Human traders need new tools

The potential for assistive/interventionist trading tools in trading financial markets

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Abstract

This thesis proposes new methods and tools for helping human traders to compete in a high-frequency trading environment. Human traders have difficulty trading against predatory algorithms and the thesis proposes methods that support the creation of assistive tools that can help human traders to compete profitably. It also develops further understanding of classical decision-making theory in a realtime trading context demonstrating that human traders improve decision-making biases when linked together in groups or with an assistive machine.

As described in the thesis human traders are monitored, and their data is captured, in realtime and in situ. The trading performance and behavioural characteristics of the traders are studied in this context in order to determine if they can be positively modified. The thesis presents a new model for studying human trading behaviour in realtime and in situ using unique software. It also describes the basis for the development of a range of interventionist and assistive tools that are designed to augment trading performance. The approach put forward is unique in its application. It also provides evidence that human traders are willing to allow machines to augment their trading decisions.

The contributions of this thesis are that it overcomes the problem of assessing human trader risk-taking behaviour in realtime and in situ, it makes sense of human trading behaviour at realtime speeds and then it shows that, with new approaches to human-machine collaboration, trading performance improves and classic decision-making biases are reduced.

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Part 1

Introduction

Chapter 1

Introduction

This Chapter introduces the thesis by providing a summary of the main areas of the research highlighting the aims and objectives and areas of interest with regard to further study. The results and conclusions are highlighted.

1.1 Overview

In most electronically traded markets speed has become everything [1] [2]. The faster markets have become the more difficult they have been to trade especially from a human perspective as human traders need to compete, in many cases, with high-frequency traders (HFTs). Extreme trading speeds have meant that sophisticated market operators with high-speed computational order routing advantages are natural winners when transactions on the exchange's central limit order book (CLOB) are ranked in price-time priority by the exchange matching-engine model. Market participants who have the money and the expertise seek to leverage technological advantage, accommodative order types and server co-location opportunities provided by exchanges, in order to gain advantage.

Researchers have recently highlighted how human traders, or low frequency traders (LFTs), are subject to predatory algorithmic trading strategies from high-frequency traders (HFTs) designed to monopolise them [3]. One result of this traded market automation, extreme transaction speed and the saturation of algorithmic trading is that the human traders have been pushed to the higher-latency, lower-frequency multiple-millisecond fringes of realtime without the tools to compete with such sophisticated machine-based competition in the single digit millisecond sphere and are very much at the mercy of predatory algorithmic trading techniques. The human trader is, in such respects, the fall guy and increasingly shows an unwillingness to participate when the odds of success are so firmly stacked against them [3].

This expulsion of human traders to the borderlands of realtime transactional activity, namely multiple milliseconds rather than single digit microseconds, has several unwanted side-effects one of which is, paradoxically, at the centre of the current financial regulatory objective [2]; that is, to improve the ethical standing of the marketplace. Given the number of high-profile scandals [4] that the financial markets have had to contend with over the last few years it is surprising that not more is made of the biased advantage that HFTs have in realtime traded markets. Indeed, recent interpretations of HFT's is that they are dysfunctional rather than a benefit to markets [5] [6] [10]. This situation is at odds with some of the current Human-Computer Interaction (HCI) literature which values the *human centric* approach [7] to computer application design.

While realtime markets become more complex, and machine trading becomes ubiquitous and all consuming, 'what is the role of the human trader?' and 'is there a space left for them to compete successfully'? Kumiega and Van Vliet [8] point out that "Finance has evolved from human traders and manual control to automation and computer numerical control" and that this is a continuing trend with automated trading accounting for 75% of financial markets now [9]. Is this a one-way street or should we be looking at a different approach with different goals? A rethink with regard to human involvement in trading markets also questions some fundamental aspects of financial services:

1. Is speed the true goal?
2. Should markets be entirely driven by machines?
3. Are they ethically sound?
4. What is the purpose of trading markets?
5. Who benefits from them?
6. Who are these markets designed to serve?

In the current climate the question is 'If there is space for human traders how can they compete with faster, more aggressive predatory machine algorithms?' There is little doubt that the human trader will need help when competing in today's electronic marketplace in order to compete with HFTs. With the growing implementation of Artificial Intelligence (AI) in high-frequency trading algorithmic development, things look bleaker still for the less sophisticated and slower LFTs. Should we expect human traders to take very little part in traded markets in the future, or to operate on the fringes of those markets as initial order instigators through asset management institutions who undertake the transactional aspect of the business?

This thesis takes the view, and seeks to show, that the human trader is far from finished with respect to trading participation in financial markets. In the same way that recent studies in neuroscience and economical decision making suggest that there is "a need for a new set of constructs to underlie economic decision making" [11] so too does the study of realtime human trader decision-making in situ.

This thesis extends the research in this domain by introducing new models, techniques and practical tools that intervene and augment decision-making in order to provide the basis for re-evaluating the position of the human trader. The new technology described in this thesis sits in its own area between autonomics [12], Directive Decision Devices (DDDs) [13], robotics and AI in that the trader has a collaborative relationship with the technology while sharing an ambivalent but positive decision-making process. This new area of interest could be referred to as 'behavioural interventionist': it relies upon augmenting realtime trader behaviour through assistive tools that seek to promote good trading abilities and to suppress those that have negative impact. The thesis deals with the formulation of the design science supporting these new tools. With new insight, concepts, models and tools, human traders can utilize useful aspects of some of the technology that the HFTs are using and extend the opportunity to create their own technology in an enhanced way.

The thesis details the behavioural study of a group of 32 LFTs made up of a mixture of professional traders and finance PhD students. Together, over a six-week period, they generated as a group a total of 150 daily trading sessions (day-trading), an average of nearly five trading sessions per trader. Each trader traded for a minimum of two hours during the individual experimental trading sessions. They could choose to trade for longer than two hours if they wished. The tick-data that was generated captured their individual behavioural characteristics in detail. This enables the realtime, and historical, assessment of their data using specifically designed software for this purpose that will be described later in the thesis.

1.2 Research Aims and Objectives

The main aim of this research is to explore and analyse human trading behaviour in realtime markets using detailed, realtime trading data and then to use the findings to produce new methods and models for interpreting and enhancing profitable trader behaviour in realtime and in situ. The price data generated by the exchange and populated in the trading software was realtime tick data. In addition, the aim is to produce new models and methods that support the potential link between the human trader and a range of newly designed behavioural interventionist trading tools (BITs) that augment trading behaviour.

The objectives of the research are:

1. To study human trading activity in realtime and in situ using newly created data capture and analysis software.
    i. The complex nature and speed of realtime trading markets has made realtime trading data analysis difficult. In the current research it is vital that every aspect of the trader's digital audit trail is captured, along with the price activity of the market, while the trader is trading if an accurate

assessment of their behaviour is to take place. A new data analysis tool (Realtime Trading Data Sampler (RTDS)) that operates in realtime while the trader is trading, was developed in order to overcome the realtime data analysis challenges and to provide detailed data analysis of the digital audit trail.

ii. This realtime analysis capability, in turn, enables researchers to link the trader data to a number of realtime processes that can interpret, modify and potentially intervene in the trader's trading activity.

iii. By examining the role of human traders in the financial markets, and how their position has changed due to the increase in speed and complexity of traded markets, a more detailed understanding of human risk and decision-making at realtime speeds can be achieved.

2. To describe the classic and current literature relating to the study of human trading behaviour and to highlight new observations in the thesis that extend their interpretations.

   i. In particular, the opportunity for researchers to study and interpret realtime trading behaviour in situ has, so far, proved difficult and elusive. Researchers suggest the increased speed of markets has created problems for practitioners and observers in being able to interpret captured data especially as it is now in microseconds [2]. As a result of these conditions in the markets the opportunity to make meaningful interpretations of trading behaviour (high-frequency and low-frequency) and market actions has become problematic at such high speeds. The thesis examines why this is the case and proposes alternative methods for researchers to overcome this problem.

3. To introduce a range of metrics (see Appendix for the full list) designed to provide researchers with new ways to interpret the data set of human trader activity.

   i. Quantifying trader behaviour in realtime and in situ requires the use of metrics to interpret the realtime digital audit trail. 127 metrics were designed and implemented into RTDS in order to do this.(See Appendix)

   ii. The metrics have eight categories:

      1. *Base metrics*
      2. *Time interval* and *Time taken* metrics
      3. *Use of Time* metrics
      4. *Trading Sequence* metrics
      5. *Confidence* metrics
      6. *Performance Taper* and *Drift* metrics
      7. *Pattern Recognition* metrics
      8. *Restoration* and *Recovery* metrics
      9. *Explosive* moments metrics

   iii. Each category of metrics is tied to specific trader activity including time in trades, time between trades, evidence of efficiency, confidence, reaction to fast-moving events, pattern recognition and the ability to recover from loss. For example, *Time interval* and *Time taken* metrics provide evidence of the trader's time intervals between trades as well as the length of time that the trader holds open trades. *Use of time* metrics show how well a trader made use of the time in the trade which is important for evidence of efficiency and can mapped directly to the winner/loser ratio of trading success and other measures that show the profitable, or loss making, outcome of the trader's activity. *Trading sequence* measures relate to the specific market condition that the trader is trading in, so it measures the trader's performance against various market conditions be they breakouts, trending momentum or sideways moving. *Performance taper* and *drift* metrics show the trader's ability to make the best of the trades he is in by observing how much profit he leaves on the table when exiting trades as well as quantifying how the trader's profitability may taper off over certain market conditions like fast markets or momentum conditions. *Pattern recognition* metrics look for signs of the trader repeating successful behaviour in similar market conditions where he has recognised a certain pattern and responds positively to it. *Restoration* and *Recovery* metrics record how well a trader recovers from loss to profit and the momentum with which this happens. The rate at which, and the success with which, the trader recovers from adverse loss making behaviour is an important observation of skill and efficiency. Lastly, *Explosive moments* metrics capture the trader's behaviour when certain unexpected events occur like event trading breakouts following the announcement of economic information, or extreme price movements. These metrics record how well the trader made use of these sudden unexpected events to improve profitability or to reduce loss. There are more metrics under development.

iv. The metrics used in this thesis are as follows:

- *Number of Winners*
- *Number of Losers*
- *Number of Consecutive Winners*
- *Number of Consecutive Losers*
- *Number of Scratches*
- *Average Trade Size*
- *Average P&L per Trade*
- *Number of Trades*
- *Number of Orders*
- *Average Time between Trades*
- *Average Time in Trade*
- *Maximum Positive Drift*
- *Maximu Negative Drift*
- *Ratio of Winners to Losers*

v. A detailed discussion of the results from the experiments using these metrics is provided in Chapter 4.

vi. The quantified trader data is then displayed on RTDS for the researcher to observe.

4. To design and implement a number of practical experiments that examine trader behaviour in realtime and in situ.

   i. The results of these experiments provide the basis for the design theory supporting the interaction between human traders and behavioural interventionist machines.

5. To design new models and methods that form the basis for improving human trader activity in realtime markets

   i. The aim is to determine if the trader's profitability can be influenced by positively modifying their trading behaviour using a series of new interventionist techniques that introduce a new level of human-machine collaboration in trading.

6. To show how the results of realtime trading experiments provide the basis for creating new models and processes to integrate interventionist trading tools into human trading activity designed to augment trading behaviour.

1.3 Structure of the Thesis

The thesis develops a structured approach to the above aims and objectives. It begins with Chapter 2 which provides a comprehensive description of the background to the study of human traders and their risk taking behaviour and describes the previous research undertaken in this area. It then provides a survey and assessment of traditional behavioural finance literature with special emphasis on heuristics and biases applicable to trading. Chapter 3 describes the detailed realtime data set and explains the problems in examining human realtime trading data in situ. It introduces new methods and processes that can be used to overcome these problems and to form a more complete understanding of the realtime data set. It introduces newly created software designed for the purpose of providing a practical method for realtime data capture and analysis. Chapter 4 identifies three classic academic studies with regard to human trading heuristics and biases, namely *Loss Aversion* [14] [15] [16], the *Disposition Effect* [17] and *Overconfidence in Predictions* [18] [19] and describes how these can be viewed in different ways following the opportunity to study trader behaviour in realtime. Chapter 5 describes a new design theory and method for potentially linking human traders with realtime interventionist tools that augment their decision-making processes and, ultimately, their profitability.

This extension of the current research understanding in the area of human trading behaviour to machine collaboration is new to financial markets and forms a promising new area of research.

The conclusion of the thesis shows that detailed realtime data can be studied and linked to behavioural clues as well as to the psychological profile of the trader. It shows that a combination of realtime data assessment, psychological and personal understanding of the trader and the market place and the modifications made to ‘critical point activities’ can enhance trading activity leading to a rethink with regard to market microstructure. Critical point activities are those immediate actions that traders take when interacting with realtime price data that are based on short-term, sometimes subconscious, appreciation of risky or critical situations that demand a high level of cognitive expense and which result in immediate positive or negative feedback. These activities, which account for trader’s profitability or loss under volatile market conditions for example, are similar to those deployed by service personnel like firemen or police officers in critically demanding situations that endanger life. Lo and Repin [45] refer to these skills in their work on emotionally-based decision making and [98] [99] refers to these skills in their work on the study of critical decision methods in firefighters at work.

1.4 Summary

This thesis describes and promotes a new level of understanding with regard to human trader behaviour through access to, and interpretation of, rich realtime data sets in the field, in situ. The findings significantly broaden the scope to create new study methods and models for behavioural analysis at realtime speeds. The outcome of this thesis, then, is to show how the results of realtime trading experiments provide the potential for creating interventionist trading tools and new realtime models that augment behaviour. By doing so, it brings into play the potential for new ideas aimed at improving financial markets design and transactional processes linked to market microstructure, HFT and market regulation. In future following the findings detailed in this thesis, there is merit in the possible modification to financial market transaction architectures, in particular, the industry reliance on realtime transactions and microsecond trading speeds. Indeed, by describing a more complete understanding of human trader behaviour in situ and in realtime we have the potential to change the way we currently think about realtime market design.

By initially showing how the results of realtime trading experiments provide the basis for creating interventionist trading tools and new realtime models associated with them, the thesis then leads forward to reassess, among other things, the role of trading ethics, human-machine collaboration, learning and training.

PART 2

Background and Literature Review

Chapter 2

Literature Review

This Chapter provides background to the study of trading behaviour and a review of the literature forming the foundations of economical risk-taking. risky decision-making and behavioural finance.

2.1 Introduction

The study of human behaviour in relation to economical risk-taking has a long history. The foundation begins in the mid-18th century and moves up to the present day through several iterations. This Chapter describes how this progress can be observed in the academic literature and how we have arrived at a point where the science is ready to move to a new level and towards the recognition that humans will have a close behavioural association with supportive machines. According to recent research the decision sciences are "undergoing a process of reframing" [20] with the acknowledgement of the requirement for a "more unified and complete understanding of decision making". This thesis examines opportunities to move forward in this area.

2.2 Background

2.2.1 Human Economical Decision-Making

The first proponent of a link between economics and psychology was the classical economist Adam Smith in the 18^{th} Century [21]. In a similar way Jeremy Bentham wrote extensively on the psychological support for the theory of Utility [22] which, he believed, was based on the rational assumption that individuals would seek to maximize their utility as much as possible. If they favored a good or service above others, they would tend to buy more of it, thus influencing the supply/demand balance. Over the ensuing two hundred and fifty years the psychological determination of economics and economic theory went through periods of popularity with strong opposition from the proponents of natural sciences in the 1850's and the developing theories of rationality and *homo economicus* [23]. In the first part of the 20^{th} Century neo-classical economists like John Maynard Keynes and Irving Fisher based much of their theory on psychological factors influencing economics and market behavior [24] [25].

2.2.2 The Rationalist Approach

By the mid-20th Century, the rationalists were back with the Expected Utility theory and Discounted Utility models began to gain widespread acceptance. Perhaps the most important development in post-war economic theory was brought about by Eugene F. Fama when he introduced the concept of the random walk in stock prices [26] and the Efficient Market Theory or the Efficient Market Hypothesis (EMH) [27], which stated that stock market prices fully and promptly reflect all publicly available information.

Random Walk theory [28], which suggested that movements and variations in stock price behavior are not predictable, gained further support following the publication of the popular book, *A Random Walk Down Wall Street* written by Burton G. Malkiel in 1973 [29] in which he famously compared highly paid stock market analysts with “bare-assed apes” throwing darts at a dartboard in their attempts to pick stock market winners.

In favor for much of the 1970’s, the rationalists sought to explain the behavior of financial markets by suggesting that stocks are priced rationally because they reflect in their prices all relevant information available to all investors and that those investors react rationally to that information in their investment behavior. This suggests that investors are not likely to improve their returns above that of the overall market because it would incur significant risk. By following a pattern of rational behavior with regard to their investments, they can only hope to equal the performance of the overall market itself because other investors have access to, and react in similar rational ways to, the same information. Stock prices therefore reflect the tension between informed investors and uninformed investors and are the best estimate of investor’s awareness of all relevant market information, therefore the market is deemed to be efficient.

2.2.3 Behavioural Finance

Rationalist theories of stock market behavior came into question as researchers began to observe that there were inconsistencies in the theory of Utility and the Efficient Markets Hypothesis. A challenge to the rational theory of markets came in the late 1960’ and early 1970’s with the growth of Cognitive Psychology [29] which began to describe the brain as an information-processing device and to study the ways in which it made decisions under stress and in times of risk.

Behavioral finance researchers have established credible scientific evidence [14, 15, 16, 33, 34] that we are not rational beings and that we react to many situations and conditions in irrational ways. The argument proposed by [16] in their seminal paper introducing prospect theory, was that human behavior is not rational and explained a number of documented anomalies in rational economic decision-making. For example, it is human nature to expect to improve upon an expected return or result by taking increased risk. If investors believed that they could not improve upon average market returns they would all be investing in index tracking funds that track an index of stocks with an expected return of no more or no less than the overall market performance itself. In addition, access to information is not uniform and hedge fund managers or professional research analysts are privy to more information about a particular stock than the majority of other investors. Prospect theory has a special relevance to electronic traders because the biases that the theory describes can be observed and documented in a range of different conditions and on varying timescales. The irrationality of human risk-taking behaviour is evident in the short-term activities of traders trading on electronic markets with regard to realizing gains too quickly and letting losses run for example. The reluctance to let profits run and the tendency to let losses accumulate is well documented in studies related to trading behaviour. This thesis seeks to extend the current literature into a new area of study where the behaviour of electronic traders is quantified in very short-term trading intervals, using a range of metrics described earlier in the thesis, and assistance is provided in the form of a supporting tool that reduces the behavioural biases that the literature describes.

As behavioural finance developed, researchers looked at a series of biases. According to [30] the foundations of behavioral finance rest on three main themes:

- Heuristics
- Framing and
- Market Inefficiencies and Anomalies

Heuristics explains that people often make decisions based upon ‘rule of thumb’ or approximation rather than on rational analysis. One application of this theory is the availability heuristic [15] which describes how people base the probability of an outcome on how easy that outcome is to imagine. Vividly described emotionally charged outcomes will take precedence over those that are harder to imagine or understand leading to cognitive bias. In addition, [15] named and described the heuristic called *Anchoring* which refers to the way in which people estimate probabilities. According to the theory, people begin with a suggested reference point, an anchor, and then estimate away from that anchor in arriving at a probable outcome. Because the reference, or anchor, is higher, the expectation is normally higher. Heuristics also include the theories of *Loss Aversion* [14, 15], *Status Quo Bias* [31] and *Self-Serving Bias* [32].

The second foundation of behavioral finance, *framing* [33], refers to the way in which a rational choice is presented to the individual, which in turn influences their decision-making processes and causes cognitive bias. For example, in the insurance industry insurers are apt to tell us that the cost of life assurance is 60 cents a day instead of $219 a year. 60 cents a day sounds ludicrously cheap in the manner in which it is framed but a single payment of $219 for a year’s insurance cover sounds very different.

The third foundation, *market inefficiencies and anomalies* [33], refers to the phenomenon of market outcomes that do not fit in with the Utility Theory of rational expectations. They relate directly to the phenomenon of investor herd instinct [34], or group bias [35], which is strongly emphasized during stock market bubbles and busts and irrational manias during which investors seem to abandon all attempts to invest according to fundamentals but instead are overpowered by the emotions of fear and greed. As related earlier in the Chapter, [27] believed that behavioral finance constitutes a collection of anomalies rather than being representative of a true branch of finance and suggested that these anomalies would eventually be eradicated through the application of the efficient market's theorem. However, the time that elapses between the preliminary deviations from the fair value of an asset to the moment when it reverts back to its fair value through the mechanics of efficient markets, can be extremely long as witnessed by several recent stock market booms and busts.

It is useful at this stage to categorise the various biases and heuristics under the following three topics that are related to the central theme of this thesis. This shows the relationship between the different biases and the specific area of interest.

Loss Aversion	*Market inefficiencies and anomalies Mistaken Beliefs: Illusory and Invisible Correlations.*
Disposition Effect	*Framing, judgment under uncertainty, the Disposition Effect* and the *Framing of Investment Choices, Risk Aversion, the Disposition Effect* and

	Mental Accounting Biases: Values and Preferences.
Optimism Bias	*Status Quo Bias, Self-Serving Bias Confirmation Bias, Under- reaction* and *Over-reaction*

Table 1 Categories of Traditional Behavioural Biases

The categories in Table 1 show links between the main themes in the thesis, *Loss Aversion*, *Disposition Effect* and *Optimism Bias* and the area of study that have been undertaken that support them.

2.2.4 Trading Psychology

Trader behaviour analysis has traditionally focused on topics ranging from *overconfidence in decision-making* [18], the *disposition effect* [17], and *judgment under uncertainty* [15]. Recently research has spread into areas that consider other topics that influence trader decision-making and success; traders' ability to learn [36] from their trading activity [37], the impact of the environment on their trading performance [35] and the effects on performance of peer group pressure [35]. In addition, emphasis has been placed on the relationship between experience and trader performance and the adoption of 'private signal precision' [36], a phenomenon whereby a trader is able to maximize higher risk-adjusted abnormal returns from more precise utilization of accurate information directly linked to trading outperformance. The broadening of research topics to include direct learning experiences, non-trading influences on risk and performance and the filtering of information with regard to its adoption in precision-tasks leading to outperformance lead to interesting insights into this developing area of study [38]. Hilton [35] identifies certain human behavioural traits that can interfere with effective decision-making and cause some degree of risk. These include *Confirmation Bias, Optimism Bias* *and the Illusion of control*, *Overconfidence in Predictions*, *Mistaken Beliefs: Illusory and Invisible Correlations. Risk Aversion, the Disposition Effect* and the *Framing of Investment Choices, Under- reaction* and *Over-reaction and Mental Accounting Biases: Values and Preferences. Confirmation Bias* is the need for confirmation in making decisions. In an interesting study, [39] researchers found that those traders who were able to resist *Confirmation Bias* actually made more money than traders who weren't. Instead of using available information from dubious sources to confirm their trading decisions, they reacted to market information dispassionately and were free from *False Consensus Bias* [40]; that is, the tendency to overestimate the number of people who share your preferences. *Optimism bias*, [19] refers to the tendency people have in believing that they are better than average and that misfortune is likely to befall someone else rather than themselves. *Overconfidence in Predictions* [35] is referred to as the "pervasive inaccuracy of expert prediction". Hilton [35] cites a number of other instances of experts making inaccurate predictions.

