# Risk Visualization: A Mechanism for Supporting Unstructured Decision Making Processes

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## Abstract

*The premise of this paper is that risk visualization has the potential to reduce the seemingly irrational behavior of decision makers. In this context, we present a model that enhances our understanding of visualization and how it can be used to support risk based decision making. The contribution of our research stems from the fact that decision making scenarios in business are characterized by uncertainty and a lack of structure. The complexity inherent in such scenarios is manifested in the form of unavailability of information, too many alternatives, inability to quantify alternatives, or lack of knowledge of the payoff matrix. This is particularly prevalent in domains such as investment decision making. Rational decision making in such domains requires a careful assessment of the risk reward payoff matrix. However, individuals cope with such uncertainty by resorting to a variety of heuristics. Prior decision support models have been unsuccessful in dealing with complexity and nuances that have come to typify such heuristic based decision making.*

## Keywords

R*isk visualization, investment decisions, risk propensity, risk perception, risk estimation.*

## 1. Introduction

In this paper, we introduce the concept of risk visualization for effective and rational decision making. Risk visualization is defined as a process that helps decision makers assess and evaluate risks of possible decision choices. Risk visualization has implications to improve decision making in unstructured environments and to reduce irrational behavior of decision makers. The ability to visualize risk may be of particular value in "exacting" environments such as brain surgery and rocket science where the consequences of small errors are very high (Kardes, 2006). We see the value of risk visualization in similar high consequence environments such as stock trading. In this context, we present in this paper a model that enhances our understanding of visualization to help support risk based decision making.

Human decision making process is an exercise in adaptive learning (Payne et al. 1993). We 'supposedly' learn and adapt by responding to feedback—'supposedly' because if all learning were adaptive then the observed irrationality should be an anomaly. But irrational behavior is apparently widespread and common place (Chen et al. 2006); human memory of events is short lived (Horowitz and Wolfe 1998); yet there is evidence that we do respond to feedback—nature, strength, and frequency of response varies across domains based on contextual and experimental variables. Therefore, evidence of our adaptability is mixed, questionable and limited, at best.

One contributing component in this unresolved issue of decision making process is the concept of risk. Risk can be inherent as a trait of the decision maker (individual risk), of the decision making situation itself (situational risk), or both. In virtually all decisions, we implicitly or consciously evaluate the risk-return trade offs (Lehner 2000). If the risk is negligible or non-existent, the problem of adaptability becomes trivial. For example, abundance of air or water (a low risk situation) has little need for any adaptive behavior. But water scarcity (a high risk situation) requires adaptive and learning behavior. In the latter case, individuals with an aggressive attitude will seek out risky choices compared with risk averse individuals. Interaction of individual risk and situational risk will likely generate interesting alternatives.

Rationality models suggest that individuals try to mitigate the effects of individual traits and adapt or learn from different situational scenarios. Clearly, the extent and quality of feedback has an impact on the adaptation and learning rate of the decision maker. The de facto approach in the literature has been to examine the impact of feedback on performance. The feedback literature has focused on the impact of varying degrees of feedback on performance (Gonzales-Vallejo and Bonham, 2007). Post feedback performance is vastly superior to performance without feedback or feedback with limited information. Feedback quality is typically proxied by the amount, timeliness and relevance of the information (Barron and Erev 2003). It is our contention that there is yet another dimension of feedback quality. Performance may be confounded by the form and format of the feedback presentation. The ability of the decision maker to process the feedback and react to consequent situations in a rational manner depends on the feedback presentation form and format. A more accurate determinant of feedback quality is whether the feedback helps the decision maker to create an alternate representation or visualization of the problem thereby, allowing for quicker learning as well as possibly interesting and creative solutions.

The paper proceeds as follows: In the second section, we identify the determinants of risk based decision making. The third section introduces the notion of risk visualization. Risk visualization is further elaborated and illustrated using an example of investment decision making in the fourth section. The paper concludes with implications of visualization for risk based decision making and decision support, and provides directions for future research.

## 2. Risk-based decision making

Dynamic decisions are featured by inter-dependent sequential choices made by the decision maker in a task system (MacKinnon & Wearing 1985). Each choice affects the task system so that the subsequent decision is made in a different state of that task system.

