INCORPORATING COGNITIVE SUPPORT IN INVESTMENT DSS

By

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Abstract

The financial well-being of individuals depends on the appropriateness of their investment decisions. As the world is moving from defined benefit (DB) pension plans to defined contribution (DC) pension plans, the burden of making the right investment decisions has now shifted to employees. One implicit assumption about this global trend is that plan participants are capable of making sound decisions themselves. However, several studies have demonstrated that people often fall prey to various psychological biases and make flawed investment decisions.

The use of computers in support of decision-making is not new. For several decades, the finance and investment sectors have extensively used different computing methods and technologies collectively known as decision support systems (DSS) to support investors. However, the type of support provided by such DSS has primarily been quantitative in nature. As such, existing investment DSS do not assist decision makers in overcoming the impact of their psychological biases, which have been shown to play a critical role in investment decision-making. The overall objective of this research is to investigate the potential for building a human-centered investment DSS that can provide qualitative support to investors.

In this research, a theoretical framework of investment decision-making is proposed by using the psychological concepts of beliefs, preferences and attitudes. Major

investment-related biases are identified and a taxonomy is suggested to classify them as cognitive, affective, and conative.

An empirical study involving 119 subjects was conducted to verify the impact of cognitive biases in investment decision-making and to assess the effectiveness of decision aids in lowering the impact of such biases on the ability of investors to make sound investment decisions. In this study, feedback and graphical aids were provided as cognitive support in six investment decision-making tasks involving framing, representativeness, and ambiguity biases. A large majority of subjects exhibited the influence of these biases in their investment decision-making. Cognitive support was found to significantly improve asset allocation decisions for most subjects. Demographic variables collected during the experiment enabled several analyses leading to some additional interesting observations. Findings from this study indicate the usefulness of personalization in investment DSS.

This research culminated with a vision toward the development of a human-centered investment DSS that may provide qualitative support to its users. Different philosophical inquiring systems were described as potential debiasing strategies for the proposed DSS. An architecture was suggested for implementing such a DSS with a detailed example illustrating the feasibility of the proposed system. The dissertation concludes with an outline of potential contributions of this study and directions for future research in this area.

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CHAPTER 1

INTRODUCTION

Due to innovations in the financial industry, the advent of the web and the proliferation of inexpensive personal computers, individuals are getting unparalleled opportunities for investment (Barber and Odean 2001). Investment refers to the current commitment of financial resources or funds for a period of time in order to derive future payments that will compensate the investor for the time the funds were committed, the expected rate of inflation, and the uncertainty of the future payments (Reilly and Brown 1997). Investors are facing 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 demonstrably flawed investment decisions due to these problems (Barber and Odean 2001, 2002; Rashes 2001). Statman (2003) observes that today's investors are not faring any better than their predecessors a century ago in terms of the quality of decisions they make despite the increase in available information. He concedes that investor psychology, as a driving force in financial markets has not changed in the last 100 years despite technological and financial innovations.

Besides short-term investors, retirement plan participants are also facing difficulty in making the judicious investment decisions. As the world is moving from defined benefit (DB) pension plans to defined contribution (DC) pension plans, the burden of making good investment decisions has now shifted to employees (Mitchell and Utkus 2003). In DB plans, employers promise according to a formula a fixed benefit amount to their employees and in so doing take on the investment risk themselves; whereas in DC plans, employees decide where and how much to invest. Currently, more than 25 million employees are enrolled in 401(k)[1] plans in the US with the total invested exceeding $1 trillion (Agnew et al. 2003). Research in retiree investment decision-making has found that plan participants jeopardize their investments as they are subject to several psychological biases (Bailey et al. 2003; Benartzi 2001; Benartzi and Thaler 2001; Bhandari and Deaves forthcoming).

The finding that financial markets are driven by human psychology is not new. An episode known as *Tulipmania* started with the speculative trading of tulip bulbs and ended with a spectacular market crash in Holland and England 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. Wright (1980) summarized information-processing biases

[1] 401(k) is the most popular pension plan in the US.

from the perspective of financial decision-making while Bateman and Schwenk (1986) discussed biases in investor decision-making using a case study.

More recently, the interest in psychology for understanding financial markets has resurfaced with the emergence of a new subfield of finance called *behavioural finance.* Using findings from cognitive psychology, behavioural finance has been able to explain many anomalous phenomena in capital markets such as high volatility of stock prices (Shiller 1981) and excessive trading of stocks (Barber and Odean 2000). Behavioural finance through empirical studies demonstrates that individuals sometimes do not make rational choices[2], and that these choices can have significant and persistent impact on financial markets (Shleifer 2000).

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), have been used in several financial sectors such as banking, financial planning, investment and trading (e.g., Braun and Chandler 1987; Bouwman 1983; Humpert 1989; Kosy and Wise 1984; Kruchten 1987; Shane et al. 1987; Sprague and Watson 1976). The focus of these DSS was primarily on providing quantitative support such as computation of fundamentals, risks, and economic trends.

[2] De Bondt (1999) very aptly makes this point by saying that "the radical insight of behavioural finance is that people are human."

More recently, researchers have proposed and developed many investment DSS tools by making innovative use of such technologies as artificial neural networks (e.g., Trippi and Turban 1993), fuzzy logic (e.g., Bagnoli and Smith 1998), genetic algorithms (e.g., Goldberg 1994) and their combinations (e.g., Leigh et al. 2002). However, none of these systems assists investors in overcoming the influence of their biases. Although technical analysis-based DSS use some indicators of market psychology, such as relative strength index, oscillators, and candlestick patterns, to predict stock price movements (Edwards et al. 2001), they are not designed to help individuals to overcome the influence of their psychological biases. There is also a major difference between behavioural finance and technical analysis. Behavioural finance is based on theories of human judgement and decision-making (e.g., Kahneman and Tversky 1979; Thaler 1980) and relies on fundamental behavioural axioms such as loss aversion and mental accounting which can be empirically tested; whereas technical analysis is devoid of such axioms (De Bondt 1995).

Despite the significant role of psychology in investment decision-making, the emphasis of current DSS is still on providing quantitative support to investors. The fact that cognitive support is becoming increasingly critical to investors underscores the importance of incorporating such support in investment DSS. This research is, therefore, guided by the following objectives:

- Propose a theoretical framework of investment decision-making
- Based on the proposed framework, suggest a taxonomy for judgment biases and explore how they influence investment decision-making.
- Conduct an empirical study investigating the effectiveness of decision aids in lowering the impact of cognitive biases.
- Based on the proposed taxonomy and findings of the empirical study, suggest an architecture for developing a human-centered investment DSS.

This dissertation is organized as follows. A literature review of the different topics involved in this research is provided in the next chapter. A theoretical framework of investment decision-making is proposed in Chapter 3. The research framework, model and hypotheses are discussed in Chapter 4. Chapter 5 discusses in detail the experiment and the results pertaining to the research hypotheses. The dissertation culminates with a vision of a human-centered investment DSS in Chapter 6. It concludes in Chapter 7 outlining potential contributions of this study and directions for future research in this area.

CHAPTER 2

LITERATURE REVIEW

In this chapter, a literature review of the topics involved in this research is provided. The discussion of human judgment and decision-making models will serve as a starting point with an emphasis on behavioural decision-making and the "heuristics and biases" paradigm since they constitute the theoretical foundation for this research. The application of behavioural decision models in the area of finance and investment will set the stage for the discussion of an emerging field called *behavioural finance*, which will demonstrate the role of psychology in investment decision-making and the failure of standard finance in explaining several anomalies observed in financial markets. The key findings from prospect theory, which is considered the most successful behavioural model of human decision-making, are then outlined. This chapter concludes with an outline of studies concerning the current use of DSS for cognitive support.

2.1 Human Judgment and Decision-Making

Human decision-making models can be divided into three broad categories: normative, prescriptive, and descriptive (Bell et al. 1988). Normative models indicate what optimal or ideal decisions should be, whereas descriptive models simply describe how people actually make decisions. Prescriptive models are designed to move people from the latter to the former. Normative and prescriptive models follow the "rational"

approach in which "1) A decision maker considers all alternatives open to him; 2) He identifies and evaluates all of the consequences which would follow from the adoption of each alternative; 3) He selects that alternative, the probable consequences of which would be preferable in terms of his most valued ends." (Meyerson and Banfield 1955, p. 314).

Simon (1960) proposed a framework for rational decision-making consisting of three sequential phases (Figure 2.1): Phase 1 - *intelligence* (searching for occasions and conditions that call for decisions); Phase 2 - *design* (inventing, developing and assessing possible courses of action); and Phase 3 - *choice* (selecting one of the possible courses of action). The outcome of the *choice* phase is a selected solution. Simon later added the *implementation* phase to consider the success or failure of the selected solution. The path joining the *choice* phase with the *intelligence* phase indicates that the decision-making process continues until the successful implementation of the selected solution.

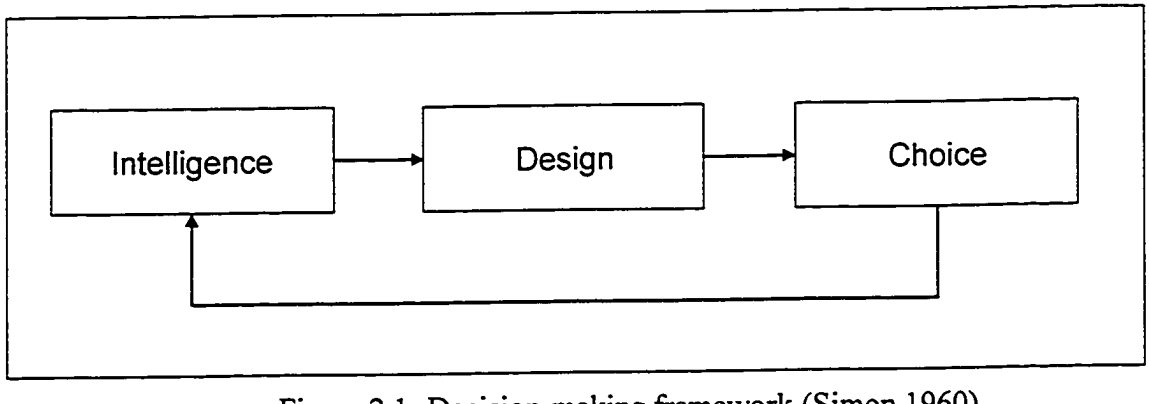

Figure 2.1- Decision-making framework (Simon 1960)

While applying this rational model in decision-making, neoclassical economists and operations researchers suggest that decision makers should strive to maximize their subjective expected utility (SEU), a term which relies on the concept of risk, uncertainty, choice and probability. According to Knight (1921), risk involves a gamble with a known probability distribution such as tossing a coin, whereas uncertainty involves a gamble with unknown probability distribution, such as investing in a completely new technology. Uncertainty is associated with ambiguity and people dislike it more than risk (Knight 1921). The notion of probability, which started almost five hundred years ago with the Italian mathematician Gerolamo Cardano, led to the concept of utility. The Swiss mathematician Daniel Bernoulli formalized utility as individuals' assessment of the subjective value of a choice. In his landmark paper first published in 1748, he demonstrated that rational people should evaluate utility and not objective economical outcomes when choosing the best option among different risky gambles (Bernoulli 1954). The foundation for the modern theory of utility began with Von Neumann and Morgenstern (1944) when they demonstrated, using a set of axioms, that a rational decision maker always prefers the highest expected utility. However, they assumed the outcomes of gambles to have known distributions. Savage (1964) relaxed this constraint by introducing the idea of subjective expected utility in which probability distributions are unknown and weighted through an individual's subjective assessment.

Kersten and Michalowski (1996) have outlined the following as the key strengths of the rational decision-making model: it allows decision makers to focus on the

resources (actions and tools) necessary for different phases of the decision-making process; it enables decision makers to position resources and stipulate their roles during the transition of the decision-making activity; and it facilitates the decomposition of the decision problem and specification between its components.

The rational model, however, is unrealistic as it assumes that decision makers have complete knowledge of alternatives and their consequences, a stable set of preferences, and the computational ability to compare alternatives (Kreitner and Kinicki 2001). Greyer (1994) and Meredith (1997) underscore the need for a perceive-interpret-respond sequence in the decision-making process, which is not present in the rational model (Simon 1960).

The rational model has also been criticised for its supposition regarding decision makers' expected utility. Although the expected utility (EU) framework is still popular because of its simplicity, it is not a suitable model of human decision-making (Ellsberg 1961; Machina 1987, Rabin and Thaler 2001). The most serious limitation of the EU framework is its assumption of linear probabilities. As early as 1953, Allais noticed that decision makers weigh not only the expected outcomes but also their associated probabilities. The subjective weighting of the probabilities makes them non-linear. His empirical findings, which violate the EU framework, constitute what is now widely known as the Allais Paradox (Allais 1953). It has been observed that not only humans but also other animals violate the expected utility axioms (Battalio et al. 1985).

To overcome the limitations of the EU framework, researchers have proposed many non-EU theories by relaxing some constraints of the former. Some major non-EU theories are disappointment aversion (Gul 1991), implicit expected utility (Chew 1989; Dekel 1986), weighted-utility (Chew 1983), regret theory (Bell 1982, Loomes and Sugden 1982), rank dependent utility theories (Quiggin 1982, Segal 1989, Yaari 1987), and prospect theory (Kahneman and Tversky 1979). Among these theories, prospect theory is the most successful in explaining the psychology of investment decision-making and is considered the backbone of behavioural finance (Barberis and Thaler 2002). A brief discussion of prospect theory is provided in the next section.

At this point though it can be noted that the success of prospect theory is largely attributable to its ability to explain many decision-making behaviours that emerged from the "heuristics-and-biases" paradigm. In order to overcome the limitation of the rational model, Simon (1955) introduced the theory of bounded rationality in which people do not maximize but "satisfice"; and do not optimize with algorithms but simplify with heuristics. A heuristic is "a rule of thumb, or informal reasoning strategy, as opposed to a mathematical formula that can be calculated" (Klein 1998, p. 307). It serves as an unconscious routine to cope with the complexity of decision-making (Hammond et al. 1998). However, through numerous tests conducted in laboratory settings, Tversky and Kahneman (1974) demonstrated that over-reliance on heuristics can result in "severe and systematic errors in judgment", or decision biases. Since then, several decision theorists

have contributed to this field resulting in the "heuristics-and-biases" paradigm (Kahneman et al. 1982).

Some researchers suggest that the significance of this paradigm is decreasing (e.g., Gigerenzer 1996), and allege that it studies cognition in a "vacuum" while ignoring the crucial role that the environment plays in shaping human behaviour. They argue that the structure of the real-world environment may enable individuals to make rational decisions even though they may exhibit irrational behaviour in laboratory experiments. Further, they propose the notion of adaptive behaviour to explain such mechanisms (Anderson 1991a). 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 them. For example, findings from behavioural finance have 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). The next section discusses the topic of *behavioural finance* that uses behavioural theories of decision-making to explain investor psychology and behaviour.

2.2 Emergence of Behavioural Finance

Behavioural finance as a research discipline has emerged to explain many anomalous phenomena in financial markets that are hitherto unexplained by traditional finance. While it is said to have started with the finding of stock market overreaction (De Bondt and Thaler 1985), it has obtained its due share of attention only recently.

The foundation of traditional finance relies on three key assumptions: market efficiency, the random walk, and rational agents. Stock market efficiency states that current stock prices reflect all relevant public information and, as such, the net present value of purchasing a stock is zero. That is, it is impossible to make consistent excess profit by trading stocks with the help of public information only. Random walk theory developed by Bachelier (1964) and Osborne (1964), states that stock price movements are random processes and changes in stock prices are independent of each other. Random walk theory implies market efficiency and normality of stock returns. The rational agents framework assumes that investors are rational beings who optimize their risk and reward opportunities.

Modern portfolio theory (Markowitz 1952) suggests that investors should seek the highest rate of return for a given level of risk. Following on its footsteps, the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965), and later modified by Black (1972), proposed a linear relationship between risk and return assuming normality of returns. However, it has been observed that stock returns do not

follow normal distributions. In fact, they exhibit high kurtosis with fatter tails and higher means than predicted by normality (Peters 1991). Some major financial anomalies that cannot be explained within standard finance are excessive volatility of stock prices relative to their fundamentals (Shiller 1981), long-term reversals (De Bondt and Thaler 1985), and short-term momentum (Jegadeesh and Titman 1993). The growing evidence that investors make systematic judgment errors seriously undermines the validity of the rational agents framework (Shleifer 2000).

Although opponents of behavioural finance acknowledge that investors are not always rational, they claim that individual irrationality would not have significant and lasting impact on the overall market and maintain that the efficient market hypothesis still holds (e.g., Ball 1996, Fama 1998). The major success of behavioural finance has been in demonstrating that individual irrationality does exert significant and persistent impact in financial markets because of limits to arbitrage. Indeed, Shleifer and Summers (1990) regard "limits to arbitrage" and investor psychology as the two pillars of behavioural finance. Some of the behavioural theories used in explaining investor psychology are *prospect theory*, *mental accounting*, and *regret theory*.

2.2.1 Prospect Theory

In prospect theory, Kahneman and Tversky (1979) propose that when people are offered a gamble (prospect) having outcome x with probability p and outcome y with probability q, they assign the following value to this gamble

$$Value = \pi(p)\, v(x) + \pi(q)\, v(y)$$

Then, they choose the option that maximizes this value. The functions $\pi(.)$ and $v(.)$ are called the probability weighting function and the value function respectively (Figure 2.2).

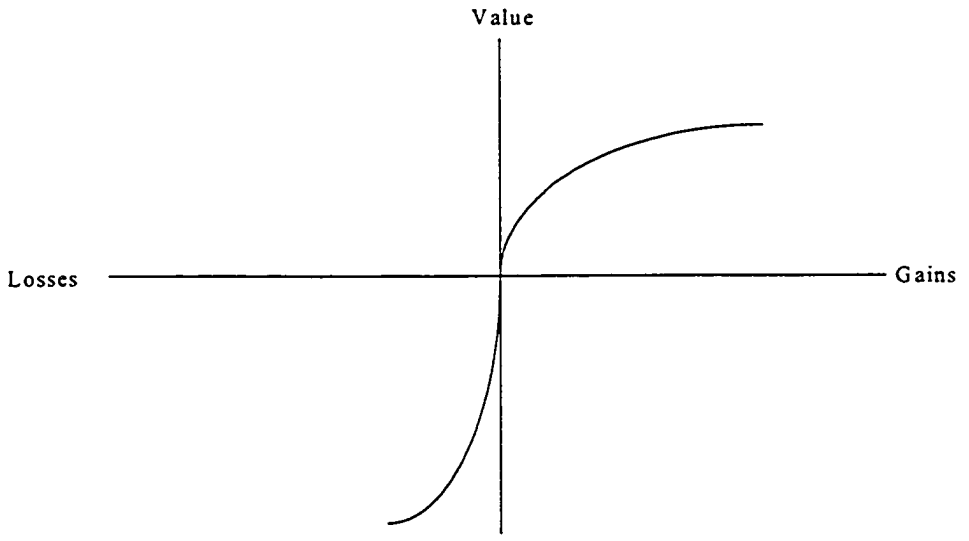

Figure 2.2 - Hypothetical value function of prospect theory

The major findings of prospect theory can be summarized as follows:

a) People perceive utility over individual gains and losses and not over the final wealth, i.e. x and y are gain/loss amounts and not the total wealth position. This finding is another blow to the EU framework, which assumes people to perceive utility over their aggregate wealth.

b) People are risk seeking in losses and risk-averse in gains, which implies that v is concave in the gain domain and convex in the loss domain (see Figure 2.2).

c) The value function v is steeper for losses than for gains, i.e. $v(x) < -v(-x)$ for $\forall$ x ≥ 0. This property suggests that people perceive the pain of losing, say $50, more acutely than the joy of gaining the same amount.

d) People overrate small probabilities, i.e. $\pi(p) > p$ for small p. This explains why people buy lottery tickets and insurance. Even though the chance of winning a lottery or making an insurance claim is very small, individuals' tendency to overrate small probabilities makes them believe that lottery winnings and insurance claims are more likely to occur than what their underlying probability distributions actually predict.

2.2.2 Mental Accounting

Mental accounting is a term coined by Thaler (1980) and refers to the process by which people perceive and compute their transactions. Due to mental accounting, people divide their transactions into different mental compartments and try to optimize each compartment rather than the whole (Tvede 2002, p. 94). For example, Shefrin and Statman (1999) notice that individual investors divide their portfolio into two parts: a safe component (that is protected from downside risk) and a risky component (that is designed for growth at the cost of risk). Similarly, Shefrin and Thaler (1988) argue that people generally divide their income sources into three categories (current salary income, asset

income, and future income) and perceive them differently. For example, people hesitate to spend out of their future income even if they are certain to receive it.

Barberis and Huang (2001) outline two forms of mental accounting: loss aversion and narrow framing. Loss aversion refers to the fact that people are more sensitive to reductions in wealth (losses) than to increases (gains). Loss aversion follows from prospect theory (Kahneman and Tversky 1979), which demonstrates that the value function is steeper for losses than for gains. Narrow framing arises when individuals "do not fully merge a gamble with pre-existing risk or fail to consider jointly all the risks they face at a given point in time whereas to some extent they evaluate them in isolation" (Frazzini 2003). Decisions influenced by narrow framing tend to exhibit near-proportionality of risk-taking, that is, individuals exhibit very little risk tolerance in small gambles and very high risk in large gambles (Kahneman and Riepe 1998).

2.2.3 Regret Theory

Regret refers to a tendency to feel pain at having made mistakes. Regret theory proposes that "we try to avoid actions that confirm we have made mistakes. This can be done if we wait for a market correction back to the point where we made our mistake, so that we can reverse it without pain" (Tvede 2002, p. 148). The kink in the value function of the prospect theory (Kahneman and Tversky 1979) indicates the pain of regret. To incorporate the impact of regret in decision-making, Loomes and Sugden (1982) propose modified utility function that combines the utility from a choice with the utility the

decision makers would have achieved from another choice had they selected it. Closely related to the concept of regret is cognitive dissonance (Festinger 1957) that occurs when "evidence shows that our assumptions have been wrong. We try to avoid such information, or distort it, and we try to avoid action that highlights the dissonance" (Tvede 2002, p. 94).

Regret theory explains why investors postpone selling stocks that have gone down in value and quickly sell stocks that have gone up (Shefrin and Statman 1985). Investors try to avoid selling stocks that have gone down because they do not want to acknowledge their earlier mistake of purchasing those stocks and feel the pain of regret. Similarly, they do not want to hold the winning stocks for fear that the stocks may go down in value in the future and they will have to face the pain of regret for not selling earlier.

The major investment-related biases are explained in the next chapter while proposing a theoretical framework of investment decision-making. The following sub-section provides an overview of previous studies involving the incorporation of cognitive aids in Decision Support Systems (DSS).

2.3 Cognitive Support in DSS

Decision support systems "are computerized aids designed to enhance the outcomes of an individual's decision-making activities" (Singh 1998). They "couple the intellectual resources of individuals with the capabilities of the computer to improve the quality of decisions" (Keen and Scott-Morton 1978). The concept of DSS originated from the theoretical studies of organizational decision-making conducted at Carnegie Institute of Technology and Massachusetts Institute of Technology in the late 1950s. The first pioneering implementation of a DSS was done by Michael S. Scott-Morton in his Ph.D. thesis entitled "Management Decision Systems: Computer-Based Support for Decision Making" in 1971. The foundation for DSS research was set by Gordon Davis of the University of Minnesota in 1974 with the publication of his seminal book "Management Information Systems: Conceptual Foundations, Structure, and Development". Since then many researchers have addressed the different aspects of DSS. In the late 1980s, Executive Information Systems (EIS) and Group Decision Support Systems (GDSS) evolved. With the emergence of data warehousing and online analytical processing (OLAP) in 1990s, DSS gained new capabilities and scope. Using ad hoc query and reporting tools, corporate intranets started to provide information exchange and knowledge management in 1996. In 1999, we began to see the incredible proliferation of Web-based DSS (Power 1999).

DSS is an umbrella term that encompasses all technologies and tools assisting in decision-making processes and its definitions have been changing. Turban and Aronson (2000) notice that the later definitions of DSS have focused more on the nature of inputs rather than what they deliver. The functionality of DSS has evolved primarily through interactions between clients, systems analysts, and software developers during a course of many development life cycles.

Decision support systems can be divided into several categories based on different factors such as targeted users, technology employed, and the specific purpose of the system. Alter (1980) developed the broadest framework, which was based on the assumption that a DSS could be solely identified in terms of its operations and be independent of problem type or area. His framework consisted of the following seven types: file drawer systems, data analysis systems, analysis information systems, accounting models, representational models, optimization models, and suggestion models. While this framework is still useful, Power (2001) proposed an expanded framework recognizing DSS tools as data-driven, model-driven, document-driven, communications-driven, and knowledge-driven.

While the majority of the earlier textbooks and research on DSS used Simon's rational decision-making model as its theoretical foundation (e.g., Bonczek et al. 1981; Sprague and Carlson 1982), some researchers criticized the model by calling it "a serious obstacle for the evolution of DSS theory and practice" (Angehrn and Jellassi 1994, p.4).

Indeed, several DSS frameworks have come into existence to overcome the limitation of the rational model. Some of these alternative frameworks are *life cycle* (Hogue and Watson 1983), *evolutionary* (Alavi and Henderson 1981; Moore and Chang 1980; Sauter and Schofer 1988), and *adaptive* (Keen 1980; Keen and Gambino 1983; Alavi and Napier 1984; Fazlollahi et al.1997).

The knowledge of a DSS can be divided into six types: descriptive, procedural, reasoning, linguistic, presentation, and assimilative (Holsapple and Whinston 1996). The first three are called *primary* types and the rest are called *secondary* types. Mirchandani and Pakath (1999) divided DSS models into four types: *symbiotic*, *expert*, *holistic*, and *adaptive*. A symbiotic DSS is a system that can alter its support behaviour to suit a user by monitoring the user's cognitive and decision-making styles. Expert DSS is a system that can reason using stored knowledge that is fragmented in rule form. Adaptive DSS is a system capable of inducing positive changes in itself to enhance its problem processing proficiency. Holistic DSS is a system capable of holistic problem solving.

Decision support systems have been used in several financial sectors such as banking, financial planning, investment and trading (e.g., Braun and Chandler 1987; Bouwman 1983; Humpert 1989; Kosy and Wise 1984; Kruchten 1987; Shane et al. 1987; Sprague and Watson 1976). The focus of these DSS has primarily been on providing quantitative support such as the computation of fundamentals, risks, and economic trends. More recently, researchers have proposed and developed many investment DSS tools by

making innovative use of such technologies as artificial neural networks (e.g., Trippi and Turban 1993), fuzzy logic (e.g., Bagnoli and Smith 1998), genetic algorithms (e.g., Goldberg 1994) and their combinations (e.g., Leigh et al. 2002). Despite the significant role of psychology in investment decision-making, the emphasis of current DSS is still on quantitative support and research involving a cognitive approach to investment decision-making is still lacking.