The behavioral finance literature also suggests that certain market anomalies are consistent with the presence of irrational trading by investors [35]. For example, [41] finds that small retail investors appear to hold losing trades longer than winning trades and also shows that this phenomenon can be costly, because the winners sold by retail traders subsequently outperform the losers that they continue to hold. Coval and Shumway [42] also infer from the observed behavior and costs that these retail traders suffer from the *disposition effect*, a combination of mental accounting (irrational analysis of existing positions) and prospect theory (asymmetric sensitivity to gains and losses). Hilton [35] also suggests however, financial markets are rife with illusory correlations not only in terms of products but also beliefs that inaccurately suppose a relationship between a certain type of action and effect. Hilton [35] describes the way in which trading managers typically over-attribute better than average trading performance to speculative positioning, while failing to take into account the consistently profitable market maker's spread. Braas and Bralver [43] attribute this false correlation to a "fundamental attribution error" in that managers can over-attribute trader performance to the person rather than to the situation. Steenbarger [44] states, success leading to overconfidence can have a negative effect on a trader's activity. "Feeling overconfident…becomes a cue that triggers cautious behavior –the opposite response from the one that normally would arise".

2.2.5 Psycho-physiological studies

Lo and Repin [45] have written extensively on the psycho-physiological characteristics of traders and how their psycho-physiology adapts and changes according to the risk processing they undertake in their trading work. Lo [46] challenges the efficient markets hypothesis. He believes that recent research in the cognitive sciences and financial economics has suggested an important link between rationality in decision-making and emotion implying that the two notions are not antithetical but in fact complimentary. Lo [46] studies professional trader's decision-making and emotion by measuring the realtime psycho- physiological characteristics including skin conductance, blood volume, pulse, heart rate, electromyographical signals, respiration, and the body temperature of professional securities traders.

Peer group pressure studies in trader behaviour include "groupthink," [35] a somewhat negative process "whereby a group of individuals mutually reinforce each other into believing that their collective viewpoint is right” [35] and that they are more likely to accept risker choices after group discussion.

In a simplified form, behavioral finance seeks to understand why people make decisions to buy or sell. Later in 2005 [42] showed that CBOT traders are subject to expected Utility theory by observing certain psychological preferences in morning and afternoon trading behaviour.

2.2.6 Emotion and Intuition

While adopting a “Closed Skill Performance”[47] is fine for scenarios that tend repeat themselves, new situations demand responses that are more likely to be governed by emotion and intuition. There is a belief among those involved in daily *critical point activities,* where the critical activity is likely to be the objective to save life or to avoid disaster, that for fire service personnel, soldiers and futures traders “in a fluid, competitive environment, the best decisions come from intuition” [48]. A fluid environment is an environment in which there is constant change and in which those involved need to constantly reappraise their actions and modify them quickly depending on the changing circumstances. Security and emergency services personnel confront *critical point activities* often on a daily basis when the must make rapid and effective decisions on the spur of the moment. Why is this the case, however? Surely a rational approach weighing up the main body of information available before making a reasoned decision to act in a certain way would be more beneficial? This is not necessarily the case. A body of research now focusing on the phenomenon of gut instinct suggests that “instinct, hunch or learning without awareness” [49] compensates for the lack of solid information available to people in uncertain and rapidly changing situations and is a real form of knowledge. The belief is that people who make decisions in chaotic or complex circumstances and situations like a battlefield, a full-scale industrial chemical fire, a trading floor or in a competitive business environment need to employ the use of intuition as readily as rational decision making processes. What then is intuition? One suggestion is that it is a naturally formed emotive response to uncertain and chaotic external stimuli of which we have little preconceived experience but must react to instantly. Emotion, one of our primeval cognitive processes, must then play a large part in decision-making. Interestingly, traders are constantly told to eradicate emotion from trading. It can be argued that it is emotion that forms the basis of all our decision-making processes, including intuition and that it should be encouraged rather than suppressed. Emotion acts like the spark plug in a car engine forming the first spark that ignites the gas in the cylinders that in turn powers the pistons. Without the spark, the engine wouldn't have a preliminary burst of energy and subsequently would not run. Similarly, if we couldn't employ emotion in trading, we would have nothing to base our best instinctive trading decisions on. Intuition, according to [50] is kick-started by emotion, which presents the conscious, logical mind with a short list of possibilities from which to choose from.

While studying firefighters under pressure to make realtime decisions at critical points during their work fighting dangerous fires, [49] concluded that under conditions similar to those experienced during war, firefighters proceed by grabbing the first good idea that comes to mind, and then the next, and then the next forming a string of reactions fashioned by instinct. While basing their reactions to difficult and complex situations on the knowledge pool they had built through experience, they still tended to fight fires largely with their gut feeling.

"The intuitive approach is more appropriate for the vast majority of…decisions made in the fluid, rapidly changing conditions of war when time and uncertainty are critical factors, and creativity is a desirable trait" [48].

On a different approach, neuroscience research has been undertaken into the activation of the reward system results in particular types of behaviour and emotion, characterized among investors as greater risk-taking, increased impulsivity, enhanced positive feelings, and greater physical arousal [51]. Loss avoidance behaviour and emotions are timid, protective, fearful, and risk-averse. When activated among large groups, reward approach behaviour can impact the economy as a whole, leading to stock market bubbles, increased consumer purchasing, higher investment risk-taking, and an increased use of credit. Loss avoidance, on the other hand, is seen when people decrease borrowing, sell off assets, and report decreased financial confidence (and even fear) [51].

2.2.7 The Structure and Process of Decision-Making

In their paper [52] began by explaining that although much research had been conducted into the structure and process of decision-making including risk-less versus risky choice, and normative versus descriptive choice models, little had been undertaken to determine if novice decision-makers can be trained to become more expert decision-makers. They believed that investment decision-making constitutes a useful example of this skill because performance can be measured exactly. They depart from the traditional behavioral finance bias of predicting and understanding market behavior that tends to have more of an impact on financial strategy, towards engendering an understanding of the individual's decision-making processes [35]. Hilton [35] also argues that psychology can be applied to "decision-training and decision-aiding as well as financial product marketing and the traditional human resource management concerns of recruitment, training, compensation and control." This fits in with current demands in the financial services industry with the need to train electronic traders and to nurture their decision-making behavior and cognitive biases. This approach also reflects a lot of the work being undertaken by psychology professionals and psychiatrists in financial markets who are being hired by prominent trading companies and proprietary trading houses to create educational and behavioral teaching environments for their electronic traders [44]. As the complexity and challenge of trading electronically increases and the profitable edge becomes more elusive, proprietary trading companies are seeking ways in which to improve or maintain the profitable performance of their traders.

2.2.8 The High Frequency Trading Market

Electronic traders have been utilizing automated order entry tools and techniques for several years. They seek to reduce error-prone human input into trading systems and to customize order entry processes according to market conditions. However, more recently automated order entry tools have become extremely sophisticated and have in many instances completely taken over from human order input. It is not surprising then that the types of order entry tool used by traders will have a direct impact on their trading environment. The use of simple automated trading tools that input limit buy and limit sell orders has at least one positive effect; that is, these tools alleviate the need for manual order entry and free up the trader's time and mental faculties so that they can concentrate on other more important things. This type of simple tool has a positive influence on traders as one of the most difficult decisions a trader has to make is at what point he should look to get into the market. Automated tools that simply input limit orders above and beneath the market best bid and offer price are not sophisticated and can be built relatively quickly using customizable scripts and programs that are readily available. Some trading companies [44] offer their traders a suite of automated order entry tools to choose from, many provided by the front-end trading software vendors for use with their own trading software, while others are created internally for the trading company independently of the software vendors. As [35] stated in 2001, research needs to be done to identify the characteristics of successful traders.

2.2.9 Replacing the human trader – developing robotic tools

Researchers and academics have been at pains to try and create models and robots to undertake the functions of human traders in competitive market settings. By doing this, they have tested and modelled results from a range of experimental conditions mostly other than those representing the real markets themselves. Recently, in 2012 for example, an attempt to interpret trader decision making "in the wild" by [20] relied upon in-depth interviews and a qualitative approach to the research. Completely automated markets where human traders do not exist have further social complications: "The changing human and social factors, emotional and otherwise, affecting business or trading practices and the sets of possible outcomes cannot all be incorporated into any model, no matter how complex" [8]. Behavioral finance research demonstrates how psychological forces influence investor decisions and cause financial markets to behave inefficiently. Through the use of theoretical models there is evidence that mispricing occurs when inexperienced traders coexist with “behavioural” agents [8] that display cognitive impairment that leads them to make a range of errors. For example, behavioral agents may be noise (irrational) traders, as in [53] or suffer from overconfidence [35]. Research suggests [34] that herd instinct is caused by a large number of agents who suffer from behavioral biases leading to “herd behavior and momentum trading that contributes to financial volatility”. Successful trading behavior has traditionally attracted interest from academics as worthy of research for several reasons: firstly, it enables the study of a synthesis of human cognitive processes and biases through decision-making under uncertainty, many of which can be defined through the practice of trading or risk taking; secondly, the act of trading itself can be replicated in a laboratory through the use of portable trading systems and equipment and simulated trading markets that perfectly reproduce real, live market conditions. Thus results gained form observations in the field and can be compared to those established under laboratory conditions; thirdly, research subjects are able to articulate their reasons for making certain trading choices to researchers; and fourthly, their physiology can be observed during changing market conditions and fluctuating emotional levels [45]. Traders have been studied in relation to the irrationality in human decision-making with regard to financial markets and [33] [34] [35] [42] [54] have been making inroads into this area of research notably with papers on information accessing, overconfidence, and psychological dispositions that affect trading behavior and financial decision making. A paper related to this subject matter titled *Training Novices to become more expert: The Role of Information Accessing Strategy* was published in 2001 [55], followed by the publication of *The Psychology of Financial Decision-Making:*

Applications to Trading, Dealing and Investment Analysis [35] in the same year, followed a year later with a joint paper published with his aforementioned associates titled *Psychological Dispositions and Trading Behavior*. With regard to securities trading, itself a stressful environment in which its participants undertake critical point decision-making, research has been undertaken by prominent academics [45] into trader intuition and the link between decision-making and emotion. In a working paper they studied the importance of emotion in the decision-making process of professional securities traders by measuring their physiological characteristics while trading. They monitored skin conductance, blood volume pulse and heart rate, electromyographic data (muscle action), respiration rate and body temperature, while simultaneously capturing the market environment in which the traders are active real time. They suggested in their results that "expert's judgments are often based on intuition, not explicit analytical processing, making it almost impossible to explain or replicate the process of how that judgment was formed." In addition, [45] states that "Traders often based their intuition about price swings and market dynamics without the ability (or the need) to articulate a precise quantitative algorithm for making these complex decisions." They suggested that a trader's "intuitive trading "rules" are based on the associations and relations between various information tokens that are formed on a subconscious level, and our findings, and those in the extant cognitive sciences literature, suggest that decisions based on the intuitive judgments require not only cognitive but also emotional mechanisms." In conclusion to their paper, [45] states "our results indicate that emotion is a significant determinant of the evolutionary fitness of financial traders."

2.2.10 The current approach to studying trader behaviour

Evaluating the micro-factors influencing the behavior of financial experts has been challenging for researchers mainly because of the difficulty in examining experts under ecologically valid conditions that are representative of the domain of expertise [56] along with the scarcity of richly detailed high-density data. Research into expert behavior has focused on available data sets which have tended to be broad and universal rather than detailed and specific. One early exception is [57] who used a data set of 334 floor traders conducting at least five trades on ten different days during the calendar year 1995 but the data set does not compare to the high-frequency data set today. "The data do not allow a sequencing of these intra-minute trades, which makes some behavioral inferences from these trades problematic." In the majority of cases, the emphasis in research is very much on 'observation and report' and much of the research that has been conducted relies on surveys and the personal accounts of the research subjects. The following excerpt from a recent piece of research highlights this fact:

> "Subjects were asked to fill out surveys that recorded their psychological profiles before and after their training program, and during the course of the program (involving live trading through their own personal accounts) subjects were asked to fill out surveys at the end of each trading day which were designed to measure their emotional state and their trading performance for that day" [58].

They went on to say that "Because our subjects were geographically dispersed throughout the United States, and because the duration of the study was several weeks, the most practical methods for assessing emotional state and psychological profile were online questionnaires. Therefore, we asked the participants to complete several survey instruments prior to, during each day of, and after the training program. Subjects filled out all questionnaires online at our web site, using their trading identifiers to obtain authorized access".

The approach to effective experience-sampling documented by [59] rests on the notion that individual behaviour and its underlying psychological mechanisms must be studied within their natural settings. They put forward three different types of experience-sampling designs:

- subjects are required to regularly report on their behaviour and experiences at pre-specified intervals (for example hourly or daily)
- subjects may complete self-reports once a certain event occurs (for example conflicts or intimacy).
- subjects may be prompted by randomly sent signals to complete self-reports. This type is referred to as signal-contingent sampling and is advantageous, as it captures the variability of experiences given sufficient numbers of responses.

Others suggest that the experience-sampling approach, 'observation and report' interpretation, does not go far enough in accurately determining the true cognitive and emotional triggers that lead to successful trading behaviour. For example, empirical studies of behavioural decision-making biases in economic situations of expected profit or loss have tended to concentrate on abstract problems (choices between gambles represented by probabilities and decision making biases). As suggested by several researchers, [15, 16, 17, 18, 35] professional traders react the same way as uninformed investors.

The study of human traders and their trading activity has, to date, involved very little interpretation of realtime transaction data in situ and in the context in which it is created. Although this has been a goal for researchers of the theory of probabilistic functioning as far back as 60 years [60] early research efforts suggested that there were few occasions when experts can be properly studied in the field [56]. We see that there has been difficulty in qualifying and quantifying the trader's digital audit trail right up to the present day. In addition, [2] remarks on the difficulties in studying HFT data in this respect.

Achieving these "few instances of real-life expertise in which superior performance can be demonstrated under relatively standard conditions" [56] is now possible in the study of data via a comprehensive audit trail showing the trading conditions of electronic markets. Through the realtime capture of trading activity via a standard Application Programmable Interface (API) and related databases, we can assimilate, observe and record a trader's complete behavioural response to market conditions. MacAndrew and Gore [20] believe that

> "We are also aware of the difficulty of comparing findings from studies of cognition in the wild with those from description and experience-based choice within the laboratory, and we acknowledge that this opens the possibility that our findings are a function of method. Future work might rectify these shortcomings by focusing attention on the development of quasi-experimental approaches to accessing cognition in applied settings. ACTA (Applied Cognitive Task Analysis) provides a

> theoretically grounded foundation for the development of instructional content for this objective."

They also stated that

> "It is also anticipated that improved understanding of how attitudes toward risk concerning gains and losses deviate from studies of description and experience-based choice in the laboratory when studied "in the wild" will hold significant implications for other domains beyond the immediate field of application"

In order to generate their own data owing to the scarcity of real-world data, academics have created experimental designs using a variety of different techniques including "purposely controlled experimental markets" [61]. For example, a popular experimental design is the call market [62] [63]. The potential problem with this type of experimental market is that it does not represent the real trading world and as such, remains theoretical in its application. Indeed [64] views experimental research as flawed because its very design forces the human subject to behave robotically, especially in light of research that appeared to indicate that market behavior was largely independent of agents being computerized robots or human subjects who participated in an automated laboratory experiment.

In their paper [56] suggest that scientific understanding of financial markets and behavior is more likely to improve from the study of financial experts in ecologically valid tasks than simply from studies of unskilled participants performing abstract laboratory tasks. Nearer to the goal [65] use individual local futures trader's trade data provided by the Sydney Futures Exchange to study the house money effect on local traders. The trade data enabled them to reconstruct the inventory positions of individual trader's accounts on a trade-by-trade basis but did not provide the granularity of the trader’s complete realtime audit trail that forms the basis of this thesis. The unique data set used in this thesis includes all limit orders, cancel replace orders, stop loss limits, the time of transaction down to the millisecond, the verb, and the profit and loss from the trader’s trading activity. There are more recent exceptions where large volume trading data sets have been available by private arrangement, [66] but the interpretation is rarely individual to each trader involved but more of an appreciation of volume trading conditions on an objective level. The difficulty in being able to access and appropriate valuable trader-defined trading data sets is due largely to private corporate unwillingness to provide such data for fear of legal compliance and losing proprietary trading secrets. This is understandable and has, so far, impeded detailed and comprehensive work related to human trading behaviour. Moreover, there has been a reluctance to draw conclusions from studying trading data and patterns in trading behaviour [67] because the conclusions have not been directly observed.

Owing to the difficulty in gathering rich realtime data sets, then, researchers have used different methods to replicate trading environments rather than to use the realtime financial markets. For example, several experimental findings have concentrated on the provision of games, constructed markets in non-contextual situations, and created call markets and double-auction type transaction environments [68]. While the research findings of these studies have been meaningful and useful, little work has been done to study the trader in situ, in realtime and in context and thus to broaden the research of human traders in the field. This has resulted in an underdeveloped understanding of human trader behaviour which, in turn, has prohibited a full appreciation of their impact on markets and their potentially positive future. By not having access to rich realtime datasets or appropriate tools and study methods, researchers have so far missed the opportunity to apply useful findings to real-world contexts and to examine the opportunity for future development of the human trader.

Instead, evaluating trader behaviour has traditionally involved gathering results from a mix of qualitative research methods including experience sampling (ESM), interviews, and questionnaires [20]. It is evident that things are changing rapidly and research techniques and approaches need to be created to keep up with these changes if data is to have meaning. Research must change to reflect the changes in the way that markets operate, in particular with regard to high frequency trading [2].

2.3 Conclusion

The study of trader behaviour has been undertaken over many years. Its long history has covered many areas. Indeed, behavioral finance is underpinned by the assumption that markets are influenced by the personal characteristics of participants and the decisions that they make. However, in the application of its findings it tends to influence financial strategy with its focus on predicting and understanding market behavior rather than on promoting understanding of the decision-making processes of the individuals that make up the markets. It is interesting to observe that the roots of behavioral finance go as far back as the 18th century and, at this stage, it would be useful to provide a breakdown as to how this came about. The array of different decision making responses can be broadly transcribed into three potential outcomes: a profit, a loss or a scratch (a scratch trade is where a trader opens and closes a position with no loss or profit.). Traders who access markets like the London Stock Exchange or the various financial futures markets have a high monetary incentive to be profitable and right in regard to their decision-making.

PART 3

Thesis Contributions

Chapter 3

Realtime Trader Behavioural Data Analysis

This Chapter describes the ways in which trading data is traditionally assessed, the many challenges confronting academics especially with regard to assessing high-frequency trading data and how human trader data could provide a meaningful opportunity to expand the behavioural work in the decision sciences. The Chapter explores the approach by academics to deconstruct and find meaning in the data sets provided by high-frequency trading and how this is becoming more difficult. The Chapter introduces a new model with which to interpret and deconstruct human trader behaviour in a realtime setting with a view to using the output in human-machine collaboration.

3.1 Introduction

It is surprising that, in 2016, the study of trading professionals in situ and in realime using realtime tools, has posed such a problem for researchers. However, this undertaking has become even more challenging owing to the intense speed of the markets. With trading speed now reduced to microseconds [1] [2] it is challenging to make sense of the data. In addition, evaluating the factors influencing the behavior of financial experts has been challenging for researchers mainly because of the difficulty in examining them under ecologically valid conditions that are representative of the domain of expertise [56] along with the scarcity of richly detailed high-density data [42]. As a result of the scarcity of rich data sets, valuable research into financial expertise and behavioral finance has relied on practical experiments using uninformed, non-expert participants in trading games and laboratory experiments in order to arrive at theories on risk, gambling or other heuristics that are then applied to experts in the field [35]. In fact, some researchers have stated that field studies can only provide for rather crude tests of qualitative predictions, because probabilities and utilities cannot be accurately measured in such contexts [29]. However, through the reliance on laboratory experiments and on non-expert participant advances in the empirical study of financial expertise have been initiated, but are far from complete. In the realm of financial expertise and trading there is a need to identify and to quantify what makes a trader successful [51].

The unique data set used in this thesis includes all limit orders, cancel replace orders, stop loss limits, the time of transaction down to the millisecond, the verb (buy or sell), and the profit and loss from the trader's trading activity. Coupled with the millisecond price changes that are linked to trading activity, the data is very detailed. With the rich data set that forms the basis of this thesis, much can be discovered that has previously been hidden or unverified. By capturing a full digital audit trail from each trader, as well as the price information generated at the exchange interface and matching engine with which they are communicating, the data set forms the basis of a unique research opportunity into human behaviour when making risky trading decisions during the trading day.

In the research we can observe realtime trader behavior in a standard data format, compare different trader's realtime data using the same time sequences, trading instruments and markets, distill individual behavioural characteristics of each trader from the standard data format, compare one or more trader's behavior using the same standard format at different time intervals, formulate a grading procedure for recognizing and comparing excellent trading behavior, observe and quantify different forms of behavior under various live market conditions, and replicate live market conditions in a simulated form so that behavioural characteristics can be observed and tested in a laboratory setting.

In addition, individual realtime trading processes can be identified and recorded, mapped to the market conditions in which they prevail and observed across different timescales, events and risk environments [44]. In this case, traders who were used in the sample can be observed over different time periods, different markets conditions and using different products as well as in relation to each other. Each component of the trader data set was mapped against the market conditions with regard to the current traded price of the trading instrument. By comparison, a significant drawback to the analysis of historical data occurs when particular segments or snapshots of trading activity cannot be accurately linked to the market scenarios to which they belong so that any assessment work that does not map the actual millisecond market event to the associated trading activity is flawed from the start. The approach adopted in this thesis is to examine microscopic trader data rather than to rely on experimental or questionnaire driven results. The data has been drawn from real live trading during the period June 2014 and November 2015. The traders in this research communicate electronically via their computers with exchange matching engines and market transaction facilities (MTFs) at realtime speed via price and trade feeds.

Traders originate electronic orders from front-end trading systems designed to transmit order messages via transaction messaging protocols at speeds as fast as microseconds. The push towards time duration of one billionth of a second, a nanosecond, is well underway. The nature of electronic markets with their capacity for recording data means that every action that a trader, trading system or other network node performs is captured in a microscopic digital audit trail. For research purposes the trader's audit trail needs to be linked perfectly with the exchange's trade and order price data so that order, transaction, time and traded price can all be perfectly synthesized. It is this comprehensive audit trail that provides a window into the richness of the trader's behavior under various rules and constraints. Of critical importance to the research into trader behaviour is that every action a trader takes on his front-end trading system, be it manual or automated, realtime order management, risk management or trade reporting is recorded via the same realtime digital audit trail as other traders to create consistency. Through the study of trading and price data captured via the digital audit trail of futures day traders, this thesis shows that it is possible to evaluate expert behavior in situ and in realtime. Such research does not rely on using uninformed, non-expert participants but instead, enables researchers to evaluate financial experts in ecologically valid conditions that are representative of the domain of expertise. Now that this opportunity has arisen, research opportunity has been opened up into many different decision making areas linked to the decision sciences.

As highlighted in Chapter 2 the thesis builds on the foundations of behavioural finance and risky-decision choice by creating a realime environment for human-decision making under risk to be studied. The objective is to observe the risk-taking behaviour of the trader in realtime and to then assist them to make meaningful trading decisions that reduce the behavioural biases described in the literature while increasing the efficiency and profitability of the trader. There are great benefits to being able to study traders in realtime with reference to their context [16]. When commenting on the *Technical Rational* model of psychology research, which forms an antithesis to the humanistic approach to psychology exemplified by counseling psychology, [69] commented in 2001 that such "research is constrained by notions of good design often inappropriate to complex life situations." Electronic trading is one of the only human activities that involve economical risky decision making that can be captured in a complete microsecond audit trail which can be studied in depth and in realtime. Being able to capture and map realtime human behaviour then leads to the opportunity to create new behavioural constructs and models at the edge of realtime. As mentioned in the Introduction to this thesis, there are recent examples of realtime analysis of market microstructure performance using a number of variables [70]. Volatility, the bid/ask spread and traded volumes are the variables commonly used in assessing quantitative trading. Where the current thesis differs is in the assessment of many more variables, the behavioural meaning behind the results and the creation of new realtime behavioural models in order to link this data with the augmentation opportunities of interventionist machines.