Given the task system, decision making under uncertainty requires the subject to construct prior probability distribution over possible states of the problem. This involves an understanding of the role risk plays in unstructured decision making environments. Despite its importance, less is known about the role of risk in dynamic environments, its visualization in the decision process, and its interaction with other constructs.

One of the better-known models of risk (and its determinants) is the prospect theory. The theory suggests that individuals are risk seeking in a loss situation and risk averse in a gain situation (Tversky and Kahneman 1981; Highhouse and Yuece 1996). However, results from the empirical tests of the theory remain inconclusive. For example, in an experiment involving multistage risky investment task, Huber (1996) could not find support for prospect theory when subjects had a choice to buy protection for any part of the invested capital. Further, arguing that multiple points of reference are important determinants of risky behavior, Sullivan and Kida (1995) found that subjects are more willing to accept risk after experiencing a prior gain as opposed to a prior loss.

Finally, compounding the inherent complexity of judgment under uncertainty is the role of heuristics and biases that humans adopt to reduce task complexity. However, evidence reveals that reliance on such biases results in severe and systematic errors despite the presence of incentives and forced motivations (Tversky and Kahneman 1974).

The bias effect is more pronounced in prediction tasks (such as the future value of stock prices) where representative-ness of the description outweighs the normative statistical theory in the mind of decision maker. Evidence pertaining to base-rate fallacy in categorical prediction tasks indicates that the effect of base rate increases systematically with a decrease in differential representative-ness (Fischhoff and Bar-Hillel 1984). Other variables investigated with mixed findings in the literature include the effects of subjective risk (Dickson 1978), cognitive style (Dickson 1978), risk factors (Baird and Thomas 1985), decision frames (Hollenbeck et al. 1994), and probabilistic information (Erev and Wallsten 1993). Figure 1 provides an overview of risk related variables commonly referenced in the literature.

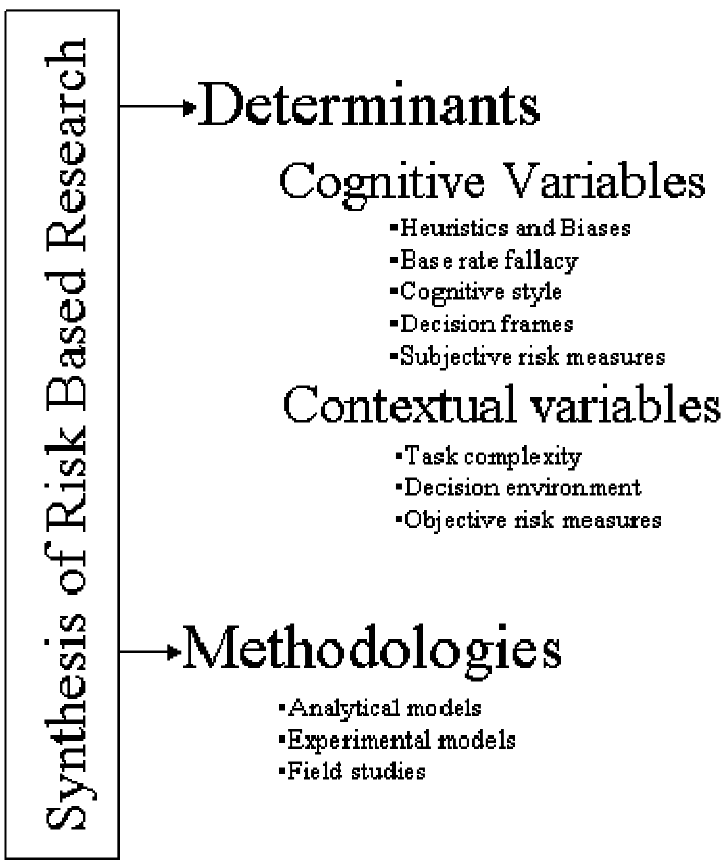


**Figure 1: Synthesis of risk based studies**

Risk propensity, risk profile and risk perception are key to understanding and improving decision outcomes (Pablo et al. 1996; Sitkin and Weingart 1995). Risk propensity is a function of perceived severity (assumed importance vis-à-vis consequence) and probability of loss (Slovic et al. 1980; Ranney 1994; Comsis Copr. 1995). It is the general tendency to either seek or avoid risks and historical patterns seem to contribute to such a trait. Increased self-confidence (due to higher positive experience) reduces risk propensity to the point of feeling an absence of risk in the situation. Prior evidence is consistent with invulnerability as a major cause of poor risk management (and, hence, decisions) in dynamic, unstructured situations (Lester and Bombaci 1984; Jonah 1986). Risk propensity and decision-making are integrally related in unstructured environments (Brown and Groeger 1988). Risk propensity is central to risk evaluation and nature of risk acceptance (Sitkin and Pablo 1992; Pablo 1998).