DSS researchers, however, have long identified cognitive support to decision makers as being a requirement for DSS. Cognition refers to a general concept embracing all forms of knowing and includes perceiving, imagining, reasoning, and judging (Chaplin 1968, p.94). 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 sceptical about the usefulness of cognitive style as a basis for designing DSS. Todd and Benbasat (1993) observed that, in some cases, the impact of decision aids might lead to the conservation of effort rather than the increase in decision quality. 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 the decision makers' strengths and compensate for their weaknesses including their biases. Kuokka and Bonzon (1996) argue that true DSS "should allow people to play with ideas and solutions as artists play with colors and forms". Beynon et al. (2002) notice a trend towards the use of models in which

experiential rather than formal representation is predominant. Nemati et al. (2002) suggest that the effectiveness of a DSS should be measured based on how well it promotes and enhances knowledge, and how well it improves the mental models and understanding of the decision maker. Sauter (1999) emphasizes that a DSS should enable intuitive decision-making. Kersten and Michalowski (1996) stress the necessity of incorporating cognitive aspects of decision tasks in DSS.

Researchers have found that several features of information systems tools such as graphs, probability maps, feedback, and multimedia could provide cognitive support and assist in the decision-making process. Information presentation and displays have cognitive implications (Kleinmuntz and Schkade 1989) and influence decision-making (DeSanctis 1984; Ives 1982). Data format (numeric versus text) can affect information processing (Stone and Schkade 1991). Graphical presentations have been found to be more effective than tables in several decision-making tasks such as forecasting earnings and sales (Anderson and Reckers 1992; DeSanctis and Jarvenpaa 1989) and reducing information overload (Benbasat et al. 1986; Diamond and Lerch 1992; Umanath and Vessey 1994). A problem representation tool called a *probability map* has been used as a cognitive aid in solving Bayesian problems (e.g., Cole 1988; Lim and Benbasat 1997b; Roy and Lerch 1996). Researchers have also observed that feedback often improves decision-making (Alpert and Raiffa 1982; Arunachalam and Daly 1995; Balzer et al. 1989; Balzer and Sulsky 1992; Sharp et al. 1988; Te'eni 1991) and benefits of feedback increase as the decision-making environment becomes more complex (Montazemi et al.

1996). However, feedback is not beneficial when decision makers have no task-specific experience or knowledge (Eining and Dorr 1991).

Several successful systems have been developed to provide cognitive support to decision makers by incorporating graphs, feedback, multimedia etc. into the DSS. 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. Multimedia used in a performance appraisal system was helpful in reducing first impression bias (Lim et al. 2000). 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.

However, there are also some applications in which different attributes of information systems have reinforced the decision makers' biases instead of correcting them. For example, the use of salient graphics in executive information systems increased overconfidence (Rai et al. 1994). In a flight management system, people allowed the system to override their judgment by using the automated setting resulting in poorer

performance (Skitka et al. 1999). Several other studies have found that decision aids do not always improve decision performance (Aldag and Power 1986; Benbasat and Nault 1990; Sharda et al. 1988).

2.4 Summary

Human decision-making models can be divided into three broad categories: normative, prescriptive, and descriptive. Normative and prescriptive models follow the rational approach which assumes that decision makers have perfect self-control and unlimited information-processing capacity. Descriptive models describe how people actually make decisions and follow a behavioural approach which acknowledges that individuals have limited self-control and information-processing capacity.

Standard finance, which relies on the rational decision-making framework, has not been able to explain many anomalous phenomena in financial markets. Behavioural finance, which stresses the role of psychology in investment decision-making, has demonstrated that individuals make systematic judgment errors and that individual irrationality does exert significant and persistent impact in financial markets. Behavioural finance relies on such theories as mental accounting, regret, and prospect theory.

Decision support systems have been used in financial sectors for several decades. Despite the significant role of psychology in investment decision-making, the support provided by such DSS to investors is primarily quantitative in nature. Researchers have

found that several features of information systems tools such as graphs, feedback, and multimedia could provide cognitive support to decision makers. However, the incorporation of such tools in investment DSS is still lacking.

Incorporating cognitive support in investment DSS requires an understanding of the nature of biases involved in investment decisions. In the next chapter, a theoretical framework of investment decision-making is proposed by using the psychological concepts of beliefs, preferences and attitudes.

CHAPTER 3

A FRAMEWORK OF INVESTMENT DECISION-MAKING

The field of behavioural finance, which is said to have started with the finding of stock market overreaction (De Bondt and Thaler 1985) emerged to explain investors' misjudgment attributed to their psychological biases. However, it still lacks a theoretical framework that explains how these biases originate and relate to each other. An investor model proposed by Shefrin and Statman (1984) consists of 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. While these models are useful in understanding different aspects of investor behaviours and biases, they do not explain the essential nature of these biases and show how they relate to each other. In fact, researchers in this field have reported so many "biases"[3], "effects", and "phenomena" without any unifying theme in a very short period that opponents of behavioural finance are calling it the "anomalies literature" (Frankfurter and McGoun 2000). As an attempt to fill this void to some extent, a theoretical framework of investment decision-making using individuals' beliefs and preferences as the foundation for decision analysis is proposed in this chapter.

[3] Biases and effects are treated as synonyms in this dissertation.

Behavioural finance stresses that individuals' beliefs and preferences are the sources to several biases that influence investment decisions (e.g., Kahneman and Riepe 1998, Barberis and Thaler 2002). Payne and Bettman (1992) consider the incorporation of human beliefs and preferences as an important feature of decision analysis. Investment decision-making is the outcome of the conflict between expectation (beliefs) and preferences (Antonides and Van Der Sar 1990). It would then follow that individuals' beliefs and preferences may serve as a starting point for understanding their investment decisions.

Simon (1955) put forward the concept of bounded rationality to emphasize individuals' limited capacity for information-processing and rational thinking. Humans, therefore, are subject to several limitations in forming beliefs (March 1978). Mullainathan and Thaler (2000) propose a concept of bounded self-control to underscore that humans are limited not only in rationality but also in self-control. Individuals, due to limited self-control, exhibit greed and fear and their preferences deviate from the optimal model as recommended by the rational decision-making theory. March (1978) stressed that individuals are subject to several limitations both in forming beliefs and constructing preferences.

Individuals' beliefs and preferences are also influenced by the environment such as social, economic, and political factors. Bisin and Verdier (2001) discuss the dynamics of preferences in different cultures and illustrate how parents shape their children's beliefs

and values. Bandura (1986) posits that in a society, human behaviours are induced by modeling and learned by imitation. Group norms and peer effects have been found to exert significant impact on individuals' beliefs and preferences in investment decision-making. For example, Duflo and Saez (2002) point out that employees often decide to join retirement savings plans when they are recommended or advised by their peers. Hong et al. (2004) find that socially active households are more likely to invest in the stock market than those who are not active.

It is now proposed that individuals' beliefs and preferences, which are influenced by their bounded rationality, bounded self-control and the environment, will determine their attitude towards investing. According to Fishbein and Ajzen (1972), a person learns or forms beliefs about an object, which then influence his attitude toward that object. Attitude is a relatively stable assessment of a person, object, issue, or situation (Petty et al. 1997) and denotes an overall degree of favorability (Ajzen 2001). Perloff (1993) posits that attitude consists of cognitive and affective (emotional) components whereas other psychologists include a conative (behavioural) component also (e.g., Oskamp 1991; Tallon 1997; Wood et al. 2003).

A cognitive component consists of our beliefs about an attitudinal object (Bagozzi and Burnkrant 1985). The belief that a *high return requires high risk* is an example of the cognitive component. An affective component includes our feelings toward an attitudinal object (McGuire 1985; Russell 2003). For example, when people say, "It is sad to lose

money", they are displaying their affective component. A conative component indicates our action tendencies toward the attitudinal object (Wood et al. 2003), which is evident when people say, "I rarely update my portfolio even though I know I should".

Rosenberg (1960) proposes that the conative component is guided by both cognitive and affective components. Romer (2000) identified that both thinking-based mechanisms and feeling-based mechanisms determine behaviour. Bagozzi (1992) posits that knowledge and emotion are translated into behaviour through conation. Conation, which is closely linked with the concept of volition or will, is critical for individuals engaged in self-direction and self-regulation (Mischel 1996). Figure 3.1 shows how an individual's attitude toward investment can be explained in terms of these three components.

Each of these components (cognitive, affective, and conative) has the potential to result in corresponding decision biases. Cognitive biases are information-processing biases which motivate individuals to misjudge the true significance of new information (Wright 1980). Affective biases consist of general moods (happiness, sadness) and emotions (fear, anger, envy), which contain degrees of valence as well as arousal (Ajzen and Fishbein 2000). According to Massa and Simonov (2002), conative (behavioural) biases are related to general human tendency (e.g., fear of unknown) and are equally likely to exist in different countries and across markets. Individuals, under the influence

of these biases (cognitive, affective, conative), are likely to make flawed investment decisions. Examples of biases belonging to each of the three categories are provided later.

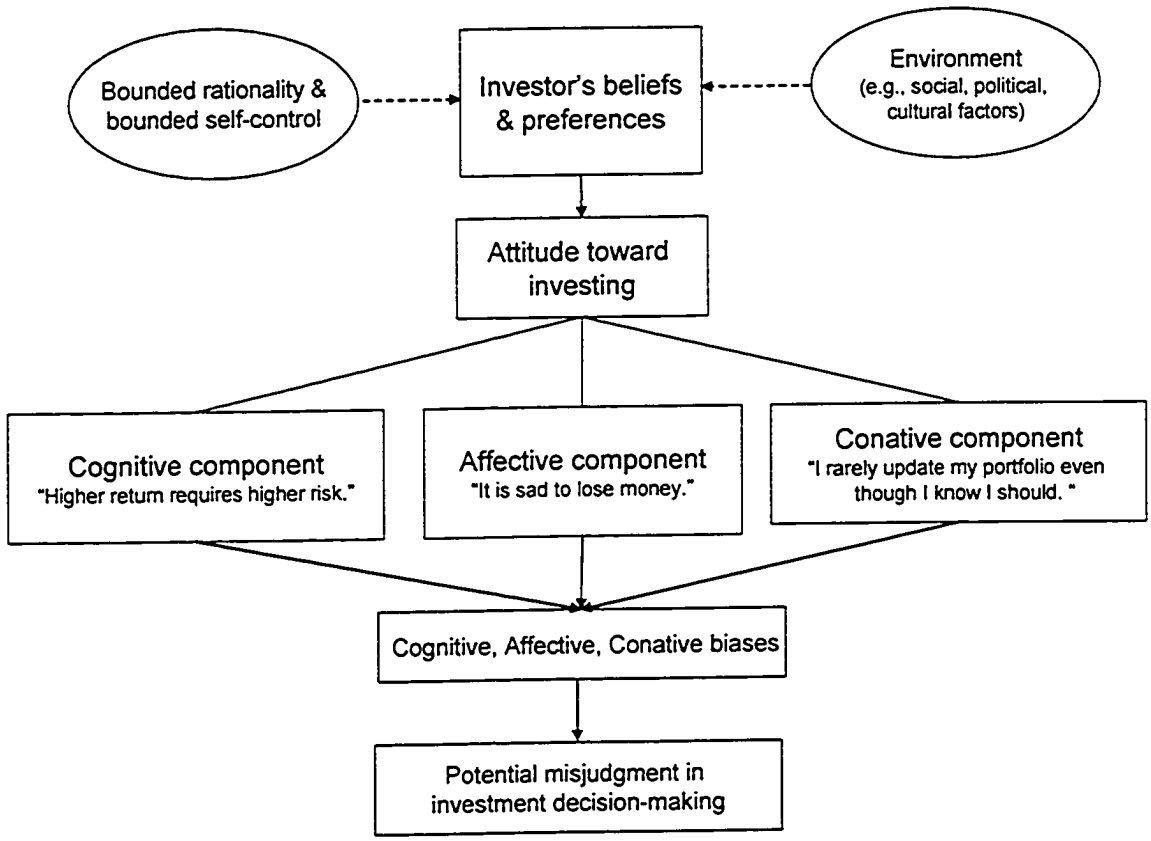

Figure 3.1 - A framework of investment decision-making

There have been several attempts to develop a taxonomy of decision biases. Tversky and Kahneman (1974) categorized biases as originating from the use of heuristics in decision-making. Others took information processing perspective to classify different biases (e.g., Remus and Kottemann 1986; Wright 1980). In his model of human judgment, Hogarth (1987) identified four decision-making stages (acquisition, processing, output, and feedback) in which biases can occur. Arnott (1998) and Kirs et al. (2001)

provide a review of several judgment biases and their possible classifications. However, they do not include biases such as the disposition and house money effects that have been observed to play critical roles in influencing investment decision-making.

The theoretical framework of investment decision-making proposed in this section makes it possible to develop a taxonomy of investment biases by dividing them into three decision-making components: cognitive, affective, and conative. Some major investment-related biases are outlined in Table 3.1 and classified according to the proposed framework (Figure 3.1).

Table 3.1 - Major investment-related biases

Category of biases	**Primary characteristics**	**Biases**
Cognitive	Information-processing biases caused by the order, salience, patterns, and amount of information received. Triggered by the arrival of new information.	Framing
		Representativeness
		Ambiguity
Affective	Involve emotional elements such as fear, regret, and greed. Triggered by the arrival of new information.	Disposition effect
		House money effect
Conative	Persistent in nature. May exert their influences even in the absence of any new information.	Overconfidence
		Status quo
		Familiarity

Definitions and examples of these biases are provided in the following subsections. Cognitive biases are discussed in detail as the empirical study (described in next chapter) involves investigating the effectiveness of decision aids in lowering the impact of these biases.

3.1 Cognitive Biases in Investment Decision-Making

Cognitive biases are information-processing biases, which motivate individuals to misjudge the true significance of the received information. These biases are primarily instigated by such factors as salience, order, patterns, and amount of information received by decision makers.

3.1.1 Framing

The formal study of the framing bias in judgment and decision-making is said to have started with the work of Tversky and Kahneman (1981) who defined a decision frame as "the decision maker's conception of the acts, outcomes, and contingencies associated with a particular choice." A framing bias is said to occur when the manipulation of such a decision frame changes the decision maker's perspective about the problem. Tversky and Kahneman (1981) illustrate the framing bias with the following Asian disease problem:

Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows:

If program A is adopted, 200 people will be saved.
If program B is adopted, there is 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved. Which of the two programs would you favor?

When this scenario was posed to subjects, it was found that 72% of subjects chose program A. The problem was then rephrased in the following way:

If program C is adopted 400 people will die.
If program D is adopted there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die. Which of the two programs would you favor?

In this case, only 22% chose program C. It can easily be seen that programs A and C are identical because in each case 200 people will be saved. The only difference between them is that A is expressed in a positive frame (number of lives saved) whereas C is expressed in a negative frame (number of deaths). This example violates the invariance axiom of rational decision-making which requires the decision makers' decision choice to be independent of the problem formulation. Prospect theory (Kahneman and Tversky 1979) explains this paradox. According to this theory, people are risk-averse in gains (positive frame) and risk-seeking in losses (negative frame). In the Asian disease problem, the majority of people chose program A because they preferred the certainty of saving 200 lives over the 2/3 chance of saving none thereby exhibiting a risk-averse behaviour in a positive frame. Similarly, only few people chose program C

because they preferred the 2/3 probability of saving 600 people over the certain deaths of 400 people thereby exhibiting risk-seeking behaviour in a negative frame.

Since their original work, the influence of the framing bias has been studied in several different contexts of judgment and decision-making such as bargaining tasks (Schurr 1987), clinical decisions (Meyerowitz and Chaiken 1987; Block and Keller 1995), credit card usage (Homer and Yoon 1992; Ganzach and Karsahi 1995), auditing (O'Clock and Devine 1995), industrial buying decisions (Qualls and Puto 1989), and project funding (Dunegan 1993).

Framing biases can be divided into three types depending upon their operational definitions, underlying processes and their results: *attribute framing*, *goal framing*, and *risky choice framing* (Levin et al. 1998). In attribute framing, some characteristics of an object or event is manipulated. For example, subjects can be asked to rate ground beef by stating that it is either 80% lean or 20% fat (Levin and Gaeth 1988). Goal framing refers to acts in which the goal of an action is manipulated. For instance, subjects are asked to indicate the initiative level for reducing red meat after reading two messages: the positive consequence of doing so and the negative consequence of failing to do so. Risky choice framing, originally introduced by Tversky and Kahneman (1981), is one in which the risk perception involving the outcome of potential choices is manipulated. Examples of this type of framing bias are explored below.

The impact of risky choice framing has been observed in several occasions of investment decision-making. Research in the area of defined contribution retirement plans has demonstrated how the design of investment menu influences plan members' investment choices. An investment menu, which refers to the number and types of assets such as stocks and bonds made available for investment, is an "opaque" frame which most plan members cannot see through and thereby do not understand the underlying risk characteristic of their investments (Mitchell and Utkus 2003). Benartzi and Thaler (2001) conducted an experiment in which they asked retirement plan members to select an investment mix given two fund offerings. Some were given a choice of a stock fund and a bond fund; others were given a stock fund and a balanced fund; the remaining participants were given a bond fund and a balanced fund. It was found that most of the participants followed a simple heuristic of 50/50 mix of the two funds offered. While such an approach is aimed at simplifying the decision-making process, over-reliance on it would not always be desirable. Benartzi and Thaler (2001) noticed that the average allocation to stocks was 54%, 73%, and 35% respectively when the participants were given choices of a stock fund and a bond fund, a stock fund and a balanced fund, and a bond fund and a balanced fund. Clearly, the investment menu available to them influenced the participants' investment decisions.

In another study, plan participants were asked to select investments from three different menus consisting of four investments ranging from A (lowest risk) to D (highest risk) (Benartzi and Thaler 2002). The first menu included options A, B, and C; the second

menu included options B and C; and the third one included options B, C, and D. Interestingly, the participants' preference of C over B depended on the menu. For example, 29% preferred option C over B in the first menu, 39% in the second menu and 54% in the third menu.

Depending on the order of presentation, individuals give different weights to the same information (Hogarth 1987). Moreover, people are generally unaware of the frames that influence their choices (Fischhoff 1983). In fact, Shefrin and Statman (1993) discuss how the framing bias can be used to design and market financial products. Kuhberger (1998) provides an excellent meta-analysis of the influence of framing on risky decisions.

3.1.2 Representativeness

Representativeness 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, 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).

The statistical phenomenon of mean reversion, which gave rise to the term "regression", was noted by Sir Francis Galton about 100 years ago. While studying the height of men, he noticed that tall men usually had shorter sons and vice-versa. In financial markets, De Bondt and Thaler (1985) compared the performance of two groups of companies: winners (companies with higher than average returns) and losers (companies with lower than average returns). They found that the winners became losers and the losers became winners after a period of time, which indicated the existence of mean reversion in stock markets.

One implication of the neglect of mean reversion is that people chase "momentum", that is, they believe the current increase in prices is not random but an indication of a trend. For example, people see patterns even in a series generated with random numbers and become influenced by the way such information is presented (Hogarth and Makridakis 1981). 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 Benartzi 1999).

Due to the representativeness bias, people overrate the significance of salient information even though less salient information might be more appropriate to the decision problem at hand (Kirs et al. 2001).

3.1.3 Ambiguity

When individuals receive conflicting, incomplete, uncertain or excessive information, they experience ambiguity and make contradictory decisions as demonstrated by Ellsberg (1961). Ambiguity in investment decision-making is often caused by two factors: the uncertainty in asset pricing model and return distributions, and excessive information. In order to handle ambiguity of the former type, Gilboa and Schmeidler (1989) proposed a decision rule in which decision makers play a game against an opponent who knows the actual distribution of the gamble and tries to beat them as much as possible. Such a rule has been incorporated into a dynamic asset pricing model to cope with the uncertainty involved in distributions (Epstein and Wang 1994).

The role of information overload causing ambiguity in investment decision-making has been well documented. With the advent of the Web, investors are experiencing severe information overload (Associated Press 2005). Studies from defined contribution pension plan demonstrate that participants tend to make their choices based on the "path of least resistance" (Choi et al. 2002). When the complexity of decision-making increases, people tend to spend less effort to make their decision (Payne et al. 1996) and select their default options if available (Choi et al. forthcoming). In fact, on one

occasion, over eighty percent of the new plan participants in a Swedish pension plan decided to invest in the default option (Weaver 2002).

Iyengar et al. (2004) observe that increasing the number of fund choices for retirement investment decreases plan participation because people become mentally paralyzed when offered excessive choices. In order to overcome the problem of information overload, people employ a "diversification heuristic" whereby they choose a bit of everything in such situations (Read and Loewenstein 1995). However, such naïve approaches to decision-making lead to insufficiently diversified portfolios (Benartzi and Thaler 2001).

3.2 Affective Biases in Investment Decision-Making

Affective biases involve emotional elements such as pride, regret and fear. Emotion influences decision-making in a major way (Elster 1998; Hermalin and Isen 2000) and the quest for pride and the desire to avoid regret often result in demonstrably unwise investment decisions (Shefrin and Statman 1985). The house money and disposition effects are major investment-related affective biases.

3.2.1 House Money Effect

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 risks in multi-stage gambles such as investing if they have recently made some profits (Thaler and Johnson 1990).

3.2.2 Disposition Effect

The 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). This is exactly opposite to what should be done due to tax consideration. Investors sell their rising stocks too early and hold their falling stocks too long due to the disposition effect (Odean 1998).

3.3 Conative Biases in Investment Decision-Making

Conative biases constitute general human tendency (e.g., fear of unknown) and likely to exist in different countries and across markets. The conative component in human judgment and decision-making is a metalevel process with strong developmental roots (Corno 1989). Conative biases are persistent in nature and may exert their influences even in the absence of any new information (Bhandari and Hassanein 2004). With the exception of status quo, these biases tend to make individuals overconfident.

3.3.1 Overconfidence

Overconfidence, which refers to the systematic overestimation of the accuracy and precision of one's knowledge, has been observed in several contexts of judgment and

decision-making (Yates 1990). It is considered the most robust finding in the psychology of judgment (De Bondt and Thaler 1995). Previous studies have found that people generally overrate their qualifications and judgment capacity (Lichtenstein et al. 1982), and investors exhibit overconfidence even in such difficult tasks as stock selection (Barber and Odean 2002). The problem of overconfidence has become acute with the advent of the Internet as a primary information source which is likely to fuel the overconfidence of individual investors by giving them the illusion of knowledge (Barber and Odean 2001).

3.3.2 Familiarity

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). Due to familiarity, individuals become too wedded to their familiar views and may underreact to potentially important information.

3.3.3 Status Quo Bias

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 (2001) find that retirement plan participants do not change their portfolios and contribution rates for a long time due to the status quo bias, thereby forfeiting potential gains. They also observe

that investors' bias toward the status quo increases as the number of investment options increases.

3.4 Summary

Behavioural finance underscores that individuals' beliefs and preferences are the sources to several biases influencing investment decisions. Such beliefs and preferences, which are influenced by the environment and individuals' bounded rationality and bounded self-control, determine their attitude towards investing. Investing as an attitudinal object comprises of three components: cognitive, affective, and conative. Each of them has the potential to instigate corresponding biases.

Cognitive biases such as framing, representativeness, and ambiguity are information-processing biases caused by the order, salience, patterns, and amount of information received by decision makers. Affective biases like disposition and house money effects involve emotional elements such as fear and greed. Conative biases such as overconfidence, status quo, and familiarity are persistent in nature which may continue exerting their influences even in the absence of any new information.

The next chapter outlines a research framework, model and hypotheses for an empirical study investigating the effectiveness of decision aids in lessening the impact of cognitive biases discussed in this chapter.

CHAPTER 4

RESEARCH FRAMEWORK, MODEL AND HYPOTHESES

4.1 Research Framework

The cognitive approach to judgment and decision-making, first introduced by Edwards (1954), became firmly established when Tversky and Kahneman (1974) outlined a collection of heuristics in their empirical findings. Simon (1979), on the other hand, took the information processing approach and proposed cognitive processes as adaptive, boundedly rational systems functioning in a complex environment. Researchers have also started representing cognitive processes with algebraic equations. For example, the integration of information from diverse sources can be represented as algebraic operations involving differences and weighted averages and construed as degrees of belief (Anderson 1991b).

Research in cognitive psychology has taken two different approaches from the very beginning. One approach assumes that cognitive activity can be decomposed into a number of separate stages, and is concerned with identifying these stages and explaining how each stage operates (Chase 1978; Sternberg 1969). The other one, which takes the information processing approach, is concerned with how different stages interact and operate in complex cognitive processes like decision-making (Simon 1979). In terms of decision variables, the human information processing paradigm identifies two categories:

differences between decision environments, and differences among decision makers (Simon 1990). Payne et al. (1993) expanded this framework and explained decision-making as a function of three variables: the context, the problem, and the person. *Context* variables refer to differences in the decision-making environment that influence the way a decision maker views the decision problem. Different levels of urgency and accountability held by the decision maker are some examples of context variables. *Problem* variables refer to differences in decision attributes (e.g., alternatives available) and decision aids (e.g., graphical display, feedback) available to decision makers. *Person* variables refer to differences in decision makers' knowledge, emotions and mental ability to solve decision problems. The decision maker formulates a decision strategy as an interaction of several decision variables and executes it in his or her cognitive problem solving space by assigning meaning and importance to decision aids, if they are available (Newell and Simon 1972). Another model divides the decision-making process into three components: the person, the task environment and the actions resulting from the judgment (Hogarth 1987). In this model, a decision maker is represented by a schema and the operations within the schema are decomposed into acquisition, processing and output stages. The schema of a decision maker varies on three dimensions: *veridicality*, *stability*, and *generality*. Veridicality assesses the degree to which the schema represents reality. Stability refers to the consistency of information collection and processing. Generality refers to the universality of the information processing rules applied.

In Figure 4.1, a framework adapted from Van der Schans (1990) is suggested for incorporating cognitive support in investment DSS. The framework divides investment decision-making into four components: *world, mental model, software agents,* and *decision aids.* The *world* refers to investment and includes all external entities such as financial markets, current economic and political environment etc. that influence an individual's investment decisions. The *mental model* refers to an individual's understanding of the investment world and is primarily determined by his or her associated beliefs and preferences. The world and mental model involve the problem perspective. The *software agents* are computational systems that reside in a complex dynamic environment, perceive and act independently in this environment, and by doing so realize a set of goals or tasks for which they are designed (Maes 1995, p. 108). The *decision aids* refer to tools such as feedback and graphs with which "a DSS enlightens or sways its users as they structure and execute their decision-making process" (Silver 1991, p. 107). The software agents and decision aids involve the technology perspective. The framework (Figure 4.1) suggests that software agents and decision aids may influence a decision maker's mental model by engaging him or her in self-reflection. It is assumed that such reflections will lead to improved decision-making.

An empirical study is proposed in this chapter to investigate the effectiveness of such *decision aids* in lessening the impact of cognitive biases outlined in chapter 3. The potential usefulness of *software agents* in assisting investors engage in self-reflection will be demonstrated in chapter 6 while discussing a vision of a human-centered investment

DSS. The software agents and decision aids may follow different debiasing strategies to alert investors about their potential biases while making investment decisions.

