (e.g. information) leaves a transient perception in the sensory registers. The *filter* determines the amount of information that can be recognized in one time. In the *pattern recognition* stage, the brain

identifies the pattern (if any) of the incoming information. In the *selection stage*, some information is selected for storage and processing in the *episodic memory,* which interacts with the *semantic memory* and gives a response. While processing the incoming information, stages such as pattern recognition, selection, and episodic memory are influenced by short-term biases whereas the processes in semantic memory are influenced by long-term biases.

In Figure 1, the formation of a pattern is attributed to the salience of incoming information. Salience is a quality inherent in stimulus displays (Higgins 1996), which can be used to draw an individual's attention and influence his/her decisions (Valkenburg et al. 1999). Salience can be visual or experiential. Visual salience refers to the idea that certain types of images are captivating, which can create "some form of immediate significant visual arousal within the early stages of the human visual system" (Kadir and Brady 2001). An example of visual salience is a graphical presentation of stock prices showing a distinct trend (sharply rising or falling). Experiential salience is subjective and experience-based and emphasizes idiosyncratic importance of a domain of information (Knobloch et al. 2002). News announcing significant dividend payments is an example of experiential salience because such news has the potential to revive pleasant experiences associated with past dividends. While salience may be useful and necessary to overcome the problem of information overload, sometimes it may exert undesirable influence on the recipients of such information (Frey and Eagly 1993).

Once the incoming information makes an impression due to its salience and is transferred to the episodic memory, several short-term biases exert their influences. Under such conditions, people rely on the strength of information rather than its weight (i.e. financial significance) to assess the value of the information received (Hirshleifer 2001). Then, long-term biases (e.g. hindsight bias, self-attribution bias) may further amplify the initial influence of short-term biases. At the end, the individual is likely to misinterpret the true significance of the information, which have been referred to as *potential* in Figure 1. In our model, the major difference between short-term and long-term biases lies in the nature of their origin and temporal duration. Kahneman (2002) makes a similar distinction while describing perceptual, intuitive and reasoning systems – though not necessarily in the context of bias origination. In the following sections, we outline some major investment-related short-term and long-term biases.

5. SHORT-TERM BIASES INFLUENCING INVESTMENT DECISION MAKING

Short-term biases originate with the arrival of new information and the level of their influence depends on the current state of an investor's portfolio. Some biases occur when the price of stocks is rising and others occur when the price is falling.

A r*epresentativeness bias* refers to an individuals' tendency to classify objects into different categories by observing only their representative or salient characteristics. The bias occurs because people judge probability in such cases "by the degree to which A is representative of B, that is, by the degree to which A resembles B" (Tversky and Kahneman 1974). The representativeness bias motivates people to ignore sample size, base-rates, and mean reversion and become overconfident about the significance of the information received (Gowda 1999). For example, if a stock in the software industry is doing well, people may erroneously believe that all stocks in that industry are also doing well (sample size neglect) and if the price of a stock has been rising for sometime, people believe it has entered an "increasing trend" (neglect of mean reversion). As an example of base-rate neglect, consider the following example similar to the cab problem (Tversky and Kahneman 1982).

Suppose an investor is a member of a website that advises its subscribers which stocks are good for investment. The website claims that it had been successful 80% of the time in classifying whether a particular stock was a good or a bad investment when the economy was predominantly strong in the past. It further emphasizes that the usefulness of its service has increased even more since investors have to be very cautious in selecting stocks now as 90% of the companies are operating under loss and only 10% are making profit in the current economy. Given such information, should an investor heed to the advice of this website and purchase the stocks recommended by it? At a first glance, it would seem that the probability of a company recommended by this website being good is 80% since this is how often the website made correct predictions in the past. When individuals reason in this way, they are neglecting base-rate as they are considering only the diagnostic information (the website's success rate) and not the prior probability of the company being good (base-rate). In this example, the probability of the recommended company being actually good is only 31%.