3.2 Modelling Trader Behaviour

The idea behind producing a new realtime behavioural interventionist model for trading is to provide a general framework for understanding and interpreting human realtime risky decisions and for providing means and methods for data capture, display and analysis. Because the modelling of realtime trader behaviour has not been achieved before in a contextual and live environment this new approach provides several promising research opportunities. Realtime trading behaviour provides a unique modelling opportunity with regard to human judgment and decision making under stress. This makes it suitable for comprehensive academic study. The examples below show a small range of the possibilities for further research work based on this model:

1. The trading environment is standardized in respect to pricing conventions and order types (limit, market, immediate or cancel, stop loss), the computerized process inherent in the transaction cycle, the formulation by the trading system of order, price and trade data and their display, storage and retrieval options and the market environment as a whole. This means that trader decision making process, actions and outcomes can be studied over time and between different traders, or groups of traders so that the data set is more complete. The standardized nature of the environment and the variable nature of trading behaviour is then comparable.
2. Traders have a strong monetary incentive to make the right trading decision that results in a profit but accept that they may well make a wrong decision resulting in a loss. The act of attempting to make the right decision means that the trading experience is directly comparable to the risks associated with it in a meaningful

way and can be viewed as being representative of a structured research environment.

3. In addition, it makes the prospect of designing laboratory experiments to replicate real-world setting more plausible.
4. Making a correct decision that results in a profit relies on a combination of experience, understanding the way in which the trading environment (the market) works, and how the trader visualizes the price activity of the trading instrument. Correct trading decisions that result in profits, for example, can then be mapped to the price activity of the market condition perfectly.
5. Traders are subject to different transaction cost constraints on their profitability with the advantage falling on the traders with lower transaction costs. Transaction cost analysis (TCA) can then be studied with regard to the market impact of trading strategy especially as an increase in the number of trades will directly increase trading costs thus reducing profitability. Economy, with regard to the number of trades, is a goal of many traders.
6. A wrong trading decision that results in a loss is often seen as being part of the job or the cost of doing business. A loss is not necessarily a bad thing, but is accepted as part of the life of a trader in the same way that any business incurs costs associated with marketing, sales and other aspects of its daily operation. As the cost of doing business, losses can be analysed in the conditions that cause them and a direct assessment can be made relating to trader behaviour.
7. Traders who make mistakes in that their decisions result in loss are able to conduct the same trading behavior or trading strategy at a different time or in a different

market condition and make a profit. The comparisons that can be made between trading times and trading scenarios are of great value as they provide evidence of strategic success or failure in nearly identical settings. The results can then be used to modify trading strategy.

8. Trading success is heavily influenced by the correct timing of orders and traders grow to recognize certain market conditions that lend themselves positively to timing in producing trading profitability.
9. The recovery time that traders require to compose themselves after making an unexpected loss, whereby they accept the loss and are then able to start trading again, differs between traders and is not necessarily a function of maturity, experience or skill.
10. The time taken to remove the emotional input from a losing trade may lengthen the time between closing a losing trade and opening a new position which could be of significance to risk management.
11. There is sometimes a positive outcome from delaying decision making processes that result in reduced loss or improved profit.

As can be seen in the above examples, the structure of the realtime trading domain, and the new way in which data sets can be analysed explained in this Chapter, lends itself to the modelling of trader behaviour in a realtime setting which has important ramifications for future research into human risky decision-making. Experiments can be devised that test a number of hypothesis regarding human realtime decision-making including those of active futures trading.

The first objective of any new model in establishing a framework for analysis is to capture and interpret the digital audit trail provided by the trading front-end system. The behavioural interventionist model featured in this thesis is explained in Chapter 5.

3.2.1 Realtime Trading Data Sampler (RTDS)

As highlighted in the recent literature, financial markets data can be captured down to the microsecond but the problem, researchers believe, is that it is complex and hard to study [2] making it nearly impossible to analyse. Researchers believe that "new tools need to be developed for empirical analysis" [3] with regard to complex high-frequency trading data sets and this thesis provides evidence of such a tool through the creation of the Realtime Trading Data Sampler (RTDS). An additional worry that researchers have is that the value of rich data sets in the discovery of behavioural decision-making processes is diminished if the data is too dense [3]. This is not the case with the approach described in this thesis. RTDS is able to provide a clean, realtime analysis of realtime data in all its complexity at the millisecond level.

The RTDS analytical software was created for the express purpose of the requirements of the experiments described in this thesis. The software was written in C#, .NET 4.0. It is a WinForms application with a Windows Service for the server and an SQLite database. The objective is to turn it into a web-based application that will make it easier to distribute and setup, and, most importantly, it will be cross-platform, running on Linux, Windows, OS X, and tablets as well as mobile devices. In this case it would be written in JavaScript, with HTML and CSS for the front-end. RTDS, with its selection of 127 metrics (see Appendix 1), links directly into the trading price dissemination, front-end order entry and order management system that the traders use for trading, so that the trader's digital audit trail is immediately visible while the trader is trading in situ. In its current form, the software captures data realtime from a communication link via the trading software Application Programmable Interface (API) whereby it receives price, order and trade data by interfacing with the exchange gateway and receiving messages from the market data API and the order and trade servers at the exchange back-end. It transposes and calculates, by way of the metrics, ratios and figures, the digital audit trail of the trader's trading activity while it is action. This coordinated activity enables RTDS to provide evidence of realtime trading behaviour that is matched perfectly with the realtime price, trade and traded volume data provided by the exchange. Figure 1 (below) shows RTDS with a range of metrics and the GUI design. The data presented in the GUI window is the number of consecutive winning trades that this particular trader has generated. The researcher can tab between the different metrics and load the visual graphic onto the GUI. Each order and trade that the trader generates is populated in the table at the base of the GUI and provides a detailed observation of each of the metrics in realtime.

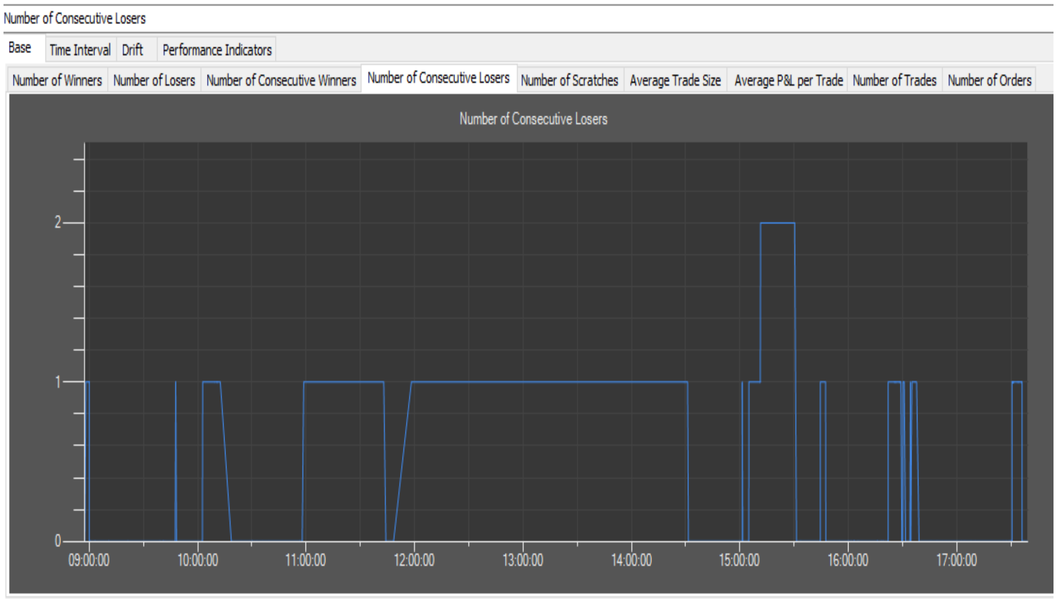

Figure 1 Realtime Trading Data Sampler (RTDS)

The RTDS clearly shows the frequency of the number of consecutively losing trades over a period of time The Y axis shows the number of consecutive winning trades and the X axis shows the time in hours.

The metrics used in the experiments (Figure 2) were made visible in the software from the database of all available metrics. For our purposes we included a number of metrics that would provide evidence of the behavioural traits that had direct relevance to *Loss Aversion, The Disposition Effect and Overconfidence*.

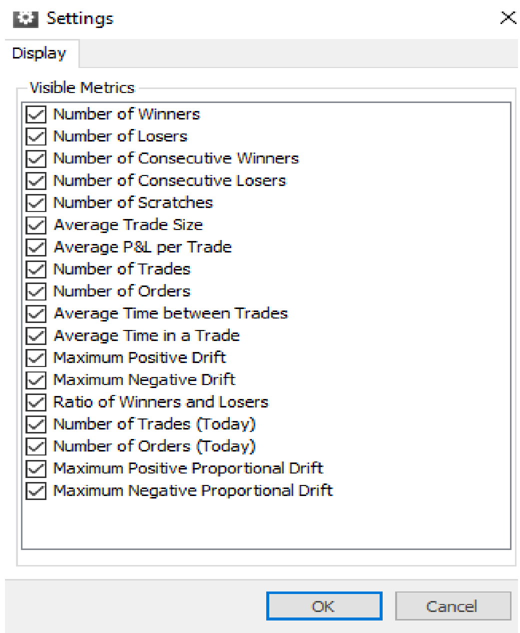

Figure 2 Realtime Metrics in RTDS

A range of Metrics can be chosen in RTDS to fit the required observation and various metrics are linked to particular biases as described in Chapter 1.

There are, in this instance, four types of metrics:

1. Base metrics including number of winning trades, number of losing trades, number of scratches (trades without profit or loss), average trade size, number of trades, number of orders, average profit and loss per trade and the ratio of winners to losers.
2. Sequential metrics including consecutive winners and consecutive losers
3. Time-based metrics including average time between trades and average time in trade,

4. Confidence metrics including maximum positive drift, maximum negative drift, maximum positive proportional drift, and maximum negative proportional drift.

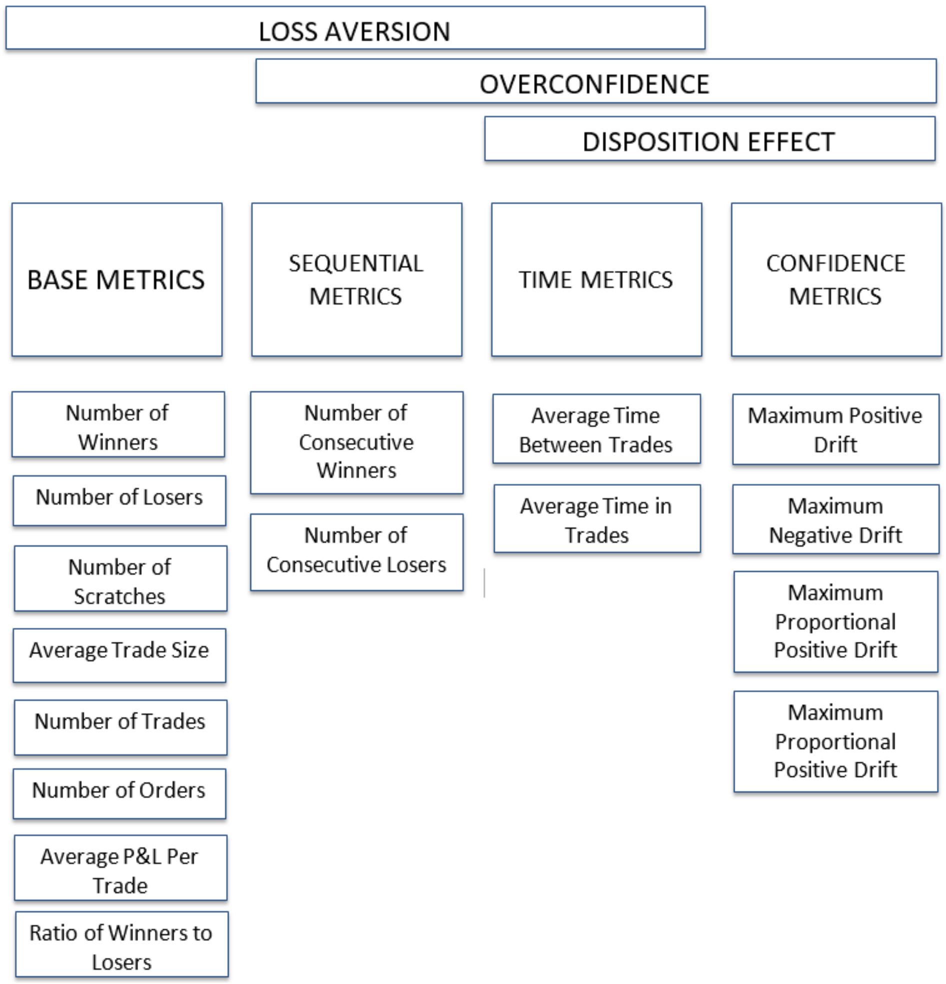

Figure 3 Base Metrics Groups in RTDS

Figure 3 shows the groups of metrics that have been selected from the main list of 127 metrics for the experiments. The choice of the metrics was based upon the main objectives of the experiments in finding evidence of change in trader confidence in the three main categories of *Loss Aversion*, *Disposition Effect* and *Overconfidence* while trading in different conditions. Each of the groups of metrics is linked to the category that is most closely associated with those metrics.

3.2.1.1 Base metrics

The base metrics form the simplest interpretation of the trader's trading activity showing how well the trader is performing in the current market conditions. This data is used to establish the overall condition of profitability and to observe how the metrics show the trader's behavioural condition; that is, are they relaxed, anxious, or indifferent to market activities? The pace of order entry is of interest showing the confidence of the trader's interpretation of the market price movements and is directly linked with their profit/loss ratio so as to provide evidence of successful trading. The average trade sizes also show a level of confidence with regard to profitability as, in some instances, traders vary their trading size according to their degree of profit or loss, increasing trade size when loss making and reducing trade size when profitable. This fits in with the research conclusions made by [57] whereby professional CBOT traders became loss averse when they became profitable and showed this in the reduction of the trading size.

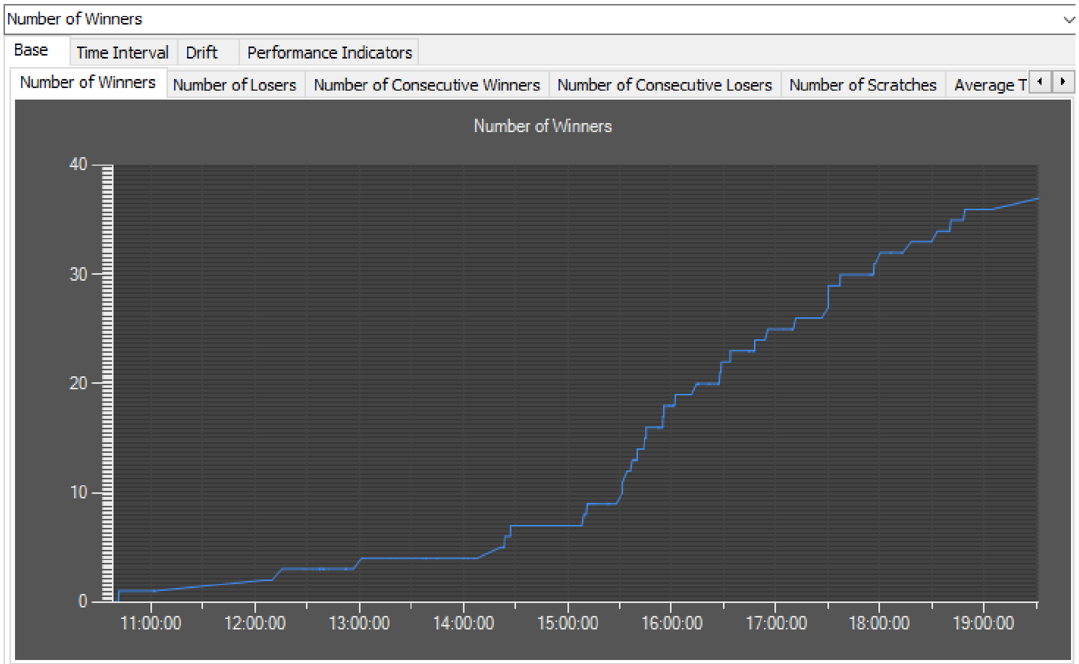

Figure 4 Base Metric Number of Winners in RTDS

In Figure 4 The Base metrics, the number of winning trades is shown and as can be seen from the X and Y Axis, the time and the proportion of winners. As can be seen from this Figure, even a simple calculation of the number of winning trades shows a tendency of improvement after 14.30. This, in itself, is an interesting observation which, compared with other metrics like the frequency of orders and the time between trades can show a change in trader confidence.

Average profit and loss per trade, as shown in Figure 5 demonstrates how trader profitability can change over time with, in this instance, a higher profitability per trade in the early part of the day and a sharp deterioration after midday and 15.00. This could be linked to the trader's reactions to specific events so the data would be linked to time-of-day activities in the market to see what caused this sudden deterioration in the metrics.

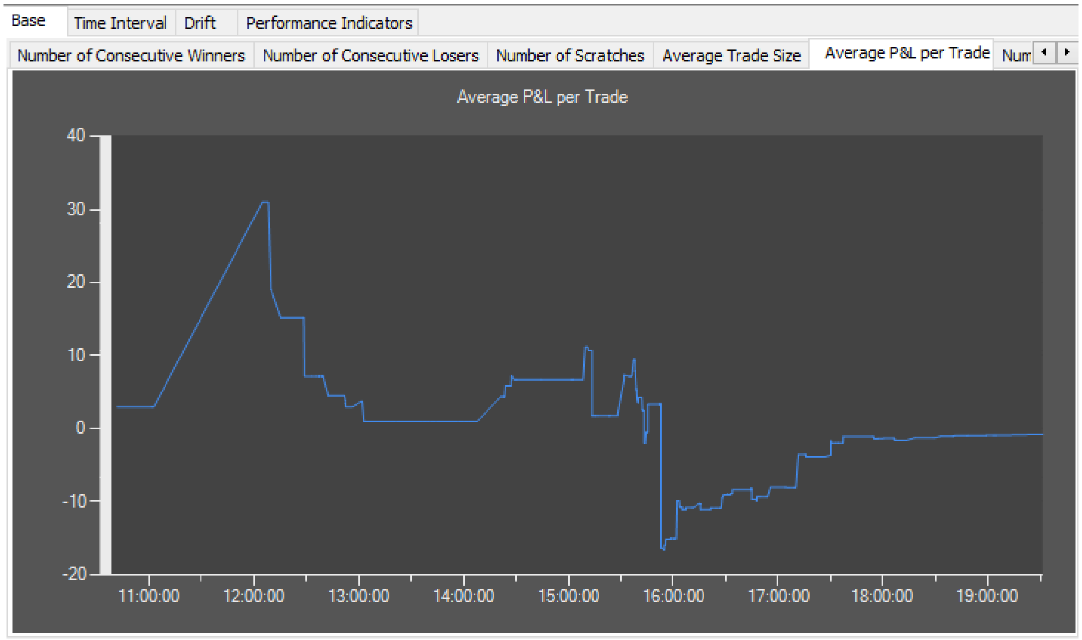

Figure 5 Average Profit and Loss per Trade in RTDS

In Figure 5 the Average profit and loss per trade is a useful indicator of the efficiency of traders with regard to long term trading activities. The example data in Figure 4 has been captured over a full trading day and shows a defined variation in the performance behind the metrics.

3.2.1.2 Sequential Metrics

Sequential metrics, including consecutive winners and losers, provide evidence of confidence by looking at the speed with which traders add additional trades in winning scenarios and in losing scenarios. If traders follow up winning trades with additional orders this is evidence of a confident attitude to the current trading results and the market conditions. If the trader adds quickly to losing positions and subsequently loses again then there is evidence of loss making behaviour leading to poor performance.

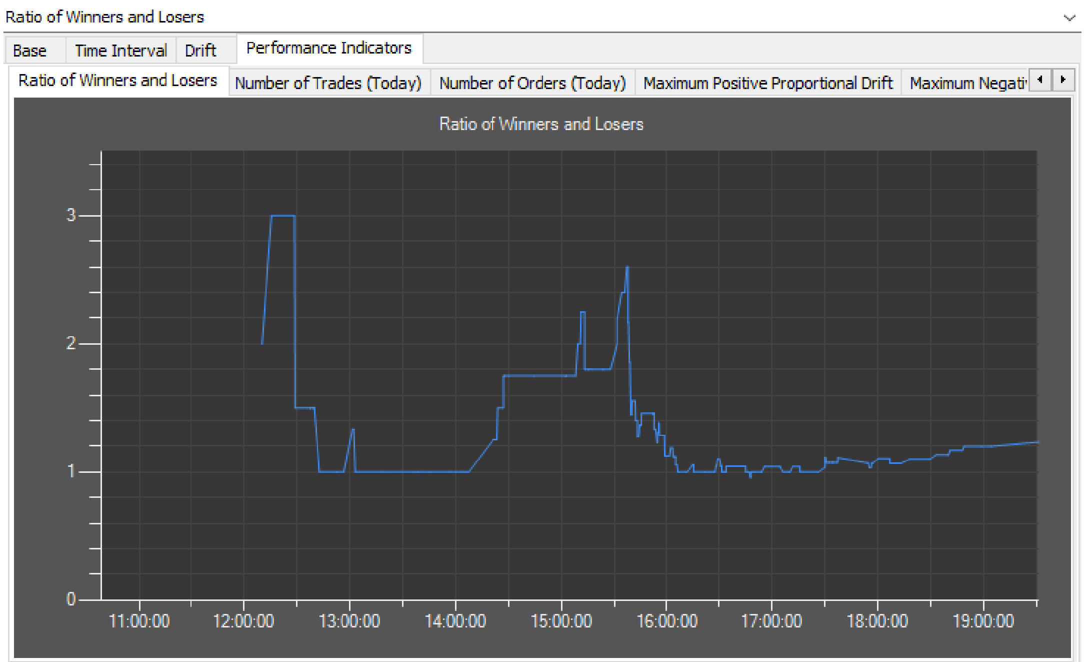

Figure 6 Ratio of Winners to Losers in RTDS

In Figure 6 we can see that the trader began the trading day with a good ratio of winning trades to losing trades but then lost (and regained) this success only to lose it after 16.00. This volatility in the ratio would suggest that the trader lacks consistency in his trading approach or that the market was very volatile.

3.2.1.3 Inter-transactional intervals (ITI's) and time taken metrics

The time intervals between trades, or transaction duration, (that is, closing an open trade and then opening a new one), can provide us with useful about the trader's behavior and, in particular, the trader's current reaction to losses or profits. Gaps between trades differ according to the trader's profit and loss condition and the state of the market. Rapid order (and subsequently trade) follow-up after a losing trade differed for winning trades. As a basis for the study the trader's data was split into time intervals between closing trades and opening new trades. Duration models focus on the times between events and, therefore, do not impose any sampling frequency assumptions.