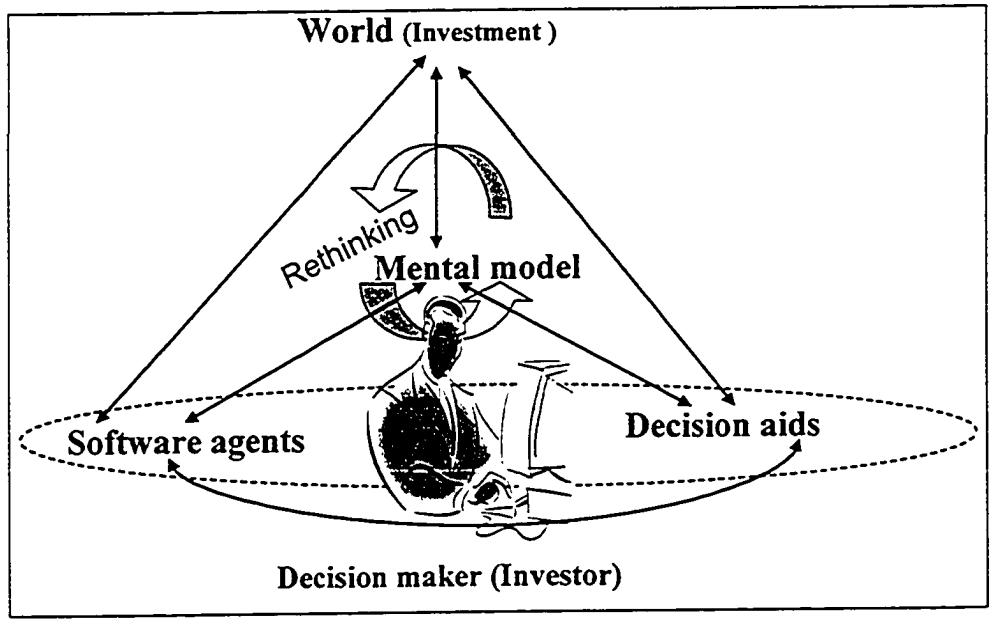

Figure 4.1 - Framework for incorporating cognitive support in a DSS
(Adapted from Van der Schans 1990)

Decision theorists and psychologists have proposed several general debiasing strategies to improve the quality of decision-making. Debiasing refers to the measures taken to lower the impact of biases in tasks involving human judgment and decision-making (Fischhoff 1982). Kahneman and Tversky (1982) make a distinction between situations where decision makers lack competence and those where they are competent yet fail to make the right decisions leading to comprehension errors and application errors respectively. Fischhoff (1982) focused on the sources of bias, which he identified as faulty decision makers, faulty tasks, and mismatches between decision makers and tasks.

For faulty (biased) decision makers he recommended four levels of debiasing activities: (a) warnings; (b) description of the problem; (c) personalized feedback; (d) and training. Similarly, Evans (1989) proposed replacement, education and training, redesign of the task environment, and the development of decision aids or decision support systems as different debiasing strategies. Researchers have proposed the incorporation of several decision aids such as feedback and graphs in DSS to combat different judgment and decision-making biases. Silver (1991) provides a framework for developing decisional guidance[4] 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. Adapting the framework used in a previous study (Lim and Benbasat 1997a), we propose a research model to assess the effectiveness of decision aids in lowering the impact of cognitive biases in investment decision-making (Figure 4.2).

4.2 Research Model

In the proposed model, the task entails decision-making under the influence of potential cognitive biases. For each task, the outcome involves two asset allocation decisions: first, in the absence of cognitive aids and then with the support of cognitive aids. Decisions 1 and 2 for each task are compared to assess the effectiveness of the cognitive aid provided for the decision task.

[4] Support, aids, and guidance are treated as synonyms in this dissertation.

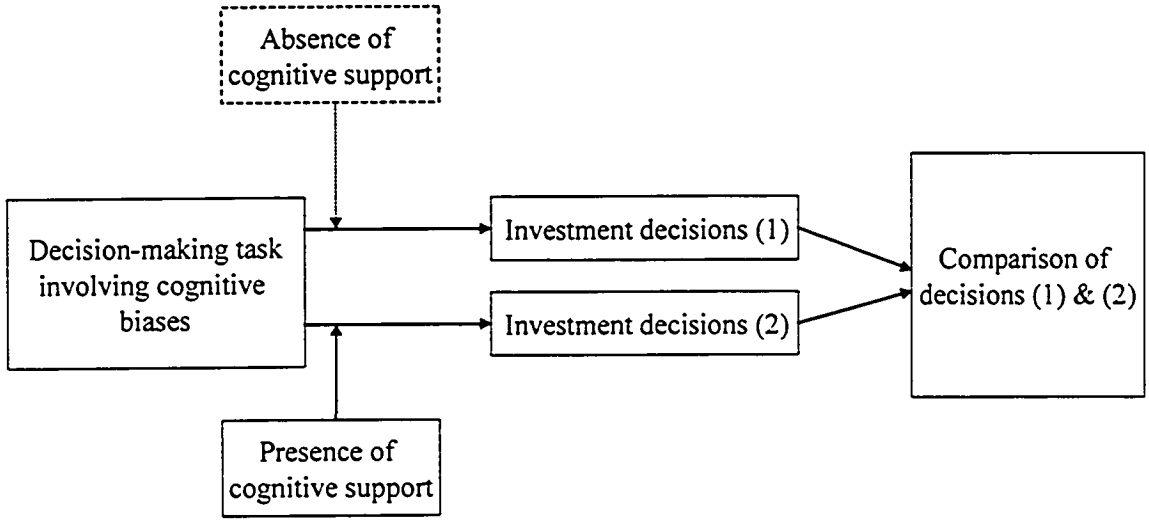

Figure 4.2 - Proposed research model

Table 4.1 outlines the three cognitive biases (framing, representativeness, ambiguity), their potential impact, and proposed cognitive aids to lessen their impact which have been found effective in previous studies (e.g., Alpert and Raiffa 1982; Anderson and Reckers 1992; DeSanctis and Jarvenpaa 1989; George et al 2000; Sharp et al. 1988).

Table 4.1- Cognitive biases, their potential impact and proposed cognitive support

Cognitive biases	**Potential impact of cognitive biases**	**Cognitive support**
Framing	Exhibit inconsistency between preferred or subjective risk level and actual asset allocation behaviour	Feedback *(Suggestive)*
Representativeness	Overrate the significance of salient information	Graphical presentation *(Informative)*
Ambiguity	Accept default choice due to information overload	Graphical presentation *(Informative)*

According to Felsen (1975), investment decision-making can be divided into two categories: asset allocation, and trading. Asset allocation is defined as the allocation of an investor's portfolio among a number of major asset classes (Sharpe 1992) and is the most important decision for an investor's long-term portfolio performance (Brinson et al 1991; Brunel 2003).

In the research model (Figure 4.2), the decision task refers to asset allocation decisions in scenarios involving either a high or a low level of one of the three cognitive bias-inducing environments. The level of bias involved in each scenario is manipulated as described in Table 4.2. For example, a scenario with a high level of framing bias will have more stock funds available for investment than the one with a low level of such a bias.

Table 4.2 - Cognitive biases and the manipulation of their levels

Cognitive biases	**Bias level manipulation by**
Framing	Different number of stock funds offered for investment *High level:* More stock funds made available *Low level :* Fewer stock funds made available
Representativeness	Varying information salience through different time-horizons and trends *High level:* Shorter time horizon with obvious trend *Low level:* Longer time horizon with less obvious trend
Ambiguity	Varying level of information load *High level:* Investment information involving more funds *Low level:* Investment information involving fewer funds

4.3 Research Hypotheses

The proposed research model and experimental setup (which will be discussed in detail in chapter 5) differ from previous studies in several ways. For example, the framing bias has been investigated as the asset allocation discrepancy between different portfolios (Benartzi and Thaler 2001) or menu choices (Benartzi and Thaler 2002). However, in this study, we consider framing as an inconsistency between an individual's stated risk tolerance level (subjective risk) and her actual investment decisions (objective risk) (Chang et al. 2004). Framing, when considered in this manner, can be used to suggest personalized portfolios and therefore, has more practical significance than previous approaches. Similarly, our experimental setup for the representativeness bias and ambiguity differ from other studies (Thaler and Benartzi 1999; Agnew and Szykman 2004) in terms of format, data and the nature of information used in designing decision tasks. This change was required to make the experiment suitable to a wide range of subjects (both with and without sufficient investment knowledge) and to be able to conduct it in one session without imposing too great a burden on participants. Despite these differences, we expect that the investment scenarios used in our experiment will also induce cognitive biases (framing, representativeness, and ambiguity) and, therefore, hypothesize the following:

H_1: Subjects experience cognitive biases while engaged in investment decision-making.

H_1 can be restated as follows for the three types of cognitive biases:

H_{1a}: Subjects experience a framing bias while engaged in investment decision-making.

H_{1b}: Subjects experience a representativeness bias while engaged in investment decision-making.

H_{1c}: Subjects experience ambiguity while engaged in investment decision-making.

Observing the complexity of the investment world, scenarios involving a high level of biases are more realistic than the ones involving a low level of biases. Vessey (1991) states that realistic experimental tasks are generally complex. Therefore, the following is hypothesized:

H_2: The impact of cognitive biases on the investment decision-making of subjects is more pronounced in high level cognitive bias scenarios than in low level ones.

H_2 can be restated as follows for the three types of cognitive biases:

H_{2a}: The impact of the framing bias on the investment decision-making of subjects is more pronounced in high level framing bias scenarios than in low level ones.

H_{2b}: The impact of the representativeness bias on the investment decision-making of subjects is more pronounced in the high level representativeness bias scenarios than in the low level ones.

H_{2c}: The impact of ambiguity on the investment decision-making of subjects is more pronounced in the high level ambiguity scenarios than in the low level ones.

Previous studies have investigated the benefit of cognitive aids such as feedback and graphs in different contexts and experimental settings (Alpert and Raiffa 1982; Anderson and Reckers 1992; Arunachalam and Daly 1995; Balzer et al. 1989; Balzer and Sulsky 1992; Benbasat et al. 1986; DeSanctis 1984; DeSanctis and Jarvenpaa 1989; George et al 2000; Ives 1982; Lim and Benbasat 1997b; Sharp et al. 1988; Te'eni 1991). We expect decision aids to be effective in lowering the impact of cognitive biases in investment decision-making and suggest the following:

H_3: Subjects, in the presence of cognitive support, experience reduced cognitive biases while engaged in investment decision-making.

H_3 can be restated as follows for the three types of cognitive biases:

H_{3a}: Subjects, in the presence of feedback, experience a reduced framing bias while engaged in investment decision-making.

H_{3b}: Subjects, in the presence of graphical aids, experience a reduced representativeness bias while engaged in investment decision-making.

H_{3c}: Subjects, in the presence of graphical aids, experience reduced ambiguity while engaged in investment decision-making.

As the decision-making environment becomes more complex, the behaviour of the decision-maker and the benefits of DSS also changes (Chewning and Harrell 1990; Einhorn and Hogarth 1981; Montazemi et al. 1996; Stocks and Harrell 1995). According

to Todd and Benbasat (1993), "the impact of the decision aid is more pronounced in task settings with a large number of alternatives to choose from." Since the scenarios with the high level of potential cognitive biases are designed to be more complex, we hypothesize the following:

H_4: The benefit of cognitive support increases as the level of potential cognitive biases in investment decision-making increases.

H_4 can be restated as follows for the three types of cognitive biases:

H_{4a}: The benefit of feedback increases as the level of potential framing bias in investment decision-making increases.

H_{4b}: The benefit of graphical aids increases as the level of potential representativeness bias in investment decision-making increases.

H_{4c}: The benefit of graphical aids increases as the level of potential ambiguity in investment decision-making increases.

The following hypothesis deals with the subjects' potential decision to use or neglect the aids provided to them. Despite the demonstrated benefit of decision aids, several researchers have found that people often do not utilize such aids (Ashton 1991; Meehl 1986; Yates et al. 2003). In a recent study, it has been observed that people's overconfidence contributes to their reluctance to use decision aids and that the reduction

in their overconfidence often leads to increased reliance on decision aids (Arkes et al. 1986; Sieck and Arkes 2005). Therefore, the following is hypothesised:

H_5: Subjects, who are overconfident in their financial knowledge, are more likely to neglect the cognitive support provided to them than those who are not overconfident while engaged in investment decision-making.

H_5 can be restated as follows for the three types of cognitive biases:

H_{5a}: Subjects, who are overconfident in their financial knowledge, are more likely to neglect the feedback provided to them than those who are not overconfident while engaged in investment decision-making involving a potential framing bias.

H_{5b}: Subjects, who are overconfident in their financial knowledge, are more likely to neglect the graphical aid provided to them than those who are not overconfident while engaged in investment decision-making involving a potential representativeness bias.

H_{5c}: Subjects, who are overconfident in their financial knowledge, are more likely to neglect the graphical aid provided to them than those who are not overconfident while engaged in investment decision-making involving potential ambiguity.

The next chapter discusses the experiment and the findings about these research hypotheses.

CHAPTER 5

EXPERIMENT AND RESULTS

5.1 Experiment

A Web-based DSS was developed using JavaScript, Active Server Pages and SQL Server for the experiment. After logging in to the system, subjects provided basic demographic data about themselves such as age, gender, education level, investment experience etc. (see Figure A.1 in Appendix I). Their risk tolerance level was assessed by asking them to identify themselves as one of the investor types outlined in Table 5.1. The table is based on the general guidelines provided by TIAA-CREF (2004)[5] and Bodie et al. (1999) for building portfolios for individual investors. TIAA-CREF is one of the most respected financial service providers in the world and includes Teachers Insurance and Annuity Association, College Retirement and Equities Fund and various affiliates.

In order to assess their investment knowledge, subjects were asked basic investment knowledge questions similar to the ones used in previous studies (Agnew and Szykman 2004; Wilcox 2003). Their tendency for overconfidence was measured by comparing the number of their correct responses to the number of questions they thought they answered correctly (see Figure A.2 in Appendix I). Subjects were then given the following instructions about the nature of the experiment.

[5] www.tiaa-cref.com

> Please imagine that you have $100,000 in a pension account and that you have control over how this money is invested. Depending on how well your investments do, you will have more or less money when you retire. In the following scenarios, you need to make investment decisions that will affect how much you have when you retire. Please take this survey seriously and make your decisions reflecting your real-world needs and behaviour. In order to facilitate your decision-making process, you may be provided with support tools.

The hypothetical nature of the asset allocation decision in the above scenarios should not be a concern as studies in judgment biases have found that hypothetical choices made by subjects do match real-world behaviour for small as well as large payoffs (Kuhberger et al. 2002).

Table 5.1- Investor types and their portfolio characteristics

Investor types	Description
Very aggressive	Someone who is willing to assume substantial risk to earn high returns; portfolio is very heavily invested in stocks.
Moderately aggressive	Someone who is willing to assume reasonable risk to earn fairly high returns; portfolio is leaning strongly towards stocks over bonds.
Growth-oriented	Someone who is willing to assume some risk for capital appreciation but wants to preserve capital; portfolio is leaning towards stocks over bonds.
Capital preservation-oriented	Someone who is willing to assume moderate risk in the hopes of somewhat higher returns; portfolio is leaning towards bonds over stocks.
Moderately conservative	Someone who is unwilling to assume much risk to earn higher returns; portfolio is leaning strongly towards bonds over stocks.
Very conservative	Someone who is unwilling to assume any risk; portfolio is very heavily invested in bonds.

Each subject made investment decisions in three scenarios. The three scenarios examined the three types of cognitive biases (framing, representativeness, and ambiguity) discussed in section 3.1. Each scenario was designed to assess only one of the three cognitive biases. The following section discusses these scenarios in detail.

5.2 Investment Scenarios

Six different scenarios (three pairs of low and high level biases) were designed for the experiment. The bias level in these scenarios was manipulated as outlined in Table 4.2. Each subject was assigned three scenarios in such a way that no two scenarios represented the same bias type. The order in which these scenarios were presented to the subjects was also completely random[6]. There were 48 different possible permutations of these six scenarios taken three at a time. The following paragraph explains how this number is derived.

Out of 6 different scenarios, the first scenario could be chosen in 6 ways. The second scenario could be chosen in 4 ways only (and not 5) because the scenario with the same bias category as that of scenario 1 must be excluded from the list. Reasoning in similar way, it follows that the third scenario could be chosen in 2 ways. From the multiplication law of counting, it follows that the total number of possible combinations is given by 6x4x2, which is 48. All possible permutations were used in the experiment.

[6] However, the program was written to ensure the presentation of almost equal number of high and low level bias scenarios to subjects. The same procedure was followed in pilot test and main experiment.

5.2.1 Scenarios Examining the Framing Bias

Due to the framing bias, individuals may exhibit inconsistency between their desired risk tolerance level and their actual asset allocation decisions as discussed in chapter 3. As outlined in Table 4.2, the level of potential framing bias in the investment scenarios can be manipulated by varying the number of stock funds made available for investment.

The scenario in Figure 5.1 involves a potential low level framing bias because the availability of only one stock fund for investment is likely to encourage individuals to allocate a lower percentage of their portfolio to stocks than that in the scenario shown in Figure 5.2 (e.g., Benartzi and Thaler 2001).

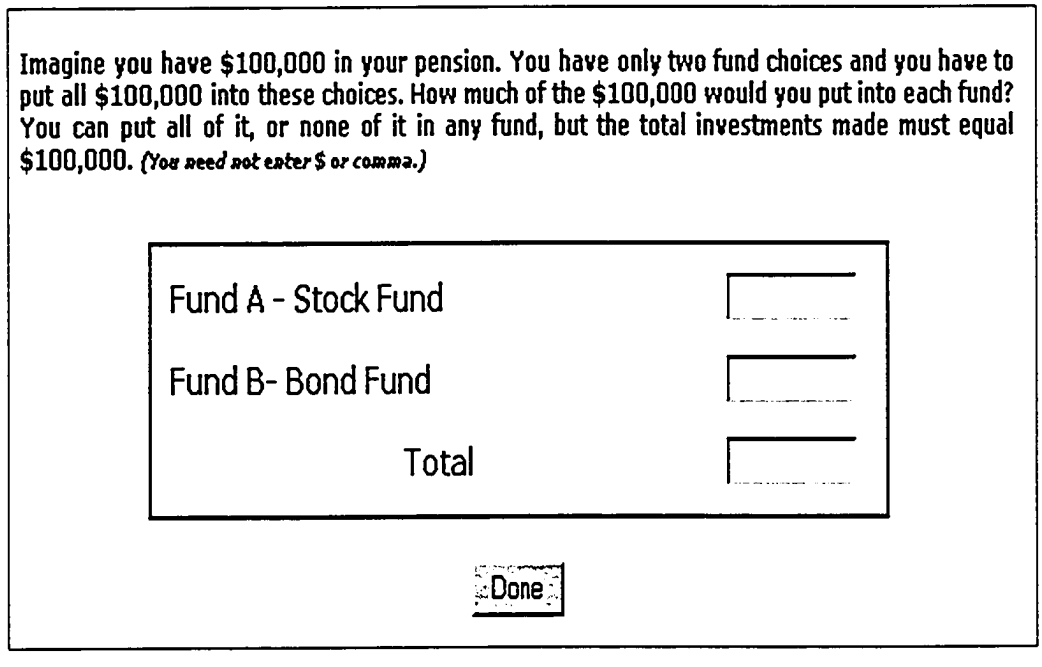

Figure 5.1 - Scenario involving a potential low level framing bias

Conversely, the scenario in Figure 5.2 involves a potential high level framing bias because more stock funds are available for investment in this case.

Imagine you have $100,000 in your pension. You have ten fund choices and you have to put all $100,000 into these choices. How much of the $100,000 would you put into each fund? You can put all of it, or none of it in any fund, but the total investments made must equal $100,000. *(You need not enter $ or commas.)*

Stock Funds (Nine choices)	
Large Cap & Value	
Large Cap & Core	
Large Cap & Growth	
Mid Cap & Value	
Mid Cap & Core	
Mid Cap & Growth	
Small Cap & Value	
Small Cap & Core	
Small Cap & Growth	
Bond Fund	
Total	

Note:

"Cap" is short for capitalization, which indicates the market size of a stock. Large cap, mid cap, and small cap refer to the size of the capital of companies issuing stocks. Value stocks are those stocks whose prices are low relative to their book value or earnings. Growth stocks are stocks whose prices are high relative to their book value or earnings. Core stocks fall between value and growth categories.

Done

Figure 5.2 - Scenario involving a potential high level framing bias

5.2.2 Scenarios Examining the Representativeness Bias

Due to the representativeness bias, individuals overrate the significance of salient information such as rising stock prices and believe that the current increase in prices is not random but an indication of a trend as discussed in chapter 3. As outlined in Table 4.2, the level of potential representativeness bias in investment scenarios can be

manipulated by varying the salience of presented information with different time horizons and trends.

The scenario in Figure 5.3 involves a potential low level representativeness bias. Due to representativeness, individuals erroneously believe that stock X will perform better than stock Y and thereby they may invest more in stock X. Since there is very little basis for the view that historical performance will be repeated in the future, the significantly higher allocation to stock X may only jeopardize the diversification of their portfolio. A roughly even split of the assets between these stocks would indicate the absence of a representativeness bias (Deaves 2005). This scenario examines a low level representativeness bias because the graph shows that stock X has not always been the clear winner. In fact, in months 3, 4, 5, and 6, stock Y outperformed stock X. Furthermore, the time-horizon in this scenario is 12 months, which is longer than the one employed in the scenario involving the high level bias (Figure 5.4). The return series for stocks X and Y were generated through an Excel spreadsheet using a random function with mean value of zero. In a randomly generated series, the longer the time horizon, the less salient the series appears.

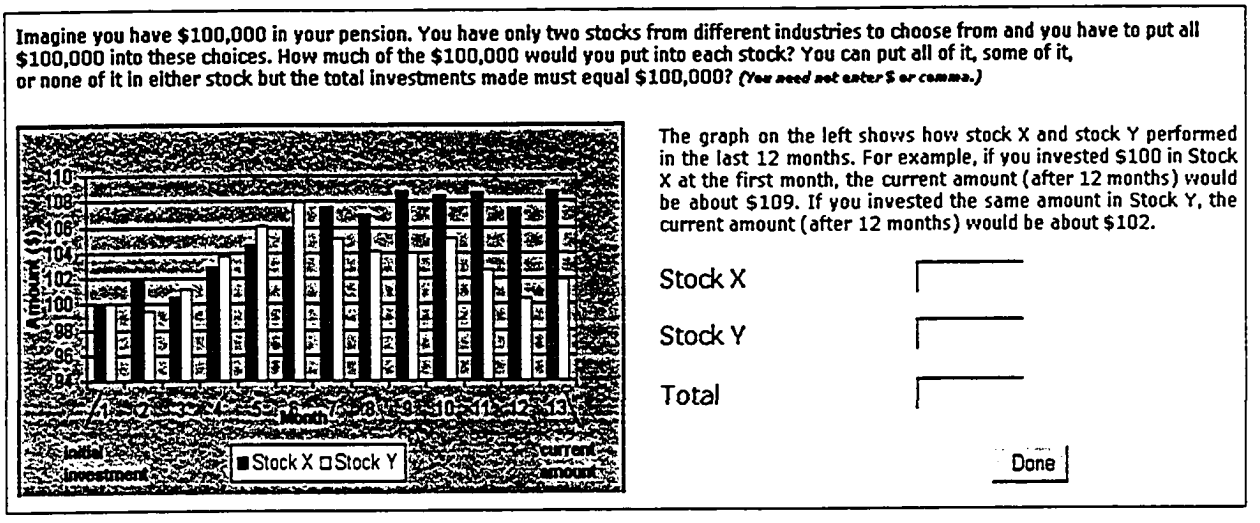

Figure 5.3 - Scenario involving a potential low level representativeness bias

The scenario in Figure 5.4 involves a potential high level representativeness bias because the graph depicts that stock A has always been outperforming stock B. Furthermore, the time-horizon in this scenario is 6 months, which is shorter than the one in the low level bias scenario (12 months). The return series for stocks A and B were generated through an Excel spreadsheet using a random function with mean value of zero. In a randomly generated series, the shorter the time horizon, the more salient the series appears due to presence of short-term trends.

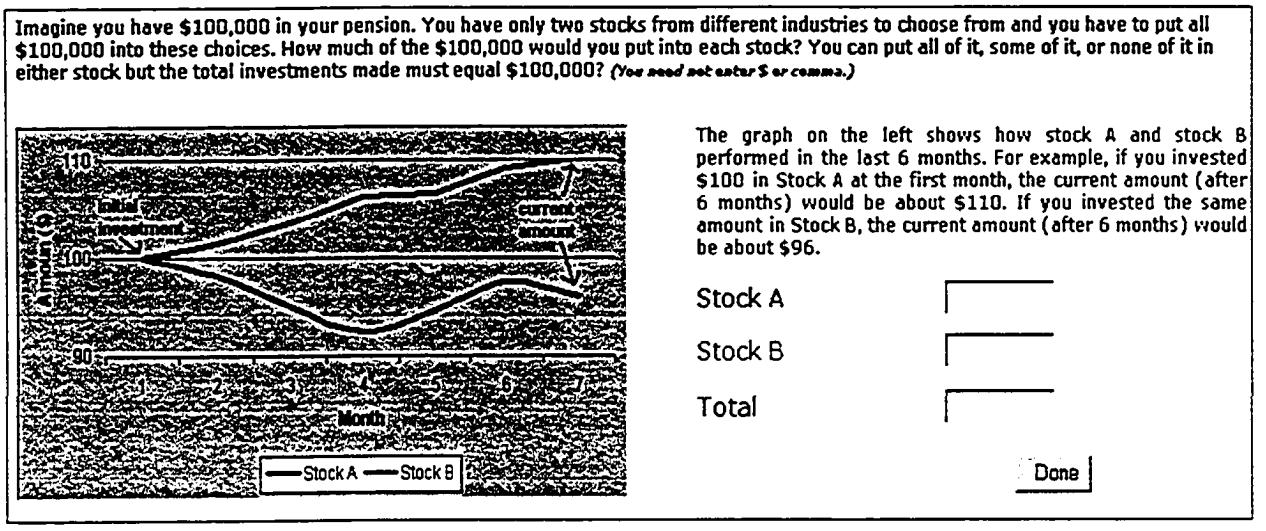

Figure 5.4 - Scenario involving a potential high level representativeness bias

5.2.3 Scenarios Examining Ambiguity

Due to ambiguity, individuals may become unable to process the information provided to them and accept the default choice (if available) even if such an option is demonstrably sub-optimal as discussed in chapter 3. As outlined in Table 4.2, the level of potential ambiguity can be manipulated by varying the level of information load given to subjects.

The scenario in Figure 5.5 provides a potential low level ambiguity situation because it involves asset allocation decisions with only three bond funds. It is expected that subjects influenced by ambiguity will accept the default investment option in which the *National Bond Fund* comprises 50% of the portfolio. However, comparing the data about its management expense and historical returns with other bond funds available for investment, it becomes apparent that this fund is an underperformer. Since there is no

other information about these funds and since the instruction given to subjects states that the performance of these funds is comparable with each other, the subjects' decision to accept the default investment option could only be due to ambiguity.