A *framing bias* is said to occur when the manipulation of a decision frame changes the decision maker's perspective about the problem. According to Tversky and Kahneman (1981), a decision frame refers to "the decision-maker's conception of the acts, outcomes, and contingencies associated with a particular choice." In investment decision making, researchers found that asset allocation decisions of retirement plan participants changed significantly depending on the period of return profiles (a one-year return profile or a 30-year return profile) made available to them. In the case of the one-year return profile, participants allocated 63% of their fund to equities. However, when they were given the thirty-year return profile, they allocated 85% of their fund to equities (Thaler and Bernatzi 1999). Framing biases like this often manipulate investors' risk perception.

The *house money effect* refers to an individual's tendency to take high risk under the influence of recent gains (Thaler and Johnson 1990). Although people are risk averse in gains and risk seeking in losses in one-stage gambles (Kahneman and Tversky 1979), they may take high risk in multi-stage gambles such as investing if they have recently made some profits (Thaler and Johnson 1990).

A d*isposition effect* refers to an individual's tendency to seek pleasure by realizing gains and avoid the pain of regret by avoiding the realization of losses (Shefrin and Statman 1985). Investors sell their rising stocks too early and hold their falling stocks for too long due to the disposition effect (Odean 1998).

Ambiguity, although not a bias per se, can influence judgment and decision making like other biases. When individuals receive conflicting, incomplete, uncertain or excessive information, they experience ambiguity and make contradictory decisions as demonstrated by Ellsberg (1961). When investors experience ambiguity, they either follow simple rules or do not make any decisions at all. For example, investors continue holding their stocks when they do not know how risky they are. While creating a portfolio, they often follow a simple heuristic such as 1/n allocation (allocating 1/n of investment amount to each of n investment options). Such naïve approaches to decision-making lead to insufficiently diversified portfolios (Bernatzi and Thaler 2001).

6. LONG-TERM BIASES INFLUENCING INVESTMENT DECISION MAKING

Long-term biases constitute general human nature in the sense that they can be observed in all types of judgment and decision making processes. With the exception of the status quo bias, these biases tend to make investors excessively confident in their judgment ability.

Overconfidence refers to the systematic overestimation of the accuracy and precision of one's knowledge. Researchers have found that people generally overrate their qualifications and judgment capacity (Lichtenstein et al. 1982). Investors exhibit overconfidence even in such difficult tasks as stock selection (Barber and Odean 2002) and engage in excessive trading (Gervais and Odean 2001) incurring potential losses (Barber and Odean 2000). The problem of overconfidence has become acute with the advent of the Internet as a major information source, which is likely to fuel the confidence of individual investors by giving them the illusion of knowledge (Barber and Odean 2001).

The *hindsight bias* is the tendency to change the estimates of the likelihood of events and outcomes after they are known (Fischhoff 1977). The hindsight bias occurs because people cannot distinguish what they presently know from what they previously knew (Gowda 1999). With hindsight bias, people overestimate their predictive power (Fischhoff 1977). Not only ordinary investors, but also experts are susceptible to the hindsight bias. The Wall Street Journal reported an interesting story about how the overconfidence and the hindsight bias of Robert Citron, the treasurer of the Orange County Investment Pool, California, led to the largest municipal bankruptcy in U.S. history (Lubman and Emshwiller 1995).

The *self-attribution* bias is the tendency to believe that the reason for one's successes is his/her own talent and hard work, while that for failures is others' ineptitude and bad luck (Langer and Roth 1975). Investors may become overconfident after several quarters of their investing success due to the self-attribution bias (Gervais and Odean 2001).

The *familiarity* bias is an individual's tendency to prefer familiar objects or situations. Investors often invest major portions of their portfolio in companies that they are most familiar

with. People may achieve familiarity due to geographical proximity or their industry knowledge and affiliation. Familiarity bias is a major cause of insufficiently diversified portfolios (Huberman 2001).

The status quo bias is an individual's tendency to do nothing or maintain one's current or previous decision (Samuelson and Zeckhauser 1988). Madrian and Shea (2000) find that retirement plan participants do not change their portfolios and contribution rates for a long time due to status quo bias thereby forfeiting their potential gains. They also observe that investors' bias toward status quo increases as the number of investment option increases.