In the current context the event is defined as a non-zero price impact trade on the S&P 500 Index futures market with the times between these events being referred to as transaction duration. A non-zero price impact trade is defined as a trade which contains a price that is different from the price observed in the previous trade. The method of examining time-interval metrics includes a number of metrics that focus specifically at times between trades. They include: *Time Since Last Trade, Time Since Last Trade Winner, Time Since Last Trade Loser, Time Since Last Trade Scratch, Standard Deviation of Times Since Last Trade, Standard Deviation of Times Since Last Trade Winner, Standard Deviation of Times Since Last Trade Loser, and Standard Deviation of Times Since Last Trade Scratches*. Inter-Transactional Intervals (ITI's) studies traditionally do not link to behaviour. Instead they focus on price. Researchers believe that ITIs fluctuate randomly as do prices [71] and that dealers move their expected price according to transaction frequency.

Time intervals between trades can show diminishing confidence when linked to losses and complacency and comfort when linked to profits. Among other methods, we used transaction duration [72] using time-interval metrics rather than transaction intensity to examine the behavior of traders with regard to loss aversion. The reason for this is that the gaps between trades tell a different story to the number of trades a trader makes during the trading day. Continuously during the business day, a trader opens a new trade and then, when he has closed that trade, follows up by opening another trade at an irregular time interval depending on his judgment and the market conditions.

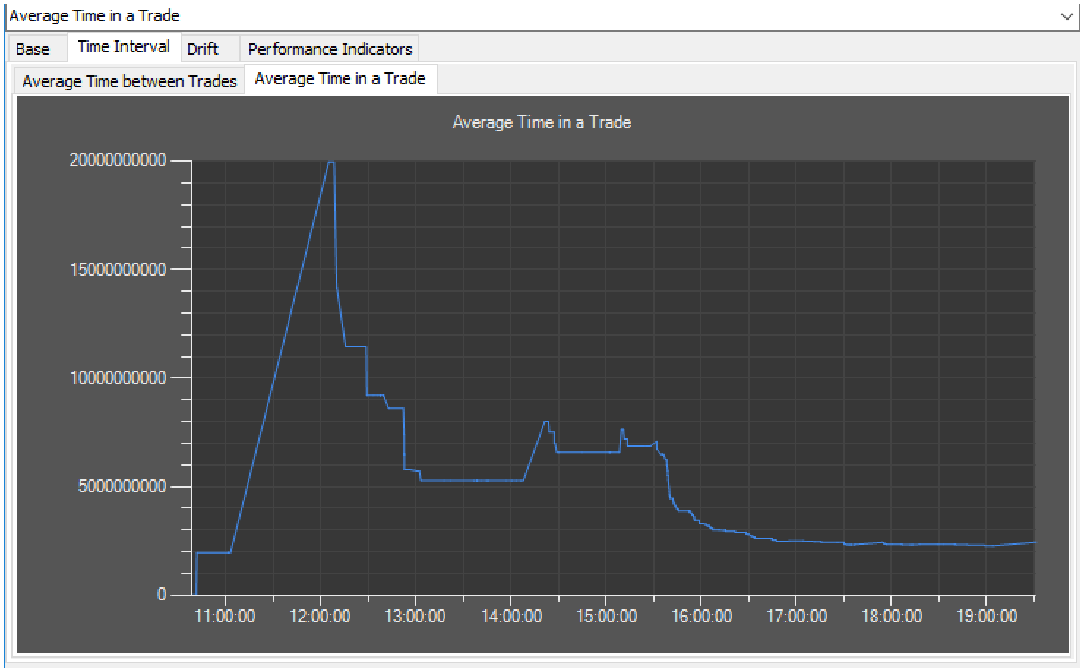

Figure 7 Average Time in Trade in RTDS

Figure 7 shows that there was a gap between the trades in early part of the day but the throughout the trading day the trader reduced the time in trades significantly. The Y-Axis is the time in Billionths of seconds, so the scale reads 5, 10, 15 and 20 seconds effectively. The objective of using billionths of seconds is to create a very granular observation of the data.

The degree to which a trader is successful is often observed in the length of the time interval between placing a winning or losing trade and the next follow-up trade. If the trader is profitable and confident of future success, his trades tend to be closer together in time, whereas if he is loss making and less confident of future success the trades tend to be further apart. This has implications for risk management. Observations in the research have shown that study of the following characteristics provides insight into trader's levels of confidence.

- Frequency of placing orders

- Frequency of pulling orders
- Time interval taken to accept a loss
- Time interval taken to accept a profit
- Use of stop loss orders
- Reaction time to sharp market movement
- Reaction time to slow market movement

Time-based metrics, then, provide evidence of trading confidence with the rate of orders and trades that follow each other. If the time between trades diminishes and the trader is profitable then their behaviour shows confidence. If the time in trade metric shows a steadily increasing measure during loss making for example, this is not such good trading behaviour and shows the trader is holding onto losses for too long.

3.2.1.4 Confidence metrics

The time-based metrics link in with the confidence metrics. The positive and negative drift metrics show how well the trader is maximizing trading opportunity. The metric measures the profitability of each individual trade and when the trade is closed for a profit or a loss it then calculates the difference between the trade outcome and the subsequent movement in the price of the trade instrument. For example, if the trader buys an oil future with a price of 45.03 and sells that future for 45.07, the trade would normally be considered as a success. However, if, once the trade is closed at 45.07 the price of the oil future rises to 45.15 in a given time period the positive drift is the difference between the traded price of 45.07 and the subsequent higher price of 45.15 showing a potential further profit was missed. The drift metrics provide evidence of selling winners too early and closing losing trades too late, the key determinant of the *Disposition Effect*.

Rapid trade frequency suggests more extreme behaviour, perhaps with the need to recover a loss or the need to capitalize on a profitable situation. Low trade frequency suggests lower levels of confidence, less opportunistic trading environment or loss of confidence. Change in time-interval metrics, that is, between actions, denotes a change in behavior.

3.2.1.5 Summary

The capabilities of RTDS enable the researcher to observe the critical point activity of the trader ‘in flight’ which then promotes the opportunity for a link between the trader and assistive machines that can intervene in the trader’s realtime trading activity in a set trading time horizon of one day, being the start and the end of the trading session [42]. The potential for this assistive and interventionist technology to positively modify the trading behaviour of the human trader in realtime opens up new fields of study in human-machine interaction as well as providing a basis for rethinking the structure of the markets and the products that are traded. This thesis looks to open up the potential for many new areas of activity and to provide the basis for further research in this area.

3.3 Trading Workflow

In order to create new models for assessing realtime trader behaviour it is important to understand the trader’s workflow. Traders workflow can be described as follows: traders have limited decisions to make: buy, add to open trades, sell, do nothing. The skill in determining profitable outcomes is in deciding when to make a trade. Decision-making processes are ruled by the alignment of certain clues as to when timing the trading decision becomes optimal. As can be seen in Chapter 5, the new behavioural interventionist model employs a Bayesian causality model [73] in order to support this.

The trader's objective is to reduce the number of clues that they rely on so as to make the job of arriving at a profitable trading decision less burdensome on working memory. Successful traders often use a process of *Progressive Reasoning* [74] rather than deliberate assessment of risky choices. Traders know they are taking risks but the risks are not in the forefront of their minds at all times. Instead, the tasks represent everyday work to them so that deeper reasoning is not performed as it is too time consuming. Instead, deeper reasoning occurs when choices become difficult to determine for a particular outcome. Profit or loss outcomes are unknown at the instigation of the trade and the objective is not to hold the open position for too long but to take single or multiple-tick regular profits. Risk *is* their business so it would seem natural to expect their attitude to risk to be different from the average person whose natural inclination is to try and avoid risk. It could be construed then that professional traders treat risk in a different way. As their livelihood is directly linked to their trading performance it is important that traders are actively trading and maintaining open positions, either short or long, that enable them to risk for profit. Outcomes are unknown at the instigation of the trade so that the trader applies an approximation of likely outcomes. The objective is to provide a number of experiments that test the augmentation opportunities for enhancing trader decision-making success based on these assumptions. Traders trading one or more financial instruments via a computer linked to an electronic transaction facility (exchange or MTF) have a set group of responses to market conditions in the form of set order types and a typical GUI. Trading from the GUI via the exchange interface, data transportation message protocols, like FIX Protocol, transmit actions generated by the trader from his computer in the following accepted formats:

- Buy order
- Sell order
- Cancel Order
- Replace order
- Limit order
- Immediate or cancel order
- Good Until cancelled

Within these activity constraints lies a huge number of behavioural responses in the form of the implementation of trading strategies. Trading strategies that rely on the deployment of these actions fall into the following categories:

- Scalping
- Short bias/Long Bias
- Momentum trading
- Position taking
- Short
- Long
- Relative value
- Spreading
- Arbitrage

3.3.1 Matching open positions with corresponding closing trades

One of the challenges identified in this thesis early in the research was that it is difficult to match open and closed orders, particularly because the shapes of orders and fills can be different and they can be partially closed at irregular intervals. For example, if a trader is trading in 25 futures and receives a partial fill for 10 futures with 15 remaining to be traded, if he then opens a new order to buy 25 futures, which original order do subsequent closing trades fill? The first or the second? It was discovered that it is possible to match the order numbers with the traded quantities which makes it a lot easier to identify completed trades where one open position is closed by another. Futures trading is unique in financial markets in that every new order that results in a trade is deemed to be an 'open' trade, but trades that reduce an open position to zero are deemed to be 'closing trades'although not specifically labelled as such by the trading system. What made order and trade identification easier is that each order has a unique identifier from its inception at the trader's computer and then a unique trade identifier at the exchange when it is transacted. It was found that if a trade is split into several different sized 'shapes' when it is transacted, each shape has an identical number. So for example, the trade below, which was an initial order for 25 contracts, was filled in six 'shapes' at the exchange. Each shape had a trade reference that was identical.

Trade Number	Exchange Identifier	Action	Verb	Volume	Contract
Trade1	03XV5TNS4	Fill	Sell	3	SPH5
	03XV5TNS4	Fill	Sell	2	SPH5
	03XV5TNS4	Fill	Sell	1	SPH5
	03XV5TNS4	Fill	Sell	1	SPH5
	03XV5TNS4	Fill	Sell	1	SPH5
	03XV5TNS4	Fill	Sell	1	SPH5
	03XV5TNS4	Fill	Sell	6	SPH5
	03XV5TNS4	Fill	Sell	3	SPH5
	03XV5TNS4	Fill	Sell	7	SPH5
Trade 2	03XV5TO7G	Fill	Buy	25	SPH5
Trade 3	03XV5TG65	Fill	Sell	17	SPH5
	03XV5TG65	Fill	Sell	5	SPH5
	03XV5TG65	Fill	Sell	1	SPH5
	03XV5TG65	Fill	Sell	2	SPH5
Trade 4	03XV5THY7	Fill	Buy	4	SPH5
	03XV5THY7	Fill	Buy	2	SPH5
	03XV5THY7	Fill	Buy	5	SPH5
	03XV5THY7	Fill	Buy	1	SPH5
	03XV5THY7	Fill	Buy	10	SPH5
	03XV5THY7	Fill	Buy	3	SPH5

Table 2 Exchange Identifier in the Trading Data

Table 2 shows the detail of the trader's trade audit trail and the exchange identifier for each subset of an individual transaction. The reason that a single trade can have multiple 'fills' is that there is seldom a matching order of the same size on the opposite side of the trader's original order to complete a transaction. The exchange's matching engine apportions available orders of various sizes to fill the trader's order.

Another characteristic of this type of trading is that traders seek to establish a flat position at the end of each trade. For example, they may send an order to buy 25 contracts which is filled at the exchange. Then they seek to make a profit by closing that position by way of a sale of 25 contracts which then brings their open position back to zero. With the order and trade identifiers we know the size of the trader's previous order as well as his current open position, and can then match the open position to the closing transaction. As we can see from the data in Table 2 that there are distinct buy and sell transactions with unique identifiers. Each transaction (Trade 1-4) is for a total of 25 contracts and after each sequence whereby one sell trade is offset by one buy trade, the trader's position becomes 'zero'.

3.4 Conclusion

Work has been accomplished in realtime behavioural models linked to risk and market regulation [2] but to date, there are no known behavioural models for capturing and assessing the realtime trading behaviour of Low Frequency Traders (LFTs) that then leads to the potential intervention of realtime augmentative tools. Chapter 5 describes the opportunity for creating such a model. Models, in general, play a large part in economic risky decision sciences. By introducing methods and means to capture, interpret and study realtime trading activity this thesis expects to form the basis for a new behavioural model application for realtime risk assessment of human critical point activities. The approach and results can be translated into a wider observation of human-machine interaction in risky environments.

The change in traded markets, whereby speed and HFT algorithmic trading activity has become ubiquitous and extreme, has caused interpretations of traditional classic economic risky decision-making to be enhanced. Now with a rich data set that can used to study trader's behavior in greater granularity, new opinions can be formed. Van Dujin [75] believes that "Unveiling the processes of higher cognitive functions, such as economical decision-making, is particularly challenging because the flow of input information is rarely under experimental control. As a result, the input/output function is vague and mechanistic decision theories remain unconstrained and hardly testable." With the availability of ‘microscopic’ individual trader data, as described in this thesis, we can overcome these difficulties.

The first objective is to see if the findings of traditional literature hold true with regard to loss aversion. Whereby laboratory experiments and uninformed non-expert subjects have been used to make valuable findings that can be applied on a broad scale, this thesis continues and extends the current push to use the richer data sets in order to examine financial experts in situ. One objective of the research is to determine if expert traders follow the same heuristic patterns and biases with regard to risk and loss aversion that non-expert experiment subjects do and to compare the results from the research with those of traditional literature. The opportunity then is to adopt the *expert-performance approach* [56]. This approach examines expert performance under ecologically valid conditions that are representative of the domain of expertise rather than in a laboratory whereupon it is not possible to extrapolate processes or mechanisms of naïve and unskilled participants to experts with extended instruction, knowledge, experience and practice. This leads to the potential positive modification of trading behaviour. By being able to accurately understand realtime decision-making through trader’s behaviour we can begin to study new areas of application like the implications of immediate feedback on risky decision-making, the impact of trader activity on market ethics, market microstructure design and human-machine collaboration. The results of the trading experiments and the use of RTDS provide a basis for future study of human critical point activity with regard to risky-decision making at the realtime edge. New models formed from the results and processes used can also form the basic design-architecture for the new human-machine collaboration with interventionist tools that this thesis introduces.

Chapter 4

Experiments

Chapter 4 describes the experiments undertaken in the research. With the introduction of realtime trader analysis a new behavioural model with new data analysis tools we can look at three classic economical decision-making theories and see if, at high frequency, the same biases exist. We can then look to modify these instances of bias using new tools and methods.

4.1 Introduction

In this Chapter we look at the structure of the trading experiments and their results in the light of classic theories of behavioural finance with reference to risk taking. Having created the tools and assessment measures to more fully understand the LFTs trading audit trail through the use of RTDS, we can now move forward to a different level of interpretation. Loss aversion is our starting point. To summarize, traditionally theory suggests that losses loom larger than profits [14] and people prefer to take profits quickly and let losses run. The behavioral implications of loss aversion are that a gain cannot compensate for a loss of equal absolute magnitude (an even gamble to win or lose some amount should be rejected, for example). These biases with regard to loss aversion extend to trading. Comparisons between expert traders and non-experts with regard to similarities or differences in the phenomenon of loss aversion have already been undertaken. In addition, those that fail to adapt to losses or to attain an expected gain induce risk seeking [16]. This may lead people to make decisions that maximize neither their wealth nor their happiness [76]. According to [77], loss aversion is an auxiliary principle introduced ad hoc to account for seemingly anomalous phenomena while [78] found that for small outcomes gains loom larger than losses. In addition, a point that is relevant to LFTs is that people might, however, learn that losses have less emotional impact than they predicted if they have the opportunity to experience repeated losses in the same domain over a short period of time [79] [80]. In addition, people believe that losses will have more impact than gains because they fail to anticipate how easily they will cope with losses. However, experienced LFTs are often more hardened to loss in short-term trading, viewing them as a cost of doing business, which suggests that losses and profits are accepted with equal disdain thus making the trader indifferent to either. By accepting that losses are a cost of doing business expert traders are engaging in business by being risk seeking while loss aware. Traders actively avoid loss but simultaneously adopt trading behavior that is commensurate with aggressively seeking profits. That is, they adopt aggressive risk taking strategies, that actively seek to acquire gains: they risk for profit while actively managing loss.

While providing a firm basis for understanding the behavioural traits of risky-choices, the traditional and current literature may not describe the true intricacies of the situation as far as the LFT is concerned, especially at the realtime edge. In fact, the findings supporting this thesis suggest that successful traders attempt to adopt a behavioral approach that reflects the concavity of Expected Utility Theory (EUT) [81] in its mathematical certainty in that consistently profitable trading is very much a function of a *repeat success scenario* [47] in that expert traders seek to repeat successful behavior as perfectly as possible in market scenarios that they recognize and have traded successfully before. During such situations the trader is adopting what could be described as a normative model of rational choice in that he is adopting the three tenets of EUT namely *Expectation, Asset Integration and Risk Aversion*, [16] in the fact that the overall utility of the prospect is the expected utility of its outcomes, *Asset Integration* in that the trader's wealth is enhanced through successful trading, and *Risk Aversion* in that the trader prefers a certain outcome to any risky prospect with an expected positive result. Expert trading behavior seeks to establish axiomatic responses upon which to act in definable individual, and repetitive, trading scenarios, even if the success of those axiomatic responses are only partially proved and, instead, form statistical likelihoods or high probabilities. As their livelihood is directly linked to their trading performance traders need to be engaged in their activities by maintaining open positions, either short or long, that enable them to risk for profit. This is evident in the research undertaken in that less experienced traders in the group were inactive while being in loss and more active when in profit while experienced traders were actively trading while in loss and less when in profit. If traders utilize an approach where they expect to make losses at least part of the time this differs with regard to EUT in that profits are always sought by the trader but loss is expected. Because they constantly entertain both outcomes they do not experience risk or loss aversion in the same way as is depicted in traditional behavioural finance research. They employ a reduced probability expectation for each single trade (they know they can do many trades so they are not overly worried about taking risks with single trades and they have less edge. They can always go back to the table if they lose) with marginal utility, in that they have a degree of disengagement from the task of trading as they are very accustomed to it. As traders become more profitable they tend to become more risk averse first seen in [42] and also in the research experiments described in this thesis. The tendency is for traders to be mostly conservative and biased towards the status quo. Loss aversion triggers status quo bias [31]; that is, not wanting to lose what one has already made. In cases where under-reaction occurs, investors who have been positively inclined towards a certain investment may continue to buy the asset even though a weight of negative information is accumulating. This offers attractive trading opportunities for traders who take the contrarian view of asset price movements. The expectation is that as soon as the weight of negative information becomes too heavy to ignore, the asset price will reverse strongly as investors overreact by selling strongly. As people have a tendency to be more loss averse than profit seeking, [17] it follows that they are likely to overreact by selling the asset too vigorously in order to avoid losses. The herding instinct is prevalent when the weight of negative or positive information available to traders creates a market-fulfilling prophecy. LFTs experience the phenomenon of under and overreaction in markets and, if they are unaware of the basis for the extreme moves, can be badly caught out. Hilton [35] uses the example where people were asked to judge from memory how many fouls were committed during a football match. One set of spectators was asked to review from memory the entire match, while the others were asked to review each half of the game and then to add the two together. The research found that those that added the number of fouls in each half tended to exceed the number estimated by those that were asked to estimate for the whole. LFTs who base their decision-making processes on memories of past events may find that, in reality, those events are exaggerated or not according to how they are framed. It is evident from the research conducted by [35] and others that there is much still to learn in trader psychology. There are so many intangibles that affect trader behavior that there is a need to be able to clearly identify when certain trading "Sins" [35] are being committed. The behavioral implications of loss aversion are that a gain cannot compensate for a loss of equal absolute magnitude. These opinions with regard to loss aversion extend to trading. [42] work with futures traders from the CBOT with traders appearing to be highly loss-averse, regularly assuming above-average afternoon risk to recover from morning losses.

In a different way, the *Disposition Effect* [17] is the observation that investors tend to realize gains more than losses. A standard explanation of the *Disposition Effect* refers to prospect theory [16] and, in particular, to asymmetric risk aversion according to which investors are risk-averse when faced with gains and risk-seeking when faced with losses. However, [82] show that for reasonable parameter values, the disposition effect cannot, however, be explained by prospect theory. The reason is that those investors who sell winning stocks and hold losing assets would not have invested in stocks in the first place. That is, the standard prospect theory argument is sound ex-post, assuming that the investment occurred, but not ex-ante, requiring also that the investment has to be made in the first place. [42] show the existence of the *Disposition Effect* in the futures market with traders appearing to be highly loss-averse, regularly assuming above-average afternoon risk to recover from morning losses.

While, some years ago, the social atmosphere of open outcry trading pits made decision-making confirmation more readily available to futures and stock traders, in electronic markets traders do not necessarily have exposure to the confirming viewpoints of others. Historically, successful traders have tended to work alone exemplifying strong dependence on their own opinions rather than seeking the approval of others. The aim of the experiments was to confront the LFTs with a different working environment that encouraged them to collaborate with each other first, and then, ultimately, with a machine. Trading electronically assists the trader in relying on his own analysis and opinions and because of the isolated and intense nature of the undertaking, traders are normally engrossed with their own trading activity on their own computer monitor screen while mostly unaware of the actions of those sitting around them. The experiments sought to turn this notion on its head by introducing other traders into the personal workspace of LFTs with the intent of seeing how well they began to collaborate in groups and influence each other. For example, each of the groups of six traders on the pods of six linked desks were encouraged to talk about their trading ideas and to move freely around to talk to each other. The effect of this collaboration can be seen in Table 4 with the reduction in the standard deviation of profitability between individual, group and machine experiments. It can be seen that traders were less likely to be risky when working in groups or trading with the support of a BIT.

With regard to electronic trading, *illusion of control* and *optimism bias* can have the effect of making traders overtrade. Encouraged by the *illusion of control* that some traders experience, they fall prey to unsubstantiated optimism that leads them to make more trades than they would normally do on average even when they are losing.LFTs were under observation for evidence of this bias in group and machine-led settings as well as in individual trading sessions. As can be seen in Table 4, the average number of trades of combined groups of LFTs fell when the traders moved from trading individually to trading in groups and then marginally again when trading with the BIT which suggests that traders were unlikely to over trade when in groups or trading with machines, while overtrading is a hallmark of *optimism bias*. Although statistically some of these trades will be successful, the overall effect of *optimism bias* on the trader's portfolio is to increase risk without the greater certainty of positive outcomes. Subsequent losses can have a damaging effect on a trader's morale and confidence if he truly believes that, unaware of his unsubstantiated optimism, he should have the upper hand. In addition to *optimism bias,* traders in electronic markets often have difficulty in identifying what information they should be paying attention to because there is so much of it. The lucrative business of selling information has created a realtime and historic mass of uncorrelated data that needs to be constantly sorted by software programs so that it should be ordered enough to make a modicum of sense to the trader. The "noise" inherent in market data and financial news is significant and traders can be fazed by the prospect of making trading decisions based upon them. The ease with which information can be grouped together and collaborated means that traders often make illusory correlations [35]. However, a popular strategy that LFTs use to determine the likely outcome of the anticipated price movements of financial instruments is to correlate them against other instruments. By buying and selling two financial instruments simultaneously so that the trader is long of one and short of another referred to as spread trading, traders expect to see the spread differential widen or narrow in the prices of the two instruments thus providing an opportunity to profit. Spreading is a popular trading strategy and can be undertaken in several ways. With futures, traders can buy and sell the same financial instrument but with different expiry cycles, they can spread related products against each other, for example, buying a 10-year Treasury Future and selling a 30-year long bond future, or they can spread seemingly unrelated products like equity index futures and short-term interest rate futures. Now that the same product is often listed by multiple exchanges, inter-market spreads are becoming very popular as a short term trading opportunity. The notion that underpins spread trading is that there is a recognizable positive or negative correlation between the products being traded and that relative movements in their prices can be tracked and anticipated with some degree of accuracy

In summary, the behavioral implications of *Loss Aversion* are that a gain cannot compensate for a loss of equal absolute magnitude and that the objective is to see if the same biases appear in the experiments undertaken in the realtime trading activity of LFTs. The data captured by RTDS provides a very clear observation of the behavioural characteristics of individual traders, groups of traders and the impact of introducing experimental BITs. The categories of metrics provide a means to be able to compare different behavioural traits in traders from a base level to a more sophisticated level. As can be seen from the outcome of the experiments, observations of the trading behaviour of the LFTs was brought into focus by the detailed data provided by RTDS.