Corporate bonds-17.2%, Provincial bonds-20.4%, Canada bonds-51.3%, and others (including cash)-11.1%.The historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 5.3%, 8.7% and 10.4%. The management fee for this fund is 0.75%.

Smart Bond Fund: The primary objective of this fund is *total return* with *interest rate anticipation* as its management style. The fund has the following asset allocation: Corporate bonds-70.7%, Provincial bonds-3.6%, Canada bonds-15.3%, and others (including cash) -10.4%.The net historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 4.3%, 8.1% and 8.5%. The management fee for this fund is 1.68%.

Suppose you have been investing $100,000 in the following manner since the last 2 years.

National Bond Fund	50000
Bond IndexFund	25000
Smart Bond Fund	25000
Total	100000

Would you like to continue making your investments as above? ○ Yes ○ No

Done

Figure 5.5 - Scenario involving a potential low level ambiguity bias

The scenario in Figure 5.6 provides a potentially high level of ambiguity because it involves asset allocation decisions with six bond funds. As before, subjects' decision to accept the default investment option could only be due to ambiguity. It should be noted that the subjects were not barred from using pencil and paper while making their decisions in both scenarios.

Smart Bond Fund: The primary objective of this fund is *total return* with *interest rate anticipation* as its management style. The fund has the following asset allocation: Corporate bonds-70.7%, Provincial bonds-3.6%, Canada bonds-15.3%, and others (including cash) -10.4%.The net historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 4.3%, 8.1% and 8.5%. The management fee for this fund is 1.68%.

Suppose you have been investing $100,000 in the following manner since the last 2 years.

National Bond Fund	50000
XYZ Bond Fund	10000
ABC Bond Fund	10000
Green Fund	10000
Bond Index Fund	10000
Smart Bond Fund	10000
Total	100000

Would you like to continue making your investments as above? ○ Yes ○ No

Done

Figure 5.6 - Scenario involving a potential high level ambiguity bias

Figures 5.5 and 5.6 show only a portion of information given to the subjects. For the complete information provided to them, please refer to Appendix II. The information provided in these scenarios is adapted from Chevreau et al. (1999).

5.3 Cognitive Support

In this experiment, feedback and graphs were provided as cognitive support to subjects engaged in investment decision-making. In each scenario, subjects gave their initial decision (without cognitive support) and the DSS recorded that information. For the same scenario, subjects were then provided with appropriate cognitive support (if needed) and their response was again recorded. This sequence was followed in all scenarios. For example, consider the subjects who received three scenarios in this order: a scenario involving a *framing bias*, a scenario involving a *representativeness bias*, and a scenario involving *ambiguity*.

First of all, they would make a decision in the first scenario involving the framing bias. Their initial response would be recorded by the DSS. Depending on their input, they might receive a feedback warning them of their inconsistency between their preferred portfolio type and their actual asset allocation behaviour. Subjects who exhibited consistency between their risk preference level and their asset allocation decisions would not receive any feedback. Subjects receiving the feedback would have the chance to reconsider their previous decision. However, they would be free to neglect the feedback as well. The DSS would record all the responses from the subjects. Then subjects would make a decision in the second scenario involving the representativeness bias. As before, subjects would make a decision without receiving any cognitive support (a graph in this case). Once their initial response was recorded by the DSS, subjects would be provided with a graph furnishing relevant information about the decision task. All subjects would

receive this information (i.e. the availability of the graph would not depend upon their initial input) as the decision support in this case is intended to be *informative* in nature. The objective of informative guidance is to enlighten a decision maker's judgment by furnishing relevant information (Silver 1991). As before, subjects would be free to reconsider their decision or neglect this information and move on to the next scenario. The procedure for issuing the cognitive support for a scenario involving ambiguity is similar to that of the representativeness bias scenarios and hence, will not be repeated here. The following subsections discuss the design of cognitive tools in detail.

5.3.1 Cognitive Support for the Framing Bias

Due to the framing bias, individuals exhibit inconsistency between their desired risk tolerance level and their actual asset allocation decisions. Feedback alerting them of their asset allocation inconsistency was employed as a debiasing tool. Depending on the level of mismatch between their stated risk preference and actual stock allocation as a percent of their portfolio, subjects received one of two types of feedback. This procedure is explained with an example.

Let us consider a growth-oriented investor who is willing to assume some risk for capital appreciation but wants to preserve capital. The portfolio of such an investor is leaning towards stocks over bonds as outlined in Table 5.1. Table 5.2, which is based on the general guidelines provided by TIAA-CREF (2004) and Bodie et al. (1999), suggests that the appropriate stock allocation for this type of investor should be 50%-70% of the

portfolio. The subject would receive level 1 feedback if she allocated 40%-50% or 70%-80% to stocks and level 2 feedback if the stock allocation is less than 40% or more than 80%. In general, the feedback is issued to subjects whose equity allocations are beyond the range of ± 10% from the mid point of their recommended allocation range (refer to Table 5.2). A similar criterion was used in a previous study involving the anchoring and adjustment bias (George et al. 2000).

Table 5.2 - Investor types, recommended stock allocations and feedback levels

Investor types	**Recommended stock allocation (% of portfolio)**[7]	**Feedback – Level 1 (stock as % of portfolio)**	**Feedback – Level 2 (stock as % of portfolio)**
Very aggressive	90-100	80-90	<80
Moderately aggressive	70-90	60-70; 90-100	<60
Growth-oriented	50-70	40-50; 70-80	<40; >80
Capital preservation-oriented	30-50	20-30; 50-60	<20; >60
Moderately conservative	10-30	0-10; 30-40	>40
Very conservative	0-10	10-20	>20

Level 1 feedback (Figure 5.7) informs the subjects that their allocation is *inconsistent* with their risk preference level whereas level 2 feedback (Figure 5.8) alerts them that they are being *very inconsistent* with their risk preference level. With both feedback levels, subjects are free to consider or neglect the feedback given to them. It should be noted that feedback was issued only once. That is, if subjects were inconsistent in their decisions even after the receipt of feedback, they were not warned further. This was designed to avoid the potential convergence of the subjects' responses to their actual

[7] For robustness, wide intervals have been used for the recommended stock allocation ranges.

risk preferences due to successive feedbacks issued by the DSS. Another important attribute of the feedback is its non-directional nature. That is, the feedback only informed subjects about their inconsistency and did not tell them whether they should increase or decrease their stock allocation.

The feedback was *suggestive* in nature in the sense that it gave some indication about the magnitude of their inconsistency (i.e., inconsistent, very inconsistent). George et al. (2000) employed similar neutral feedback in their experiment involving the anchoring and adjustment bias.

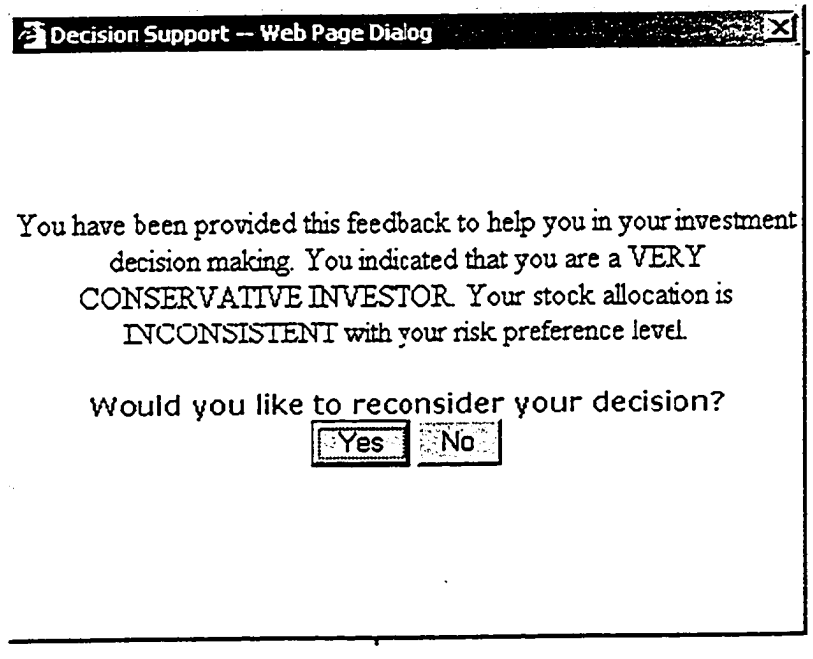

Figure 5.7 - Level 1 feedback for the framing bias

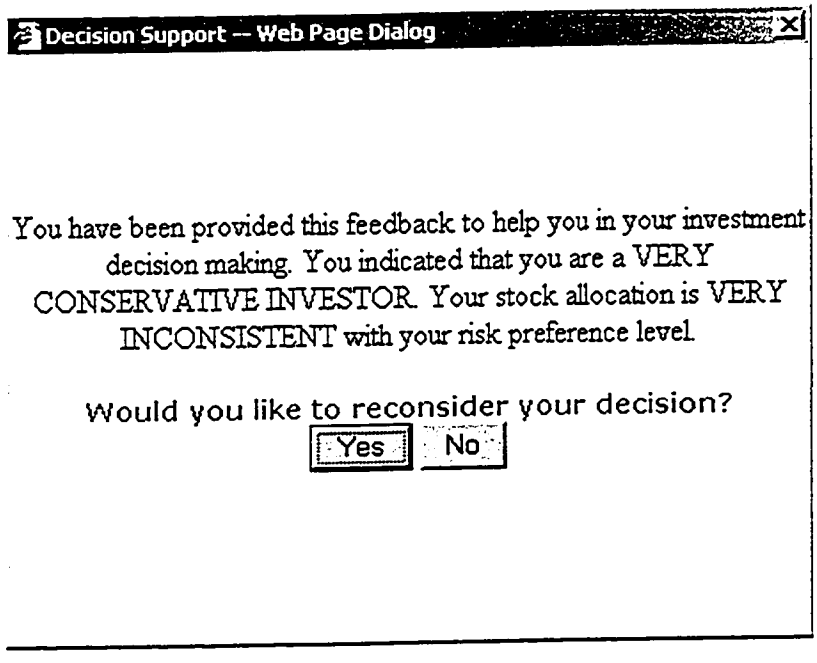

Figure 5.8 - Level 2 feedback for the framing bias

5.3.2 Cognitive Support for the Representativeness Bias

Due to the representativeness bias, individuals overrate the significance of salient information such as rising stock prices and erroneously believe that the current increase in prices is not random but an indication of a trend. The graph in Figure 5.9 is intended to serve as a decision aid in overcoming the influence of the representativeness bias inherent in the scenario shown in Figure 5.3.

By observing the returns for the longer time horizon (3 years), subjects may correctly infer that there is no significant difference in the historical performance of stock X and stock Y since the cumulative returns for both of them for the last three years are

almost equal. It is expected that subjects will allocate roughly equal amounts to these stocks after observing this graph (e.g., Thaler and Benartzi 1999).

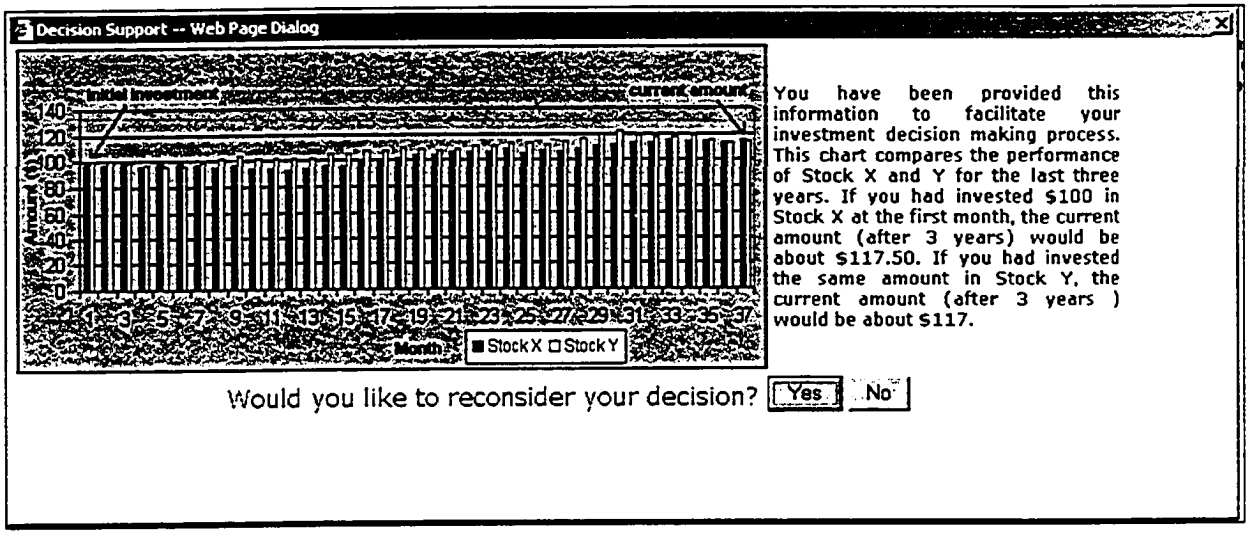

Figure 5.9 - Graph for the scenario involving a potential low level representativeness bias

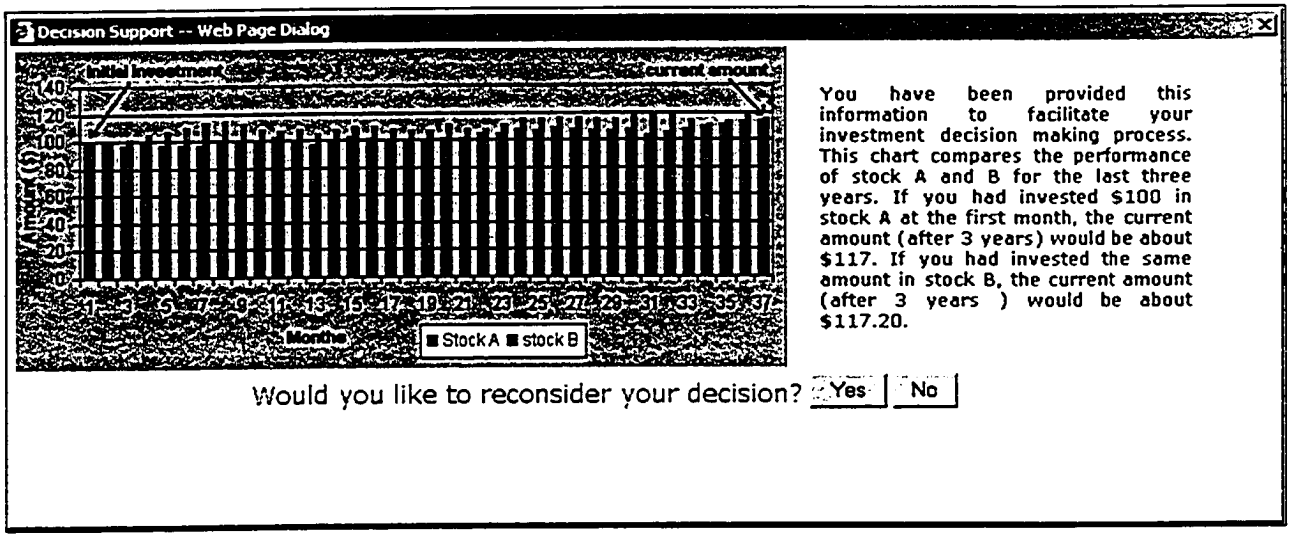

Figure 5.10 - Graph for the scenario involving a potential high level representativeness bias

Similarly, the graph shown in Figure 5.10 is intended to serve as a decision aid for the scenario shown in Figure 5.4. As before, the subjects may correctly infer that there is no significant difference in the historical performance of stock A and stock B since the cumulative returns for both of them for the last three years are almost equal. It is expected that subjects will allocate roughly equal amounts to these stocks after observing this graph. This cognitive support (i.e. graph) is informative in nature as it is expected to enlighten the subjects' judgment by furnishing relevant information to them (Silver 1991).

5.3.3 Cognitive Support for Ambiguity

Due to ambiguity, individuals may become unable to process the information provided to them and accept the default choice (if available) even if such an option is demonstratively sub-optimal. The graphs (Figure 5.11 and 5.12), which show the relevant information (net compound returns) as bar diagrams, are intended to serve as decision aids in overcoming the influence of the ambiguity inherent in the scenarios shown in Figures 5.5 and 5.6 respectively. It is expected that subjects will not accept the default choice (which is not optimal) after seeing the graphs as they depict the *National Bond* fund as the clear loser in both scenarios. This cognitive support (i.e., graph) is informative in nature as it is expected to assist the subjects' decision-making by presenting the information in a more understandable format (Silver 1991).

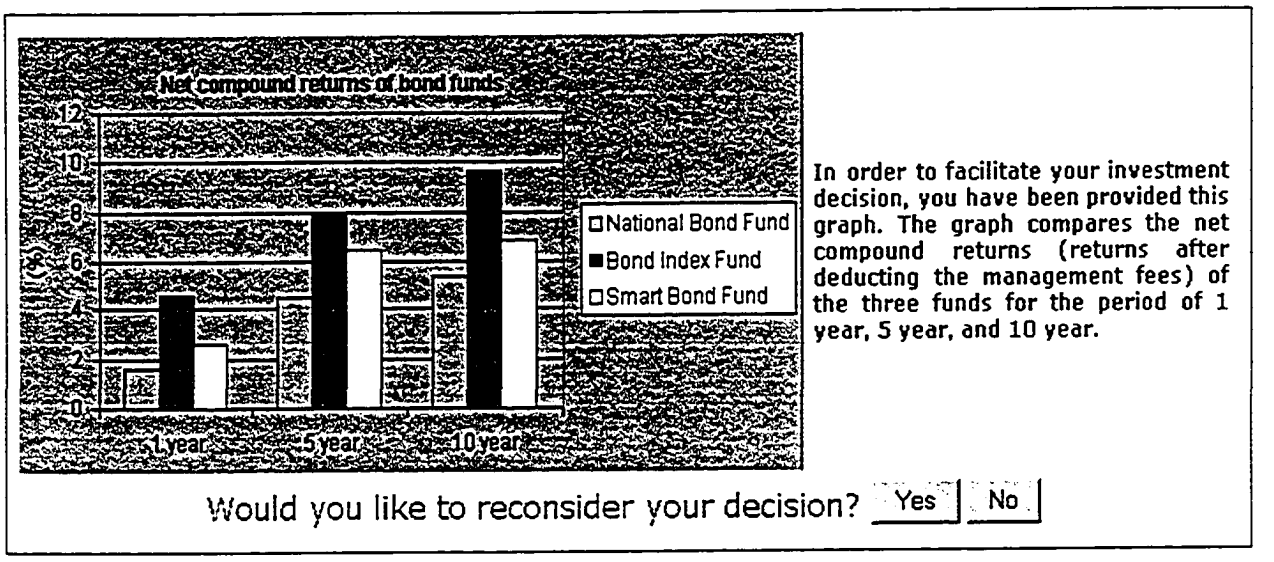

Figure 5.11 - Graph for the scenario involving a low level ambiguity bias

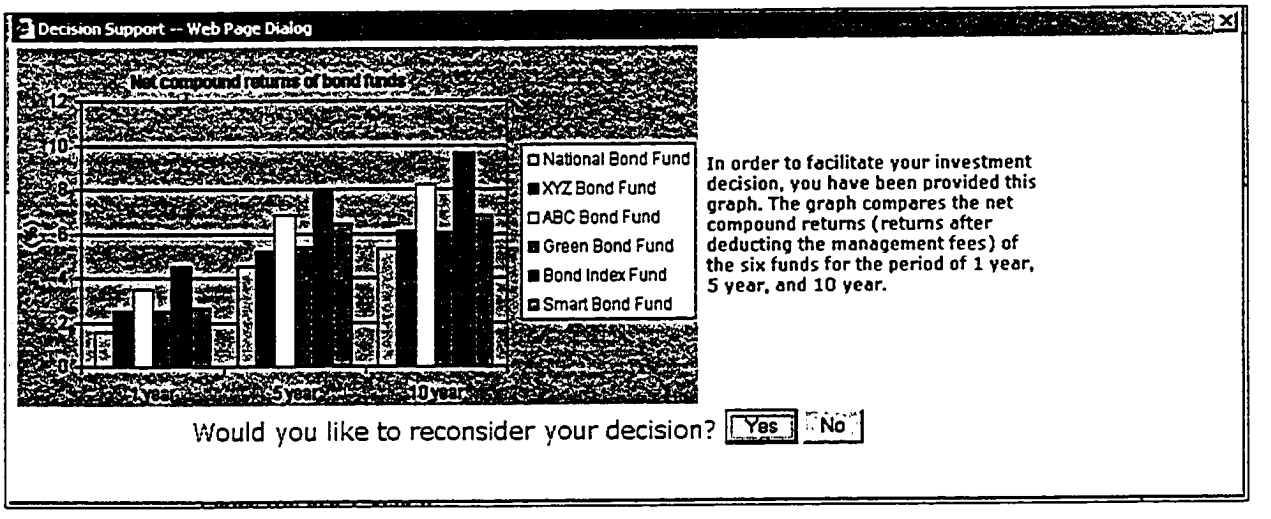

Figure 5.12 - Graph for the scenario involving a high level ambiguity bias

5.4 Data Analysis Methodology

In this section, we discuss the data analysis methodology for investigating whether the research hypotheses outlined in chapter 4 are supported for each of the three cognitive biases of framing, representativeness, and ambiguity. The proposed hypotheses are tested following the guidelines suggested by Aaker et al. (2000, p. 447). When the sample size in each group is more than 30, the t-statistic is used for comparing sample proportions and means. When the sample size is less than 30 and more than 4, the chi-square test is used to test the independence of two samples. A brief description of the chi-square test of independence, its relevant test statistics (Pearson χ^2 and Maximum-Likelihood χ^2) and measures of association (φ coefficient and contingency coefficient) is provided in Appendix III. A brief description of proportions, means, and frequency distributions in the context of our experimental setup is provided below.

Proportions: A statistical significance test involving proportions examines the equality of sample proportions such as the number of subjects exhibiting the framing bias across low and high bias level scenarios.

Means: A statistical significance test involving means examines the equality of sample means of some numerical variables such as amounts (in $) invested in stock A and stock B.

Frequency distributions: When the sample size in a group is less than 30, the data will be analyzed in terms of their frequency distributions. A statistical test involving frequency distributions examines the equality of sample proportions in a 2x2 table. For example, consider a 2x2 table that reports the number of subjects exhibiting the framing bias across low and high level bias scenarios depending on whether the subjects are overconfident or not.

Tables 5.3, 5.4, and 5.5 outline the data analysis approaches used for the framing, representativeness, and ambiguity biases respectively. All hypotheses are tested at the significance level of 5%. Observations such as *mean stock allocation (MSA)* and *standard error (SE)* are also reported for some hypotheses involving the framing bias to demonstrate how the average stock allocations for each type of investors (e.g., very aggressive, aggressive etc.) have differed from their corresponding *recommended stock allocation (RSA).* The rationale for the proposed tests and acronyms involved in different hypotheses will be evident while discussing findings for each research hypothesis.

Table 5.3 - Data analysis approach for the framing bias

Null Hypotheses	Test	Test statistics/ observations
For H_{1a} - ASA is within the RSA.	Proportions	t
For H_{2a} - Deviations of ASA from the RSA in high level scenarios are equal to or smaller than those in low level scenarios before feedback.	Means	MSA & SE
	Proportions	t
For H_{3a} - Deviations of ASA from the RSA before feedback are equal to or smaller than those after feedback.	Means	MSA & SE
	Proportions	t
For H_{4a} - Deviations of ASA from the RSA in high level scenarios are equal to or smaller than those in low level scenarios after feedback.	Means	MSA & SE
	Proportions	t
For H_{5a} - Feedback usage by overconfident subjects is equal to or higher than that by subjects who are not overconfident.	Proportions	t

ASA- Actual Stock Allocation; RSA – Recommended Stock Allocation; MSA- Mean Stock Allocation; SE - Standard Error

Table 5.4 - Data analysis approach for the representativeness bias

Null Hypotheses	Test	Test statistics
For H_{1b} - AAWS is less than or equal to the cutoff level*.	Means	t
	Proportions	t
For H_{2b} - AAWSs in high level scenarios are equal to or smaller than those in low level scenarios before the receipt of graphical aids.	Means	t
For H_{3b} - AAWSs before the receipt of graphical aids are equal to or smaller than those after the receipt of such aids.	Means	t
	Freq. Dist.	χ^2
For H_{4b} – ACAs/AAWSs in high level scenarios are equal to or smaller than those in low level scenarios after the receipt of graphical aids.	Means	t
For H_{5b} – Graphical aid usage by overconfident subjects is equal to or higher than that by subjects who are not overconfident.	Proportions	t

AAWS — Actual Allocation to Winning Stocks; ACA – Average Correction Amount; Freq. Dist. – Frequency Distributions; * refers to the amount of $55,000 (allocation more than this amount will indicate the influence of the representativeness bias)

Table 5.5 – Data analysis approach for the ambiguity bias

Null Hypotheses	Test	Test statistics
For H_{1c} – The number of SADC is less than or equal to the number of subjects not accepting such choices.	Proportions	t
For H_{2c} - The number of SADC in high level scenarios is equal to or smaller than that in low level scenarios before the receipt of graphical aids.	Proportions	t
For H_{3c} - The number of SADC before the receipt of graphical aids is equal to or smaller than those after the receipt of such aids.	Freq. Dist.	χ^2
For H_{4c} – The change in the number of SADC in high level scenarios is equal to or smaller than that in low level scenarios after the receipt of graphical aids.	Proportions	t
For H_{5c} – Graphical aid usage by overconfident subjects is equal to or higher than that by subjects who are not overconfident.	Proportions	t

SADC – Subjects Accepting the Default Choices

5.5 Pilot Study

Seventeen graduate students of McMaster University were involved in a pilot test of the experiment conducted in the university's Decision Centre. After logging in to the Web-based DSS, the participants provided basic demographic data about themselves as outlined in section 5.1. Each participant was assigned three scenarios as described in section 5.2.

During the pilot test, we noticed that the color and the size of the font used in the feedback (for scenarios involving the framing bias) had little impact on the subjects' decision whether to take the feedback seriously and consequently, we decided to use the standard font (Times New Roman, 12 size, black) for the feedback in the main

experiment. Participants recommended the use of capital letters to highlight the investor type and level of inconsistency in the feedback message. They also suggested providing a note explaining the different terminologies used in the high level framing bias scenario (see Figure 5.2).

In the exit survey, students were given both low level and high level scenarios for each type of bias to check the validity of the manipulation of bias levels (as outlined in Table 4.2). They were asked to indicate their level of agreement (on a scale of 1 to 10; 1 being the minimum agreement and 10 being the maximum agreement) with statements comparing different aspects of low and high level scenarios for the three types of biases. For example, they were asked whether their stock allocation would be more in the scenario of Figure 5.1 than that of Figure 5.2. The null hypotheses that there were no differences between low and high level scenarios for each type of bias were strongly rejected (at the 5% significance level) with p-values of 0.0000 in all cases.