7. ARCHITECTURE OF A COGNITIVE INVESTMENT DSS

As shown in Figure 1, our conceptual model is based on the premise that long-term biases (e.g. overconfidence, self-attribution) develop with time and become a part of an investor's nature. On the other hand, the influence of short-term biases (e.g. framing, representativeness) is effected by new information and is short-lived. We now propose an architecture that uses this distinction as a framework for the development of an investment DSS. We underscore the fact that the proposed architecture considers only the web as a source of investment information and does not take into account the influence of other sources such as television, newspapers, investment clubs and personal acquaintances. The complexity involved in identifying and analyzing biases generated by information received from such non-digital sources makes it virtually impossible to implement in a working DSS. This approach is also justified given that the Web has become a major source for investment-related information.

The DSS architecture (Figure 2) consists of two primary modules: a domain knowledge management system (DKMS), and a personal experience management system (PEMS). When the investor desires to make a trading decision, he/she needs to provide several pieces of information such as trading decision (*buy/sell/hold*), reasons for making such a decision (e.g., *feeling that the price will soon be going down*) and confidence in each reason (e.g., *not very sure, very confident* etc.). The investor also provides URLs of the websites he/she has visited to get information for making the trading decision. Figure 3 shows a prototype of a trading user interface.

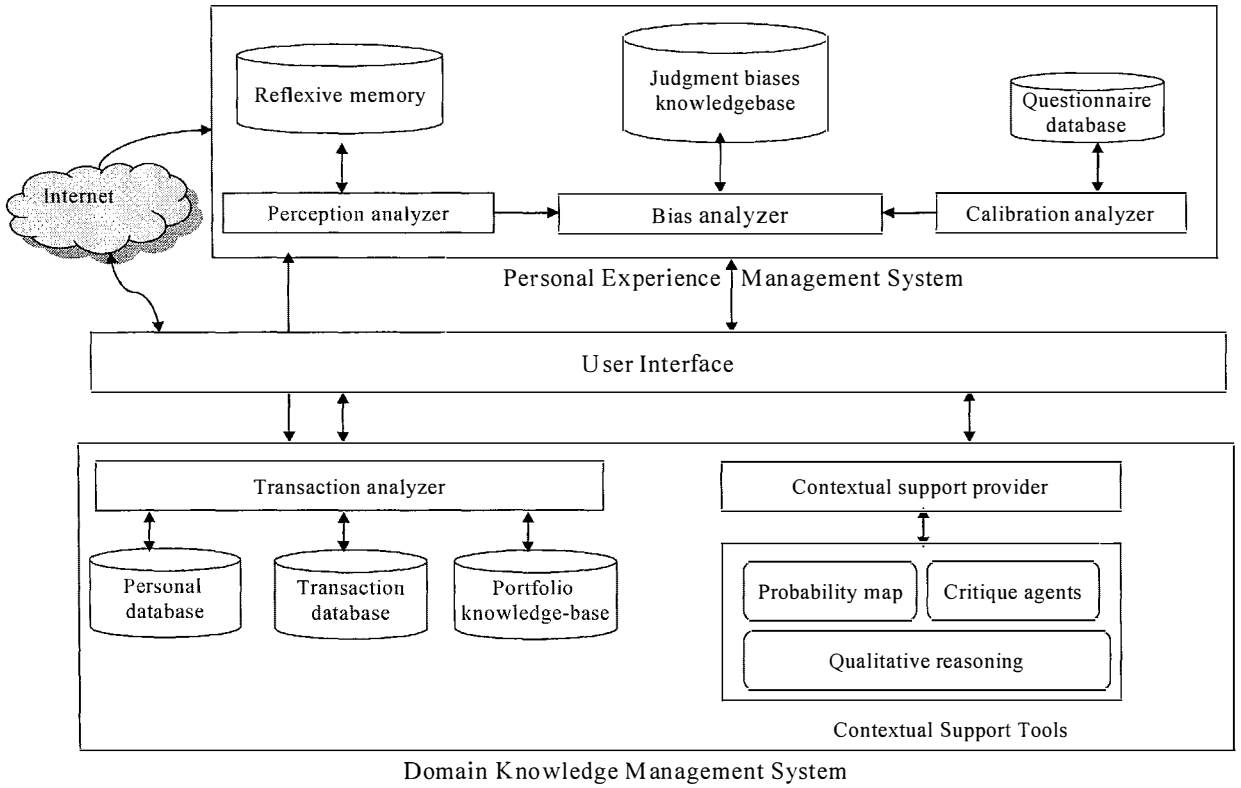

Figure 2. Proposed DSS Architecture

The information regarding the initial trading decision, reasons and confidence is examined by the Transaction Analyzer (a component of the DKMS) to identify any potential biases related to the current trading decision. The Transaction Analyzer communicates its findings to the Bias Analyzer (a component of the PEMS). The URLs of the consulted websites are received by the Perception Analyzer (a component of the PEMS). After examining these websites, the Perception Analyzer determines their potential influence on the investor's initial trading decision and sends the result to the Bias Analyzer. The Bias Analyzer also receives information about the potential overconfidence of the investor as assessed by the Calibration Analyzer on a regular basis (e.g., monthly). The Bias Analyzer combines the information received from the Transaction Analyzer, the Perception Analyzer and the Calibration Analyzer and enables the PEMS to issue appropriate feedback to the investor through the user interface (the popup *Bias Analysis* window in Figure 3) if it finds evidence for potential bias. The investor will then have the option of incorporating this feedback in making her/his final trading decision.