4.2 Experiment design

The study group for this thesis comprises 32 LFT day traders trading in E-Mini S&P 500 futures™ traded on the Chicago Mercantile Exchange (CME). There is a mix of trading experience amongst the group. They use a computer mouse to click trade in the exchange central limit order book (CLOB) rather than to automate their trading in an algorithm. The experiments took place over six weeks and involved several sessions all trading the same futures product. As mentioned in Chapter 1 traders performed, on average, up to five trading sessions of two hours at minimum each over the six-week experimental period. Many of the traders in the experiments are self-employed but under the risk and clearing control of an established trading company. They risk the trading company's money in order to attempt to make profits and share a proportion of their winnings with the trading company. The professional trader's income is derived from trading individual futures contracts in realtime using proprietary trading software. Operating as day traders, (that is trading within a set time period, referred to as 'exchange hours', dictated by the opening and closing time of the exchange that lists the products they trade), they buy and sell single or multiple E-Mini S&P 500 futures™ continuously throughout the day when the opportunity for profit presents itself. Their objective is to observe the price fluctuations of the futures through a Graphical User Interface (GUI) linked to the CME CLOB and trade matching engine and to take short-term long or short open positions through manual order entry by way of a computer mouse or a keyboard, in order to capitalize on favourable price movements in the fluctuating price movement of the instrument. LFTs actively place orders in the market so as to provide themselves with the potential for profit. They operate within a set time period during the trading session and begin the trading day with a flat book and end the same trading day with a flat book. That is, they start with zero open positions and end the day with zero open positions. They are then left with a net loss or a net profit depending on the overall return from their trades. They do not, as a rule, carry open trades from one exchange trading day over to another. This, in itself presents a useful research opportunity because the research period neatly fits into a single time period within which the first opening trade and the last closing trade of the day forming a closed set of trades. In addition, by trading the same financial instrument, in this case the E-Mini S&P 500 futures™, traders can be compared during the same market conditions and the same time intervals. During the hours that they are trading they monitor the realtime changes in the price of the trading instrument and gauge when to buy or sell in order to take advantage of movements in the price of the instrument. LFTs are placing orders to execute trades throughout the trading day. Their overall objective is to spot opportunities to go long or short with a new opening position and then to profit from a fall or rise in the price of the instrument before closing the open position hopefully at a profit. The skill of the LFT is to determine the most advantageous time to open a new trade and the equally best time to close it given the market price fluctuations in the instrument. The main point is that the trader is not encouraged to hold a lengthy trading position unless it is moving in a distinctly profitable direction for a long period of time, but to engage in 'short-termism' by opening and closing trades in quick succession. This is commonly referred to in the industry as *scalping*. The trader's objective is to take as many short-term profits as possible and to minimise the prospect of losses by closing losing trades quickly.

Traders open new trades through filled orders and then, when they have closed the trade, follow up by opening a new trade at various timescales. A significant drawback to the analysis of historical data without automated tools, occurs when particular segments or snapshots of trading activity cannot be accurately linked to the market scenarios to which they belong so that any assessment work that does not map the actual millisecond by millisecond market event to the associated trading activity is flawed from the start.

4.2.1 The trading room environment

The environment in which a trader trades can have an impact on their trading behaviour [83]. The experiment trading room was designed to provide all the amenities and tools that an LFT would normally expect to use. Each LFT was allocated a trading desk with a wide-screen computer that hosted the trading front-end order entry and trade management systems and provided access to charts and news information. The LFTs were spaced approximately three feet apart and were split into groups of six and seated around a six-desk oval design. The objective was to make the trading room more congenial than a traditional computer lab with bench-style table design set out in rows. As soon as LFTs entered the room and took their seats they were already beginning to feel more associated with their peers. This was an important objective because one of the objectives of the experiments was to measure the ways in which LFTs would communicate and collaborate. Some of the LFTs knew each other while others knew no-one present in the room. Once the LFTs had taken their seats, switched on their trading software and established their GUI set-up they were briefed that they were going to trade for up to three periods during the trading day each of around two hours, and at each new period they would be experiencing a change in set-up.

1. Period 1 required the LFTs to trade on their own.
2. Period 2 required them to collaborate with each other in sharing trade ideas and opportunities
3. Period 3 introduced the behavioural interventionist trading tool (BIT) as a component of the trading set up for each trader

While many traders in financial markets tend to trade on their own, the objective of these experiments was to introduce LFTs to a collaborative and synergistic trading environment in order to see if they behaved differently when in groups or linked to a machine. The three sets of experiments were repeated at intervals over the weeks of the experiment duration and the results were compared to the three areas of classic decision-risk economics using realtime trading scenarios in order to understand the following:

1. Do LFTs suffer from the behavioural biases and heuristics described in the theories of loss aversion, disposition effect and overconfidence?
2. Do any of these biases change when
    i. They trade as part of a group in a collaborative form
    ii. They trade in the knowledge that they are being overseen by an interventionist tool that is designed to assist and augment their trading behaviour and activity?
3. Do LFTs improve their trading activity, profit and loss and risk position when
    i. They trade as part of a group in a collaborative manner

ii. They trade in the knowledge that they are being overseen by an interventionist tool that is designed to assist and augment their trading behaviour and activity?

4.2.2 Behavioural interventionist tools (BITs)

An interactive tool that reads human trader's decision-making responses to realtime market conditions, reacts to those market conditions and formulates a response whereby it intervenes positively in a trader's realtime trading activity does not currently exist in commercial form but it does in experimental form. A prototype BIT was created to work with individual traders and utilized the sample set of metrics provided by RTDS as a basis for its activity. Some examples of the BIT activity relative to the trader's profitability are described later in the chapter. Following the results of these experiments, a full-production model of the BIT is now in preparation. Using newly formed constructs and design series (explained in Chapter 5) the tools are being created with the use of models that involve artificial-intelligence. The objective of the experiments was to prepare the groundwork for such machines by observing what happens when LFTs believe they are interacting with them on a realtime basis. If such a tool did exist would it have a positive effect on the trading behaviour of LFTs? Then, if results were positive, to propose constructs and models for the creation of such tools. Using the trading behavioural model described in Chapter 5, the results from the experiments can be used to create the basis for forming human-machine collaboration in that there are clearly identifiable strengths and weaknesses in a trader's behaviour that can be positively modified, or augmented, or blocked. The experiments, therefore, were designed very carefully to give the participants the impression that these behavioural interventionist tools (BITs) did exist, were being used in the experiment, and were successfully intervening in their trading activity. They did not see the tool as it was 'hidden' on a separate computer away from the trading computers. However, the outcome of the tool's 'observations' were sent via messaging software to the desktop of the trader. The result was the LFTs acted upon the belief that their trading behaviour was being observed, analysed and potentially improved by the BIT.

As highlighted, the LFTs concentrated their trading efforts in one financial futures instrument during the same time period and in the same market. The idea was not to give the traders too many choices regarding the instruments to trade as this would have made decision-making collaboration difficult if they were trading in different instruments. This approach is consistent with the findings of [84] in that the most successful day traders tend to concentrate their efforts on a small number of instruments for which they can develop an expertise in anticipating news information and its effect on prices.

4.2.3 The null hypothesis

The null hypothesis states that there will be no change to the LFTs trading behaviour when grouped with colleagues or linked to a performance-enhancing BITs and that there will be no statistical significance to the findings. The expectation was that there would be no statistical significance observed in the behavioural metrics which were applied to the trader's behaviour, whether the trader was trading as an individual, as part of a group or working with a BIT. Statistical significance ranges of 10%, 5% and 1% were applied through a t-test as shown in Table 3. Nine metrics were selected to provide the basis for the assessment of the trader's trading activity. The table below identifies these nine metrics and the Alternative Hypothesis.

Metric	Alternative Hypothesis
Number of consecutive winners	There is an improvement in the number of consecutive winners
Number of consecutive losers	There is a reduction in the number of consecutive losers
Number of scratches	There is a reduction in the number of scratches
Average trade size	There is an Increase in trade size
Average time between trades (sec)	There is a decrease in average time between trades
Average time in a trade (sec)	There is an increase in the average time in trades
Maximum positive drift	There is a reduction in max positive drift
Maximum negative drift	There is a reduction in negative drift
Ratio of winners to losers	There is an Improvement in the number of winning versus losing trades

Table 3 The Alternative Hypothesis

The Alternative hypothesis in Table 3 shows the expectation for the alternative result from the experiments over the null hypothesis. Using the metrics as a guide, the table lists the observations that would support the alternative hypothesis.

In line with traditional theories of behavioural finance as discussed in Chapter 2, the null hypothesis suggests we should not expect to see any change in the trader's behavioural responses to trading scenarios trading either as an individual, in a group or with the support of a BIT. In relation to the *Disposition effect* and *Loss aversion* and *Overconfidence* we would not expect to see any significant improvements as described below:

The Disposition Effect

1. Traders would not form a comfort level with profits or losses beyond which they would become risk averse (with profits) and risk seeking (with losses)
2. When the groups and machines were introduced the incidence of *disposition effect* would not change.

Loss Version and Overconfidence

3. When the groups and BITs were introduced the incidence of *loss aversion* would not improve and that there would be no change to the variance in losses, the degree of inter-transactional intervals or to the volume of trades
4. *Overconfidence* as seen in the incidence of over trading would not change
5. The ratio of time in winners to time in losers would not improve and the degree of positive and negative drift would be unaffected

4.3 Results

Once the data had been collected for all the experiments from RTDS and had been analysed, a set of descriptive statistics was created, the details of which are seen here in Table 4.

	Individual	Group	Machine
Mean Profitability (US$)	10.1	15.59	16.67
SD Profit	49.09	32.62	34.97
Max Profit	100.5	97	80.35
(Min Profit)	(72.5)	(42.75)	(33.75)
Skewness	0.38	0.66	0.39
Average Number of Trades	28	19	22

Table 4 Descriptive Statistics based on Trader Profitability

The Descriptive Statistics show a range of data for individual, group and machine-based trading. Mean, Standard Deviation, maximum and minimum winning or losing trades, the skewness and the number of trades are included. Mean profitability was recorded in US$ as the trading instrument that was use, the S+P500 Index Future, is denominated in US$.

The observations from these statistics show a number of useful findings:

1. Although profitability was low across all experiments due to a broad mix of traders who made losses and profits, the mean improved between Individual, Group and Machine. The rate of improvement was not substantial but it was positive.
2. The average number of trades dropped significantly in the Group statistics compared to the Individual statistics and then recovered again slightly in the Machine statistics. This may have been due to a number of factors including the fact that trading in groups was a new experience for many of the traders and they were less willing to risk themselves in front of their peers. This observation was confirmed when the rate of trades increased as the LFTs moved onto the Machine led experiments from the

Groups suggested that the lack of peer group observation made them more confident to risk themselves again.

3. Maximum and minimum profitability dropped from Individual, to Group to Machine. This indicated the adoption of a more cautious approach to risk as the LFTs started to work in groups or with the BIT.
4. The Standard Deviation reduced as the LFTs worked together and with the BITs which also suggested that a lower risk approach was being taken. This also fits in with the lower number of trades with the group and machine options.

4.3.1 Direction of change – descriptive statistics

Direction of Change- Positive

1. **Mean profitability increased** – the degree of profitability increased over the experimental period when LFTs moved from trading as individuals and were introduced to group trading sessions and machine trading sessions.
2. **Standard deviation improved** – Compared to trading individually, LFTs were less risky when trading in groups and with machines, although marginally riskier when trading with machines than in groups.
3. **Minimum and maximum profitability reduced** – the maximum and minimum profitability reduced for winning trades and losing trades on average so that more extreme trading losses and profits were seen when traders traded individually,

Direction of Change- Negative to neutral

4. The number of trades reduced between Individuals and Groups but improved slightly when working with the BIT-

Following on from the descriptive statistics, the data from the metrics was assessed in relation to the differences between the group trading activities, and a number of calculations were made including standard deviation, and t-test in order to show how statistically significant the results were. Statistical significance was achieved with a t-test result within 10%, 5% and 1% level of significance.

Time	t-test indiv/Group	t-test Group/Machine	t-test Machine/Indiv
Number of consecutive winners	(1.53)	(2.91***)	(3.09***)
Number of consecutive losers	(1.44)	(1.50)	(1.82*)
Number of scratches	(3.94***)	(4.13***)	(4.31***)
Average trade size	(2.94***)	(3.06***)	(3.22***)
Average time between trades (sec)	(1.98**)	(2.83***)	(2.79***)
Average time in a trade (sec)	(0.91)	(1.06)	(1.76*)
Maximum positive drift	(1.09)	(1.73*)	(2.22**)
Maximum negative drift	(1.27)	(1.36)	(1.87*)
Ratio of winners to losers	(0.34)	(1.17)	(1.19)

Table 5 Experiment Results

Results from the trading sessions have been split in this table into three columns showing the different results between trading Periods and their variability. The objective is to show that there were statistically significant improvements in some of the metrics between the Periods

4.3.2 Direction of change – individual-group-machine results

Direction of Change- Positive

1. **Number of Consecutive Winners** – the number of consecutive winners improves significantly from individual to group to machine, an example of which can be seen in the RTDS screen shot in Figure 15 on page 107. This statistic is key to the improvement of trader profitability as it suggests that the trader is following winning trades with other winning trades.
2. **Average Time Between Trades** – Another statistically significant observation as the time between trades reduces as traders become more confident of their trading ability and profitability.
3. **Maximum Positive Drift** – the maximum positive drift statistic improves between individual/group and group/machine significantly as the efficiency with which traders run winning trades improves.
4. **Maximum Negative Drift** – there is a slight improvement in the statistics but running losses is still a feature and reflects the mixed ability of the experiment trading group of LFTs.

Direction of Change- Neutral

5. **Ratio of Winners to Losers** - the ratio of winners/losers does not improve significantly. However, what does improve is the efficiency with which traders run winners so that the improvement in Maximum Positive Drift means that the winners are more profitable than the losers are loss making. Even with a similar number of winners to losers the overall profitability (as shown in the descriptive statistics) can improve.

The results refuted the null hypothesis and supported the alternative hypothesis in most instances as can be seen in Table 4 and 5. What is interesting with regard to the use of BITs is that the level of significance confirms the positive response of LFTs to working with machines like BITs and forms the basis of Chapter 5.

4.3.1 Data analysis and observations

The data from RDTS was examined during and after the trading activity had finished and each individual trader’s activity was transposed into graphic form via Matlab in order to establish a visual observation of behaviour. During Period 1 the LFTs actively traded with an average of 15 trades per hour. The overall profitability in each subsequent Period 1 experiment was similar but the frequency of trades undertaken in Period 2 and Period 3 diminished. The collaboration in Period 2 between groups of traders encouraged a degree of thoughtfulness with regard to trading decisions not seen in Period 1 and reduced the frequency with which traders entered orders. As a general observation, the LFTs were visibly open to working in groups and to allow the BIT to guide them in their trading decisions while hypothetically ‘intervening’ in their trading activity. This willingness to engage with each other and with the BIT was evident in the overall drop in traded volume and not so directly by trading profits. However, the classic behavioural biases observed in *loss aversion*, *disposition effect* and *overconfidence in predictions* were reduced as LFTs moved from Period 1 to Period 2 and then to Period 3. The following list identifies the Figures in this Chapter that correspond with the different experimental periods:

- Period 1: Figures 7-11,
- Period 2: Figure 12
- Period 3: Figures 13-17

4.3.2 Working with the BIT

One of the critical determinants for achieving the goal from the experiments, the basis for successful human-machine collaboration, was that immediate feedback was given to traders from the BIT. Because the price data coming from the trading system was realtime, it was possible to construct a 'machine decision' while the LFT reacted to the near to realtime data. In addition, some of the initial experiments were conducted when market conditions provided evidence of price trends and this helped to demonstrate profitable 'machine decisions' (by suggesting that traders follow the trends) thus reinforcing the belief that the BIT was making improvements to LFT's decisions. LFT's volume of orders dropped, they relaxed more and began to collaborate with ideas for trading strategies in Period 3 when the BIT was supposed to be active. The urgency with which individual LFTs conducted their isolated trading experiment was not evident in the machine experiment.

4.3.3 Developing the prototype BIT

In order to see the BIT in action a prototype version was created following the successful outcome of the experiments. Although the thesis experiments were conducted without a fully-functioning BIT, the results bore evidence of the positive response a trader would have to such a machine and a full version was put into construction immediately. The initial results from the prototype have bee encouraging and supported the results from the experiments.

4.3.4 RTDS data results

Starting with Figure 8, the graphic denotes the Profit & Loss of the trades undertaken during the trading day and shows the time intervals between the closing out of trades and the opening up of new ones. As can be clearly seen, the LFT has entered into loss as soon as he has started to trade. He continues to trade throughout the day gaining from some winning trades but losing from others so that he has a net loss at the end of the day. The pattern of his trading as seen in the right graphic, shows that there are short time intervals between closing trades and new open trades suggesting that the trader is opening a series on trades and holding these open positions for a short period of time before closing them, but following up with a new open position quickly.

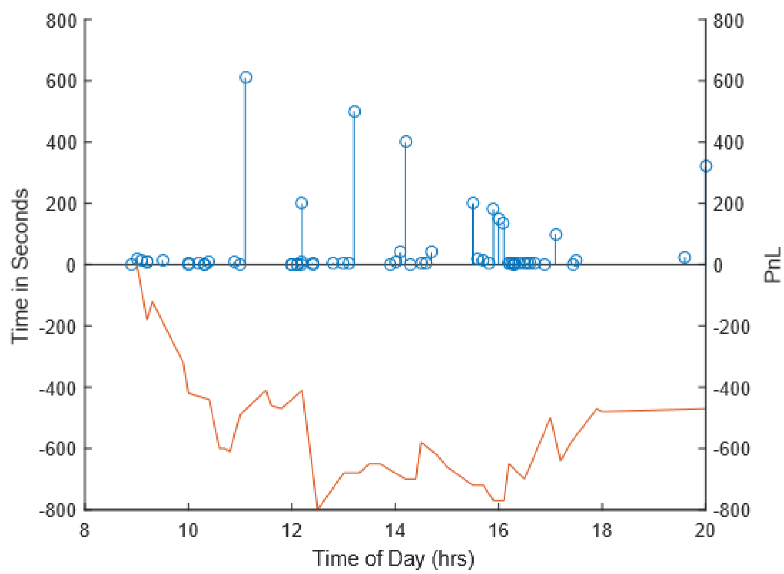

Figure 8 Period 1: Profit and Loss with Durations between Trades: Losing Day

Figure 8 shows a losing day with a series of small clusters of trades at certain times and short intervals between them as the trader tries to recover from the losing situation unsuccessfully. The short length of the intervals between trades and the rapid order entry of several trades in very short time intervals suggest that the trader is not following a method but is merely gambling.

As can also be seen in Figure 8 the data provides evidence of responding to extreme loss leading to initial flurry of activity and then long lapses between trades. The LFT was not risking further loss after an initial attempt to improve the situation but then picked up trading activity later in the session to try and reduce losses. The high frequency of trades and shorter time duration between trades suggests risk taking. After conditions began to improve and profitability increased, the frequency of trading picked up again and led to a flurry of trades towards the end of the trading session. A lower frequency of trades with longer duration between trades suggests a degree of risk averse behaviour. The trader was risk taking as he became more profitable, but became risk averse in losses. It became evident as more data was analysed that that LFTs clearly behave differently when in loss as denoted by the transaction duration. Trade frequency tends to increase while transaction duration is reduced [42]. In Figure 8 there are also small clusters of high density trades when the trader is confronted with losing already acquired profits. In an effort to recoup losses, the professional trader conducted a high number of short term trades with very few seconds duration. However, the losses mounted as the shorter trades were unprofitable, then as the trader was making further losses of -800 he stopped and the time between trades increased until he started making more profit. This is not typical of what happens when the non-sophisticated trader's trades.

Do LFTs risk the losses and the profits rather than just the losses? It has long been believed that traders should see trading losses as the cost of doing business in that losing in trading happens as frequently as winning and should, as a result, be expected. By adopting an attitude to *risk for profit* traders are able to be opportunistically profit seeking while actively managing loss. Evidence from the experiments shows that LFTs do not risk profits. Loss aversion also triggers status quo bias [31] whereby people tend not to want to lose what they already have. However, when the LFT is trading his objective is to gain additional profit, an open ended objective, and not to settle for the status quo. In this regards, the LFT has an in-built bias to challenge the status quo.

4.3.3 Trade density

It is a central view in this thesis that LFTs demonstrate, through time intervals between placing their trades, an increase or decrease in confidence and in their attitude to risk taking. In addition, it is also suggested that the density of trades has an outcome on risky decision-making. As keen be seen in Figure 9, taking an individual trader from the group, the trade density intensifies during the periods of higher profitability. This suggests that the trader is risking for profits. During loss making time periods the traders trade duration intervals become longer.

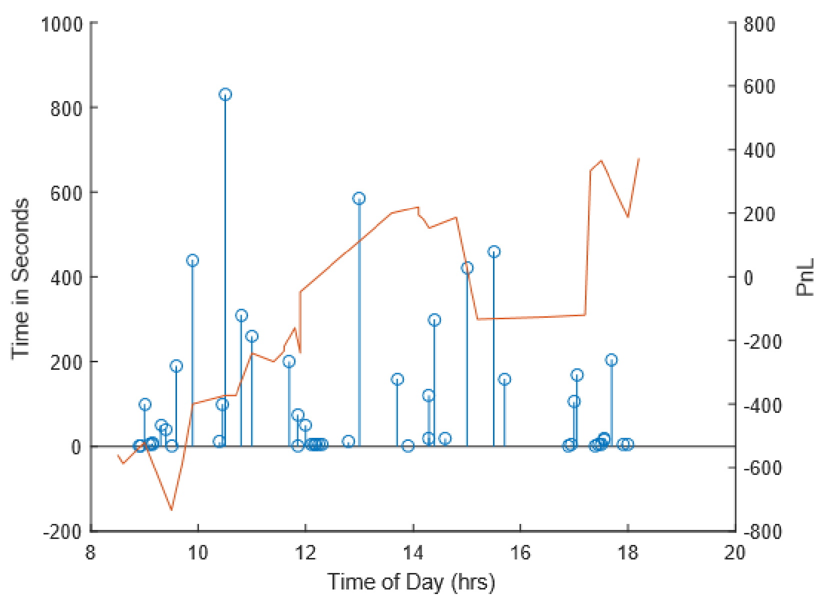

Figure 9 Period 1: Profit and Loss with Durations between trades, Winning Day

In Figure 9 the featured trader shows he is 'risking for profits' as the cluster of short term trades and the short time intervals between trades suggests greater confidence and profitability.