Risk profile is innate to the decision maker. Inherent risk aversion or risk seeking behavior is characteristic of each individual. Viewed in this sense, risk profile is long term trait; risk propensity is acquired and short term trait. A person with a specific risk profile can generate differential response to varying situations of riskiness; this response can be elicited by training, education, experience, effective decision support or cues.

Risk perception helps a decision maker identify feedback, evaluate its value and estimate its impact on a decision choice (Hunter 2002). In other words, risk perception is the recognition of risk through identification, estimation, and evaluation. According to Johan (1986) risk perception can be affected by decision support, training, education, and experience. Risk perception is a process; nature and degree of perceived risk would vary according to the situation.

The relation between various concepts of risk is illustrated in Figure 2. The figure illustrates the relationship between risk strategies (guided by subjects' risk profiles) and decision choices. Risk tolerance and risk perception influence risk preferences of subjects in a decision context. Transient characteristics (defined as risk propensity) and innate characteristics (defined as risk profiles) together determine subjects' risk tolerance. Thus, contextual uncertainty may moderate subjects' risk propensity to provide specific risk tolerance. Differences in decision contexts can yield varying levels of risk tolerance acceptable to same subjects. Risk perception is an exercise in identification, estimation and evaluation of risk in a decision context and effect on risk-return payoff.