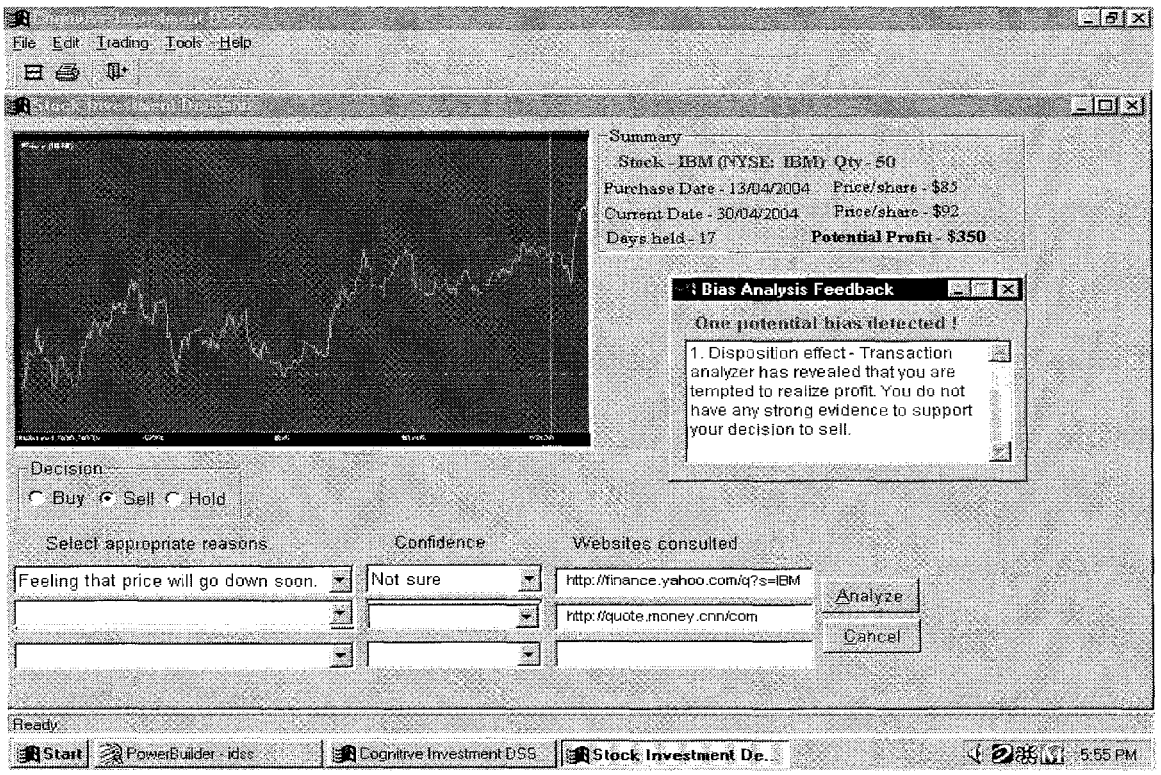

Figure 3. Prototype of a Trading User Interface

8. DOMAIN KNOWLEDGE MANAGEMENT SYSTEM (DKMS)

The DKMS consists of personal database, transaction database, portfolio knowledge base, transaction analyzer, contextual support provider, and contextual support tools. The personal database stores the investor's personal information such as family size and income, investment goals, education field and level, industry knowledge and affiliation. The transaction database stores all relevant information involving past transactions such as lists of consulted websites, main reasons for making a trading decision, the level of confidence shown in each reason etc. The portfolio knowledge base is a repository of information about stocks (currently held or of potential interest) such as fundamentals, historical data, economic and industry data etc.

TRANSACTION ANALYZER (TA)

The TA's function is to identify any potential biases related to the current trading decision based on the information supplied by the user. It communicates its findings to the Bias Analyzer for further processing within the PEMS. When the investor decides to make a trade, he/she has to provide all relevant information involving the decision as shown in the Figure 3. The TA

examines these current inputs from the investor: trading decision (e.g., *sell*), reasons for making such a decision (e.g., *feeling that price will go down soon)*, and confidence in the reason (e.g., *not sure*). The TA then examines the price trend of the stock under consideration, i.e. whether the stock's price has risen or fallen since the investor purchased it. It also examines how the stock's price has reached the current level. For example, is the price continuously rising? Is it starting to drop after reaching a high? Using the stock's price trends and current inputs from the investor, the TA looks for the evidence of potential biases. For example, the TA may detect the disposition effect (see Figure 3) if the investor is trying to sell his/her rising stocks giving weak reasons (e.g., *feeling that the price