Figure 9, in comparison to Figure 8, shows a different type of behaviour during a winning day. The time intervals between the closing trades and opening new trades are longer in Figure 9. At the peak of his profitability in Figure 9 the trader's order frequency diminished and the time interval between trades widened. The LFT in Figure 8 was more active in loss making than in periods of profitability which supports loss aversion theory. What does this suggest? Firstly, it shows that the LFT is taking less time over his trade selection in Figure 8 but is opening and closing trades in quick succession in order to attempt to secure regular small profits and to avoid large losses. In Figure 9, the LFT is taking more time to select his trades and has longer time intervals between most of his trades compared with Figure 8. The rapid opening and closing out of trades in Figure 8 may point to a lack of confidence in the trader's ability to pick winning trades and a fear of falling further into loss. The longer time intervals between closing out trades and opening new ones in Figure 9 may suggest that the trader is deliberately taking his time to select profitable trades and to avoid taking unnecessarily risky trades that may result in loss. His objective is to preserve profit but to continue to trade with the potential of further profit while limiting unnecessary loss. The LFT's data also shows that when he is confident of a trade he increases the size of that trade. Gaps between trades differ according to the trader's profit and loss condition and the state of the market. Rapid order (and subsequently trade) follow-up after a losing trade differed than for a winning trade. As a result of the research, we find that more experienced LFTs have higher risk tolerances and thresholds, are more likely to treat losses and profits in an equal way, as a cost of doing business, rather than risking losses and not profits.

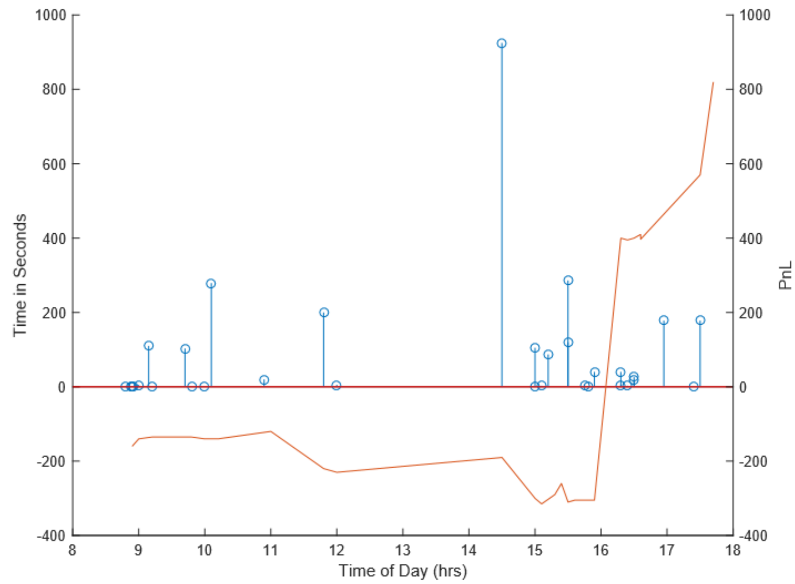

Figure 10 Period 1: Profit and Loss with Duration Between Trades, Losing to Winning Day

In contrast to Figure 8. Figure 10 shows a longer losing period with a finishing leap in profitability. There is a small cluster of short duration trades around 16.00 which suggests that the trader is adding to winning positions and building profitability.

In Figure 10 the trader is confronted with a different scenario in that he is trying to move, in the early part of the trading day, from a loss to a profit. There is a long period of inactivity during the loss making period but as soon as the trader turns profitable, the frequency of trades increases and the profitability improves further. There is a visible reduction in the time between trades during this period of improved profitability suggesting that the trader is reinforcing the profits with a selection of other profitable trades.

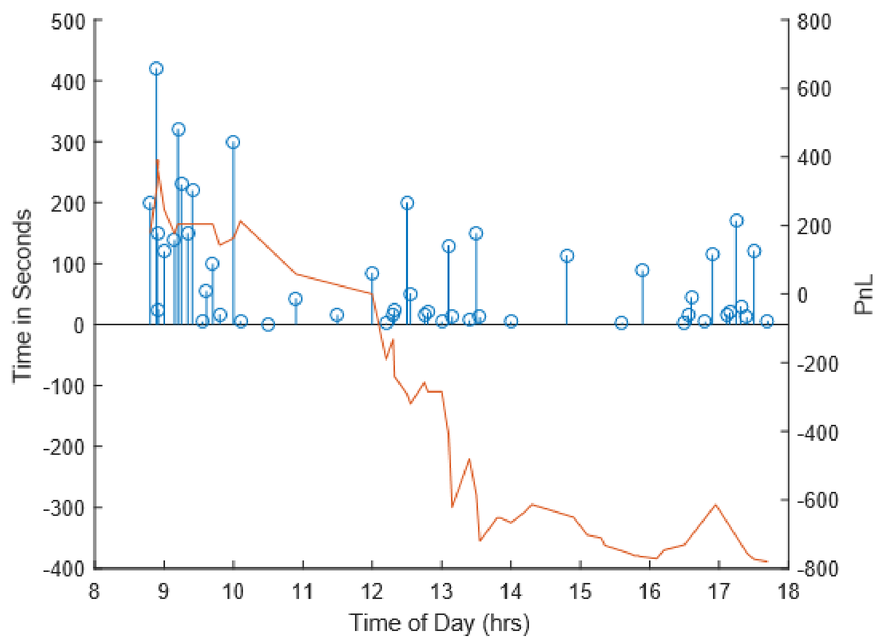

Figure 11 Period 1: Profit and Loss with Duration Between Trades, Winning to Losing Day

Figure 11 shows a depreciating number of trades and time intervals between trades as the trader tries desperately to recover profits and to avoid loss. However, the short lifespan of the trades does not suggest confidence in the trader's positions.

In Figure 11 the scenario is based on an initial winning day then moving into a period of loss making. The interesting point here is that the trader has a high frequency of trades early in the day and then as losses become more apparent, he reduces the number of trades and then attempts to get back into profitability quickly around 12.00 by introducing a flurry of trades which prove to be loss-making. This trading behaviour suggests that the trader is lacking a plan of action for profitability and, instead, is engaging in gambling behaviour, by trying to catch a profitable trade from a large number of orders. As often happens, once the loss has been incurred, the inexperienced trader reduces the number of trades for fear of additional losing right up to the oint when he decides to risk again before the close of the market. This last minute flurry of trades with very short time intervals between them and short lifespans does not prove successful.

The outcome of the data analysis supports [78] the research conclusion in that the traders are trading for small outcomes which are incrementally likely to lead to larger profitable outcomes. In a series of three experiments, [78] found that for small outcomes, this pattern is reversed, and gains loom larger than losses. The reversal was explained on the basis of (a) the hedonic principle, which states that individuals are motivated to maximize pleasure and to minimize pain, and (b) the assumption that small losses are more easily discounted cognitively than large losses are. New thoughts regarding reference points is one area of future research. How do LFTs establish a reference point and is this point continuosly changing? The trader's objective is made more difficult because of the short time intervals between price movements and changes in market conditions when they are engaged in scalping. The fact the prices are constantly changing as well as market conditions favouring profit making activity or not, suggests that reference points are also continuosly changing, although they may have a proportional relationship to the price movement that is independent of the actual price. The influence of reference points on the shape of indifference curves has been given a comprehensive treatment by [85]. By *Loss aversion*, they refer to a local distortion in a person's global preference structure, produced by a reference, or "status quo" point. Figure 11 which shows the direct overlay of time durations between trades and profitability during Period 2 supports the above findings.

Time between trades grows longer demonstrating a lower level of confidence in risking profits as when profitability grows then the time between trades lengthens.

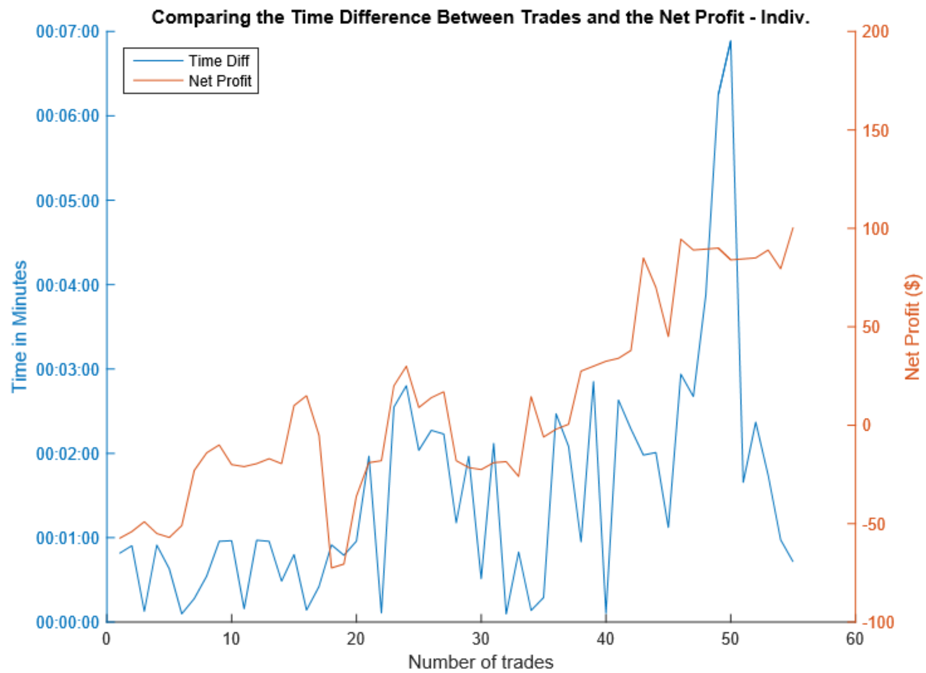

Figure 12 Period 1: Profit and Loss with Duration between Trades, Winning Day

In Figure 12 the graph shows that the time between trades increases as the LFTs, trading as individuals, become more profitable thus supporting the *Disposition Effect* and *Loss Aversion*. As the LFT Group becomes more profitable, the time between trades increases showing lower confidence in opening new trades.

Figure 12 represents the trading data from all of the LFTs while trading as individuals in period 1 during the entire experimental period and without a connection to the BIT. In Figure 13, the LFTs are trading in their Groups and then in Figure 14, the BIT is introduced. In Figures 12 and 13 the data shows evidence of the traditional *Disposition Effect* and *Loss Aversion* biases we would expect to see according to our literature review. As traders become more profitable they seek to minimize risk and the frequency of new opening trades diminishes and profits are taken more quickly in line with risk avoidance irrespective of the market conditions, be they positive or negative. As can be seen from Figure 12, the time interval between trades increases as the LFTs, trading individually, become more profitable thus supporting the *Disposition Effect*. As the LFT Groups become more profitable in Figure 13, however, the time interval between trades also increases, although not so pronounced as in Figure 12, showing lower confidence in opening new trades.

Figure 13 Period 2: Profit and Loss with Duration between Trades, Winning Day

In Figure 13 the graph shows that the LFT Groups are risk averse when profitability increases as identified in the left Y axis. As the LFTs become more profitable, the frequency of trades decreases as the time difference between trades increases with lower confidence. However, the time differential between trades is not as pronounced as in Figure 11.

However, in Figures 14 and 15 during period 3, when the traders were subject to observation by the BIT and the BIT was supporting them in their trading decisions, their trading behaviour changed. As the traders became more profitable the shorter the durations between trades and the more willing the traders were to risk for profits. This activity showed that the traders were encouraged by the support of the BIT and were confident enough to increase trading activity through the frequency of orders and trades.

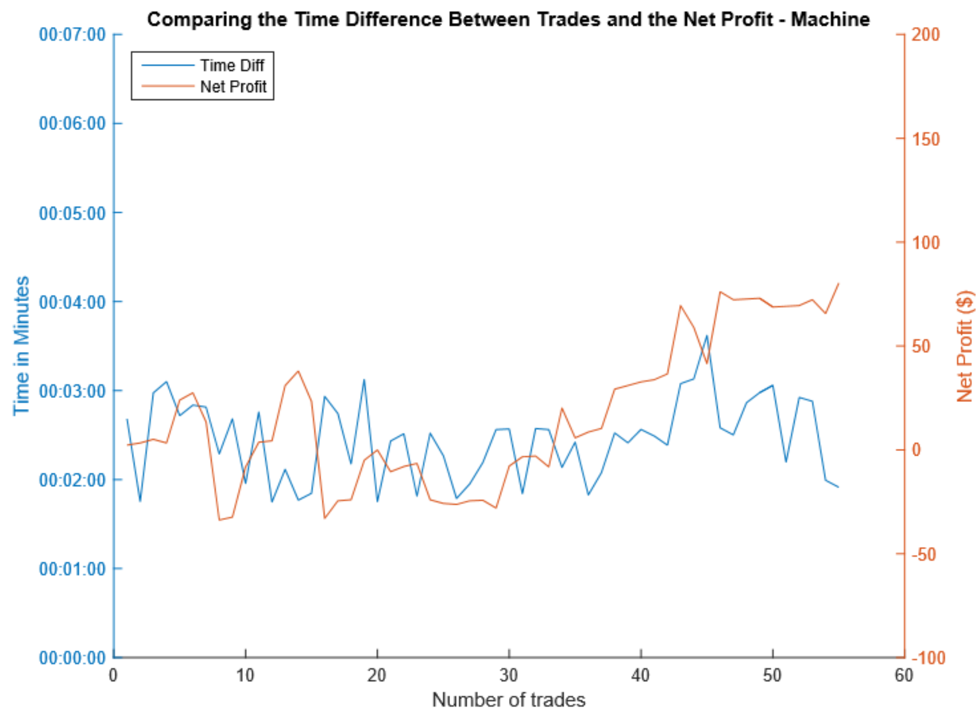

Figure 14 Period 3: Profit and Loss with Duration Between Trades with the BIT, Winning Day

In Figure 14, the graph shows a difference in the LFT's trading behaviour when the BIT is introduced. The time between trades is lower than in Figure 12 and 13 when the LFTs were trading as individuals or in groups. With the BIT being introduced, as the LFTs becomes more profitable, the time between trades remains the same or decreases slightly, showing greater confidence in placing opening new trades.

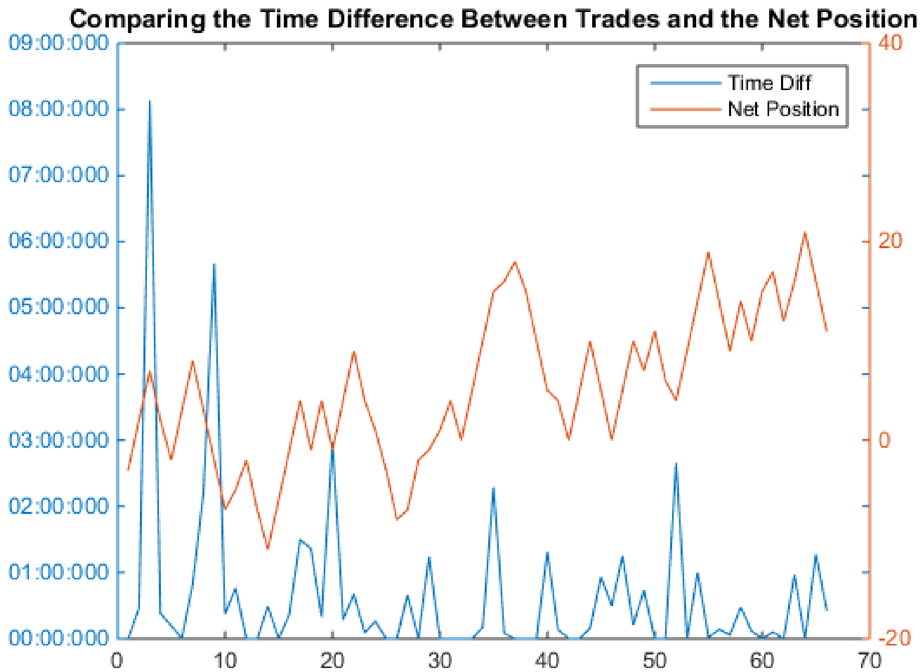

Figure 15 Period 3: Time between Trades and Open Net Positions: Winning Day

The graph in Figure 15 clearly shows that the LFTs are adding to winning positions with the net position, as identified in the right axis, increasing. As the LFTs become more profitable, the frequency of trades increases as the time difference diminishes showing greater confidence

Comparing the net open positions with the time difference between trades shows that trades were more frequent and the size of trading positions increased. The negative net position as shown between the first trade and the 30 following trades denotes short positions, the net position being negative. Winning positions shown on the graph from trade 30 to 70 were long trades rather than short, so that the net position went positive. At times when the traders were experiencing high profitability, the average net positions exceeded 20 contracts showing overall high levels of confidence.

In addition, when the BIT was introduced while trading in period 3 the trader’s rate of consecutive winners increased as seen in figure 16. There is a distinct increase in the incidence of consecutive winners which denotes an increase in confidence and a willingness to risk more. The rate of consecutive winners also suggest that the trader is reading the market conditions well and is reacting to the conditions in a positive way.

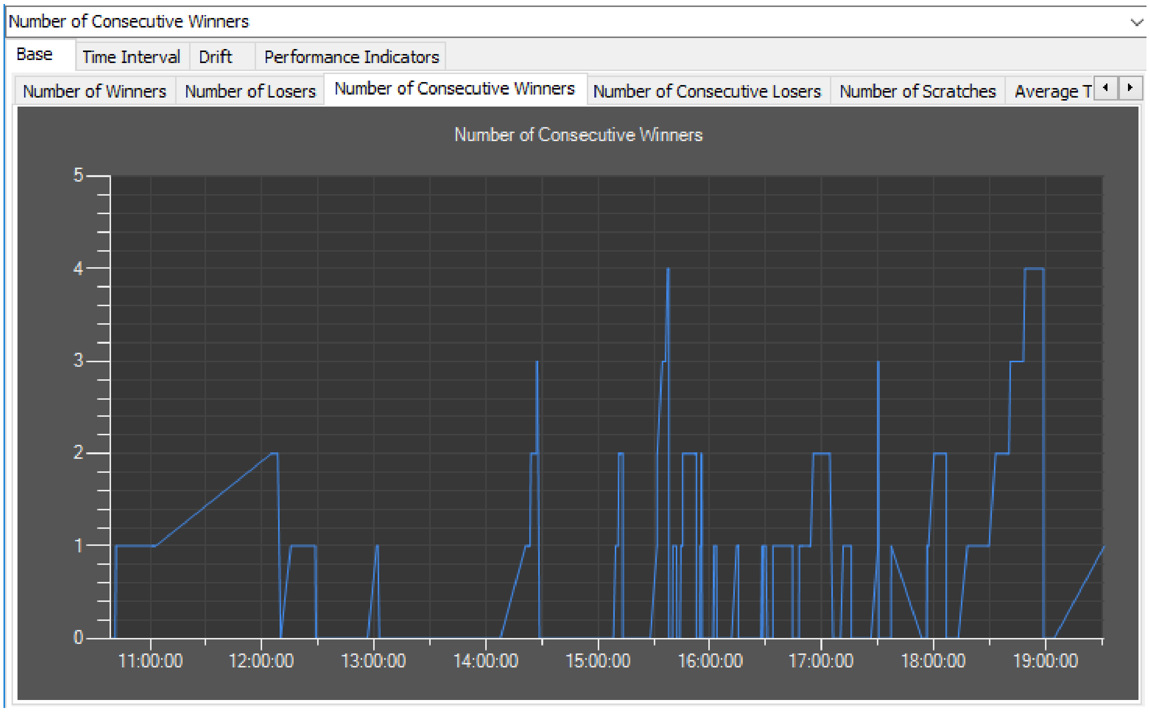

Figure 16 Period 3: Number of Consecutive Winners

In Figure 16 the RTDS clearly shows there is an increase in the frequency of the number of consecutively winning trades. The Y axis shows the number of consecutive winning trades and the X axis shows the time in hours. The higher frequency of consecutive winning trades shows the tarder is feeling more confident in his choice of trades.

In Figure 17 it can also be seen that the instance of Maximum Negative Drift has reduced during Period 3 with the same trader. This means that the trader was cutting losing trades effectively without incurring loss.

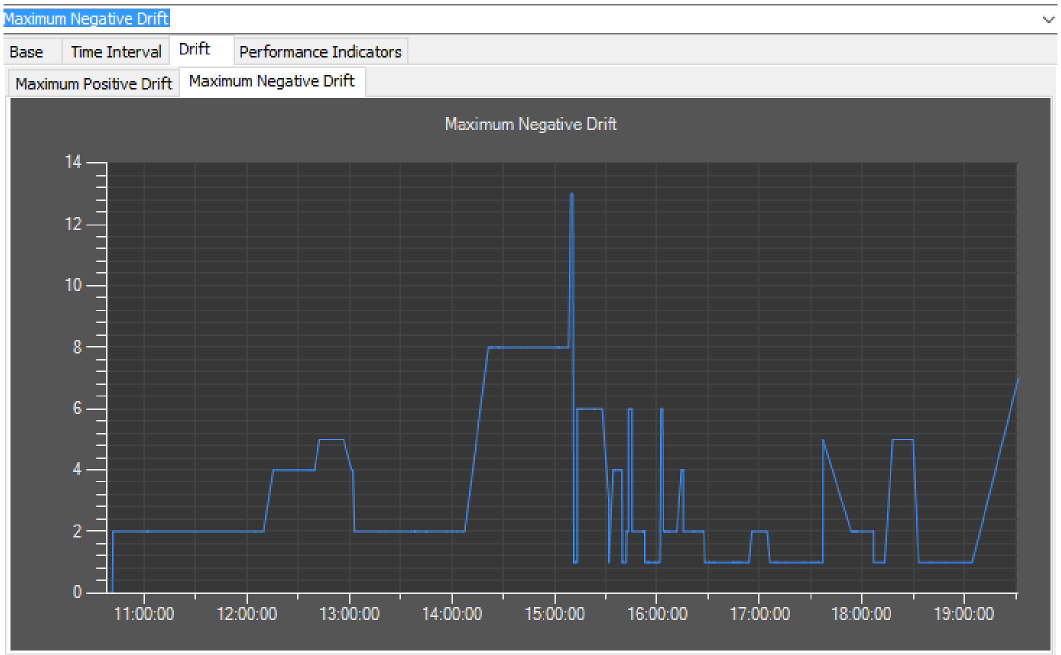

Figure 17 Period 3: Maximum Negative Drift

Figure 17 shows an improvement in Maximum Negative drift showing that the trader is seeking to reduce risk exposure by cutting losing trades quickly. The Y axis shows the number of price ticks and the X axis shows the time in hours. In this instance, the trader is taking no more than 1-4 ticks loss after 15.00.

In a separate observation, the trader confirms the level of confidence, by increasing the flow of orders during Period 3 as seen in Figure 18. This trading behaviour normally shows that the trader is in a series of winning positions and is adding to those winning trades. The higher the gradient of orders shown in RTDS, the more confident the trader appears during a winning day. If, however, he was in a losing day, a steep increase in orders could suggest fear of further loss and an attempt to gamble in order to recover those losses.