In the exit survey, participants also agreed that the information and instructions provided to them were clear enough to complete the experiment on their own. It was also observed that the average time required to complete the experiment was 16 minutes with 12 minutes and 22 minutes as the minimum and maximum respectively. Some minor technical issues (e.g., database update, browser compatibility, screen resolution and refreshing etc.) encountered during the pilot test were resolved later.

5.6 Subjects

Ethics clearance to involve human participants in this research was obtained from McMaster University's research ethics board. For the main experiment, McMaster University employees (faculty and staff) were recruited by sending an email to the employee mailing list. A general announcement requesting the participation was also made on the university's daily news website. Subjects were required to use their email addresses for logging into the system. At the beginning of the experiment, subjects were informed about the nature of the experiment, their ability to terminate the experiment at any time, eligibility, expected duration, demographic data collected etc. Subjects needed to electronically sign a consent form to start participating in the experiment. Subjects used their own machines to participate in the experiment and were not monitored. The experiment was open for a period of three weeks.

A total of 143 university employees (faculty and staff) participated in the main experiment of which 21 did not complete the full experiment. Three subjects spent very little time (5 min, 5 min, and 7 min) in the experiment. Their data were not included in the analysis as it was inferred that they could not have taken the experiment seriously in such a short period of time. All other participants had spent more than 10 minutes in the experiment. The validity of the email addresses provided by the subjects was checked by sending a confirmatory message to them informing the successful completion of their experiment. All email addresses were found to be valid. As compensation for participating in the experiment, participants were given the chance to enter their email

addresses for a random draw involving four cash awards. At the conclusion of the experiment, four subjects received $250 each. Similar incentive structure was used in previous studies (e.g., Benartzi and Thaler 2001). Table 5.6 summarizes the demographic data collected from subjects who participated in the experiment.

Table 5.6 – Summary of the subjects' demographic data

Variable	
1. Age	Mean: 39.9 years
2. Gender	Male: 41 (34.45%), Female: 78 (65.55%)
3. Marital status	Married: 76 (63.87%), Single: 43 (36.13%)
4. Education (1-no college; 2-some college; 3-graduated; 4-PhD)	Mean: 2.98
5. Currently investing?	Yes: 90(75.63%), No: 29 (24.37%)
6. Investment experience in years	Mean: 6.8 years
7. Profession	Faculty: 22 (18.49%; Staff: 97 (81.51%)
8. Self-rated knowledge (1-very little to 10-very much)	Mean: 5.51
9. Portfolio type (1- very aggressive to 6-very conservative)	Mean: 3.65

Subjects had an average of 6.8 years of investment experience, with the maximum being 30 years. About 24% of the subjects had no investment experience at all. The average age of the participants was 39.9 years. Figures 5.13, 5.14, 5.15 show the histograms of the subjects' age, years of investment experience, and self-rated knowledge respectively.

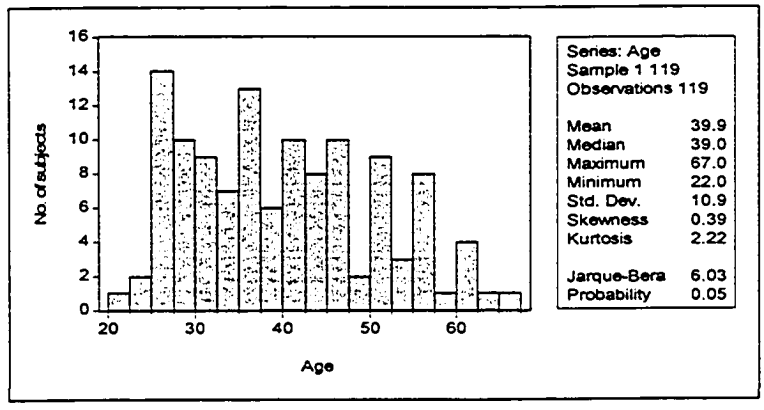

Figure 5.13 - Histogram of the subjects' age

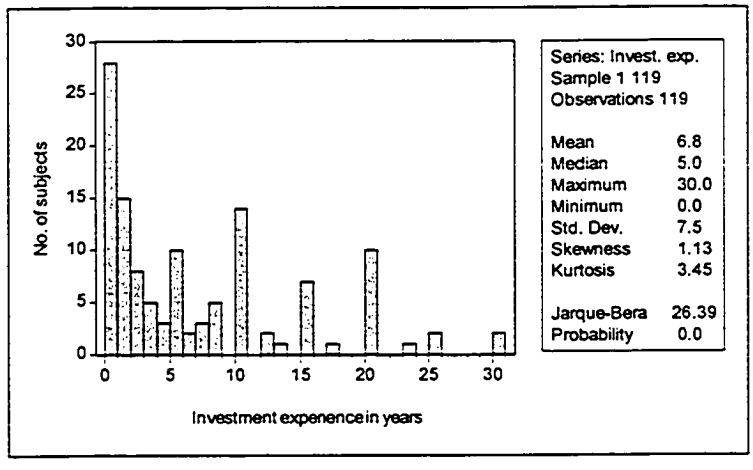

Figure 5.14 - Histogram of the subjects' investment experience

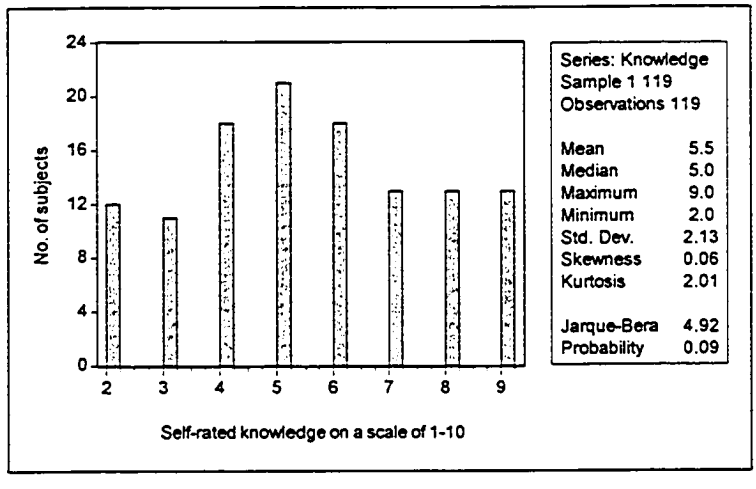

Figure 5.15 - Histogram of the subjects' self-rated knowledge

5.6.1 Overconfidence Assessment of the Subjects

One of the research hypotheses (H_5) outlined in chapter 4 postulates that subjects, who are overconfident in their financial knowledge, are more likely to neglect the cognitive support provided to them than those who are not overconfident. This section discusses the procedure followed in the experiment to assess the subjects' tendency for overconfidence.

When people are asked to rate themselves relative to others on certain personal qualities such as financial knowledge or driving skills, it has been observed that more than 50% believe they are better than average leading to the so-called better-than average effect (Svenson 1981). In an experimental setting, overconfidence can be assessed in several ways. A calibration test (Lichtenstein et al. 1982) is one way to measure overconfidence. 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, some doubt the robustness of such a calibration metric (e.g., Juslin et al. 2000).

In our experiment, we used the *illusion of knowledge* (Barber and Odean 2001) as a way to measure overconfidence. Due to illusion of knowledge, individuals believe they know more than they actually do and thereby become overconfident in their judgment. In the experiment, we asked subjects five basic investment questions and requested them to also provide the number of questions they thought they answered correctly. These questions (see Figure A.2 in Appendix I) are similar to the ones used in previous studies

(e.g., Agnew and Szykman 2004; Wilcox 2003). The tendency for overconfidence is measured using the difference between the subjects' estimated number of correct answers and their actual number of correct answers. A person with a higher estimate of correct answers than the actual number of correct answers would be categorized as overconfident. The findings regarding the overconfidence of subjects in our experiment are presented below.

The first question was answered correctly by 73%, the second by 52%, the third by 43%, the fourth by 61%, and the last one by 91% of the subjects. The total of 1, 2, 3, 4, and 5 questions were answered correctly by 8%, 18%, 34%, 29%, and 12% of the subjects respectively. As shown in Table 5.7, 39.4% of the subjects were observed to be overconfident.

Table 5.7- Overconfidence assessment of the subjects

Difference between actual and estimated number of correct answers	No. of subjects	%	Overconfident
-4	1	0.8	Yes 49 subjects (39.4%)
-2	14	11.8	
-1	34	26.8	
0	43	13.1	No 70 subjects (60.6%)
1	18	15.1	
2	7	5.9	
3	2	1.7	
Total	119	100	

5.7 Results

In this section, we present the results of the experiment involving asset allocations decisions and discuss whether the research hypotheses outlined in chapter 4 are supported. The proposed hypotheses will be tested by following the data analysis methodology discussed in section 5.4.

5.7.1 Framing Bias and Feedback

It has been discussed before that individuals, due to the framing bias, may exhibit inconsistency between their preferred risk level and their actual asset allocation behaviour, and that feedback as a cognitive tool could lower the impact of such a bias in investment-decision-making. In the experiment, subjects who exhibited a framing bias received feedback making them aware of their inconsistency. The conditions and the types of feedback issued in the experiment were outlined in Table 5.2 and Figures 5.7 & 5.8.

For 31 subjects, no feedback was issued as their asset allocation was consistent with their desired portfolio. 48 subjects received level 1 feedback and the remaining 40 subjects received level 2 feedback. 20 subjects neglected the feedback and did not alter their allocation even after receiving the warning. 68 subjects changed their allocation upon receiving the feedback. Of these, five people actually moved in the wrong direction and consequently, their asset allocation became worse after heeding the warning issued to them. 50 subjects adjusted their allocations correctly after receiving the feedback.

Thirteen subjects moved in the right direction but did not adjust their allocation sufficiently to be consistent with their risk preferences. Table 5.8 summarizes these results.

Table 5.8 - Impact of feedback on the framing bias (119 subjects)

Framing bias present? (Before feedback)	Impact of feedback	No. of subjects	Percent
No 31 subjects (26%)	Feedback not issued (risk consistent subjects)	31	26
Yes 88 subjects (74%)	Moved in the right direction with sufficient adjustment	50	42
	Moved in the right direction but without sufficient adjustment	13	11
	Feedback ignored	20	17
	Performance degraded	5	4
	Total	119	100

H_{1a}: Subjects experience a framing bias while engaged in investment decision-making.

From Table 5.8, it is evident that 74% of the subjects exhibited a framing bias and therefore received feedback. In order to test the significance of this result, the presence of the framing bias was coded as 1 and its absence as 0. A one-tailed t-test was conducted against the null hypothesis that the mean framing bias was less than or equal to 0.5. The value of 0.5 indicates the assumption that the framing bias is equally likely[8] (50% chance) to be present or absent in investment scenarios. The obtained p-value of 0.0000 strongly

[8] Such an assumption, although conservative, leads to robust conclusions. Subsequent analyses of other hypotheses will also make similar assumptions when relevant.

rejected the null hypothesis at a significance level of 1% and confirmed the existence of the framing bias in investment decision-making thereby supporting H_{1a}.

H_{2a}: The impact of the framing bias on the investment decision-making of subjects is more pronounced in high level framing bias scenarios than in low level ones.

In order to test H_{2a}, two types of analyses were conducted: *portfolio level* and *aggregate level*. In the portfolio level analysis, the subjects' actual stock allocation amount (in $) before receiving the feedback were examined by categorizing them under their portfolio type. The findings are presented in Table 5.9.

Table 5.9- Portfolio level analysis for the framing bias before feedback (119 subjects)

Investor type	**Mean stock allocation before feedback (Standard error)**	
	High level	Low level
Very aggressive (0.8%) RSA: 90-100%	100,000 (NA)	----
Moderately aggressive (16.8%) RSA: 70-90%	94,750 (977)	64,167 (5,106)
Growth-oriented (35.3%) RSA: 50-70%	77,455 (2,726)	49,500 (3,888)
Capital preservation-oriented (23.5%) RSA: 30-50%	60,818 (5,003)	40,294 (4,276)
Moderately conservative (12.6%) RSA: 10-30%	51,250 (1,250)	38,571 (2,369)
Very conservative (10.9%) RSA: 0-10%	34,286 (6,117)	16,667 (3,575)
Total subjects: 119		

RSA- Recommended Stock Allocation

An explanation of Table 5.9 is in order. The percentage of subjects belonging to each investor type is indicated by the percentage in the parentheses in column 1. For example, the first entry in the table indicates that only one subject (0.8% of 119) belonged to the *very aggressive* category. The acronym RSA refers to the *recommended stock allocation.* For instance, the RSA for a very aggressive investor is 90%-100% as outlined in Table 5.2. In the rest of the columns, the actual mean stock allocations before feedback for both levels is reported for each investor type. The entries in parentheses in columns 2 and 3 refer to the standard error of the mean stock allocation for the corresponding investor types.

The one subject who belonged to the *very aggressive* category allocated 100% in stock and therefore was risk consistent. All other investor types, who received the scenario involving the high level bias, exhibited an overall framing effect as evidenced by their mean stock allocation before receipt of feedback. In the low level bias scenario, all investor types except *capital-preservation-oriented* ones became susceptible to the framing bias as well.

In order to assess the statistical significance of the overall framing effect, an aggregate level analysis was conducted. The type of portfolio selected by the subjects was not considered in this analysis. Table 5.10 shows the t-test result of the framing bias across the two bias levels.

Table 5.10 – t-test (one-tailed) examining the framing bias before feedback across two levels (119 subjects)

Category Statistics				
		Framing bias before feedback		
Bias level	No. of subjects	Mean	Std. Dev.	Std. error of Mean
Low	62	0.65	0.482	0.061
High	57	0.84	0.368	0.049
All	119	0.74	0.441	0.040
$t(117) = 2.49$, $p = 0.007$ ($p<0.01$)				

As shown in Table 5.10, the mean framing bias in the high level scenario is 0.84 (i.e., 84% of the subjects exhibited the bias) whereas that in the low level scenario is 0.65 (i.e., 65% of the subjects exhibited the bias). The p-value of 0.007 for the one-tailed t-test is statistically significant at the 1% significance level and rejects the null hypothesis that the average framing bias in high level scenarios is less than or equal to that in low level scenarios. It can be concluded that the impact of the framing bias is more pronounced in the high level scenario than in the low level one and therefore, H_{2a} is supported.

H_{3a}: Subjects, in the presence of feedback, experience a reduced framing bias while engaged in investment decision-making.

In order to test hypothesis H_{3a}, only the performance of the 88 subjects who exhibited the framing bias initially and therefore received the feedback were considered for analysis. Two criteria will be used to determine whether debiasing is complete or

partial. Debiasing is complete if the final allocation is within the recommended stock allocation range after receiving feedback (*complete debiasing*). It is partial if the final allocation, although not within the *recommended stock allocation* range, moves in the right direction after feedback (*partial debiasing*).

Table 5.11 – Impact of feedback on the framing bias* (88 subjects)

Impact of feedback	No. of subjects	Percent	Framing bias still present?
Performance degraded	5	5.7	Yes 38 subjects (43.2%)
Feedback ignored	20	22.7	
Moved in the right direction but without sufficient adjustment	13	14.8	
Moved in the right direction with sufficient adjustment	50	56.8	No 50 subjects (56.8%)
Total	88	100	

* based on complete debiasing criterion

While the majority of the subjects (56.8%) exhibited the absence of the framing bias after feedback (see Table 5.11 above), the null hypothesis that the mean framing effect is less than or equal to 0.5 could not be rejected (p-value = 0.1013 for a one-tailed test) suggesting the lack of evidence for the effectiveness of feedback under the complete debiasing criterion at the 5% significance level. The value of 0.5 for the mean framing effect signifies that the framing bias is equally likely (50% chance) to be present or absent in the investment scenarios. However, when the partial debiasing criterion was used, 63 subjects (71.6%) exhibited the absence of the framing bias after feedback. A p-value of 0.0000 was obtained for the same null hypothesis suggesting the effectiveness of the

feedback at the significance level of 1% under the partial debiasing criterion and therefore supporting H_{3a}. The results of the portfolio level analysis of the 63 subjects are summarized in Table 5.12.

Table 5.12 – Comparison of mean stock allocations of 63 subjects before and after feedback

Investor type	**Mean stock allocation (Standard error)**	
	Before feedback	After feedback
Very aggressive (0%) RSA: 90-100%	---	---
Moderately aggressive (19.1%) RSA: 70-90%	78,750 (6,829)	79,583 (4,583)
Growth-oriented (31.8%) RSA: 50-70%	70,500 (4,728)	62,250 (2,473)
Capital preservation-oriented (19%) RSA: 30-50%	58,750 (6,488)	48,750 (3,023)
Moderately conservative (17.5%) RSA: 10-30%	47,273 (2,273)	28,182 (2,161)
Very conservative (12.7%) RSA: 0-10%	30,000 (6,050)	15,000 (2,673)
Total subjects: 63		

RSA - Recommended Stock Allocation

It is evident from Table 5.12 that the average stock allocations of all investor types (except the *moderately aggressive*) improved after acting on the feedback as the final allocations came closer to the corresponding recommended stock allocation ranges after utilizing the feedback. For example, consider the *very conservative* subjects. The recommended stock allocations range for them is 0-10%. Their average allocation before

feedback is $30,000 (30%); whereas it is $15,000 (15%) after feedback. While the final allocation is still out of the recommended range of 0-10%, it definitely has come closer to the desired range after feedback.

H_{4a}: The benefit of feedback increases as the level of potential framing bias in investment decision-making increases.

Feedback is considered beneficial when the previously biased subjects adjust their stock allocation in a correct manner after receiving it. Two criteria will be used to determine whether the adjustment is complete or partial. The debiasing is complete if the final allocation is within the recommended stock allocation range after receiving feedback (*complete debiasing*). Debiasing is partial if the final allocation, although not within the *recommended stock allocation* range, is in the right direction (*partial debiasing*).

For example, out of 62 subjects who received a low level framing bias scenario, 42 were biased. Out of the 42 biased subjects, 27 adjusted their asset allocations in the correct direction after receiving feedback. Therefore, using the partial debiasing criterion, the overall benefit of the feedback in a low level bias scenario is 27/62. That is, 44%. Similarly, using the complete debiasing criterion, the overall benefit of the feedback in a low level scenario is 23/62 (37%) as 23 subjects became completely debiased after feedback. For robustness, hypothesis H_{4a} was tested with both portfolio level (in terms of allocated $ amount) and aggregate level (in terms of number of subjects) analyses.

Aggregate level analyses were also conducted using both *complete* and *partial debiasing* criteria.

Comparing mean stock allocations across high level and low level scenarios before and after feedback (see Table 5.13), it appears that feedback is beneficial in both high and low bias level scenarios. For example, consider the second row of Table 5.13. The mean asset allocation of moderately aggressive investors in the high level scenario before feedback is $94,750; whereas that after feedback is $90,000, which is within the recommended stock allocation range. It appears that the feedback was successful in reducing the impact of framing bias for subjects belonging to this category and receiving the high level bias scenario. Similarly, the feedback is also beneficial to those subjects who belonged to this category and received the low level bias scenario. The last two columns in Table 5.13 report the percentage of subjects still exhibiting the framing bias after feedback. Looking at these columns, it appears that the benefit of feedback is more evident in the high bias scenario than in the low bias scenario for all investors except the *capital preservation-oriented* and *very conservative* ones.

Table 5.13 – Comparison of mean stock allocations of 119 subjects before and after feedback across low level and high level framing bias scenarios

Investor type	**Mean stock allocation under high bias level (Standard error)**		**Mean stock allocation under low bias level (Standard error)**		**Mean framing bias* after feedback (Standard error)**	
	Before feedback	After feedback	Before feedback	After feedback	High level	Low level
Very aggressive (0.8%) RSA: 90-100%	100,000 (NA)	100,000 (NA)	----	----	0.000 (NA)	NA
Moderately aggressive (16.8%) RSA: 70-90%	94,750 (977)	90,000 (1,637)	64,167 (5,106)	67,500 (4,417)	0.125 (0.125)	0.250 (0.131)
Growth-oriented (35.3%) RSA: 50-70%	77,455 (2,726)	70,182 (2,572)	49,500 (3,888)	50,000 (2,487)	0.182 (0.084)	0.200 (0.092)
Capital preservation-oriented (23.5%) RSA: 30-50%	60,818 (5,003)	51,727 (3,449)	40,294 (4,276)	39,118 (2,720)	0.273 (0.141)	0.176 (0.095)
Moderately conservative (12.6%) RSA: 10-30%	51,250 (1,250)	34,375 (2,903)	38,571 (2,369)	27,857 (3,426)	0.125 (0.125)	0.286 (0.184)
Very conservative (10.9%) RSA: 0-10%	34,286 (6,117)	22,143 (3,426)	16,667 (3,575)	13,333 (4,216)	0.429 (0.202)	0.167 (0.167)

* Analysis is based on the complete debiasing criterion.

Table 5.14 shows the result of aggregate level analysis using the complete debiasing criterion. A one-tailed t-test was conducted for the null hypothesis that the benefit of feedback in a high level scenario is less than or equal to that in a low level scenario. While the feedback is more beneficial in a high level bias scenario (47%) than in a low level one (37%), the insignificant p-value of 0.1302 suggests that this difference is not statistically significant at the 5% level.

Table 5.14 – t-test (one-tailed) examining the benefit of feedback across high and low level framing bias scenarios (complete debiasing)

Category Statistics				
		Benefit of feedback		
Bias level	No. of subjects	Mean	Std. Dev.	Std. error of Mean
Low	62	0.37	0.487	0.062
High	57	0.47	0.504	0.067
All	119	0.42	0.5	0.045
$t(117) = 1.13$, $p = 0.1302$ ($p>0.1$)				

Table 5.15 shows the result of aggregate level analysis using the partial debiasing criterion. As before, a one-tailed t-test was conducted for the same null hypothesis. In this case also, the feedback is more beneficial in a high level bias scenario (63%) than in a low level one (44%). The p-value of 0.0162 suggests that this difference is statistically significant at the 5% level. A comparison of these two tables (Table 5.14 and Table 5.15) reveals that more subjects did directional adjustment in high level bias scenario than in low level one. Based on the partial debiasing criterion, H_{4a} is supported.

Table 5.15 – t-test (one-tailed) examining the benefit of feedback across high and low level framing bias scenarios (partial debiasing)

Category Statistics				
		Benefit of feedback		
Bias level	No. of subjects	Mean	Std. Dev.	Std. error of Mean
Low	62	0.44	0.5	0.063
High	57	0.63	0.487	0.064
All	119	0.53	0.501	0.046
$t(117) = 2.17$, $p = 0.0162$ ($p<0.05$)				

H_{5a}: Subjects, who are overconfident in their financial knowledge, are more likely to neglect the feedback provided to them than those who are not overconfident while engaged in investment decision-making involving a potential framing bias.

In order to test this hypothesis, a t-test (one-tailed) was conducted for the null hypothesis that the average feedback usage by overconfident subjects is more than or equal to that by subjects who are not overconfident.

Table 5.16 – t-test (one-tailed) examining the impact of overconfidence on the feedback usage tendency

Category Statistics				
		Feedback usage		
Overconfident	No. of subjects	Mean	Std. Dev.	Std. error of Mean
No	51	0.80	0.401	0.056
Yes	37	0.73	0.450	0.074
All	88	0.77	0.421	0.045
$t(86) = 2.49$, $p = 0.209$ ($p>0.1$)				

As shown in Table 5.16, the insignificant p-value suggests that the null hypothesis cannot be rejected at the 5% level. That is, the subjects' overconfidence does not seem to influence their decision to use feedback. Therefore, hypothesis H_{5a} could not be supported.

5.7.2 Representativeness Bias and Graphical Presentation

As discussed previously, investors, due to the representativeness bias, tend to overrate the significance of salient information such as rising stock prices and believe that the current increase in prices is not random but an indication of a persistent trend. Graphs presenting longer time-horizon information were employed as potential debiasing aids for the representativeness bias.

H_{1b}: Subjects experience a representativeness bias while engaged in investment decision-making.

A histogram of investments (in $) in winning stocks (A and X) gave a striking evidence for the presence of the representativeness bias (see Figure 5.16) as the mean investment on these stocks is $72,185, which far exceeds the judicious allocation of roughly around $50,000. For robustness, all results will be analyzed by coding the allocation of more than $55,000 (rather than the strict criterion of $50,000) to winning stocks as 1 (presence of representativeness bias) and less than that amount as 0 (absence of the bias). Only 18% of the subjects allocated less than or equal to $55,000 to these stocks. Among them, 3 people probably followed the contrarian strategy and allocated less than 50% to the winning stocks.

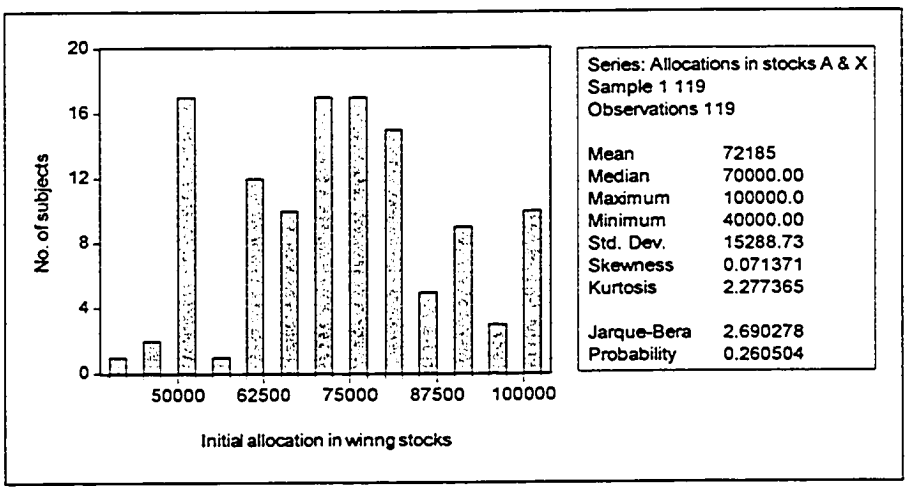

Figure 5.16 - Histogram of initial investments in winning stocks (A & X)

In order to test H_{1b}, the null hypotheses that the mean allocations in winning stocks (A & X) is $55k was tested. The hypothesis was strongly rejected with a p-value of almost zero (0.0000) for the two-tailed test. A large majority (82%) of the people were found to be influenced by the representativeness bias. A one-tailed t-test was conducted against the null hypothesis that the mean representativeness bias is less than or equal to 0.5. The value of 0.5 indicates that the representativeness bias is equally likely to be present or absent in these investment scenarios. The p-value of 0.0000 strongly rejected the null hypothesis at the 1% significance level and confirmed the existence of representativeness bias in investment decision-making thereby supporting H_{1b}.

H_{2b}: The impact of the representativeness bias on the investment decision-making of subjects is more pronounced in the high level representativeness bias scenarios than in the low level ones.