will soon drop*) for doing so. In a similar way, the TA can identify the house money effect. By examining the overall portfolio, the TA detects the familiarity and status quo biases. For example, a high correlation between the investor's background (e.g., industry experience and affiliation) and assets in her/his portfolio would indicate the likelihood of a familiarity bias. If the investor has not made any transactions for a long time, that may indicate the influence of status quo bias.

The TA also assists in examining the self-attribution bias and hindsight bias of the investor. In order to assess the self-attribution bias, the TA retrieves past transactions (e.g., three-month old) and asks the investor to state reasons for their successes or failures. By comparing the currently provided responses with the stored ones, it is possible to find out whether the investor is exhibiting the self-attribution bias or not. The hindsight bias could be assessed similarly.

CONTEXTUAL SUPPORT PROVIDER (CSP)

The objective of the CSP is to lower the influence of biases originating in specific contexts such as base-rate neglect and information overload. The Perception Analyzer and the Transaction Analyzer invoke the CSP when they become aware of such contexts. Depending on the type of potential biases, the CSP activates one of its tools: probability map, critique agents, and qualitative reasoning.

Probability Map - A probability map is a useful problem representation tool that can help individuals in overcoming the representativeness bias caused by the base-rate neglect (e.g., Lim and Benbasat 1997; Roy and Lerch 1996). While analyzing the websites consulted by the

investor, the Perception Analyzer (discussed later) may detect information that will cause the base-rate neglect problem. The Perception Analyzer then informs the CSP (through the Bias Analyzer) of its findings. In the previous section, we gave an example of the base-rate neglect occurring due to the information published in a website. We now revisit the same example and show how this problem can be overcome with a probability map.