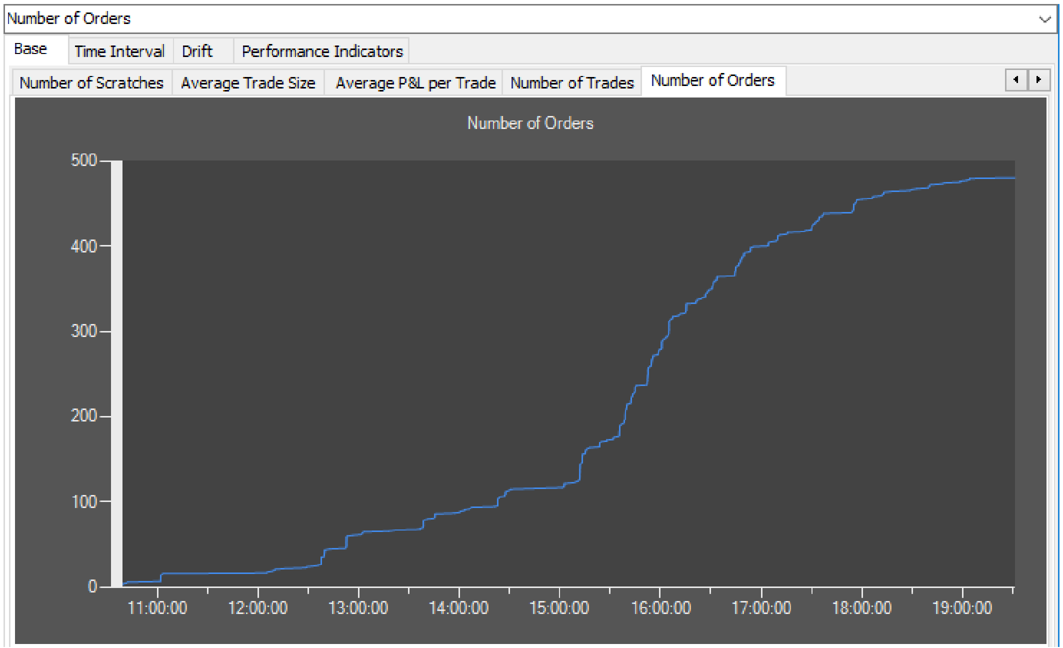

Figure 18 Period 3: Number of Orders

As shown in Figure 18, Increases or decreases in the number of generated orders can suggest both confidence in winning positions and lack of confidence in losing positions so this data has to be viewed alongside winner/loser ratio and the time interval statistics for it to have meaning.

4.3.4 Identifying trading frequency within time windows

There are further interesting observations when trader's activity is broken down into regular time slots. It appears that although the early part of the day often sees most activity, the range of number of trades and the frequency are not easily slotted into regular time windows. As can be seen from Table 6, the trade size and frequency appears to be randomly distributed with several time gaps between the trades. a) Trading activity is more concentrated during busy times in the market so early in the trading day in the first half hour and then less so after this period.

Number of Trades	Time window (approx. 10 Minutes)	Gaps in trading activity
30	08:58:17 to 09:09:02	
27	09:09:03 and 09:18:45	
GAP		9 minutes
9	09:27:22 to 09:36:08	
GAP		22 minutes
7	09:58:26 to 10:00:38	
GAP		21 minutes
13	10:21:54 to 10:31:23	

Table 6 Trading Activity in the First Hour and a Half

Number of Trades	Gaps in trading activity
9	
3	
GAP	4 minutes
1	
12	
7	
GAP	21 minutes
13	

Table 7 Trading Windows within 30 Minutes

Table 6 and 7 show the granularity of the data that is provided by RTDS. The trader's behaviour can be mapped down to the millisecond.

As we saw previously from Figure 9 on page 99, around the time periods 9.00am and 4.30pm there is a distinct clustering of short-term trades that open positions with short time durations between the closing of one position and the opening of another. As the LFT becomes more loss making however after 10am, the frequency of new positions following on from closed positions reduces and the duration between positions becomes wider. This denotes the reluctance on behalf of the trader to take on new risk. Then, during the period between 4pm and 5pm when the LFT moves rapidly into profit the gap between closing trades and opening new ones becomes much shorter. Then at 4.30pm when the LFT has achieved a profit of 400 and 5.30pm, his trade frequency diminishes and the length of time between trades expands. This suggests risk aversion and the objective to retain profits.

4.3.5 Recovery Time from Losing Trades

Through observing the activity of the LFTs in RTDS we can see occasions when the traders are successful and unsuccessful in recovering from a series of loss making positions. This is an interesting phenomenon because it often shows the level of experience and efficiency with which the trader trades. The more experience, the more efficient traders appear to be with lower numbers of trades, higher winner/loser ratios and fewer gaps between trades. They also reduce the *Disposition effect* by ‘risking for profits’ more frequently. In Figure 9 and Figure 10 on page 101 the traders increase risk exposure by reducing time between trades during profitable periods. In Figure 10, the trader is struggling to recover from the losses he has made in the middle of the day and increases his trades and reduces the time between trades as he loses. Instead of recovering those losses, however, his desperate trading activity compounds those losses. Good *Recovery* metrics point towards improved and ultimately successful trading. Traders recover from making losses at different times to each other. Some traders treat losses and profits with equal disdain without being fazed by loss making trades, while others see loss making as a part of the business and something to expect. However, some traders take loss making very personally and their subsequent trading behaviour is adversely influenced by losses. The recovery time subsequent to a loss depends largely on the following:

a) The magnitude of the loss and the means with which the trader has to make back that loss or not

b) The number of consecutive losses and the erosion of confidence that may ensue

c) The impact of unexpected loss as opposed to experimental loss (a trader may use a strategy to anticipate trading volume by sacrificing a small loss in order to locate liquidity)

d) The impact of deep loss or high profit on stress levels impeding decision making processes and whether the trader is more deeply influenced by the loss or the profit. (some traders are adversely affected by high levels of profit)

e) The temptation traders have in risking profits as well as losses (traders who make large profits sometimes risk those profits as a result of a somewhat misguided confidence that they will not lose them and that if they do, they are more likely to be able to replace them. This overconfidence arises from a misguided attribution of the trader's skill in succeeding in a certain market condition that is forever changing (what worked profitably a few minutes ago may not work profitably now)

4.5 Conclusion

We can see that during each trading period there were changes in trader behaviour. Individually LFTs exemplify expected traits and biases reflected in *loss aversion*, *disposition effect* and *overconfidence in predictions*. However, in Period 2 when they were collaborating and in Period 3 when they believed they were trading with the assistance of a BIT, the LFTs were more relaxed and modified their behaviour. By undertaking these experiments we have found that by linking LFTs together (something they are not used to doing) and by linking them with a realtime machine, they improve upon the traditional behavioural biases outlined in the literature in Chapter 2. What can we deduce from this? Human traders modify their behaviour if they work collaboratively and with a machine. In most cases the LFTs improved performance when they were a) linked together, b) collaborated with the BIT. We now move on to Chapter 5 in the light of these findings and provide the basis for developing models and processes for the BITs.

Chapter 5

New Tools for Human Traders

This Chapter describe design processes, new models and insights into the creation and use of realtime behavioural interventionist tools (BITs) which capture and interpret the realtime digital audit trail of a human trader with the objective of positively modifying performance. It describes methods, tools and concepts that seek to broaden the scope of realtime data analysis of human critical point activity through trading leading to a greater participation of human traders

Such tools can be used to gather important performance information into human critical point activity and help us to rethink the ways in which we observe traders, how we research them and how we look at risk and decision science at realtime speeds.

5.1 Introduction

The headlong pursuit of machine-driven exchange-based centralized marketplaces benefits a number of market operators including those HFT trading operations in private hedge funds, HFT trading companies and the exchanges themselves. There is a history of business union between HFT's and exchanges that has, at times, moved beyond the legal (1) and indeed, the ethical standards of the industry. The proliferation of HFT trading has been encouraged by exchanges as they provide substantial order flow by entering a proliferation of passive limit orders which directly add to short-term exchange liquidity. In return for their liquidity, exchanges have returned the favour by providing bespoke order types that give HFTs a winning advantage at the top of the central limit order book (CLOB). Such order types include Spam and Cancel, Hide and Light, and queue jumping and give HFTs top-of-the-order book advantage. This means that inevitably, the trading success of LFTs who do not have access to the exchange's bespoke order types, are easy prey for the HFTs and form the majority of the group that the HFTs target. This situation is unethical and self-interested on the part of the HFTs and the for-profit exchanges and does not provide a marketplace that encourages the participation of LFTs. While things continue in this way and financial regulators fail to intervene, LFTs have no protection against privileged order trading activity at the top-of-the-order-book and are likely to experience lower profitability as a result. This market speed condition has caused an imbalance between human traders and HFT's providing HFTs with a big advantage over LFTs. For example, recent research into the imbalance between the outcomes of faster HFTs, mostly via algorithms and trading machines, and slower LFTs without machines shows that HFT traders exact rents from slower human traders [86] and [87] in that they are paid by exchanges, via the rebate system, for order flow.

Much of the advantage of HFTs is their ability to adjust their trading strategy via their limit orders following the announcement of news that changes the basis for the trade. Biais et al [88] find that HFT have a greater opportunity to find profitable trades than their slower human counterparts. Another area of study that lends itself to comparative analysis of HFTs and human traders is the way in which human traders show evidence of *Anchoring*, and how intently HFTs anchor their bids and asks to previous traded prices [89].

This thesis poses several questions one of which is ‘can human LFTs improve their trading performance with the help of assistive and interventionist machines that augment their trading decisions and compete with HFTs?’ Evidence from the experimental studies conducted for this thesis suggest that human traders respond very well to collaboration with a supporting tool and that their behaviour changes positively with respect to the traditional biases seen in behavioural finance. One of the interesting observations we can make from the analysis of the experiment data is that traders appear to modify their order entry frequency more efficiently while trading with a BIT when opportunity presents itself as seen in the frequency of order entry and trades. The inclusion of smart tool trading linked to human cognition through realtime analysis of trading behaviour could potentially form the basis for a new style of market behaviour which is slower and more reasoned and which does not rely on ever faster transaction speeds that encourage the activity of HFTs. Reducing the reliance of market participants on microsecond trading which only rewards those with faster execution speeds and preferential order types could be attractive to regulators as well as human traders, from an ethical standpoint. This thesis also takes the view that human traders are needed in the markets even though they are often viewed as lesser participants by other opportunistic and predatory higher frequency participants. As market microstructure studies have shown, markets are designed to favour certain participants and the issue of market ethics and fairness becomes an important and challenging concept to determine and implement [90].

5.1.2 Identifying trading frequency within time windows

5.1.2.1 The Human Trader

The ideas related to combining human traders with assistive machines proposed in this thesis breaks new ground in several ways; firstly, in the way in which the human trader is analysed in realtime and in situ; secondly, with the design science supporting human-machine interaction and collaboration through interventionist trading tools in realtime; thirdly, through the implications of this novel partnership between LFTs and assistive machines with regard to market micro-structure design and the potential abandonment of realtime transactional requirements; and fourthly, with regard to the creation of a more ethical marketplace that does not encourage HFT predominance or the consistent requirement for 'winner takes all' at the cutting edge of realtime.

The thesis proposes new methods of examining and interpreting human trader critical point activity which significantly broaden the opportunities for research and introduces the previously unlikely opportunity of creating tools for these traders. In fact, human traders form a new subject group for decision sciences study now that realtime data can be analysed in situ. As [2] suggests, new approaches to research and assessment tools need to be created that are operational in the real marketplace so that results that are being generated are current, creating an accurate portrayal of realtime transaction and market class statistics. In addition, such tools are useful in assessing the performance of *assistive* trading tools using automated order entry processes. As [91] pointed out in 2008,

> "Unfortunately, given the experience of market professionals who hoped to harness machine intelligence for their own enrichment, it may be a long time before robot traders can exhibit the ability to learn and adapt necessary for them to earn their keep in the marketplace".

The question is, 'why try and replicate the human brain in trading when the human trader is very capable when linked to a responsive and interventionist machine?' The human brain is still the most complex and able computer in existence and there is great benefit to augmenting it rather than replacing it. Miller [91] believes that

> "The real problem lies in the determining how much intelligence an agent requires to match human performance in a dynamic setting with constantly changing market conditions,"

By trying to surpass the human trader by creating a robot to trade instead, researchers and market operators have been missing the point, with the more logical approach being to assist and augment the actions of the human trader with technology. Two things have prevented this to any great extent so far: first, the difficulty in studying the human trader in situ in the real markets and, secondly, then being able to create methods and practices that form the basis of technology that can truly augment the trader's activities and reduce the behavioural biases and heuristics. It should be repeated that currently the tools with which to augment human realtime decision-making in financial markets are in the early stages of production so the research experiments that were undertaken had to be constructed very carefully in order to give the impression that the LFTs were experiencing the intervention of fully-functional artificially intelligent tools. This lack of available technology can be easily understood when we consider what these tools would need to be able to do if they were active. Firstly, they would need to understand market conditions with the many thousands of informational inputs, then translate those conditions into expected actions, then analyse the trading activity of the human trader and identify if their behaviour is optimal given the market conditions, and then intervene in real time if the human trader's actions did not look like they were going to optimize those market conditions, and then to decide how much leverage the actions should take. The BIT that forms the basis of this thesis is the first of its kind to be built to perform with these complexities and activities as a production tool.

5.1.3 Are financial services trading 'Smart' tools really smart?

The financial services industry that deals with trade execution services has taken hold of the term 'smart' to label a number of responsive services and functions in their software packages that do not belong in this category but are used more as a marketing ploy. 'Smart' tools used by non-expert traders in the industry currently amount to a series of functions that repackage already available services and data in the form of Asset Relationship Pricing, Price aggregation services (that purport) to link prices, transaction services and self-learning algorithmic order routing processes, Execution services and order management and wearables. The types of tools that this thesis proposes are closely related to autonomics and augmented reality in that they deal with complex environments, have an element of self-learning but they do not become self-managing in that they need the input of the trader in order to function and cannot enact tasks independently of the trader. They are responsive and augmenting and need a well-structured design and model. This thesis provides such a model. This opportunity is supported from the observations of the results of the experiments highlighted in Chapter 4, as we can see that human traders are willing to work with (what they believe) are highly intelligent machines and to allow them to intervene in their trading activity in order to exact improvements to trading behaviour. The experiments focused on human traders working together and working with machines for a shared beneficial outcome. We also see improvements to certain trading performance criteria including consecutive winners, negative drift thresholds and time in trade measures when human traders trade together or with machines as seen in RTDS in Figures 13, 14, 15, 16 and 17. In addition, in Table 5, The Experimental Results, the improvements in these measures is seen as being significant when a BIT is introduced. This provides a basis for creating models that rely on accurate realtime assessment of prices and time, sequence and repetition of profitable trading conditions with a view to supporting the trader with an *Assistive* tool that augments trading behaviour. Under the umbrella title of interventionist and assistive tools, smart interventionist and augmentation tools that propagate improvements to trader's risky economical decision-making activities are a step into a new collaborative relationship between humans and machines in trading and may be the way forward for LFTs. This

Chapter makes the first move in supporting this relationship by suggesting a viable learning rule and decision rule approach to a model of operation for a BIT.

5.2 Behavioural interventionist tools

Soon it will be unthinkable for a human trader's profitability to suffer because of simple loss-making errors that he or she has avoided before under the same or similar market conditions. Although the trader may not be able to recall the exact behavior they exercised in a previously experienced market condition which proved to be profitable or loss-making, a new range of *Assistive* trading tools recognize the market scenarios, the trader's realtime behavior in response to the market scenario and whether the trader is likely to trade profitably or not from his current actions. If not, then the tool intervenes and prevents errors from being made. By design, risk mitigation tools have been in use for many years in the form of automated stop losses, trailing stops, limit orders and others. *Assistive* and *Interventionist* trading tools may soon have the potential to intervene in a trader's trading activity in a way that stop loss engines cannot, to limit mistakes and losses and to enhance successful behaviour. These tools have the potential to positively modify the trader's experiences and activities over time through the consideration of the trader's behaviour. They seek, among other things, to prolong good performance by extending profitable trades while reducing poor performance by limiting exposure to loss. It is likely that the successful outcome of certain critical point activities undertaken by human beings will increasingly rely on integration with advanced computer systems that augment human cognitive processes and abilities. Referred to as *augmented cognition*, [92] the objective is to integrate computer based systems that interweave with human cognitive tasks so that the human response is elevated and enhanced. With regard to trading, performance analysis tools already capture data that enables us to evaluate the cognitive processes of human traders and Automated Trading Systems (ATS). These tools record, and enable us to make sense of, cognitive human responses to realtime data and information. For the human trader, deploying cognitive process-enhancing technology is still not a reality. In this thesis we look to form the foundations for current and future work to introduce a range of semi-cognitive augmentation tools that can assist the behavior of the electronic trader and automated trading system called *Assistive* trading tools.

BITs, which are a newly proposed form of *Assistive* trading tool, can be designed to augment the decision-making activities of LFTs but not to control them. Unlike Direct Decision Devices (DDDs), prevalent in commerce and industry and involved in managerial and decision-making process that are either designed to completely displace the need for human intervention and to operate as autonomous entities or are used in conjunction with human activity but with the human as a subservient participant [93], BITs have ambivalence and collaboration as their goals enabling either LFT or BIT to intervene in actions instigated by the LFT depending on prevailing market conditions. While some research into DDDs forecasts the seismic shift in the balance of practical power from people to computer apparatus [93], this thesis points towards a different outcome. In the near future, a trader's assistive tools may contribute to his decision-making processes in much the same way as artificial cognitive systems might in the future influence a range of human critical point activities. For example, profit-making behavior should be encouraged and loss-making behavior should be inhibited and different *Assistive* tools will be used for each of these purposes. If LFTs are to be successfully linked to semi-autonomous agents that offer assistive choices and use a method close to that of DDD's how are these tools able to gain knowledge and understanding of the market place in order to augment the opportunity for successful trading activity? BITs enable the use of a number of processes to reduce poor decision-making. Whereas algorithmic tools or rules-based trading tools are based on investment criteria including risk and cost estimates, certain behavioral interventionist tools can select trading preferences based on the behavior of the LFT in current and past market scenarios. For example, a LFT who has never made a loss in a particular market scenario will be prevented from making a loss by the BIT if his behavior deviates when presented with that same market scenario. The BIT recognizes that the LFT does not normally make the type of trade he is making in this particular market scenario, or condition, and that such a trade is likely to be disadvantageous to the trader should the market continue in its current movement. The tool therefore inhibits the trader from placing more orders by restricting order placement of the same type and encourages him, be exhibiting a warning message, to trade out of the open position. This *Assistive* tool is called a *Blocker* and its sole purpose is to prevent a LFT from making uncharacteristically poor trades. The actions of the *Blocker* are described later in this chapter in section 5.2.2. How far should a BIT be trusted to intervene in the trading activity of a black box or a human trader? This question is open to debate and depends a great deal on the efficiency of such tools in being able to identify the characteristics of the open position or expected trade, the status of the marketplace and the behavior of the trader or automated trading system. Behavioral interventionist tools provide a new generation of *Assistive* services for traders and automated trading systems. The opportunity is to be able to examine and understand the behavior of the LFT in realtime while looking for ways to positively modify their behavior and trading performance while the LFT is still trading. That is, to use learning reinforcement techniques linked to *Assistive* tools that identify profitable trading behavior and intervene while enabling the software to support the LFT in trading more successfully. In effect we create an intelligent collaborative system involving LFTs and BITs that understands its trading behavior in relation to the prevailing market conditions and the products it is trading. Realtime performance measurement tools are already being used to evaluate the performance of black box trading systems. *Assistive* tools can go one step further and positively modify LFT behavior in realtime. The practice works in the following way. With regard to black box systems, the performance measurement tools API is hooked up to the black box trading system and as the system is communicating with the market by sending orders or receiving fills, the data is sent via TCP/IP socket connections realtime to the central database server where parameters have been set to measure a range of performance levels. This then lays the basis for linking in methods for positively modifying the black box performance. Human trader *Assistive* tools, while in prototype form as described in this chapter have yet to be put into full production.

5.2.1 Design Theory for BITS

Loosely allied to that of DDDs and Decision Support Services (DSSs), the design theory for BITs is based on system causality [94]. LFTs are viewed as parts of a system which includes the interface from the trading engine, the BIT and elements of price data, trading volume and others. Each part acts and reacts to different conditions in different ways. Causality enables the BIT to observe which activities are caused by one component of the system and which by another, thus being able to establish an observation of which events are likely to happen, which events will happen as a result of the previous event, and which events will not happen. Then the BIT can exclude certain responses that represent "causal loops" [94] which are operationally impossible. For example, if the LFT and the BIT were about to support trades in opposite directions, one buying and one selling simultaneously, which would net out the position while incurring the cost of the dealing spread once traded. Researchers can refer to these as automata-constructs [13]. The BIT requires a multifunction ambivalence which continuously questions 'who leads who?' in the actions of the system components. There are examples in commercial use today with airline manufacturers like Boeing and Airbus providing DDDs that directly intervene and shut-off the pilot's involvement in flying the plane if there is an imminent collision with a building for example [95]. The DDDs will take over and make the behavioural adjustment in isolation. Although outside of the scope of this thesis, there is also opportunity for linking together modules for data analysis, modelling, and prediction at runtime to support agent decision-making adding behavioural components in the Common Language Runtime (CLR) for BITs.

5.2.2 The market conditions

If you are not a HFT with access to privileged order types, successful trading is a direct result of the interpretation of market conditions. This is an inexact science and has fostered the burgeoning growth of the technical and fundamental analysis industries in financial markets as a result. No one has prior knowledge of market movements unless they are competing illegally or have a queue-jumping order book advantage like HFTs. The BIT is not trying to make sense of market conditions, that are probably unlimited in their scope, but instead, is making sense of the LFTs reaction to market conditions. An example of this can be seen in Figure 19 below.

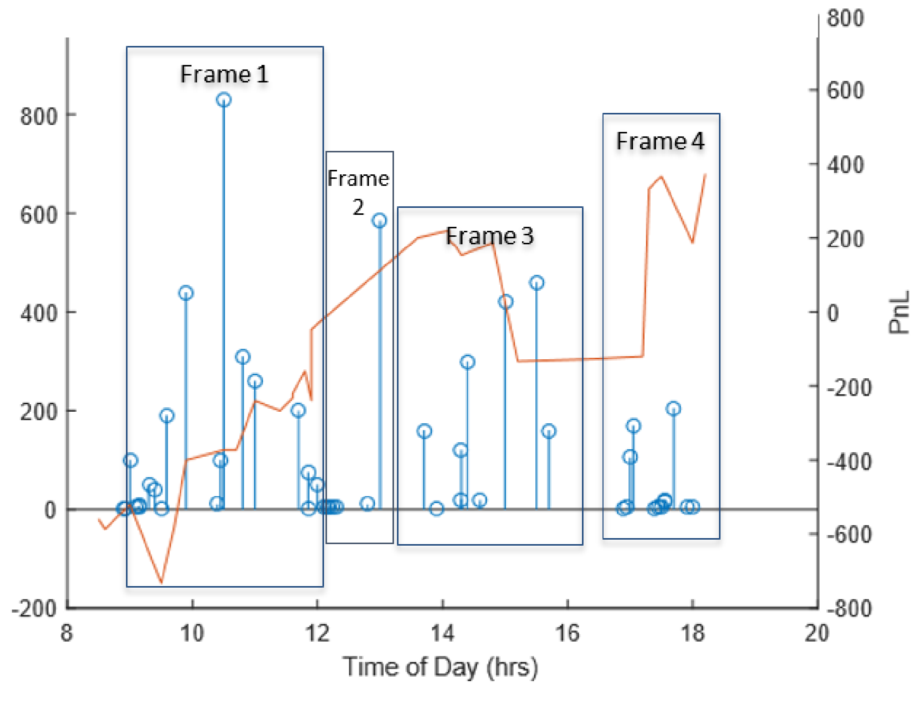

Figure 19 Trading Frame Identities and Actions

Figure 19 shows the way in which the BIT identifies Frames Identities that are caused by certain actions by the trader in different market conditions.