To test hypothesis H_{2b}, a one-tailed t-test was conducted (Table 5.17). The mean allocation to stock X (winner in low level bias scenario) is $65,862 while that of stock A (winner in high level bias scenario) is $78,197. The null hypothesis that the mean allocation to a winning stock in high level bias scenario is less than or equal to that in low level bias scenario is strongly rejected (p-value = 0.000) at 1% significance level. Therefore, H_{2b} is supported.

Table 5.17 – t-test (two-tailed) examining the impact of bias levels on allocation to winning stocks (before receiving graphical aids)

Category Statistics				
		Allocation to stocks X & A		
Bias level	Count	Mean	Std. Dev.	SE of Mean
Low	58	65,862	10967.97	1440.17
High	61	78,197	16432.51	2103.97
All	119	72,185	15288.73	1401.52
t(117) = 4.79, p = 0.0000 (p<0.01)				

H_{3b}: Subjects, in the presence of graphical aids, experience reduced representativeness bias while engaged in investment decision-making.

The histogram of investment to the winning stocks A & X after the issuance of graphical aids (Figure 5.17) is markedly different from the one in Figure 5.16. Final mean allocation to stocks A & X is $56,303 which is significantly lower than the initial allocation of $72,185. With a p-value (two-tailed t-test) of 0.1549, the null hypothesis that the mean allocation to winning stocks is $55,000 could not be rejected at 5% significant level. That is, the influence of the representativeness bias is reduced after the issuance of graphical aids. The chi-square test for the null hypothesis of independence of initial bias and final bias was strongly rejected (see Table 5.18). As shown in Table 5.18, 98 subjects (82%) exhibited the representativeness bias before receiving graphical aids. However, only 45 subjects (38%) showed the bias after receiving the graphical aids. The null hypothesis of the equality of these percentages (82% and 38%) was strongly rejected at

the 1% significance level with p-value of 0.000. Therefore, hypothesis H_{3b} is also supported.

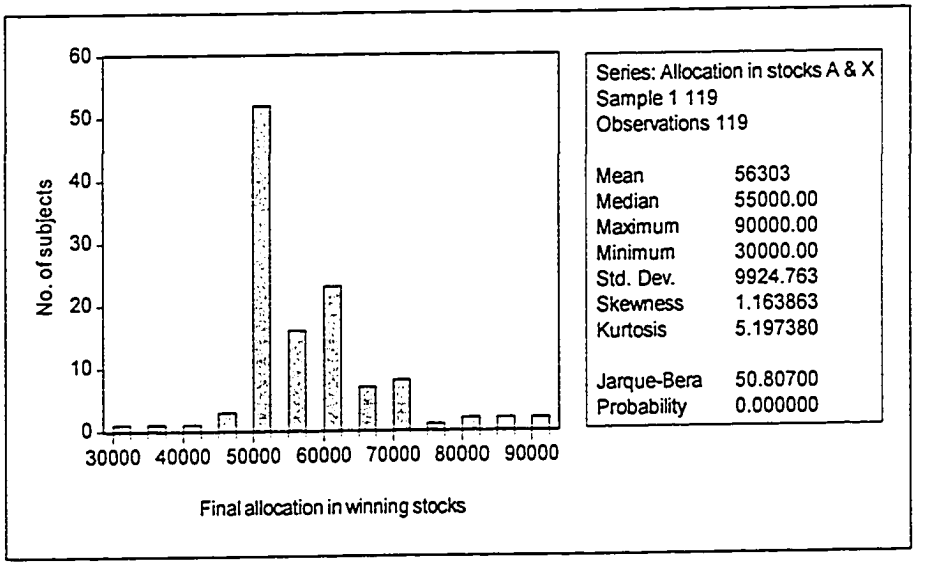

Figure 5.17 - Histogram of final investments in winning stocks (A & X)

Table 5.18 - Chi-square test for the independence of the representativeness bias before and after the graphical aids

		Bias after graphs		
		No	Yes	Total
Bias before graphs	No	21	0	21
	Yes	53	45	98
	Total	74	45	119
p-value for Pearson X2: 0.0000; df: 1				

H_{4b}: The benefit of graphical aids increases as the level of potential representativeness bias in investment decision-making increases.

The graphical aids are beneficial when the previously biased subjects adjust their allocation to winning stocks (A & X) in a correct manner after receiving such aids. Two criteria will be used to determine whether the adjustment is complete or partial. The debiasing is complete if the final allocation to winning stocks is less than or equal to $55,000 after receiving graphical aids (complete debiasing). Debiasing is partial if the adjustment is in the right direction but the final allocation is still more than $55,000 (partial debiasing). For robustness, hypothesis H_{4b} was tested with both allocation level (in terms of $ amount) and aggregate level (in terms of number of subjects) analyses. Aggregate level analyses were conducted using both *complete* and *partial debiasing* criteria.

In the allocation level analysis, the change in allocation to winning stocks before and after graphical aids was computed. Suppose a subject invests $80,000 initially in stock X. If the same subject, after viewing the graphical aid allocates $60,000, then the *correction amount* is $20,000. As shown in Table 5.19, the average correction in the low level bias is $9,741 whereas that in the high level bias is $21,885. The one-tailed t-test (Table 5.19) strongly rejected the null hypothesis that the average correction amount in a high level bias scenario is less than or equal to that in a low bias scenario at the significance level of 1%. Therefore, hypothesis H_{4b} is supported with the allocation level analysis.

Table 5.19 - t-test (one-tailed) examining the average allocation correction amount across high and low level representativeness bias

Category Statistics				
		Correction in allocation amount		
Bias level	Count	Mean	Std. Dev.	SE of Mean
Low	58	9,741	10489.03	1377.277
High	61	21,885	16910.65	2165.186
All	119	15,966	15352.87	1407.396
t(117) = 4.68, p = 0.0000 (p<0.01)				

Table 5.20 shows the result of aggregate level analysis using the complete debiasing criterion. A t-test was conducted for the null hypothesis that the benefit of graphical aids in a high level bias scenario is less than or equal to that in a low level bias scenario. The graphical aids are more beneficial in the high level bias scenario (52%) than in a low level one (36%). The p-value of 0.037 suggests that this difference is statistically significant at the 5% level. Therefore, hypothesis H_{4b} is also supported with the aggregate level analysis using the complete debiasing criterion.

Table 5.20 – t-test (one-tailed) examining the benefit of graphical aids across high and low level representativeness bias scenarios (using complete debiasing criterion)

Category Statistics				
		Benefit of feedback		
Bias level	No. of subjects	Mean	Std. Dev.	Std. error of Mean
Low	58	0.36	0.485	0.064
High	61	0.52	0.504	0.064
All	119	0.45	0.499	0.046
t(117) = 1.79, p = 0.037 (p<0.05)				

Table 5.21 shows the result of aggregate level analysis using the partial debiasing criterion. As before, a t-test was conducted for the same null hypothesis. As shown in Table 5.21, the graphical aids are more beneficial in a high level bias scenario (72%) than in a low level one (62%). The p-value of 0.123, however, suggests that this difference is not statistically significant at the 5% level. Based on the partial debiasing criterion, H_{4b}, therefore, is not supported.

Table 5.21 – t-test (one-tailed) examining the benefit of graphical aids across high and low level representativeness bias scenarios (using partial debiasing criterion)

Category Statistics				
		Benefit of feedback		
Bias level	No. of subjects	Mean	Std. Dev.	Std. error of Mean
Low	58	0.62	0.489	0.064
High	61	0.72	0.452	0.058
All	119	0.67	0.471	0.043
$t(117) = 1.17$, $p = 0.123$ ($p>0.1$)				

H_{5b}: Subjects, who are overconfident in their financial knowledge, are more likely to neglect the graphical aids provided to them than those who are not overconfident while engaged in investment decision-making involving a potential representativeness bias.

Out of the 98 subjects exhibiting the bias, 81% decided to change their initial allocation after observing the longer time-horizon return information in the graphical format while the remaining 19% neglected such information. The average usage of the graphical information was 79% and 83% respectively between the subjects who were not overconfident and those that were overconfident. Table 5.22 shows the result from a t-test (one-tailed).

Table 5.22 – Impact of overconfidence on graphical aid usage

Category Statistics				
		Graphical aid usage		
Overconfident	No. of subjects	Mean	Std. Dev.	Std. error of Mean
No	56	0.79	0.414	0.055
Yes	42	0.83	0.377	0.058
All	98	0.81	0.397	0.040
$t(96) = 0.58$, $p = 0.5599$ ($p>0.1$)				

The p-value of 0.5599 suggests that the null hypothesis that the graphical aid usage in a high level bias scenario is more than or equal to that in a low level bias scenario cannot be rejected at the 5% significance level. Therefore, H_{5b} could not be supported.

5.7.3 Ambiguity and Graphical presentation

As discussed previously, investors, due to ambiguity, may become unable to process the information provided to them and accept the default choice (if available) even if such an option is demonstrably sub-optimal. For ambiguity, effort reduction may be

more important than decision quality enhancement (Johnson and Payne 1985; Todd and Benbasat 1991). Therefore, the data are analyzed by comparing the number of subjects who accepted the default choices before and after the receipt of graphical aids. The actual amount allocated in different funds is not considered in our data analysis. In the experiment, the level of ambiguity was manipulated by varying the information overload given to subjects. Graphs showing the relevant information (net compound returns) as bar diagrams were employed as cognitive support.

H_{1c}: Subjects experience ambiguity while engaged in investment decision-making.

Out of 119 subjects, 70 (59%) selected the default choice indicating the impact of ambiguity. In order to test the significance of this result, the presence of ambiguity was coded as 1 and its absence as 0. A one-tailed t-test was conducted against the null hypothesis that the mean ambiguity was less than or equal to 0.5. The value of 0.5 indicates that ambiguity is equally likely (50% chance) to be present or absent in the investment scenarios. A p-value of 0.027 rejected the null hypothesis at the 5% significance level. Therefore, hypothesis H_{1c} could be supported at that significance level.

H_{2c}: The impact of ambiguity on the investment decision-making of subjects is more pronounced in the high level ambiguity scenarios than in the low level ones.

To test hypothesis H_{2c}, a one-tailed t-test was conducted (Table 5.23). The mean ambiguity in the low level bias scenario is 0.38. That is, 38% of the subjects receiving such a scenario exhibited this bias. The mean ambiguity in the high level scenario is 0.79. That is, 79% of the subjects receiving such a scenario exhibited this bias. The p-value of 0.0000 strongly rejected the null hypothesis that the mean ambiguity in a high level bias scenario is less than or equal to that in a low level bias scenario at the 1% significance level. Therefore, H_{2c} is supported.

Table 5.23 – t-test (one-tailed) examining the impact of bias levels on inducing ambiguity (before graphical aids)

Category Statistics				
		Ambiguity		
Ambiguity level	Count	Mean	Std. Dev.	SE of Mean
Low	58	0.38	0.489	0.064
High	61	0.79	0.413	0.053
All	119	0.59	0.494	0.045
$t(117) = 4.92$, $p = 0.0000$ ($p<0.01$)				

H_{3c}: Subjects, in the presence of graphical aids, experience reduced ambiguity while engaged in investment decision-making.

To test H_{3c}, a chi-square test was conducted (Table 5.24). The mean ambiguity before the receipt of graphical aids is 59% (70/119). The mean ambiguity after the receipt of graphical aids is 18% (22/119). The p-value of 0.000 strongly rejects the null

hypothesis that the mean ambiguity after the graphical aids is more than or equal to that before the graphical aids at the significance level of 1%. Hypothesis H_{3c}, therefore, is supported.

Table 5.24 – chi-square test examining the impact of graphical aids in lowering ambiguity

		Bias after graphs		
		No	Yes	Total
Bias before graphs	No	48	1	49
	Yes	49	21	70
	Total	97	22	119
Pearson X2 p-value: 0.000; df: 1				

It is worthwhile to note that all subjects who decided not to accept the default choices (before or after the receipt of graphical aids) significantly reduced their investment in *National Bond Fund* (underperforming fund) from the default allocation of $50,000.

H_{4c}: The benefit of graphical aids increases as the level of potential ambiguity in investment decision-making increases.

The graphical aids are beneficial if the subjects who selected the default choices before decide not to accept such choices after receiving the graphical aids. Table 5.25 shows the result of a one-tailed t-test was conducted for the null hypothesis that the benefit of graphical aids in a high level bias scenario is less than or equal to that in a low level bias scenario. As shown in Table 5.25, the graphical aids are more beneficial in a

high level bias scenario (56%) than in a low level one (26%). The p-value of 0.0004 suggests that this difference is statistically significant at the 1% level. H_{4c} is, therefore, supported.

Table 5.25 - t-test (one-tailed) examining the benefit of graphical aids across high and low level ambiguity bias scenarios

Category Statistics				
		Benefit of graphical aids		
Bias level	No. of subjects	Mean	Std. Dev.	Std. error of Mean
Low	58	0.26	0.442	0.058
High	61	0.56	0.501	0.064
All	119	0.41	0.494	0.045
$t(117) = 3.44$, $p = 0.0004$ ($p<0.01$)				

H_{5c}: Subjects, who are overconfident in their financial knowledge, are more likely to neglect the graphical aid provided to them than those who are not overconfident while engaged in investment decision-making involving potential ambiguity.

Out of 119 subjects, 49 showed no ambiguity bias. Out of the 70 subjects exhibiting the bias, 37 (53%) were not overconfident. The average usage of the graphical aid was 76% and 64% respectively between the subjects who were not overconfident and those that were overconfident respectively. With a p-value of 0.1396, the null hypothesis that the graphical aid usage in a high level bias scenario is more than or equal to that in a

low level bias scenario cannot be rejected at the 5% significance level. Therefore, H_{5c} could not be supported.

Table 5.26 – t-test (one-tailed) examining the impact of overconfidence on graphical aid usage

Category Statistics				
		Graphical aid usage		
Overconfident	No. of subjects	Mean	Std. Dev.	Std. error of Mean
No	37	0.76	0.435	0.072
Yes	33	0.64	0.489	0.085
All	70	0.70	0.462	0.0552
$t(68) = 1.09$, $p = 0.1396$ ($p>0.1$)				

5.7.4 Overall Results

Figure 5.18 depicts findings regarding the impact of decision aids (feedback and graphical aids) on lowering the influence of cognitive biases (framing, representativeness, and ambiguity). As outlined in Figure 5.18, 8 subjects (6.7%) were not influenced by any of these biases while 54 subjects (45.4%) were influenced by all of these biases before the receipt of cognitive aids. After receiving cognitive support, 53 subjects (44.5%) did not exhibit any bias at all while only 6 subjects (5%) were still influenced by all of the three biases. It is evident from Figure 5.18 that the number of subjects influenced by 2 or more biases reduced significantly after receiving cognitive support.

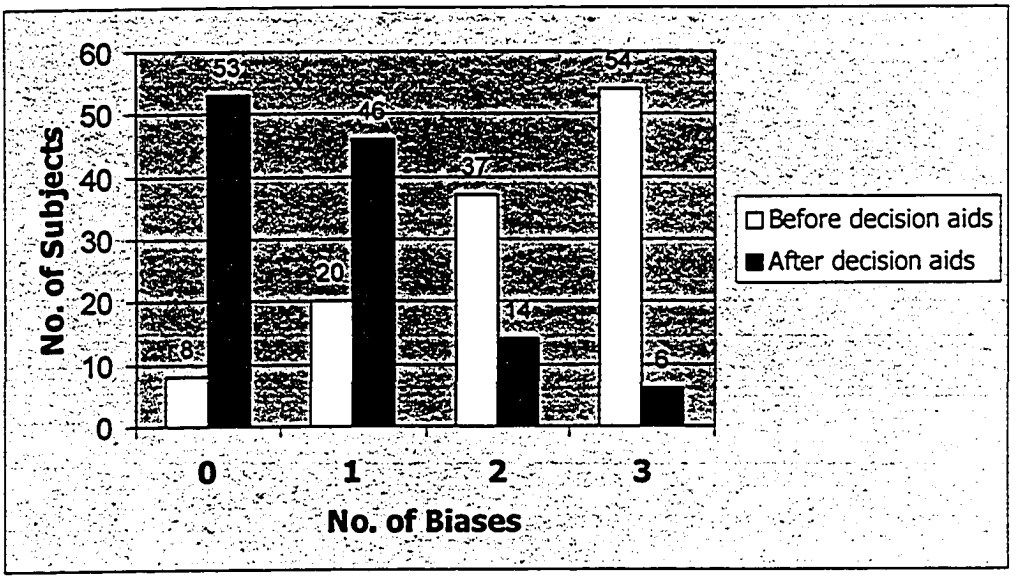

Figure 5.18 – Impact of decision aids on lowering the influence of cognitive biases

Based on this observation, it is reasonable to conclude that decision aids are useful and effective in lowering the impact of cognitive biases involved in investment decision-making. This section concludes by outlining findings pertaining to the proposed research hypothesis (Table 5.27).

Table 5.27 – Findings on proposed research hypotheses

Research Hypotheses	Cognitive Biases	Hypotheses Supported?
H_1: Subjects experience cognitive biases while engaged in investment decision-making.	Framing	√***
	Representativeness	√***
	Ambiguity	√**
H_2: The impact of cognitive biases on the investment decision-making of subjects is more pronounced in high level cognitive bias scenarios than in low level ones.	Framing	√***
	Representativeness	√***
	Ambiguity	√***
H_3: Subjects, in the presence of cognitive support, experience reduced cognitive biases while engaged in investment decision-making.	Framing	√***1
	Representativeness	√***
	Ambiguity	√***
H_4: The benefit of cognitive support increases as the level of potential cognitive biases in investment decision-making increases.	Framing	√**1
	Representativeness	√**2
	Ambiguity	√***
H_5: Subjects, who are overconfident in their financial knowledge, are more likely to neglect the cognitive support provided to them than those who are not overconfident while engaged in investment decision-making.	Framing	X
	Representativeness	X
	Ambiguity	X

*** $p<0.01$; ** $p<0.05$

1- supported with the partial debiasing criterion; 2–supported with allocation level analysis as well as aggregate level analysis with the complete debiasing criterion

5.8 Discussion

In this section, we discuss the potential relationships between demographic variables and different cognitive biases along with the tendency for decision aid neglect. The need for developing personalized DSS will become clear. Several studies indicating the potential usefulness of incorporating investors' psychological profiles and temperament in personalized DSS will also be outlined.

5.8.1 Cognitive Biases and Demographic Factors

In order to explore potential relationships between demographic factors and different cognitive biases, we conducted regressions, where the presence or absence of a cognitive bias (*framing, representativeness, and ambiguity*) was used as a dependent variable. We started by regressing on the full set of demographic variables (see Table 5.6) and then sequentially dropping that variable whose p-value was highest until all included variables passed a 5% p-value criterion. Since the dependent variable is binary, probit regression was carried out. The final regressions are as following:

Framing bias = 4.14 – 0.67 Education – 0.18 Knowledge .....*(equation 1)*
McFadden R^2 *= 0.06, Coefficient p-values = {0.002, 0.086, 0.079}*

Representativeness bias = 2.17 – 0.08 Experience .....*(equation 2)*
McFadden R^2 *= 0.06, Coefficient p-values = {0.000, 0.01}*

Ambiguity bias = 4.13 – 1.05 Education – 0.09 Experience .....*(equation 3)*
McFadden R^2 *= 0.13, Coefficient p-values = {0.001, 0.01, 0.003}*

Demographic factors such as education, knowledge, and experience appear to have significant influence on cognitive biases involved in investment decision-making. Subjects with higher levels of education and investment knowledge were less susceptible to framing bias even though only 6% of the variation is explained by these factors (refer to equation 1). In some previous studies, women were found to be more susceptible to framing bias than men (Fagley and Miller 1990; Belenky et al. 1986). In this study we did not observe any impact of gender, which is consistent with a study by Levin et al. (2002).

In the case of the representativeness bias, only investment experience was found to be significant (refer to equation 2). Subjects with less investment experience are more likely to be influenced by this bias. However, as before only 6% of the variation is explained by this factor. Educational level and self-rated knowledge of subjects were not found to be significant. It should be noted that the correlation between the subjects' self-rated knowledge and investment experience was high (0.72).

Finally, in scenarios involving ambiguity bias, both education and investment experience appeared to influence subjects' decisions regarding whether to accept the default choices (refer to equation 3). About 13% of the variation in ambiguity bias was explained by these factors.

These findings are expected as individuals with a higher level of investment knowledge and experience may have learned not to chase momentum or be manipulated

by the way information is presented. Individuals with a higher level of formal education may have better critical thinking ability and thus, be more efficient and accurate in processing information such as that presented in the ambiguity bias scenarios. In light of this information, it can be concluded that formal education, investment knowledge and experiences are important in making sound investment decisions. However, there could be many other factors (social, psychological) that may influence an individual's decision-making style. For example, Levin et al. (2002) found that several of the "Big Five" personality traits (McCrae and Costa 1987) - extraversion, neuroticism, conscientiousness, agreeableness, openness to experience are predictive of the intensity of framing effects. They found that people with a neurotic personality are most vulnerable to framing bias. Their findings as well as ours suggest the usefulness of developing a personalized investment DSS that takes into account the relevant background information (e.g., economic, social, psychological factors) of investors and assists them in making sound investment decisions by providing appropriate decision aids. In the next subsection, we explore potential relationships between subjects' demographic characteristics and their tendency for decision aid neglect and discuss their implications.

5.8.2 Decision Aids and Demographic Factors

One of the research hypotheses (H_5) postulated that subjects, who are overconfident in their financial knowledge, are more likely to neglect the cognitive support provided to them than those who are not overconfident while engaged in investment decision-making. This hypothesis could not be supported in any of the three

types of cognitive biases in our study. Sieck and Arkes (2005) notice that the topic of overconfidence is still not well-understood. Furthermore, several factors may contribute to decision aid neglect by the subjects (Yates et al. 2003). In the following paragraphs, we discuss our findings regarding potential relationships between demographic factors and subjects' tendency to utilize decision aids available to them.

In scenarios involving framing bias, 20 subjects neglected the feedback issued to them. Out of these 20 subjects, only three rated themselves as possessing above average knowledge and only one subject gave more than three correct answers in the general investment knowledge test. It, therefore, appears that lack of knowledge, rather than overconfidence, is a potential factor for feedback neglect. At this juncture, it is worthwhile to emphasize the non-directional nature of the feedback provided to the subjects in our study. Since the feedback only informed them about their inconsistency and did not tell them whether they should increase or decrease their stock allocation, it is likely that subjects with little investment knowledge and experience could not benefit from such feedback and thus, decided to neglect it altogether. This is consistent with a previous finding that feedback is not beneficial when decision makers have no task-specific experience (Eining and Dorr 1991).

In scenarios involving representativeness bias, 19 subjects who exhibited this bias neglected the graphical aid issued to them. Out of these 19 subjects, 6 rated themselves as possessing above average knowledge, and 12 subjects had investment experience not

more than 1 year. It is notable that 12 subjects who neglected feedback in the framing bias scenarios also neglected the graphical aids in the representativeness bias scenarios. This suggests that decision aid neglect is not necessarily a random phenomenon.

In the case of ambiguity, 21 subjects who exhibited this bias neglected the graphical aid provided to them. Out of these 21 subjects, 13 and 7 subjects had 0 and 1 year of investment experience respectively. In general investment questions, only 4 people gave more than 3 correct answers.

Findings from our study indicate that low levels of knowledge, experience, or education may contribute toward decision aid neglect. Therefore, design of decision aids must take into consideration such demographic factors. A brief discussion of previous studies focused in this direction is now provided.

Palma-dos-Reis and Zahedi (1999) designed a personalized financial DSS to find out potential relationships between investors' personal characteristics such as gender, age, risk aversion, and their preferred models for security selection. They observed a strong correlation between subjects' risk tolerance level and security selection models employed by them. For example, risk-averse subjects selected technical analysis model more frequently. They also found that subjects' gender strongly correlated with security selection models. For example, male subjects relied more on the factor model and less on the CAPM (Capital Asset Pricing Model).

Statman and Wood (2004) stress the need for looking into individuals' investment temperament for better understanding their financial "goals, hopes, and fears" and recommend the Keirsey Temperament Sorter[9] (KTS) for this purpose. The KTS, which is based on Keirsey's (1998) temperament theory, divides people into four basic groups (*artisans, guardians, rationals, idealists*) and sixteen temperament variants. The KTS is also useful in identifying an individual's tendency for biases. For example, *artisans* and *guardians* exhibit greater familiarity bias than *rationals* and *idealists* (Statman and Wood 2004).

Marconi and Utkus (2002) divide retirement plan members into five groups based on their "money attitudes". Investors belonging to one such group called *planners* are people who are motivated and at ease with their investment decisions. *Avoiders*, on the other hand, feel uncomfortable in making their financial decisions. The impact of demographic factors on equity allocations was also observed in a survey conducted with about 2,000 Canadian defined contribution pension plan members. It was found that younger, more-educated, higher-earning, advice-receiving males with a planner mindset hold more equity (Bhandari and Deaves 2005).

With our empirical study, we have been able to confirm the deleterious impact of such cognitive biases as representativeness, framing, and ambiguity on an individual's investment decision-making. We found that decision aids such as feedback and graphs are

[9] www.advisorteam.com

quite effective in lowering the influence of those biases. It was observed that the benefit of such aids increases as investment scenarios become complex and hold more potential for instigating cognitive biases. Findings from our study indicate that the low levels of knowledge, experience, or education may contribute toward decision aid neglect. Therefore, such demographic factors must be taken into account while designing a personalized DSS.

Our study, however, did not examine the potential impact of such decision aids and demographic factors on affective and conative biases. The primary reason for such a limited focus is that the investment-related biases (see Chapter 3) belonging to the other two types of biases (affective and conative) necessitate longitudinal transaction data which is not possible to get in an experimental session. However, in the next chapter, we propose a vision for building a human-centered DSS that may assist individuals in all three dimensions (cognitive, affective, and conative) of investment decision-making as well as provide personalized support to them.

CHAPTER 6

TOWARD A HUMAN-CENTERED INVESTMENT DSS

This chapter proposes a vision for developing a human-centered investment DSS (hereafter HIDSS) and outlines some conceptual requirements and characteristics of such a system. The empirical study discussed in the previous chapter demonstrated the usefulness of decision aids in lowering the impact of major cognitive biases. However, as outlined in Chapter 3, investors are also influenced by several affective and conative biases thereby necessitating a "holistic" human-centered system to improve their investment decision-making.

Human-centeredness is an emerging technological tradition in which the primary focus is on supporting a decision maker's different needs and enhancing his or her potentiality (Gill 1991). The human need in the context of a HIDSS may correspond to "liberation" from decision-making biases while skill, creativity, and potentiality refer to the decision makers' potential for acquiring self-knowledge and control. Beynon et al. (2002) define human-centeredness as "an activity of observing and reflecting upon the external environment, situation by situation." This definition emphasizes the necessity of observing the world in different contexts and eliciting knowledge from such observations and experiences. It is, therefore, evident that the HIDSS must be capable of: (i) assisting users in understanding the investment world, their investment goals and values; (ii)

identifying and warning investors about their potential decision-making biases; and (iii) providing them an environment to learn from their past behaviour and experiences.