The probability map is a 10x10 grid consisting of 100 cells, which are divided into two groups: 90 grey cells representing the percentage of companies that would be considered bad investments and 10 white cells representing the percentage of companies that would represent good investments, given current economic conditions. This representation captures the base-rate information given in this example. Since the website's success rate is 80%, it will recommend 8 good companies (80% of 10) and 18 bad companies (20% of 90) as good investments. So, the probability that a company is in fact a good investment when the website recommends it as such is 8/(8+18), which is only 31%! As this example shows when the economy is in a downturn and investment advisors exaggerate their success rates, the impact of representativeness bias could be serious.

Critique Agents- Researchers have long identified that DSS need to offer several forms of support to decision makers. Criticizing decisions, monitoring decision makers' actions and providing appropriate warnings are some of them (Fazlollahi et al. 1997). In this context, Vahidov and Elrod (1999) propose a framework for developing positive and negative critique agents. The positive critique agent called *angel* analyzes the advantages of the proposed solution considering the user's profile whereas the negative critique agent called *devil* tries to come up with counter-arguments. Since framing bias occurs due to change in decision makers' perspectives, critique agents could help them overcome this bias by providing both aspects of a decision problem (e.g. long-term returns and short-term returns). For example, the TA may request the CSP to invoke its critique agents when the former detects that the investor is making excessive trading, which may indicate that the investor is being shortsighted (Bernatzi and Thaler 1995).

Qualitative Reasoning- Qualitative reasoning (QR) analyzes a decision problem by understanding the relationships between structure, behavior, and function of a system (Bobrow 1984). The architecture of a QR tool can be divided into two modules: qualitative simulation, and qualitative synthesis (Benaroch and Dhar 1995). The qualitative simulation module shows the structure of a system by simulating how a change in one parameter propagates throughout the system and alters its overall behavior. On the other hand, qualitative synthesis derives a structure given the desired behavior. The use of a QR tool can help overcome the complexity and ambiguity associated with investment risk management (Benaroch and Dhar 1995). When an investor decides to make a transaction, the TA calculates the potential change in the portfolio risk. If a new level of risk exceeds the investor's risk tolerance level, the TA requests the CSP to invoke its QR tool. The QR tool then assists the investor with its simulation and synthesis modules in understanding the risk implications of his/her current decision.

9. PERSONAL EXPERIENCE MANAGEMENT SYSTEM (PEMS)

The objective of the PEMS is to make a final decision regarding potential biases of the investor by combining information received from several components of the DSS. It then issues feedback to the investor through the user interface (the popup *Bias Analysis* window in Figure 3) if it finds evidence for potential bias. The PEMS has three processing units: Calibration Analyzer, Perception Analyzer, and Bias Analyzer.

CALIBRATION ANALYZER (CA)

The objective of the CA is to regularly examine the investor's tendency for overconfidence. Researchers have observed that overconfidence is a major factor motivating investors to make wrong investment decisions (Barber and Odean 2002, 2001). Psychologists assess an individual's level of confidence by finding out how well calibrated that individual is. A person is said to be well calibrated if he/she is correct n% of the time while making a statement with a confidence level of n%. However, people are generally correct only 75% of the time when their confidence level is 90% and 85% of the time when they report 100% confidence (Lichtenstein et al. 1982). While some doubt the robustness of such a calibration metric (e.g. Juslin et al. 2000), Kahneman and Riepe (1998) recommend it to financial advisors as a way to guard against their

potential overconfidence. The use of general knowledge questions has been the most common means of measuring confidence-related calibration (McKenzie forthcoming).

We propose the development of a tool called *Calibration Analyzer (CA)* as a way to check the investor's overconfidence. For this purpose, the CA uses a set of general knowledge questions with numerical answers stored in a questionnaire database. The CA asks the investor to answer these questions in a predefined level of confidence (say 90%). Once the investor answers all questions, the CA automatically checks whether he/she is exhibiting overconfidence due to the illusion of knowledge. The question bank of the CA could be replenished automatically. For example, the CA may visit some predefined websites (e.g. http://finance.yahoo.com), retrieve some numerical data from there and generate a question such as "What do you think was the level of Dow Jones Industrial Average (DJIA) last month?" The CA reports its finding to the Bias Analyzer.