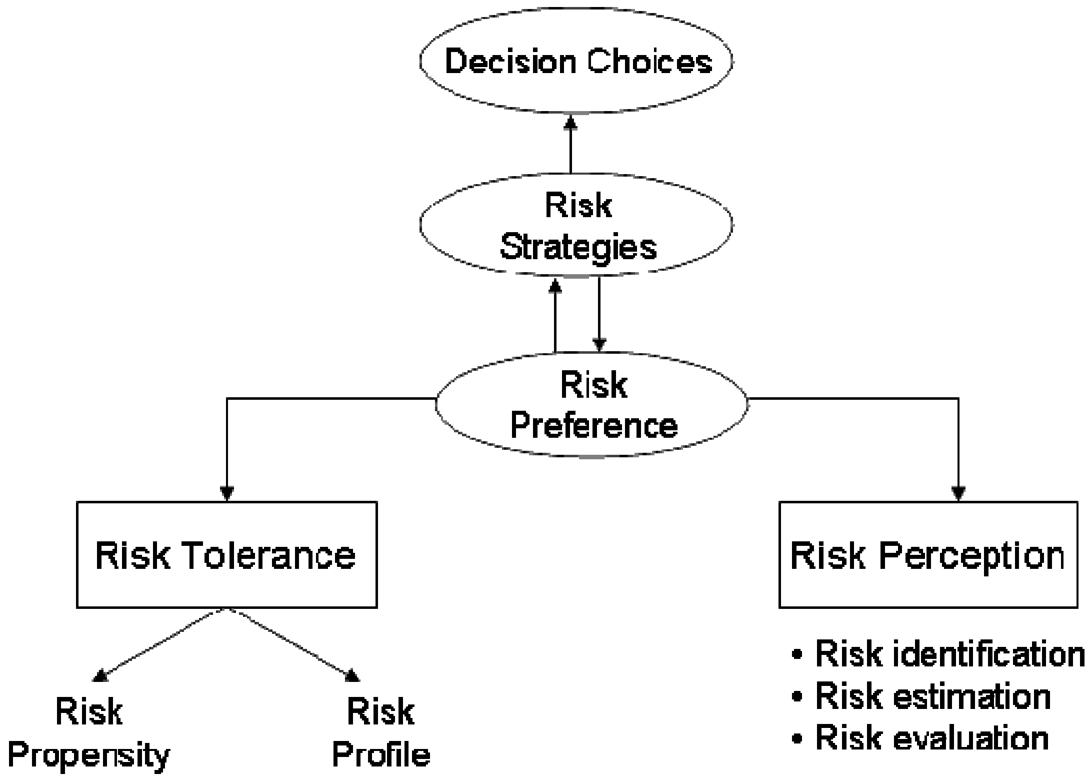


**Figure 2: Model of risk hierarchy**

Figure 3 illustrates the basic model of risk based decision making. Efficient decision-making requires a careful understanding of a three-staged decision process, i.e., risk perception, risk estimation, and decision choice. Individuals make conscious risk based decision choices based on their perception of the environment. At a concurrent level, they also apply heuristics or models for estimating or quantifying the impact of the risk. It is possible that the models or heuristics used for quantifying risk may be moderated by the nature and complexity of the decision task. The outcome of a decision choice in turn affects the environment and more importantly reframes their perception of the risk and uncertainty underlying this dynamic environment. The outcome of the decision choice also tends to affect the confidence of the individual with respect to the heuristic used to estimate risk.

The knowledge of the relationship between risk propensity and risk profile can be used to devise means to alter long-term (and sometimes negative) risky behavior. This knowledge is usually cultivated and acquired over long periods of time. However, learning time can be reduced with the help of models, which enable decision makers to visualize the impact of risky preferences. In the following section, we develop a model of risk visualization as a means to facilitate learning and adaptation in unstructured decision making environments characterized by risk and uncertainty.

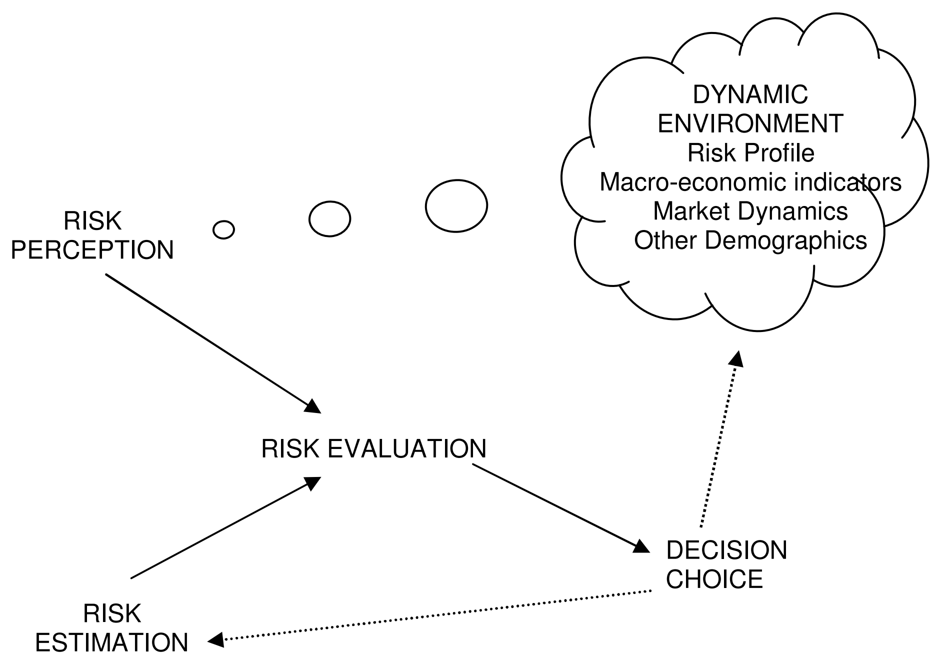


**Figure 3: Risk based decision making model**

## 3. The Visualization of Risk

Traditionally, the term visualization has been used in the final stage of the decision making process to convey the graphical presentation of results. We use the term in a broader sense to include visualization as a process of helping the decision maker form a mental model of the problem.

Visualization creates an alternative representation that is external and explicit to the decision maker. It enables a more efficient understanding of the problem (Powell, 1995). Visualization helps to create, refine, and use a mental model for problem space understanding (Johnson-Laird, 1983).