The value-orientation of investors is gaining prominence with the emergence of such concepts such as "ethical investing" and "socially responsible funds" (e.g., Skinner 2001; Sparkes 1995). Spranger (1966) identifies six types of personal values: theoretical, social, political, religious, aesthetic, and economic. Theoretical values refer to the discovery of truth and knowledge in a scientific way. With social values, individuals seek human interaction and prefer societal welfare over personal ones. Political values motivate people to acquire prestige and power. Religious values are based on faith and love for wisdom. People seek form, harmony and beauty in their lives due to aesthetic values. Economic values which stress the maximization of monetary and material pursuits are considered as the embodiment of rational behaviour in modern civilization. From the perspective of designing a human-centered investment DSS, it is, therefore, necessary to identify and incorporate investors' value-orientations in such a system. There is also a need to extend the concept of rationality beyond its usual economic connotation, which is discussed next.

The issue of rationality, in the context of investment decision-making, is a two-edged sword. While the objective of building a system such as HIDSS is to improve individuals' investment decisions and help them achieve their investment objectives, the requirement of incorporating the investors' values and preferences into such a system may sometimes conflict with the profit maximization objective. For example, consider an

investor whose ethical values do not allow him to invest in companies involved in alcohol and tobacco production. Suppose the fundamental analysis of these companies indicates a huge profit potential. What recommendations should the DSS give to that user? The apparent dilemma can be resolved by acknowledging that a decision maker should be free and autonomous in the determination of his values and moral imperatives (Oshana 2001). Therefore, the DSS should just inform users about the potential conflict and not be paternalistic by forcing or coercing them one way or the other. Such an approach, which is called *shared decision-making,* is prevalent in medical sectors (Charles et al. 1999).

Rationality as a conscious self-reflection (Brubaker 1984, p. 107) is appropriate in the context of a HIDSS because it is founded on the idea that people are susceptible to several biases and do not engage in self-reflection. Habermas (1984, p. 21) stresses: "Anyone who systematically deceives himself about himself behaves irrationally. But one who is capable of letting himself be enlightened about his irrationality possesses not only the rationality of a subject…he also possesses the power to behave reflectively in relation to his subjectivity and to see through the irrational limitations to which his cognitive, moral-practical, and aesthetic-practical expressions are subject." It is, therefore, expected that the HIDSS should engage investors in critical self-reflection so that they become aware of their various judgment and decision-making biases. Functioning in this manner, the HIDSS will lead to rational decision-making as defined by Habermas (1984) and Brubaker (1984).

This chapter is organized as follows. In section 6.1, the HIDSS will be described as an inquiring system using Churchman's (1971) framework. In section 6.2, an architecture based on the conversational framework (Angehrn 1993) employing stimulus agents is proposed for the HIDSS. In section 6.3, a detailed example illustrating the overall functionality of the HIDSS will be provided. The chapter concludes with a discussion and implications of the proposed system in section 6.4.

6.1 HIDSS as an Inquiring System

Decision support systems have come a long way since their inception in the early 1970s. As discussed in Chapter 2 (section 2.3), a current trend in DSS research is shifting towards finding ways to provide qualitative support to decision makers. A need for a broader definition of DSS is emphasized by Alter (2004) who defines decision support as "the use of any plausible computerized or non-computerized means for improving sense making and/or decision-making in a particular repetitive or non-repetitive business situation in a particular organization." In light of this discussion and the subjective nature of biases involved in investment decision-making, the importance of a holistic framework for building HIDSS cannot be overemphasized. Churchman's (1971) inquiring systems is proposed as such a framework in this context.

Churchman's inquiring systems framework (Churchman 1971), which is based on systems theory and different philosophical systems, has been used as a basis for decision-making models in several organizations (e.g., Keen and Wagner 1979, Malhotra 1997,

Richardson and Courtney 1999). According to systems theory, meaning and understanding are generated through cognition and communication by an intensive feedback between what an organism perceives, how it acts and communicates, and what it receives as responses from the environment (Brier 1995). It is proposed that a HIDSS based on the Churchmanian framework will enable investors to understand and adapt to the complexity of the investment world through self-reflection and knowledge. Table 6.1, which is explained in detail below, outlines bias categories, their corresponding DSS supporting modes, and underlying philosophical systems. Chen and Lee (2003) divide decision guidance into three temporal dimensions: retrospective (past), introspective (present), and prospective (future), and suggest different strategies for each of these dimensions. The bias categories outlined in Table 6.1 follow from the proposed framework of investment decision-making discussed in chapter 3.

Table 6.1 – HIDSS as an inquiring system

Bias category	DSS supporting mode	Philosophical systems	
Cognitive	*Introspective* Strategy: Challenge the assumptions and belief systems	Hegelian (dialectic) Kantian (multiframe)	SINGERIAN
Affective	*Prospective* Strategy: Warn of possible consequences of decisions	Kantian (multiframe)	
Conative	*Retrospective* Strategy: Question past decisions and behaviours	Lockean (empirical)	

Cognitive biases are information-processing biases, which motivate individuals to misjudge the true significance of the received information. The proposed debiasing strategy for cognitive biases involves challenging the current assumptions and belief systems of the decision maker. The DSS supporting mode is introspective because it is primarily focused on the decision maker's present state of knowledge, assumptions, and beliefs.

Affective biases involve emotional elements such as pride, regret, and fear. The debiasing strategy for these biases involves warning decision makers about the potential impact of their decisions. In this case, the DSS supporting mode is prospective because it analyzes their current decisions by assessing the potential impact of such decisions on their financial future and investment goals.

Conative biases are persistent in nature and may exert their influences even in the absence of any information. For example, some people are habitually overconfident in their judgment and decision-making regardless of the type of information they receive. In the case of conative biases, the support mode is retrospective because the debiasing strategy is to question their past[10] decisions and behaviours.

We next discuss how each of these debiasing strategies may complement the underlying philosophical systems used as inquiring systems (Churchman 1971). Named

[10] Life can only be understood backwards, but it must be lived forward. (*Kierkegaard*)

after their thinkers, these systems are *Leibnizian, Lockean, Kantian, Hegelian,* and *Singerian.*

Leibnizian System: The Leibnizian system is a formal, analytical system based on formal logic and mathematical models. The quantitative support necessary in investment decision-making such as computation of fundamentals, macroeconomic trends, and risk is provided with this type of system. In this sense, most of the existing investment DSS are Leibnizian in nature. While such quantitative support is necessary, it is not sufficient as investors also need to be assisted qualitatively as discussed previously. Emphasizing the limitations of the Leibnizian system, Mitroff and Linstone (1993) call it "old thinking". The Kantian System, which is described later, subsumes the Leibnizian system in its fold.

Lockean System: The Lockean system is an interpretive and empirical system relying on the knowledge obtained from past observations. In investment decision-making, the system is useful in examining the existence of conative biases such as overconfidence and status quo by observing their past behaviours. For example, if investors have not updated or rebalanced their portfolio for a long time, the Lockean system may detect a status quo bias.

Hegelian System: The Hegelian system is a dialectic system based on the assumption that a good decision requires the examination of the decision problem from two diametrically opposite perspectives. The Hegelian system is effective in challenging

the assumptions and beliefs of a decision maker and is therefore useful in lowering the influence of cognitive bias such as framing.

Kantian System: The Kantian system is a multiframe system, which stresses that a decision task can be viewed in different ways resulting in different potential solutions. The Kantian system combines both Leibnizian and Lockean approaches in formulating its decision strategies. The influence of affective biases can be detected with this system. For example, consider a case of a *house money effect* in which an individual has decided to invest in highly risky assets under the influence of recent gains. The analytical module in the Kantian system can compute the risk of the present portfolio. The empirical module in the Kantian system, on the other hand, can retrieve data from similar historical transactions. The Kantian system will synthesize the results from these two modules and if necessary, forewarn investors about the possible consequences of taking such decisions.

Singerian System: The Singerian system is a teleological (goal-oriented) holistic system. Its objective is to come up with a well-balanced solution. It is based on the belief of interconnectedness of everything, which emphasizes that a decision problem cannot be separated from its decision maker. Due to its holistic nature, the Singerian system can be used as a framework for combining the results obtained from other philosophical systems.

Having explained how a HIDSS can be viewed as an inquiring system, an architecture for building such a system is now discussed in the following section.

6.2 An HIDSS Architecture

A DSS architecture is the conceptual representation of the layout of the DSS components, the functionality associated with each component, and their interaction with each other and the external world. The architecture facilitates communications between management, end-users, and vendors about a proposed DSS and provides a conceptual foundation for its physical implementation.

The proposed architecture for the HIDSS (Figure 6.1) considers only the Web as a source of investment information and does not take into account the influence of other types of sources such as newspapers and acquaintances. The complexity involved in identifying and analyzing biases generated by information received from such non-electronic 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 obtaining investment-related information as well as a primary reason for information overload and other biases (Associated Press 2005; Barber and Odean 2001, 2002; Rashes 2001). An architecture based on the conversational framework (Angehrn 1993) employing a set of stimulus agents is discussed below.

According to Angehrn (1993), the conversational framework refers to "a process driven by (1) the analytical and reflective learning skills of the decision maker, and (2) the dynamic intervention of a set of stimulus agents." Agents are computational systems that reside in a complex dynamic environment, perceive and act independently in this

environment, and by doing so realize a set of goals or tasks for which they are designed (Maes 1995, p. 108). Stimulus agents are capable of assessing dynamic environments, taking initiatives, adopting alternative strategies, and intervening in the ongoing process (Angehrn 1993). The conversational framework is appropriate for HIDSS because investment decision-making involves a complex and dynamic environment with need for issuing alerts to investors about their potential biases. The proposed architecture consists of three main layers: *user level, domain level, and agents level*, which are described below.

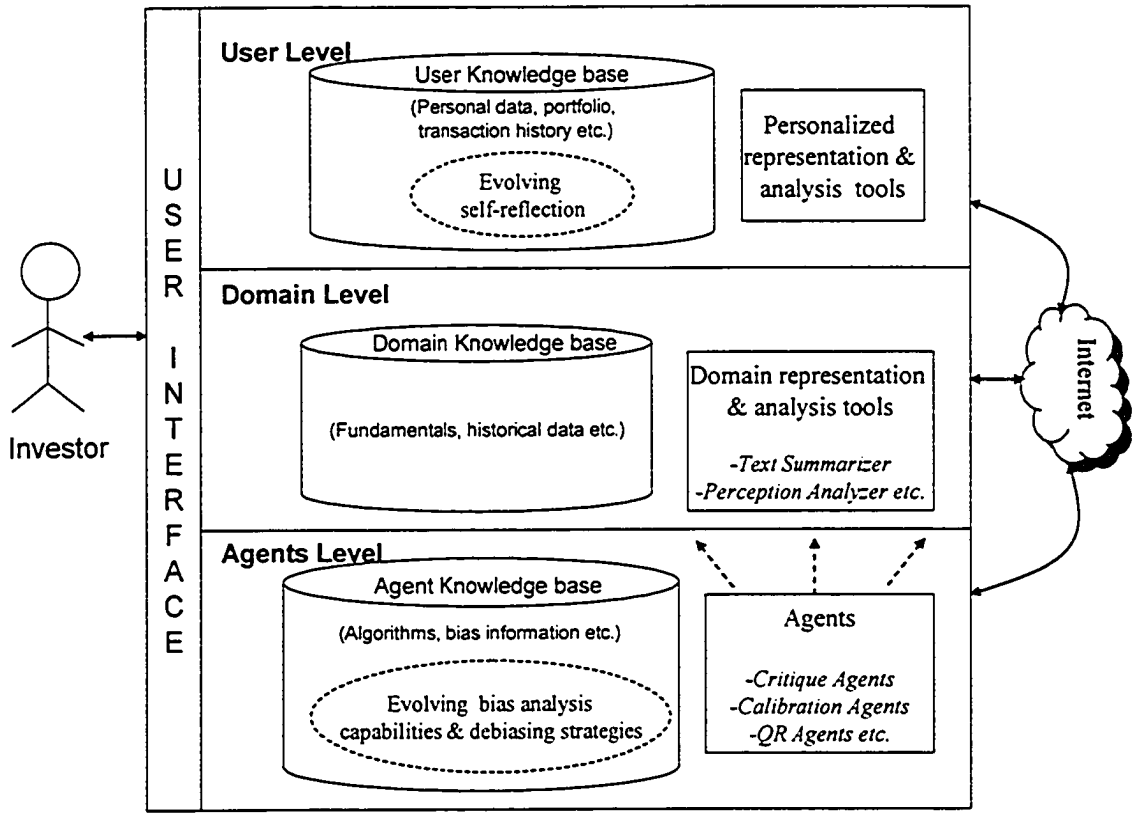

Figure 6.1 – Proposed architecture for the HIDSS (adapted from Angehrn 1993)

6.2.1 User Level

The user level consists of *user knowledge base,* and repositories of *personalized representation and analysis tool.* The *user knowledge base* stores personal information of the investors such as their income, age, risk tolerance, investment goals, family size, portfolio, past transaction details etc. as well as the record of potential *self-reflection* conducted by the user.

One of the objectives of the proposed system is to engage the investors in *self-reflection* so that they become aware of their biases and hopefully learn from their past mistakes. The proposed system gives investors opportunities for self-reflection when it identifies their potential biases, warns them about these biases, and implements the relevant debiasing strategies. The system explicitly suggests that investors engage in self-reflection in such situations by furnishing all the information necessary for that purpose. The system stores all relevant information (e.g., context, bias, and an investor's responses associated with such self-reflection) to evaluate the potential learning experiences by the investors. Such a repository evolves with the continual usage of the proposed system.

Personalized representation and analysis tools help the investors to understand the investment world. These tools are personalized to match with the background and needs of the investors. For example, an investor without any quantitative skills may not understand the mean-variance analysis of her portfolio while she may find graphical simulations depicting potential risk and returns of her portfolio useful and enlightening.

6.2.2 Domain Level

This level contains information pertaining to the investment world such as macroeconomic data, asset classes and their historical returns, fundamentals and industry information etc. It also contains a repository of several domain representation and analysis tools which can be personalized and transferred to the user level. Some of the tools available in this level are a *Text Summarizer* and a *Perception Analyzer*, which are described below.

(1) *Text Summarizer:* The proposed architecture uses the Internet as a primary source for getting investment-related information. While the Internet is an inexpensive and efficient medium for obtaining such information, it also leads to information overload. The use of text summarizing tools similar to TextAnalyst and Cogito can alleviate this problem. TextAnalyst is a text-mining software developed by Megaputer Intelligence that can summarize multiple documents, develop a tree-like topic structure and perform natural language queries (Megaputer 2004). Cogito is a text analysis tool developed by Expert System that can elaborate and simplify the concept of a text (Expert System 2004).

(2) *Perception Analyzer:* The *Perception Analyzer (PA)* is internally used by the system to assess the perception and potential influence of information published on websites on the decision-making process of the investor. For example, investors need to provide the URLs of the websites they have consulted in making their investment

decisions. The *PA* analyzes the content of these websites and reports its findings to the final recommending system of the HIDSS known as the Singerian agent. (This procedure will be made clear later in this section.) At this juncture, a brief description about the working principle of the PA is provided.

The PA may be based on a computational model that uses linguistic processing and textual affect sensing (Liu and Maes 2004). After receiving the text, graphics and charts from the websites consulted by the investors, the PA converts that information to standard format such as newsML of Reuters. The newsML is an XML-based mark-up 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. For example, 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 information, the PA generates an affect valence for each piece of information called *exposure.* An affect valence is a numeric triple based on the PAD model (Mehrabian 1995), which measures three affective dimensions - ***Pleasure-Displeasure*** (e.g. the market is bullish or bearish); ***Arousal-Nonarousal*** (e.g. potential for high gain or loss); ***Dominance-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, 0.7, 0.8]. The score of 0.6 for the Pleasure-Displeasure dimension indicates that the news is likely to please the investor (since the decrease in interest rate may drive stock prices up). The score of 0.7 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. Such affect valences are retrieved from large lookup tables built from the knowledge involving financial news and their potential impact on investors. After analyzing the content of the websites in this manner, the PA computes the overall influence of such websites and sends that information to the Singerian Decision Agent.

6.2.3 Agents Level

The agents level consists of an *agent knowledge base* and repositories for several bias identifying stimulus *agents*. The *agent knowledge base* contains algorithms and information about the stimulus agents employed by the DSS to detect investment-related biases. Based on detected biases, it then employs appropriate debiasing strategies. The knowledge of these stimulus agents is represented with an object-oriented data structure called frames. Frames are suitable for this purpose because of their high expressive power, ease of creating specialized procedures and ease of including default information (Turban and Aronson 2000). These frames are partitioned into different slots which contain the agent's objectives, methodology, algorithms, debiasing strategies, bias context, and communication and coordination protocols with other agents etc.

Depending on the type of biases they investigate, these stimulus agents are termed cognitive agents, affective agents, or conative agents. The debiasing strategies employed by these agents are as outlined in Table 6.1. Each of these agents will have subagents exploring specific biases. As an example, three agents (*Critique Agents, Qualitative Reasoning Agents, and Calibration Agents*) that are useful in lessening the influence of framing, ambiguity, and overconfidence respectively are discussed below.

(1) *Critique Agents* - Researchers have long realized 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 the framing bias occurs due to change in the decision maker's perspectives, critique agents could help overcome this bias by providing both aspects of a decision problem. For example, when investors decide to make a transaction (buy or sell) on particular stocks, critique agents can furnish information both in support and against their proposed trading decision.

(2) *Qualitative Reasoning Agents* - Qualitative reasoning (QR) analyzes a decision problem by understanding the relationships between the structure, behaviour, and function of a system (Bobrow 1984). QR is a dynamic method as it is generally applied to

systems involving the passage of time (Cohn 1995) such as stock markets. QR is useful when the available information is imprecise and ambiguous to make inferences (Iwasaki 1997).

The functionality of a QR agent 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 behaviour. For example, such a module may depict how the potential returns from a retirement portfolio depend on the values of several economic factors such as inflation rate, interest rate etc.

Qualitative synthesis module, on the other hand, derives a structure given the desired behaviour. For example, investors may wish to have at least $1 million at the time of their retirement. The *qualitative synthesis* module may generate several investment portfolios that could potentially meet this objective, given the investors' current financial position and estimated future earnings and savings. The use of a QR agent can help overcome the complexity and ambiguity associated with investment risk management (Benaroch and Dhar 1995).

(3) *Calibration Agents (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 flawed 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). The use of general knowledge questions has been the most common means of measuring confidence-related calibration (McKenzie forthcoming).

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 the person is well-calibrated or not and stores that information in its knowledge base. 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 may assess the confidence level of the investors on a periodic basis (say, once every two months) and use this information to assess their tendency for overconfidence. A large number of such calibration tests with questions from different fields will hopefully make it possible to gauge their overconfidence in a reliable manner.

Calibration agents can also use the concept of *illusion of knowledge* (Barber and Odean 2001) to measure overconfidence. Due to illusion of knowledge, individuals believe they know more than they actually do and thereby become overconfident in their judgment. The CA can ask a number of questions to investors and inquire how many questions they think they answered correctly. The tendency for overconfidence can then be measured with the difference between the their estimated number of correct answers and actual correct answers. A person with a higher estimate of correct answers than the actual number of correct answers would be categorized as overconfident. We followed such an approach in our empirical study (chapter 5).

In any situation, it is likely to have more than one agent involved in a decision-making task and the inputs from all of these agents must be synchronized, examined and shared (Jamali et al. 1999). These agents meet in a neutral, blackboard-like platform where the Singerian Decision Agent (SDA) issues a final alert (if necessary) considering several factors such as the overall goal of the investor, the strength and types of biases reported by the stimulus agents etc. A blackboard refers to an area of working memory designed for agent communications (Nii 1986). The blackboard platform enables all the available knowledge sources to incrementally and opportunistically contribute to the solution of the problem at hand (Hayes-Roth 1985). Several decision fusion techniques (Rahman and Fairhurst 1998; Yu 2001) such as fuzzy logic (e.g., Machacha and Bhattacharya 2000), and belief functions (Yager et al. 1994) can be used by the SDA to come up with a final alert.

6.3 Trading with HIDSS: An Example

In the previous sections, several components of the HIDSS were discussed. This section provides a detailed stock trading example that illustrates how the HIDSS can alert investors about a potential affective bias called the house money effect. Consider an investor (say Joe) who is currently thinking of buying 120 IBM shares. Suppose the calibration agent has recorded him as being overconfident from previous calibration tests that he has done. A trading session with HIDSS is shown in Figure 6.2.

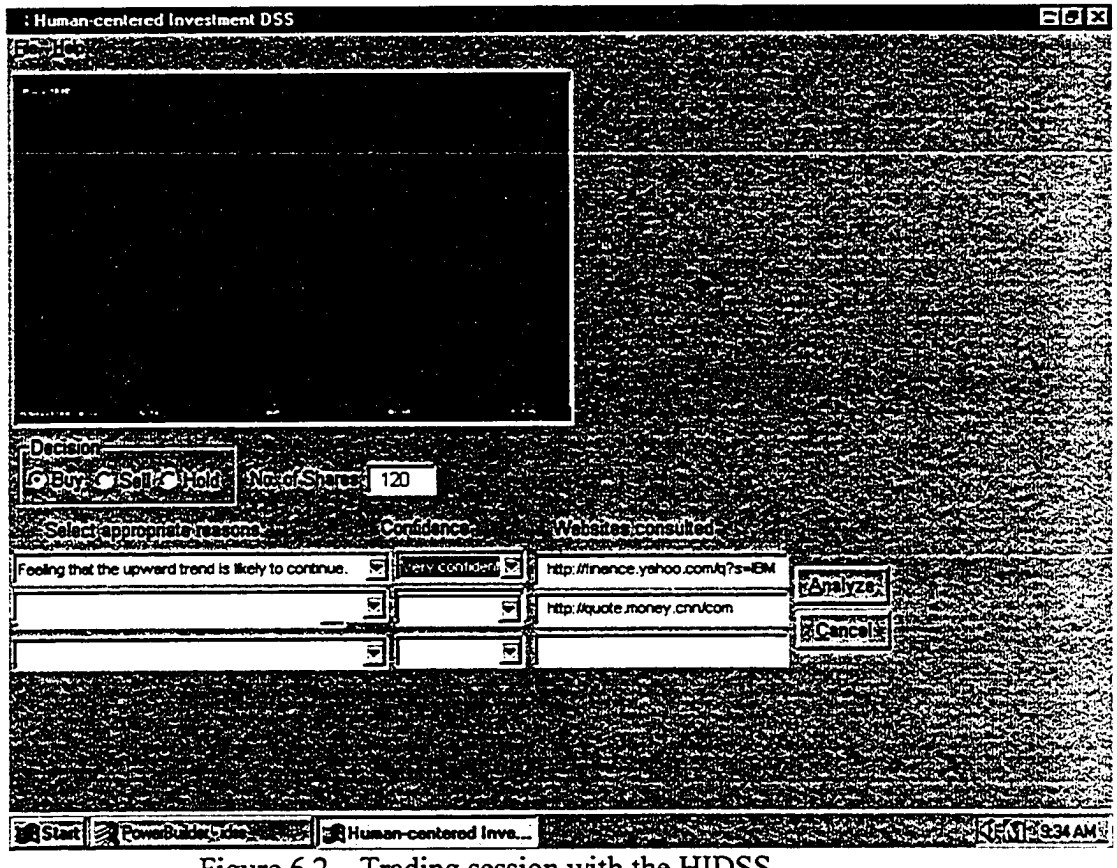

Figure 6.2 – Trading session with the HIDSS

As shown in the trading interface (Figure 6.2), Joe provides several pieces of information such as reasons for his current purchase decision, his confidence level, and

the Websites he has consulted for making such a decision. After receiving these inputs from the user, the HIDSS starts its decision analysis in the following manner. First, the HIDSS passes the URL of the Websites to the *perception analyzer* (PA). The PA evaluates the overall perception of the content of these Websites and provides its results to the Singerian Decision Agent. In addition to the PA, several agents are working in parallel to analyze Joe's current purchase decision. For example, a *cognitive agent* investigating representativeness bias notices a short-term upward trend in IBM stock prices. It then calculates the strength (slope) and duration of the trend to determine the potential existence of the representativeness bias. Similarly, an *affective agent* investigating the house money bias observes that Joe has made a profit of $350 from a recent transaction. The agent, therefore, acknowledges the possibility of a house money bias occurring in this situation. A *conative agent* considers Joe an overconfident person from its past interactions with him. These agents pass their inputs to the Singerian Decision Agent (SDA), which combines their results holistically to issue a final alert. For example, the SDA may assign a high probability of a house money bias in this situation in light of these facts: Joe is usually overconfident; the potential representativeness bias present in the current trend is likely to reinforce his conviction; he has made a profit of $350 from a recent transaction; and the websites content has also scored high along the PAD dimension. Therefore, the SDA decides to warn Joe about the house money effect potentially influencing his current decision (Figure 6.3).

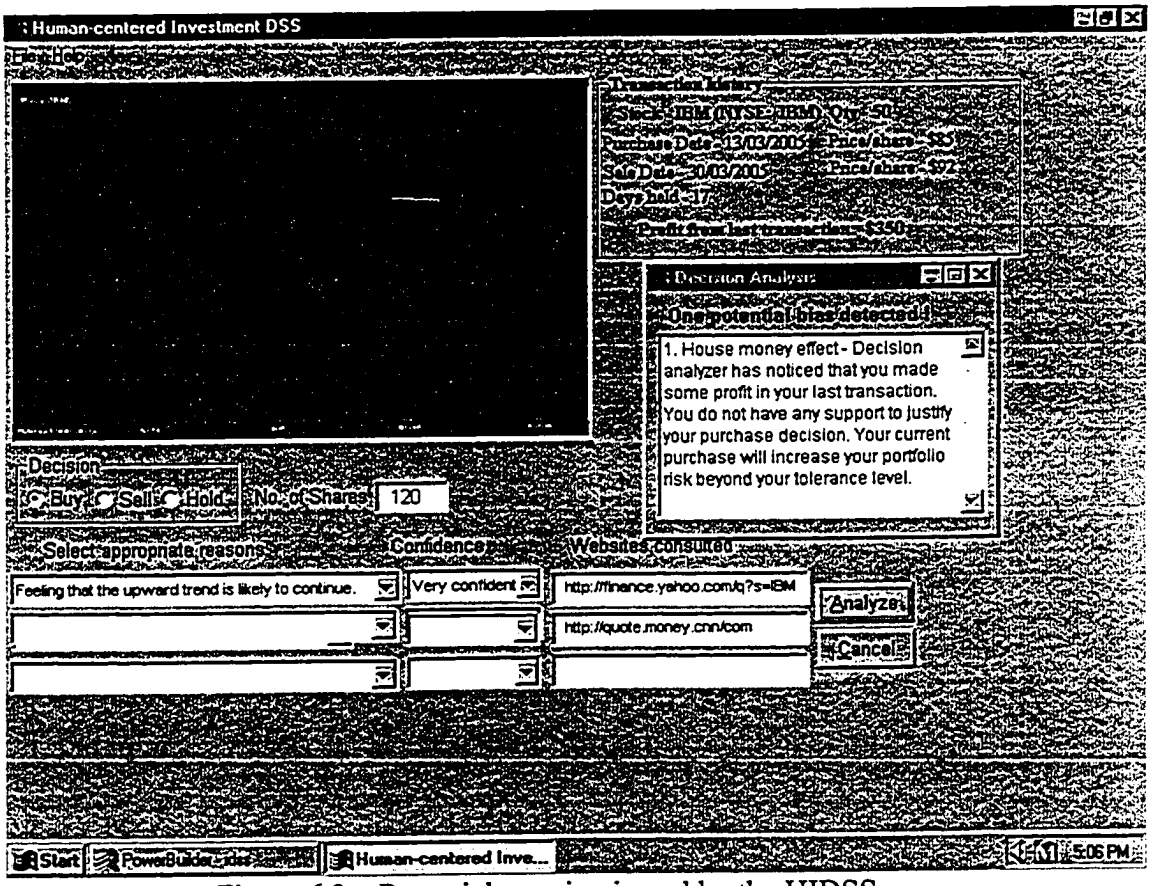

Figure 6.3 – Potential warning issued by the HIDSS

In addition to issuing this alert, the HIDSS may adopt different debiasing strategies. For example, it may show Joe the IBM stock prices in different time horizons. Also, it may inform him how the proposed transaction will tilt his portfolio towards stocks and make it riskier than his preferred risk tolerance level. Furthermore, the HIDSS may retrieve past transactions and outline how many times he had been wrong in similar situations. It is expected that after receiving such information and warning, Joe will reconsider his current decision and engage in self-reflection.