PERCEPTION ANALYZER (PA)

The objective of the PA is to evaluate the perception of the websites' content. The working principle of the PA has been adapted from Liu and Maes (2004) in which they developed a computational model of an individual's attitudes by analyzing his/her personal texts (e.g. weblog diaries, emails, speeches, interviews) through linguistic processing and textual affect sensing.

When the investor makes a trading decision, he/she needs to provide URLs of the consulted websites. The PA receives these URLs, retrieves texts from these websites, and converts them to standard format such as newsML of Reuters. The newsML is an XML-based markup language for formatting investment-related news (Reuters 2004). Using this format, the PA can parse, search, retrieve and analyze all types of text and graphics. By analyzing the presence of such key words as "rise", "jump", "climb", "fall", "bear", "bull" etc. in the Reuters news, researchers have been able to assess the general sentiment of financial markets (Ahmad et al. 2003).

After parsing the formatted texts and graphics, the PA generates an affect valence for each piece of information called *exposure.* The affect valence score for each exposure is stored in the reflexive memory (see Figure 2). Affect valence is a numeric triple based on the PAD model

(Mehrabian 1995), which measures three affective dimensions - ***P****leasure-Displeasure* (e.g. the market is bullish or bearish); ***A****rousal-Nonarousal* (e.g. potential for high gain or loss); ***D****ominance-Submissiveness* (e.g. reliability of information). The range of values for each dimension is from +1 to -1. As an example, suppose that the website has the text, "Federal reserve bank decides to lower interest rates by 2%." The PA may assign it an affect valence of [0.6, 0.5, 0.8]. The score of 0.6 for the Pleasure-Displeasure dimension indicates that the news is likely to please the investor (e.g. the decrease in interest rate may drive stock prices up). The score of 0.5 for the Arousal-Nonarousal dimension may indicate that the news is likely to create some arousal in the market and the score of 0.8 for the Dominance-Submissiveness dimension may indicate the high reliability of the news. Besides affect valence, the PA also assigns a salience score to the exposure. Such salience scores may be obtained from a lookup table developed from real-world knowledge of how investors react to different types of news. For example, people react more strongly and quickly to news announcing dividends than announcing earnings (Bernard 1992). After calculating[1] the total affect valence (multiplying each valence score with the corresponding salience score and taking the average) for each exposure, the PA determines the overall influence of the website texts on the investor and sends that information to the Bias Analyzer.

BIAS ANALYZER (BA)

The objective of the BA is to synthesize the information received from various logical units and warn the investor of potential biases. From the transaction analyzer, the BA receives information about the likelihood of these biases: hindsight, self-attribution, familiarity, status quo, house money effect, and disposition effect. Since the hindsight bias and the self-attribution bias tend to make an individual overconfident (Fischhoff 1977; Gervais and Odean 2001), the estimate of these biases will be combined with the overconfidence estimate received from the Calibration Analyzer. From the Perception Analyzer, the BA receives a perceptual assessment of the websites' content along the PAD dimension (Pleasure-Arousal-Dominance). In order to make the final decision, the BA combines the information received from the Transaction Analyzer, the Perception Analyzer and the Calibration Analyzer using decision fusion techniques (e.g. Rahman and Fairhurst 1998).

[1] See Liu and Maes (2004) for their formula.

10. DISCUSSION AND CONCLUSION

Having presented the proposed cognitive investment DSS architecture, we now provide a summary in Table 1 of major biases and corresponding DSS tools to lower their influences using a three-mode support framework adapted from (Chen and Lee 2003). The three supporting modes; retrospective, introspective, and prospective refer to the provision of cognitive support determined from the decision maker's past behavior, present beliefs and future needs respectively. The potential for long-term biases is determined primarily from the investor's past decisions. On the other hand, the likelihood for short-term biases is assessed by analyzing the current situation and contexts.