Existing literature provides some reference to such a concept of visualization. According to Pracht (1990), visualization enables and supports the creative and unstructured task of discovering and modelling complex problem domains. This could also represent the crucial link between problem and a set of solutions, and understanding how those solutions vary with respect to changes in key assumptions (Bell 1994). This school of thought is consistent with the concept of early visualization that is attributed to Blaser et al. (2000). The idea is to help problem solvers create a mental image, which would help them comprehend the initial problem space and further assist them in problem formulation (called intelligence by Herbert Simon, 1997).

Some efforts in risk visualization are reported from other domains. Regan et al. (2000) developed a training tool to develop risk perception skills in novice drivers. Individuals in loss (gain) situation perceive risky alternatives as opportunities (threats). Novices tend to take unbalanced (and higher) risk, as they are unable to realize (thus, visualize) the risky situations when those situations develop (Jonah 1986).

Anecdotally, failure to properly visualize and manage risk in dynamic unstructured environments is often identified as one of the major factors in poor decisions. Inaccurate assessment of risk can lead decision makers to ignore or misinterpret pertinent signals that demand immediate and effective attention. Generally, decision makers don't perceive the danger applying to them personally. Therefore, DeJoy (1992) advocates for developing interventions to personalize risk to the decision maker.

Risk visualization is appropriate in an iterative task such as investment decision-making where the problem space needs to be continually reformulated given the changing dynamics. Both the manner in which investment outcomes are communicated and the content of those outcomes affect the decision making process.

## 4. Risk Visualization for Investor Decision Support

The assessment and management of risk is a significant part of decision making in unstructured tasks like investments. Investing in volatile asset classes such as stocks is characterized by a high degree of uncertainty and risk. The movement of stocks is typically affected by economic, political, market, industry, and other environmental dimensions. Often it is difficult for an investor to assess the collective impact of such influences. To be successful in such an environment requires knowledge of investment dynamics and risk management. According to an investment literacy segmentation study conducted by Applied Research and Consulting in 2003, investment demographic groups differ in their knowledge of investment decision making. Specifically, investment sub-groups which exhibit lower investment knowledge than the norm include younger population, low income groups, women and retirees. As a result, investors resort to naïve heuristics to compensate for their lack of knowledge. Herd mentality observed in the stock market is a consequence of this behavior.

In an iterative and interactive scenario, visualization captures relevant knowledge and restructures it to enable further learning. Risk visualization, thus, has the potential to make the process more structured where the decision makers learn by processing the knowledge from one iteration and, adapt and apply it to subsequent iterations. This is done by helping the decision maker develop schemata that represent internal representations of the spatio-temporal features of the situation. Schemata help individuals perceive risk and opportunities as they arise in investment decisions. The objective is to moderate risky behavior by shifting the decision process from a mode of uninformed speculation to one that is more informed and based on intelligent data.

Figure 4 illustrates the application of the three stage risk based decision making process (risk perception, decision choice, and risk estimation, see Figure 3) in the context of investment decisions. A risk visualization model can enable adaptive learning for investors who understand and learn the relation between risk and return for varying contextual risk scenarios in repeated investment decisions. We envision a model based decision support system for training where feedback about investor's actual returns for a risk level and potential returns for an alternate risk level can be provided at each decision point. The model estimates and presents information to the investor about the actual payoff they earned for each investment decision and the potential payoff they could have earned if they had adopted an alternate (aggressive or conservative risk) strategy. This feedback in turn helps investors visualize and adjust their risk preferences to maximize total returns.