6.4 Discussion

The vision of a human-centered investment DSS discussed in this chapter opens new possibilities in investment decision-making support. However, the proposed system is also faced with many challenges[11] especially with the realization that it encompasses many fields such as behavioural finance, human judgment and decision-making, and emerging computing technologies. A thorough discussion of each of these topics is a significant undertaking in itself, not to mention the scope of a study targeting their synthesis. The objective of this section, therefore, is not to dwell on these topics in depth but to provide an overview of potential challenges and implications of the proposed system from different perspectives such as complexity of financial markets, user interface design, and technical issues involving affective and agent-based computing.

With findings from chaos theory and fractal mathematics, researchers have begun to regard financial markets as complex adaptive systems (CAS) (Arthur et al. 1997). According to the framework developed by Holland (1995), a CAS possesses key attributes such as aggregation, adaptation, non-linearity, and feedback.

Aggregation refers to the emergence of a complex macro phenomenon from the interactions of many simple microagents and their behaviours. The Internet bubble burst in the year 2000 is an example of such aggregation resulting from the behaviour of individual investors. Adaptation refers to the tendency of agents in a system to cope with

[11] Progress imposes not only new possibilities for the future but new restrictions. (*Norbert Wiener*)

the uncertainty and complexity of their environment through some schema or decision rules. Different investment strategies developed or followed by investors are examples of such an adaptation. Non-linearity indicates that the relationship between cause and effect in financial markets cannot be explained in a simple, linear manner. With feedback, a system is able to use its output from the last stage as an input to the next stage. Momentum investors who decide to invest in currently winning stocks drive the prices further up and create positive feedback effect while contrarian investors who follow the opposite strategy generate a negative feedback effect. George Soros, the famous financier and philanthropist, has developed his "Theory of Reflexivity" based on this feedback mechanism and has attributed his phenomenal success to this subjective model rather than some sophisticated mathematical models (Soros 1994). Emphasizing the social and behavioural aspects of financial markets, Lo (2004) proposes the adaptive markets hypothesis by applying the fundamental principles of evolution such as competition, adaptation, and natural selection.

The field of investment decision-making spans several topics and, therefore, the development of the HIDSS entails a systems perspective. The HIDSS is necessarily a dynamic system which is trying to manage complexity from different perspectives such as computational, social, economic, and psychological (Edmonds 2000). While it is not possible to have the best model in such a complex system (Beer 1996), the HIDSS must be capable of knowing which action to execute in which circumstance (as stipulated by the law of requisite knowledge) and not be affected by the perturbations from its

environment (Heylighen and Joslyn 2001). It can, therefore, be concluded that the emerging paradigms in financial markets point toward a complex economic system in which individuals' qualitative attributes such as beliefs, preferences, survival instincts, and values play as dominant a role as their financial needs and skills do. The HIDSS, therefore, must take into account all such factors.

The proposed system needs to incorporate findings from cognitive engineering. For example, Rasmussen (1983) developed his human performance model in which short-term stores are associated with rule-based systems and long-term stores are associated with knowledge-based systems. This model has been used as a framework for the development of cognitive system architecture (e.g., Putzer and Onken 2003). The specific cognitive architecture to be employed by the system, however, may not be crucial as Gershenson (2004) points that there is no best model and that "any system performing a successful action can be considered to be a cognitive system." What are the requirements of HIDSS from the perspective of cognitive engineering? Such an analysis is beyond the scope of this study and, therefore, will not be attempted. However, a few general observations in this context are outlined below.

More than two decades ago, Sprague (1980) argued that DSS need to be adaptive over time and must evolve to accommodate different behaviour styles and capabilities in the long run. In the context of the proposed system, such an adaptation would mean the progressive ability of the system to understand the emotions and beliefs of its users.

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. 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).

The importance of the user interface in such a system cannot be overemphasized. Sanker et al. (1995) emphasize that the proper design of user interface is critical to the success of DSS and stress that such interfaces must be adaptable to different decision-making needs and also be able to communicate consistently with users. They notice that the interface design cost can be as high as 60 to 70 percent of the total development cost of DSS. The usability of the system (Nielsen 1993) which involves learnability, efficiency, memorability, errors, and satisfaction is absolutely critical for the successful adoption of the proposed system. Findings from HCI (human-computer interaction) research suggest that aesthetics or "visual appeal" influences the perceived usability of a system (Tractinsky et al. 2000) and therefore has a critical implication for a user interface design. Lindgaard and Dudek (2003) from their Web design experiments find that both

visual appeal and usability are important and need to be considered by designers of such systems. It is reasonable to believe that "beauty" as well as other aspects of usability would have a significant impact on the overall design of the proposed HIDSS.

In addition to the conceptual requirements discussed above, the proposed system faces several technological challenges. While the agent-oriented programming (Shoham 1993) has been used to develop several agent-based systems and agent-based architectures have been implemented in several areas (e.g., Chuang and Yadav 1998; Lee et al. 2000), the proposed HIDSS is a rather complex system requiring knowledge elicitation from multiple domains. Multiagent systems may be necessary as they are "suited to representing problems that have multiple problem solving methods, multiple perspective and/or multiple problem solving entities" (Jennings et al. 1998, p. 277). The BDI agent model (Rao and Georgeff 1995), which divides the agent's mental state into three components (Belief, Desire, and Intention) may be employed in the HIDSS. The BDI agent model closely matches the theoretical framework of investment decision-making (discussed in chapter 3) which divides biases into three categories: cognitive, affective, conative.

The proposed architecture proposes affective computing for the development of the *perception analyzer*. 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 its development

possible in the near future. However, the validation and evaluation of a complex system such as the HIDSS is challenging. Validation refers to "the process of testing the agreements between behaviour of the DSS and that of the real world system being modeled" (Finlay 1989) whereas evaluation refers to the assessment of decision support systems' overall value (O'Keefe et al. 1987). Lindgaard (2004) also underscores that it is not easy to come up with a measure of success of such systems involving behavioural issues as "interpretation of behavioural results is a tricky business that is just as fraught with potential errors as are other types of measures".

We now outline some factors that may influence the potential adoption and usage of the proposed system.

The technology adoption model (TAM) (Davis 1989) posits that perceived usefulness and perceived ease of use together determine an individual's technology adoption and usage behaviour. However, in the case of a complex system like HIDSS, the TAM may explain only a small component of user acceptance as there could be several other factors such as social pressure and prestige, risk attitudes, trust, necessity to interact with other investors etc. that may influence individuals' acceptance of the HIDSS. In order to overcome the limitation of the TAM, Konana and Balasubramanian (2005) propose the social-economic-psychological (SEP) model of technology adoption and usage for online investing. We believe that the SEP may be adapted (with due adjustment

and extension) to identify and explain potential antecedents to the user adoption of the HIDSS.

Other core adoption issues such as user satisfaction and trust are still critical in the HIDSS. The concept of trust which refers to "the willingness of a party to be vulnerable to the action of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al. 1995) is very important in the HIDSS because users have to rely on the system not only for comprehending the external world (investing) but also for understanding their own shortcomings and biases. Trust in such a system can only be developed with passage of time after continual usage by investors. Lindgaard (2004) stresses that the issue of trust in a system involving affective computing is critical. The overall user satisfaction in the HIDSS may result from the combination of utilitarian gains, hedonic gains, and trust (Konana and Balasubramanian 2005) provided by the proposed system and individuals may attach different levels of importance to these components. All of these factors must be taken into account while building the proposed human-centered investment DSS.

We started this chapter by discussing several concepts underlying a human-centered investment DSS. The need for incorporating an investor's values into the DSS was emphasized. It was also argued that the notion of rationality should include a decision maker's conscious self-reflection effort. Relying on the Churchmanian

framework, we described how different debiasing strategies could be implemented in the HIDSS. An architecture based on the conversational framework was proposed for the HIDSS. The feasibility of the proposed system was demonstrated with a trading example. We outlined some conceptual and technical challenges of the proposed system. After summarizing potential limitations and contributions of this research in the next chapter, this dissertation concludes.

CHAPTER 7

CONCLUSION

This research was undertaken with the need for qualitative support in investment decision-making. The study, therefore, necessarily ventured into three academic fields: judgment and decision-making, behavioural finance, and decision support systems and accomplished the following:

- A theoretical framework of investment decision-making was proposed by using the psychological concepts of beliefs, preferences, and attitudes.
- A taxonomy was suggested by classifying decision-making biases into three categories: cognitive, affective, and conative. Fundamental characteristics of these biases were discussed. We outlined major investment-related biases belonging to each of these categories and described their potential impact on investment decision-making.
- With our empirical study, we were able to confirm the deleterious impact of such cognitive biases as representativeness, framing, and ambiguity on an individual's investment decision-making. We found that decision aids such as feedback and graphs are quite effective in lowering the influence of those biases. It was also observed that the benefit of such aids increases as investment scenarios become complex and hold more potential for instigating cognitive biases. Findings from our study indicated that the low levels of knowledge, experience, or education may contribute toward decision aid

neglect. Overall findings from our empirical study indicate the usefulness of personalization in investment DSS as well demonstrate the need for a "holistic" DSS for judicious investment decision-making.

- In the above context, a human-centered investment DSS (HIDSS) was proposed. Using Churchman's inquiring systems framework (Churchman 1971), it was discussed how the HIDSS could use different philosophical systems as a basis for its debiasing strategies. An architecture based on the conversational framework (Angehrn 1993) employing a set of stimulus agents was suggested for the HIDSS. The feasibility and usefulness of the proposed system was demonstrated with a stock trading example.

This research has benefited from the interdisciplinary approach and made the following contributions to theory and practice.

7.1 Contributions to Theory

A conceptual framework of investment decision-making was proposed by using the psychological concepts of beliefs, preferences and attitudes. The proposed framework demonstrated that an investment decision-making involves three components: cognition, affect, and conation. The cognitive component refers to the beliefs and assumptions of a decision maker. The affective component involves emotional elements such as greed, regret, and fear. The conative component refers to the action tendency of the decision maker. Major biases belonging to each of these three components were identified and

described in terms of their roles in influencing investment decision-making. Although this framework has been developed from the perspective of investment decision-making, it may be applicable in other areas of human judgment and decision-making as well.

While envisioning a human-centered investment DSS, this research employed the concept of inquiring systems to suggest possible debiasing strategies for a human-centered investment DSS. The Singerian inquiring system was recommended for integrating the analyses received from other systems examining the existence of specific biases in investment decision-making. While discussing the implications of such a DSS, the necessity of a value-based decision-making approach was emphasized. It was also argued that only "a consciously guided life" engaged in self-reflection could be appropriately called "a rational life".

Overall, this research is expected to make significant theoretical contributions in the area of decision support systems and investment decision-making. The significance of this research is also highlighted by the fact that, to the best of our knowledge, this is the first comprehensive study to explore new research opportunities in information systems by using findings from behavioural finance. By undertaking this study, this research has attempted to bridge the current gap between these two disciplines.

7.2 Contributions to Practice

In addition to the theoretical contributions outlined above, this research also contributes to practice. In an experimental setting, the study demonstrated the existence of several biases that influence investment decision-making. The study empirically validated the effectiveness of feedback and graphical aids in lowering the impact of framing, ambiguity, and representativeness biases in asset allocation decisions and thereby demonstrated the usefulness of incorporating such support in investment DSS. The study also showed the potential need for personalized aids in investment decision-making.

The neglect of decision aids is a serious issue in DSS development. While some studies attribute such neglect to decision makers' overconfidence, this study could not support that hypothesis. It was observed that factors such as knowledge, experience and education of users might contribute towards their reluctance to use decision aids. These findings may have important implications also to decision support systems being used in other areas. Overall, the empirical study investigated several practical issues involved with the incorporation of cognitive aids in investment DSS.

While the empirical study investigated the effectiveness of decision aids in lessening the impact of cognitive biases, the proposed architecture for a human-centered investment DSS outlined the possibility of combating affective and conative biases as well. It was shown that such an architecture could be built upon the conversational framework employing agent technology and affective computing methodologies. Having

outlined the technical requirements of the proposed system, this study may serve as a starting point for developing such a system in the future. Individual investors as well as software entrepreneurs are anticipated to realize practical benefits from this research. The proposed system can be developed as an educational tool to make individuals aware of their decision-making biases. Overall, it is rightfully expected that this study has made important contributions to the both theory and practice of decision support systems.

7.3 Limitations and Directions for Future Research

Our empirical study was based on the theoretical framework of investment decision-making we proposed in chapter 3. The proposed framework divides judgment and decision-making biases into three broad categories: cognitive, affective, and conative. Several biases influencing investment decision-making were identified and placed under one of these three categories depending on the nature of their origin and potential impact. While there could be many biases that may influence investment decisions, this study focused on well documented and major investment-related biases only.

One shortcoming of the empirical study is that it investigated the usefulness of decision aids in lowering the impact of cognitive biases only. The primary reason for this focus is that the other two types of biases (affective and conative) necessitate longitudinal transaction data which is not possible to get in an experimental session. Furthermore, due to the very nature of affective and conative biases, the risk of introducing noise is also very high.

Another limitation is that the scenarios used in the experiment might appear to be simplistic and not necessarily match the complexity of the real world. However, such an approach is necessary as the use of scenarios provides experimental control (Kirs et al. 1989). The control of external variables is critical for behavioural research (Benbasat and Todd 1996). Furthermore, many IS researchers (e.g., Alavi 1984; Benbasat and Dexter 1982; Courtney et al. 1983) have used scenarios in their experiments.

From the perspective of experimental design, the investment scenarios and their corresponding cognitive aids may have carried implicit task demands by virtue of presenting different amounts of information in different conditions and thereby potentially influencing subjects' judgments. However, results from the experiment confirm that the scenarios were successful in inducing the three types of cognitive biases which were the focus of this empirical study.

Another potential limitation of this study is the hypothetical nature of asset allocation decisions. However, several important studies in finance and information systems have asked their subjects to consider imaginary situations. For example, Benbasat and Dexter (1982) asked their subjects (university students) to act as managers in a hypothetical firm. Asset allocation decisions studied by Benartzi and Thaler (2001) also involved a hypothetical situation. More importantly, studies in judgment biases have found that hypothetical choices made by subjects do match real-world behaviour for small as well as large payoffs (Kuhberger et al. 2002).

From the perspective of DSS, this study uses only decision quality (reduced judgment bias) as a measure of the effectiveness of decision aids even though researchers have also suggested other criteria such as user satisfaction (e.g., Aldag and Power 1986; Davis 1989; Doll and Torkazadeh 1988), user learning (e.g., Alter 1980; Dos Santos and Bariff 1988), and decision-making efficiency (e.g., Benbasat and Dexter 1982; Wilson and Zigurs 1999). However, decision quality is the most commonly used criterion (Singh 1998; Wilson and Zigurs 1999).

Future studies could extend this work by investigating the efficacy of personalized decision aids in combating the influence of cognitive biases. The present study focused on asset allocation decisions only. It would be interesting to find out whether decision aids are also useful in trading decisions. While it is difficult to develop investment scenarios that could correctly examine affective and conative biases, it is worthwhile to make future research effort in that direction. Success of such studies will have a significant impact on both the theory and the practice of investment decision-making. Future studies can also investigate other measures of decision guidance effectiveness such as satisfaction, efficiency, and user learning. As an extension of this work, we suggest to develop a prototype of the HIDSS. An empirical study regarding the applicability of the social-economic-psychological model of technology adoption and usage (Konana and Balasubramanian 2005) can then be conducted for such a system.

This dissertation now concludes with reiterating our faith that the central task of a natural science is to make the wonderful commonplace (Simon 1999). Although the

design of a human-centered investment DSS is more like an "artificial science" than a natural one, and the proposed system is yet to be realized, we believe this study demonstrates where the true wonder in investment decision-making lies. 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." The purpose of this dissertation will be served if it has been successful in demonstrating the necessity and feasibility for such retooling in investment decision-making.

> We shall not cease from exploration,
> And the end of all our exploring,
> Will be to arrive where we started,
> And know the place for the first time.
> (T. S. Eliot in *Little Gidding*)

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APPENDIX I

Screenshots for demographic information and general investment knowledge test

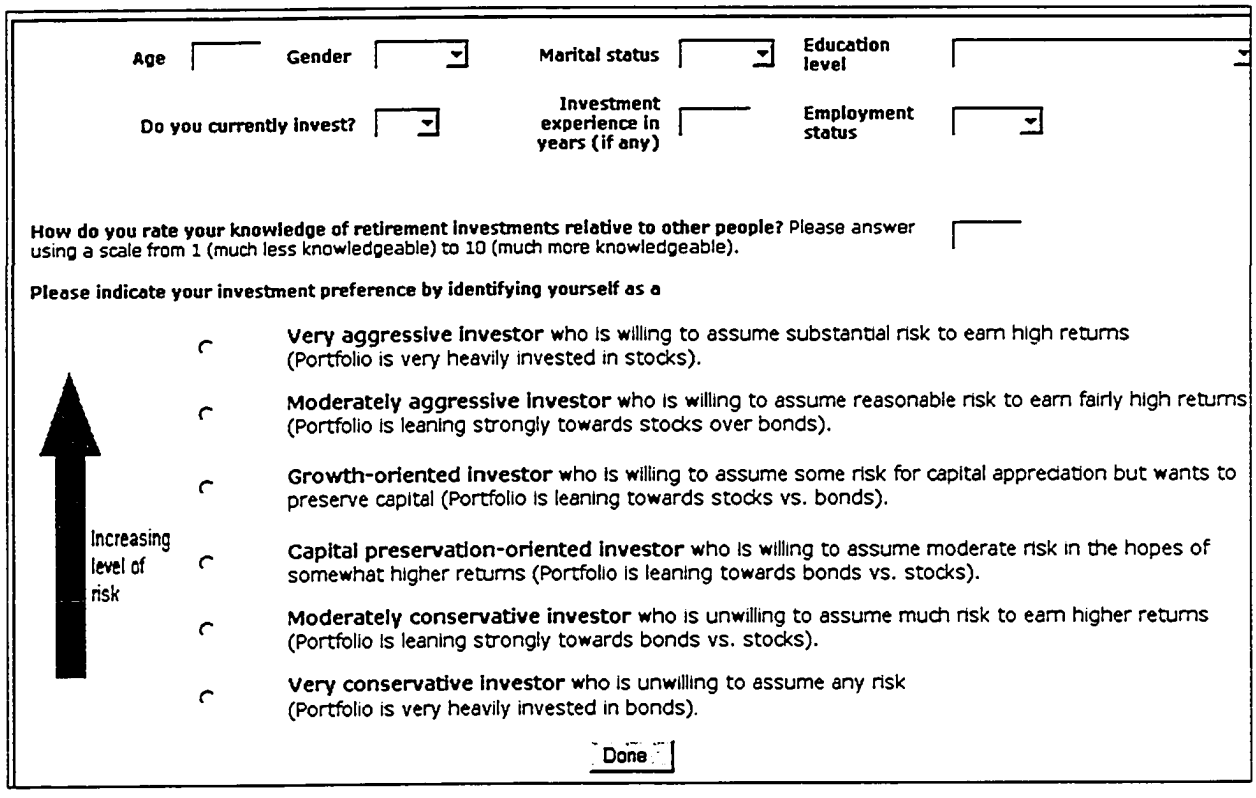

Figure A.1 – Screenshot of demographic information

General Investment Knowledge Questions

Please answer *True* or *False* to the following questions to the best of your knowledge.

- It is conventional for a financial planner to argue that an individual's investment on stocks should decline as he/she approaches retirement.

  ○ True ○ False

- If interest rates rise, the price of a bond will rise.

  ○ True ○ False

- The price of a stock increases after the payment of a dividend.

  ○ True ○ False

- Investing in bonds does not incur any risk.

  ○ True ○ False

- All investment earnings are taxed at the same rate.

  ○ True ○ False

Please enter the number of questions you think you answered correctly:

Done

Figure A.2 – Screenshot of general investment knowledge questions

APPENDIX II

Information provided in low and high level ambiguity scenarios

Subjects were given following information in the low level ambiguity scenario.

Suppose you have $100,000 in your pension account. You have only the following three bond funds to invest in. The performance of these funds is comparable to each other. Please read the following information about these funds carefully.

National Bond Fund: The primary objective of this fund is total return with interest rate anticipation as its management style. The fund has the following asset allocation: Corporate bonds-65.7%, Provincial bonds-3.6%, Canada bonds-19.3%, and others (including cash) -11.4%.The historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 4.1%, 7.0% and 7.8%. The management fee for this fund is 2.5%.

Bond Index Fund: The primary objective of this fund is total return with passive management style. This fund tries to add value against the Scotia Capital Markets Bond Universe with the following asset allocation: Corporate bonds-17.2%, Provincial bonds-20.4%, Canada bonds-51.3%, and others (including cash)-11.1%.The historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 5.3%, 8.7% and 10.4%. The management fee for this fund is 0.75%.

Smart Bond Fund: The primary objective of this fund is total return with interest rate anticipation as its management style. The fund has the following asset allocation: Corporate bonds-70.7%, Provincial bonds-3.6%, Canada bonds-15.3%, and others (including cash) -10.4%.The net historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 4.3%, 8.1% and 8.5%. The management fee for this fund is 1.68%.

Subjects were given following information in the high level ambiguity scenario.

Suppose you have $100,000 in your pension account. You have only the following six bond funds to invest in. The performance of these funds is comparable to each other. Please read the following information about these funds carefully.

National Bond Fund: The primary objective of this fund is total return with interest rate anticipation as its management style. The fund has the following asset allocation: Corporate bonds-65.7%, Provincial bonds-3.6%, Canada bonds-19.3%, and others (including cash) -11.4%.The historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 4.1%, 7.0% and 7.8%. The management fee for this fund is 2.5%.

XYZ Bond Fund: The primary objective of this fund is total return with interest rate anticipation as its management style. The fund invests mainly in Triple "A" Government of Canada bonds of varying maturities. The fund has the following asset allocation: Corporate bonds-17.4%, Provincial bonds-7.0%, Canada bonds-60.2%, and others (including cash) -15.4%.The historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 3.9%, 6.6% and 7.5%. The management fee for this fund is 1.43%.

ABC Bond Fund: The primary objective of this fund is total return with interest rate anticipation as its management style. The fund invests in A-rated bonds with the following asset allocation: Corporate bonds-38.5%, Provincial bonds-25.5%, Canada bonds-33.5%, and others (including cash)-2.5%.The net historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 5%, 8.3% and 9.7%. The management fee for this fund is 1.5%.

Green Bond Fund: The primary objective of this fund is total return with interest rate anticipation as its management style. The fund has the following asset allocation: Corporate bonds-65.7%, Provincial bonds-3.6%, Canada bonds-19.3%, and others (including cash) -11.4%.The net historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 4.2%, 7.1% and 7.8%. The management fee for this fund is 1.74%.

Bond Index Fund: The primary objective of this fund is total return with passive management style. This fund tries to add value against the Scotia Capital Markets Bond Universe with the following asset allocation: Corporate bonds-17.2%, Provincial bonds-20.4%, Canada bonds-51.3%, and others (including cash)-11.1%.The historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 5.3%, 8.7% and 10.4%. The management fee for this fund is 0.75%.

Smart Bond Fund: The primary objective of this fund is total return with interest rate anticipation as its management style. The fund has the following asset allocation: Corporate bonds-70.7%, Provincial bonds-3.6%, Canada bonds-15.3%, and others (including cash) -10.4%.The net historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 4.3%, 8.1% and 8.5%. The management fee for this fund is 1.68%.

APPENDIX III

The Chi-Square Test of Independence

The Chi-Square Test

If the variables are statistically independent, that is, the null hypothesis is true, then the sampling distribution of the chi-square statistic is given by a continuous curve called a chi-square distribution. The chi-square statistic is defined as

$$\chi^2 = \sum_{i=1}^{k} (O_i - E_i)^2 / E_i$$

with (r-1)(c-1) degrees of freedom, where

O_i = observed number in cell i

E_i = observed number in cell i expected under independence

r = number of rows

c = number of columns

Test Statistics

(1) Pearson Chi-square - The Pearson *Chi-square* is the most common test for significance of the relationship between categorical variables and is based on the fact that *expected* frequencies can be computed in a two-way table. Expected frequencies refer to the frequencies that one would expect if there was no relationship between the variables (Hays 1988). The results of the chi-square test are reliable only if the expected frequency in each cell is at least 5. One limitation of the chi-square statistic is that it is proportional to the sample size, thereby making it difficult to interpret in an absolute sense (Aaker et al. 2000).

(2) Maximum-Likelihood Chi-square - The Maximum-Likelihood Chi-square tests the same null hypothesis as the Pearson Chi-square statistic. Its computation is based on Maximum-Likelihood theory and is usually very close to the Pearson Chi-square statistic (Fienberg 1977).

Measures of Association

(1) Phi Coefficient - The Phi-square (φ^2) is a measure of correlation between two categorical variables in a 2 x 2 table. Its value can range from 0 (no relation) to 1 (perfect relation) between the two factors in the table. Unlike the chi-square statistic, φ^2 is not proportional to the sample size (Siegel and Castellan 1988) and is computed as

$$\varphi^2 = \chi^2/n$$

(2) Contingency Coefficient - The strength of the association between two categorical variables can be measured by the contingency coefficient (C) given by

$$C = [\chi^2/(\chi^2+n)]^{1/2}$$

The value of C varies between 0 and 1, where 0 indicates that the variables are statistically independent and 1 indicates their complete dependence. One disadvantage of this coefficient is that its maximum value depends on the size of the table (number of rows and number of columns) (Aaker et al. 2000).