While the architecture we proposed is a step towards providing cognitive support in investment DSS, we acknowledge that it is also fraught with many challenges. The development of the Perception Analyzer is one such challenge. However, recent advances in the design and development of computational models that successfully simulate human attitudes and emotions (Gratch and Marsella 2001; Liu et al. 2003; Minsky forthcoming) may make the development of the PEMS feasible.

Table 1: Summary of Major Biases and Potential DSS Supports

Nature of biases/effects	Biases/effects	DSS supporting functions/tools	DSS supporting modes
Long-term	Overconfidence	Calibration Analyzer	RETROSPECTIVE *Strategy* - Examine past decisions and behaviors. *Goal* - Lower the influence of overconfidence and Long-term biases.
	Hindsight Self-attribution Familiarity Status quo	Transaction Analyzer	
Short-term	Representativeness	Probability Map	INTROSPECTIVE *Strategy* - Reflect on and examine the assumptions and belief system. *Goal* - Challenge the decision maker's beliefs.
	Framing	Critique Agents	
	House money effect Disposition effect	Transaction Analyzer	
	Ambiguity	Qualitative Reasoning	PROSPECTIVE *Strategy* - Understand possible consequences of decisions. *Goal* - Assist in envisioning future states.

From the theoretical perspective, the conceptual model of investor misjudgment that we proposed relies on the heuristics-and-biases paradigm (Tversky and Kahneman 1982). Some researchers opine that the significance of this paradigm is decreasing (e.g. Gigerenzer 1996) and say that it studies cognition in a "vacuum" ignoring the crucial role that the environment plays in shaping human behavior. They argue that the structure of the real-world environment may enable individuals to make rational decisions even though they may exhibit irrational behavior in laboratory experiments and propose a notion of adaptive behavior to explain such mechanism (Anderson 1991). However, Gilovich et al. (2002) assert that the heuristics-and-biases paradigm is not only historically important but also a growing area of active research. Furthermore, in the case of investment decision-making, the environment, in fact, seems to amplify the decision makers' biases rather than correcting for them. Research in behavioral finance has firmly established that the Internet, which is a major platform for investment decision making, amplifies psychological biases by fostering the illusion of knowledge (Barber and Odean 2001, 2002).

More than two decades ago, Sprague (1980) identified that DSS need to be adaptive over time and must evolve to accommodate different behavior styles and capabilities in the long run. In the context of our proposed system, such an adaptation would mean the progressive ability of the system to understand emotions and beliefs of its user. Hence, adaptation is closely linked with knowledge acquisition. In this context, the concept of cognitive flexibility (Spiro et al. 1988) may serve as a framework for acquiring knowledge about the decision maker's self. Cognitive flexibility is based on the philosophy of constructivism, which assumes that individuals construct their own knowledge and understanding of the world through their experiences. The constructivist approach is appropriate in investment decision making because investors' beliefs, preferences, emotions and experiences constitute their knowledge and understanding about the investment world. One implication of this approach is that the DSS must assist investors in conceptualizing multiple representations of knowledge, interconnecting different knowledge sources and constructing knowledge from experiences (Spiro et al. 1991).

From the perspective of technology adoption, several critical issues such as user satisfaction and trust must be explored before the potential benefits of the proposed system can be realized.

The empirical validation of such DSS is also daunting. However, these challenges could not undermine the necessity and usefulness of a cognitive DSS for investment decision making.

We conclude this paper with the conviction that the central task of a natural science is to make the wonderful commonplace (Simon 1999). Although the design of a cognitive investment DSS is more like an "artificial science" than a natural one and we have not made the wonderful commonplace, we believe we made an effort to show where the wonder is. Describing the role of tools and artefacts in bringing paradigm shifts in historical context, Kuhn (1970) states, "... retooling is an extravagance to be reserved for the occasion that demands it. The significance of crises is the indication they provide that an occasion for retooling has arrived." We hope this paper has shown the necessity and feasibility for such retooling in investment decision making.

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