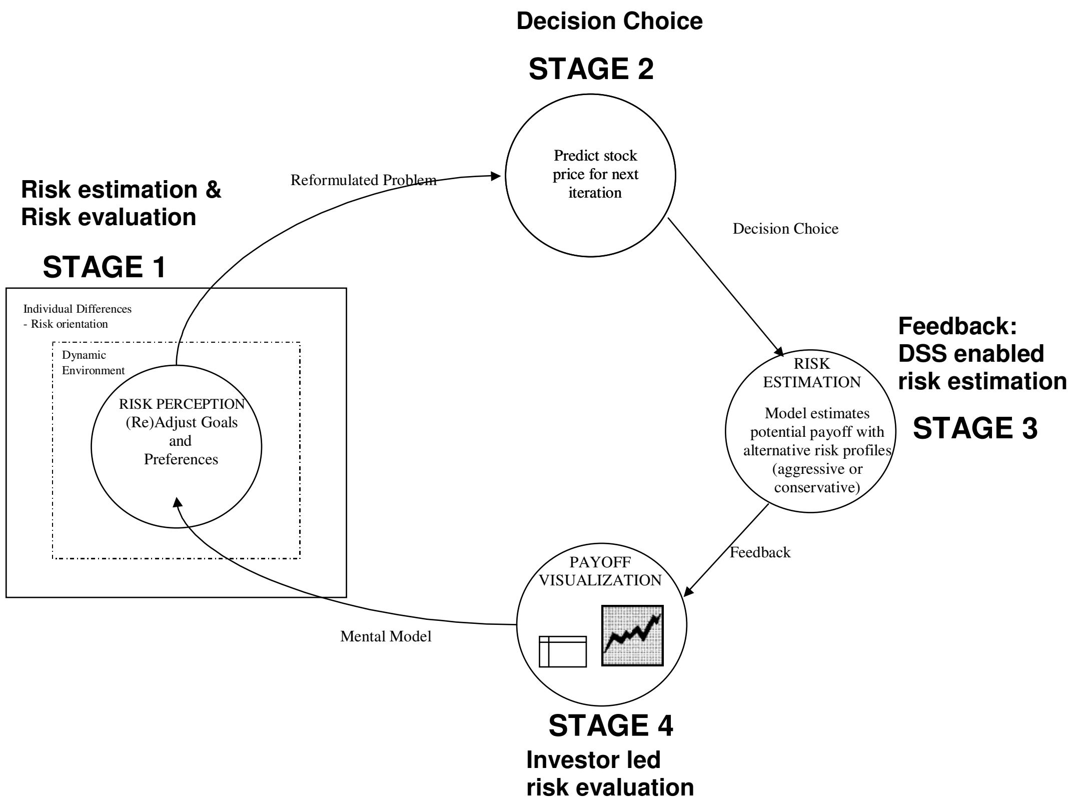


**Figure 4: Risk visualization for investor decision support**

***Model Description***: The model operates in a four-stage process. In the first stage, the model begins by providing subjects with a set of company specific, industry specific and macro economic information about a stock at time $t_0$. Such information may include current and historical performance of company's stock prices, financial details, financial ratios, prospective analysis of company's growth, trends in the industry to which the stock belongs and general macro economic information that may have impact on stock's performance. The reason for including a wide range of information to enable realistic stock price prediction is that stock price in reality is affected by company specific, industry trends and economy wide developments. Precise impact of these factors is debatable but the value of including these in the information set for making stock price prediction is generally acceptable.

In the second stage, subjects include such information in their decision model and make stock price prediction for the following period (time $t_{0+1}$) based on an assessment of their risk profile, risk tolerance and risk propensity.

In the third stage, the decision support system provides feedback to subjects of their decision choices. The feedback includes the actual payoff associate with subjects' decision choices and alternative payoffs subjects could have earned for various levels of risk profiles (i.e., aggressive, conservative etc.). The feedback is presented both in graphical and tabular format. Subjects may choose either or both formats to help understand the impact of their decision choices. In generating feedback, the decision support system may be leverage conventional heuristics, statistical tools, intelligent algorithms or some combination of these. The essential feature of the decision support system is to help subjects 'visualize' the effect of their actual and alternative decision choices.

In the fourth stage, the model updates all information for the current period ($t_{0+1}$). Subjects analyze the update information in the light of the feedback obtained by the decision support system to make stock price prediction for the next succeeding period, $t_{0+2}$. Their prediction is again followed by feedback from the decision support system with information about payoffs for alternative risk profiles. This four-stage exercise is repeated several times. The premise is that in several iterations, subjects should be able to learn if their decision choices are sub-optimum commensurate with their risk profiles.

It should be noted that in the first stage (Figure 4) both estimation and evaluation is investor driven. In the third stage, estimation (of the risk) is done by the decision support system but the evaluation of the estimated risk (of the prior period) is done by subjects. Thus, the estimation and evaluation is divided in the third stage. The estimation and evaluation of risk for the following period is always done by subjects (stage 1 in Figure 4).

***Implication of the Model***: A risk visualization based decision support model is ideally suited for investment decision making due to several reasons. First, the assessment and management of risk is part of the broader process of investment decision-making. Stocks are considered to have among the highest risk (and returns) of all asset classes. Evidence from popular press and academic studies suggests that decision makers substantially underestimate investment risk, and that herd behavior is more typical of investment decisions (Ottaviani and Sørensen 2000, Scharfstein and Stein 1990). Risk propensity is moderated more by environmental variables than by the underlying fundamental variables. Irrationality in investors' decisions is a common underlying feature. Therefore, understanding the psychology of risk based investing is essential to understand the working of the market.

Second, while numerous decision aids are developed for predicting stock prices and indices (Tsaih et al. 1998; Wang 2002), the idea of creating a model for visualizing risk has largely been unexplored. A systematic theory of risk visualization is needed also because of the rapid rise of the individual stock investor (as opposed to the dominance of institutional investors) up until late 1980s. Individual investors often do not have sophisticated tools and infrastructure available to their institutional counterparts. Further, the abnormally rising stock market of the nineties seems to have given a false perception of positive experience effect—a changed opinion of market risk, and more certain (and appealing) higher returns, when there are none or substantially lower returns. Abnormally high losses suffered especially by individual investors during the dot-com meltdown reflect the need for caution—over-reliance on data for formulating future strategy. Data cannot serve as measures of risk—it could be that a low risk was perceived (due to larger number of positive experience effect) and risky decisions were taken.

Third, in view of the subjectivity of human decision making process and the complexity of naturally occurring economic phenomena, it is difficult to capture and decipher with precision decision processes in a risky situation (Smith 1986; Plott 1986; Bisseret 1982). Understanding the consequences of risk is vital, particularly in investment decisions. Studies report sub-optimal decisions when subjects fail to adopt action-oriented strategies for superior performance (Kleinmuntz and Thomas 1987). A very conservative investor in a bullish market might not realize the entire potential return. On the other hand, an aggressive investor might face crippling losses in a volatile market.

Unstructured environments are characterized by information overload, uncertainty about the relevance of variables, time pressure, and shifts in underlying payoff distributions. However, decision-making is judgmental and is often affected by inherent biases. One such bias is the decision maker's propensity to risk. The American Financial Services Associations' Board of Directors group identifies overconfidence and mis-framing the issue as two major biases that have a negative effect in a risky environment (Smith 1989). Realistically, it will help the quality of decision outcome if decision makers could visualize the impact of risk and learn to manage their risk while making unstructured decisions in a dynamic environment.

## 5. Conclusions

In this paper, we proposed a model of risk visualization for adaptive learning. The goal is to provide a decision support to help the decision maker assess and evaluate risks in making choices. There are several implications of this research. Negative consequences of an overtly aggressive risky behavior at the individual, family and societal level are well known from recent experiences. The 2003 study by Applied Research and Consulting found that these investment demographic groups do not have sophistication and expertise to make balanced investment decisions, assess and manage investment risks. Our risk visualization model would serve as a critical decision support for the target audience. Further, the meteoric and significant rise of individual investors in the later eighties has only increased over the years. However, the decision support to help individual investors make balanced investment decisions and manage risk is still missing. The negative effect of this imbalance and the need for an effective decision support is evidenced from the large number of investors who lost their hard-earned savings in the aftermath of corporate scandals (such as Enron, WorldCom, and Tyco) of 2000.

From a practical standpoint, understanding the impact of risk in dynamic unstructured environments may help moderate the potentially damaging effects of aggressive risky behavior on families at the unit level, and on society at the macro level. Also, there are significant strategic value chain implications of a responsible risky behavior of investing community (both at individual and firm level) and a contributing effect on those sections of the public who it serves in a business setting. For example, high speed investing must avoid the social consequences of highly publicized failures, and reputation damage of ignorant risky behavior (Conway et al. 2000).

From a pedagogical standpoint with medium and long-term implications, the model can be used in the classroom and training institutes to visualize risk management. We anticipate using the concept and process of risk visualization for teaching risk management with the hope that when students graduate to the real world, they understand the impact of risk in dynamic decision-making environments, and act in a more controlled, optimized and balanced manner. Finally, from a theoretical perspective, model of risk visualization should yield advances in decision-making, cognitive modelling and adaptive learning behavior.

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