In Figure 19 the LFT has made a series of trading actions which have been split into four frames. The frames are distinct because they record different actions in different conditions with different outcomes. A database of such frames is built up from historical data and forms a repository that the BIT can access. The four frames in Figure 19 focus on different trading activities and outcomes which are referred to as ‘Frame Identities’. This means that different frames can be grouped together over time if they show similar identities making the selection of BIT responses to those frames much easier than having to recalibrate the BITS understanding of them each time they appear. In Frame 1 For example, the trader begins with a flurry of trades that initially leads to a small loss but then translates into a reasonable profit of 400 by the end of the frame. The Identity of this frame is that it is a *Loss to Profit* Frame with an initial series of short-burst trades that add to *Consecutive winners*. The *Time between Trades* is lengthy while the profit is increasing which denotes that the trader is holding a winning position that becomes more profitable over time. At the end of the frame there is a short burst of trading activity which, again, is profitable and which leads to an additional open position that is a *Consecutive Winner* to the previous trade. By establishing that Frame 1 has resulted in a profit with its associated trade activities, the BIT then adds this to its repository of frames. The BIT is focused on the trader's actions while constantly referring to the market conditions and its database of frames. The actions that make the BIT begin a new frame are those which show a marked difference from previous actions. In Figure 19 Frame 2 sees the rapid entry of several short time-interval trades which lead to further profit then followed by a a significant period of calm where, again, the trader holds a long winning position which goes further into profit. Frame 3 sees a series of lengthy *Time between Trades* that, eventually coincide with a drop in profitability. There is then a gap of around an hour where the trader has no position but then in Frame 4, he shows some rapid trading activity which leads to a recovery in profitability.

With an understanding of the various Frame Identities associated with the trader's activity the BIT can then begin to intervene in the trader's activity in a supporting and augmentative role. An example of the frame identity that would cause the BIT to intervene to reduce loss making behaviour can be seen in Figure 20 below.

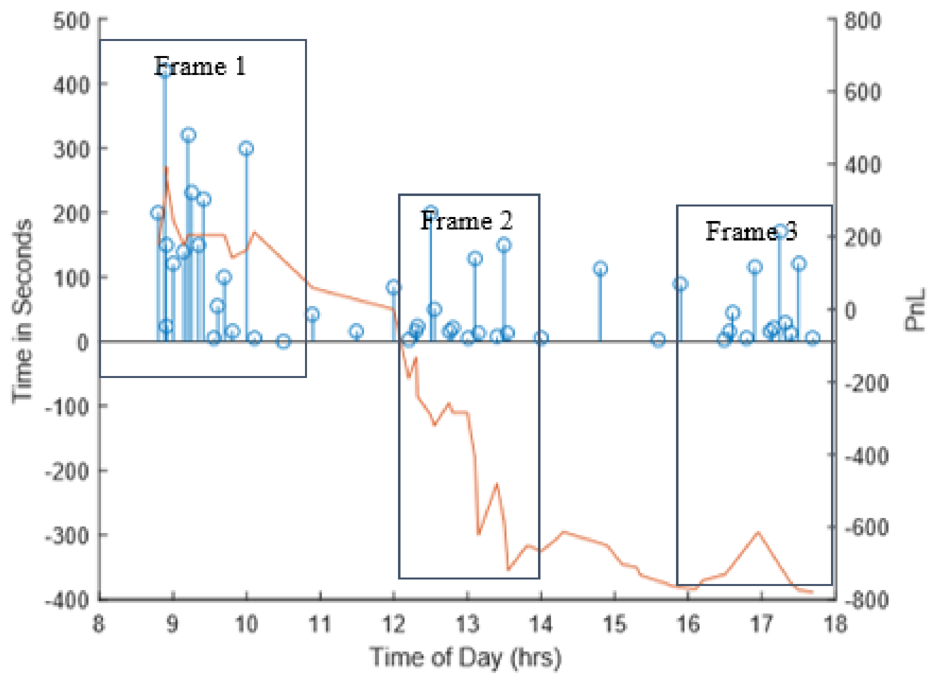

Figure 20 Frame Identities showing Loss-Making Behaviour

Figure 20 shows three Frame Identities which are associated with losing trades, a clear basis for NIT to deploy and interventionist blocking tool to prevent the trader from making additional losing trades in the same market condition.

In Figure 20 we see a very different outcome to the trader's activity compared with Figure 19. Frame 1 shows a number of trades with varying lengths of time between them which are, on the whole, loss-making. This type of trading behaviour is often associated with a form of activity called *averaging* where a trader adds to losing trades by instigating additional long losing trades as market prices fall. This has the effect of compounding losses. It can be seen from Frame 1 that the trader is holding onto a losing position as there is hardly any trading activity while the profit deteriorates. In Frame 2 the trader consistently loses with new open long positions compounding losses quickly. He then, does nothing for two hours and then, in Frame 3, ends the trading day with a flurry of trades that don't prove to be profitable. What would be the optimal action from the BIT to overcome these clear failures in trading activity? In this example, the BIT would have identified in Frame 1 that the trader was overtrading and losing gradually. It would have compared the frequency of *new orders* and subsequent *new trades* generated by the trader with the *Winner/Loser ratio* to determine how successful these trades were. It would also have logged the *Consecutive Losing Trade* rate which would have led it to reduce the order size of the trader's activity as his actions and outcomes became more erratic. In Frame 2 the BIT would have intervened by using a *Blocker* to prevent the trader adding new long trades and from making further losses. From the early results of the Prototype BIT we can see that this blocking action works.

5.2.3 The BIT Prototype

The prototype BIT was developed as an extension to the RTDS, using a historical database of the trader's trading activity as a basis for qualifying the current trading data captured by RTDS. The thresholds for activating BIT intervention were colour-coded so that, while the back-end of the programme was being built, it would be possible to see when the BIT would have acted from the colour changes in the respective fields. In Figure 21, for example, there are multiple observations of the trader's activity over a trading session that show a graded colour-coded response from bright green to dark red. The boxes with green cells are positive and the boxes with red cells are negative. The BIT would have responded to any of the data that caused the box to go red. There are several tabs in the software that identify certain classes of data including the main categories of metrics identified in the Introduction on page 16, so that the user can tab between the different sets of metrics. Market conditions are broken down into four subsets: *Sideways, Breakout, Trending and Reversal*. While many more iterations to these basic market conditions will be added, these four base conditions are useful in identifying which trades were undertaken during which conditions so that a better understanding of the trader's activity can be achieved.

	SIDEWAYS	BREAKOUT	TRENDING	REVERSAL
Number of Trades	3.00	1.00	8.00	3.00
Number of Winning Trades	2.00	1.00	7.00	2.00
Number of Losing Trades	1.00	0.00	1.00	1.00
Trade Class P/L	2.00	1.00	68.00	12.00
Average P/L	0.67	1.00	8.50	4.00

	RATIO		RATIO
Avg Time in Trade (W/L)	1.42	Max Trade (W/L)	5.00
SD Time in Trade (W/L)	5.09	Total Time In Trade (W/L)	3.03
Avg Time Since Last Trade (W/L)	-0.08	Avg P/L per Contract Traded (W/L)	1.31
SD Time Since Last Trade (W/L)	0.26	Sharpe	0.32
Avg P/L per Trade (W/L)	1.31	Avg P/L per Contract /Avg Time (W)	0.05
SD P/L per Trade (W/L)	4.29	Avg P/L per Contract /Avg Time (L)	-0.06

Figure 21 BIT Graphical User Interface (Prototype)

Figure 21 shows the early prototype of the BIT with two sections. The first section shows the range of market conditions and the second section a range of base metrics. The colour-coded boxes denote of an action has resulted in a positive or negative result, green being positive and red being negative.

In order to assess the performance of the trader, the BIT observes that during condition 'Trending' the LFT normally trades in a profitable way and therefore the BIT expects a certain type of positive behaviour to result. If the LFT does not follow the normal approach, which in most cases has led to a profitable trading opportunity, the BIT intervenes to modify and enhance the LFTs trading actions. As the LFT is likely to be trading in short time intervals the universe of possible outcomes is low and repetitive, making the function of arriving at an optimal decision more likely. The most logical approach to encompassing market conditions and recognizing patterns and repetitive movements is to chunk up the price activity into frames of reference which are not time dependent but activity dependent as seen in Figures 19 and 20, so instead of trying to read the flow of the market conditions, the BIT has a database of a multitude of market condition frames that it can select if the current market conditions are the same or similar to that seen before. The BIT is not expected to provide a perfect reading of market conditions in order to facilitate the ever improving profitability of LFTs. It is designed to augment the LFTs decision-making processes by providing support and intervening when necessary rather than when it can. In this way, the LFT has not found a magic genie in the form of a BIT that will make them extraordinarily profitable but a tool that augments their decisions and prevents them from making unnecessary mistakes. With this in mind, the core operating model must be designed in a causal manner.

During the early prototype developmental process, the BIT was used to monitor the trader's reaction to the two market conditions that lead to the trader's behaviour in Figure 19 and Figure 20 above.

1. A period of price momentum (Figure 19)
2. A sudden directional change to prices (Figure 20)

The results from the use of the prototype were encouraging. In one key improvement, the deviation from historically successful trading behaviour was reduced by the activities of the prototype BIT. For example, the BIT identified occasions in the trader's historical trading data when market *Sideway*s and *Trending* conditions were evident, mapped the trader's historical responses to these conditions and graded the optimality of his current trading activities in the current market conditions. The relevant boxes changed colour, from green to red or red to green, signifying that the BIT would have acted at certain points during the trading activities.

1. A Period of Price Momentum

Market price momentum in a *Trending* condition, was identified by the BIT on several occasions in Figure 19 and were mapped as periods of up to seven minutes when prices increased on average by 0.15%-0.35% above the initial trigger price, the price that caused the trader to open the trading position. Trader's reactions to periods of price momentum were to generally hold an open position without adding to it. The optimal trading response would be to add to winning positions and not to close the open position. The BIT would promote the opportunity to add to winning positions. The BIT also identified occasions when the trader closed a profitable trade before the price momentum move had concluded, thus registering a high *Positive Drift* score. This was not an optimal trade and reflected the findings of the *Disposition Effect*.

2. A Sudden Directional Change to Prices

Sudden directional price change, like that which happened in Figure 20, can cause the trader to keep losing positions open in the hope that the negative price movement will be short lived and will quickly return to the mean average price. This is a good example of where the BIT would prove useful by preventing traders from holding losing positions over such periods or by blocking their attempts to open new losing trades in the opposite direction to the price movement (known as ‘averaging’ in the industry). The BIT function is to block attempts to open new trades that might potentially lose if the price continues to move negatively against already established open losing position. This function proved to work well in the prototype and blocked the trader from making this type of loss-making behaviour.

5.2.3 BIT core operating model

Unlike algorithmic trading, a human trader model is not based on price evaluation but on behaviour evaluation so that the market environment is a component of the design structure not the starting point. The model recognizes good performance through the metrics (see Appendix 1) that it uses to grade a multitude of framed market conditions. When the model recognizes good performance it then equates the actions that caused the good performance to the prevailing market conditions which causes a feedback loop. The BIT is not designed to think for the trader but to provide a degree of assistive reasoning in order to support the functional use of trading software as an *Assistive* trading tool. Before long, traits and patterns begin to appear in the behavioral statistics of traders given similar market scenarios and the more a trader practices in simulated markets to perfect a response to these market conditions using his good behavioral traits, the greater his chances of success should a similar market scenario present itself. When the LFT is certain that he has encompassed the necessary responses to a particular market scenario that, over time, is likely to repeat itself, he can do one of two things; build himself an automated black box to trade automatically when the scenario presents itself without flexibility or employ the services of a BIT with a behavioral profile helps him to deploy his trading skills in the correct way.

5.2.4 Using a Bayesian causal model

The reason for selecting a Bayesian causal model rather than a statistical probability model is that there is a difference between causality and statistical analysis. Statistical analysis deals with the interpretation of uncertainty under static conditions while causal analysis deals with changing conditions [100]. Traded markets are in a state of constant change and the trader must make some sense of them in order to trade effectively and profitably. However, these changing conditions occur within a set of parameters in that there are a finite number of market conditions that can occur. As explained in 5.2.3, markets have four basic conditions but a large range of subsets of those conditions. With a defined range of scenarios, trading is then an excellent environment to use a Bayesian Causal Model as the universe of probable outcomes is restricted making the BIT's job easier. The first objective in introducing a Bayesian causal model is to establish Learning Rules and then secondly to establish Decision Rules.

5.2.4.1 Learning and Decision rules

In the model, the BIT has a prior based on the probability of an outcome in the shape of a frame. The BIT forms an estimated value of a possible outcome according to the prior condition and the available data resources it interacts with in intermediate and historical memory. As seen in Figure 22, each time there is a price change, or market event that causes a new condition, this probability is updated. The prior condition added to the new condition creates a new outcome. The BIT establishes an estimated value of a future outcome which is modified once there is an observed value. .

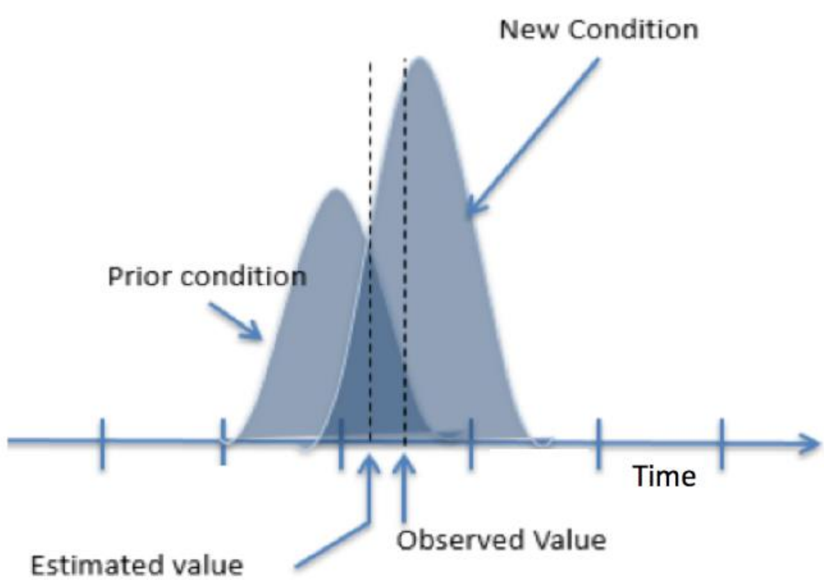

Figure 22 Bayesian prior and expected probability distribution

With an evolving set of observed outcomes, the BIT is able to select from this database to compare the current market conditions and actions of the trader with historical results. The larger the database the more scenarios the BIT has to work with and the more focused the observation of probable success (or not) of new scenarios. By applying a weighting of higher value to outcomes that prove to be more profitable, the BIT then ranks new scenario outcomes in order of the quality of return or the least loss. As more trading data and related price activity are generated by the LFT, the BIT reassesses the potential of likely outcomes and modifies the approach according to Bayes theorem. As the number of potential outcomes become more focused, each old outcome is conditionalised with the new outcome drawn from incoming data. New data that is inconsistent with optimum results is discarded, and the BIT then arrives on a learning rule and, potentially, a decision rule based on maximum utility. The BIT then utilizes its learning rule and decision rule to intervene positively in the LFT's trading activity if it falls inside the optimal trading scenario or prevents the trader executing a particular action if it falls outside of the decision rule maximum utility.

The process whereby BITs take in new data and readjust their actions via a feedback loop with the comparison to prior states is a dynamic one. This has inherent flexibility for the BIT to adjust prior assumptions in the light of new conditions and observations in realtime. Much in the same way that human brains adjust their outlook and actions based on ever-changing conditions, the BIT adds a new dimension to LFT decision-making processes by providing near-to-parallel utility constructs that always seek the optimum action.

5.2.5 BIT momentum trading model

If we take a common trading procedure called *pyramiding*, that is adding to winning positions, this is one of the problems that LFTs have and is identified as an outcome of the Disposition Effect. If a LFT makes a profit, as described in Chapter 4, they are more likely to close the position with an element of profit still remaining in the subsequent price movement of the instrument. This was referred to as 'Positive Drift' in that the trader forsakes a degree of profitability by closing out the position too early. An assistive trading tool could work to prolong and enhance the LFT's profitability by holding the trade for longer in the following way:

1. The BIT recognises that the market is in a trend by registering the range of higher highs and higher lows in the market as a particular frame.
2. Through the frame components, the BIT knows that the price at 2040 has been moving steadily upward from 2032 and has maintained this upward momentum for a number of minutes
3. There are no changes in the prevailing market condition or activity in that the price momentum continues to build
4. There are no timetabled events in the way of news, statistical announcements or corporate events scheduled to interrupt this momentum
5. Market characteristics like trade volume, market participation levels, time of day, other markets in similar domains and other instruments in similar

domains are all pointing towards the continuation of this momentum pattern with no interruption

6. The trader however, decides to close the position ahead of time at 2043, disregarding the benign conditions of the market
7. When the trader makes the action to close the position, the BIT prevents this from happening, sending a comment on the GUI to the trader that "all is well: keep with the trade"
8. Taking some precaution, the machine adds a trailing stop to the position 6 ticks away at 2037 from the current price and then narrows this range of this stop as the momentum takes the price 10 ticks higher to 2053.
9. Market conditions change and suggest the instrument is overbought and the machine then brings the trailing stop to within 2 ticks of the prevailing price to 2051
10. The price continues to move up a further 4 ticks to 2055 and then drops to 2053 where the stop is activated and the trader closes the position
11. By intervening to continue the open position, the machine has enabled the trade to gain a further 10 ticks.

5.2.6 BIT breakout trading model

In another example, if a futures trader has a short open position in five contracts in the CME E-Mini S&P 500 futures™ traded on the Chicago Mercantile Exchange and is worried about the slowly upward trending market suffering from a sudden breakout scenario on the upside, he can cover his position risk by making use of *stops* to *stop* himself out at three ticks above the current level for a limited loss. However, when he is out of the market he is likely to miss opportunities for selling short when the upward market move loses momentum. Traditionally he has always sold into a breakout or a rally far too early and has ended up losing heavily covering his loss making short positions, while being too afraid to sell short at the apex of the upward move even though he recognizes it almost 90% of the time. By practicing the behavior required to take advantage of this particular market scenario on a simulated market, he is now in a position to control his behavior and to wait until the right selling cue presents itself in such a market scenario. He is however, afraid that he might sell too early so he uses a BIT with a *Blocker* tool and a *Refiner* tool. The BIT *blocker* tool stops him from selling too early and the BIT *Refiner* tool inhibits him from taking too large a position in the initial short move by reducing the number of contracts the LFT wishes to trade. This may seem a simple example, but LFTs who have a bias for selling short tend to have two main failings: selling short too early in a breakout or a rally and selling too many contracts at what they believe is the apex of the upward move. This is a simple example of the uses of two tools currently under development.

5.2.7 Data assistive BITs

The objective of using any BIT is to enhance the probability of profitability while reducing the likelihood of loss. What is unique to these tools is the way in which they interact with order flow and market price data. The degree of interaction varies according to the level to which the trader wants to be assisted. Some LFTs prefer to be at liberty to make as many mistakes as they wish while others may prefer to have the surety that a BIT *blocker* tool will inhibit them from selling into a rising market if the market scenario starts to turn suddenly from negative to positive. The range of data *Assistive* trading tools that could be developed include those BITs that aggregate useful data in the way of news information and research that support the selection of market condition frames when the trading conditions of the LFT are in line. In addition, a BIT could provide a realtime strategy compilation and could select and vary information it provides to the LFT according to what product he is trading and where it is in the trade cycle. For example, if the trader has taken an open position in a particular asset or derivative, the BIT will create useful and potentially profitable strategy profiles by simulating the combination of the open position with a group of related other products. In this way, if a trader takes a position in a CBOT US 30-year Treasury Bond future, the BIT will present a profile of the same position combined with a CBOT US 10-Year Treasury note future, a volatility trade including treasury options and the cash underlying. If the trader likes what he sees, he can select a particular strategy and trade it instantaneously. The difference between having an on-screen template of all the possible combinations of US Treasury derivative and cash products is that the BIT only selects those strategies that fit the trading profile of the trader and switches between possible strategies realtime as soon as particular variables change like price, traded volume, time before expiration, economic announcements and the level of interest rates.

5.2.8 Data aggregation BITs

A data *Aggregator* tool aggregates performance data sets that correspond with the best and worst trades an LFT executed during a trading session. By doing this, the LFT is then able to see clearly what happened during the particular trading scenario. Traditionally data aggregation tools provided by financial markets data vendors sort and arrange market information, product prices, financial news and other information that has been selected by the LFT in prefigured screen templates and then present the data to the trader in easily recognizable forms. The difference between this type of data processing service and BIT technology is that the latter will vary the information it selects for the LFT according to his trading circumstances. For example, the objective of the data *Assistive* BITs is to concentrate on performance metrics, behavioral data and strategy compilation. The data *Aggregator* BITs unscramble the volume of performance data being presented to the trader so that it is sorted, collated and delivered quickly and efficiently whilst the data that isn't important is disgarded. For example, if the trader is successfully *pyramiding* his open positions, the *Assistive* BITs will highlight other metrics that work in conjunction with *pyramiding* like *performance taper* (trading performance is diminishing) and *momentum* (the trading position is becoming progressively profitable) and the *alpha trade* (an optimum trading scenario). In another example, the data *Assistive* tool may recognize the onset of an *alpha trade* and bring it to the LFTs attention. The point behind the use of these tools is that their deployment is directly linked to the behaviour of the LFT, be it successful or not. By interfacing with performance metrics, BITs actively seek to influence a LFT's behaviour either directly, in the case of a *blocker* BIT or indirectly in the case of data *Assistive* processes. There are undoubtedly times when *Assistive* tools should be used in moderation, in particular when the trader has a firm conviction about a market move that he has not experienced before. There are mechanisms that can be incorporated into the model that the LFT can use to control the sensitivity of the BITs.

However, experience sometimes shows that a high percentage of trader losses occur when the trader is bored and paying little attention to what he is doing, implied volatility is low, or trading volume is particularly low. During these periods, if the LFT does not have the discipline to stay out of the market until a more favorable scenario presents itself, then the BIT will make him.

5.3 Conclusion

We are just beginning to comprehend the vast array of automated tools and process that can be used to augment reatime trading behavior and time will tell which tools become prevalent. One thing is for sure, however, and that is that the industry market microstructure may not remain in its current form for too much longer. The centralized electronic exchange infrastructure of contract markets with their enclosed limited membership and central limit order books have to give way to more distributed models at some point in the near future and when that happens, the trading ‘wild west’ will be upon us. When we get there we are likely to see multiple asset class assembly by complex data sifters and combinatorial tools, esoteric arbitrage opportunities between dissimilar products, deep website database mining by sophisticated electronic ‘eyes’ and dynamic portfolio adjustment by self-learning interventionist tools.

PART 4

Conclusions and Contributions

Chapter 6

Conclusion and Contributions

This Chapter concludes the thesis by providing a summary of the main areas of the research, highlighting the aims and objectives and areas of interest with regard to further study. The results and contributions are highlighted.

6.1 Introduction

The objective of the research is to determine whether there is a basis for linking human traders with a range of newly created *Assistive* trading tools in order to improve performance by removing or controlling several previously documented biases and behaviours (*Loss Aversion*, *Disposition Effect*, and *Over-confidence in predictions*) associated with unprofitable trading. The objective is to form the basis for creating a range of *Assistive* trading tools that intervene positively in the decision-making processes of the LFT enhancing profitable behavior and actions and reducing the impact of loss making behavior. The opportunities and challenges are as follows:

- How to evaluate LFTs in realtime
- How to create *Assistive* tools and algorithms that support the LFT

- How to measure the success or failure of the LFT's activities in relation to these tools
- How to use the findings to reinforce productive trading behaviour and how to reduce loss-making behaviour

The thesis takes three traditional methods of measuring and assessing human trader activity (*Loss Aversion*, *Disposition effect*, *Overconfidence*) and applies a new collaborative and machine approach to them to see if there are differences in LFT trading behaviour. By doing this the thesis extends and enhance the current research into trading decision-making and behavioural biases into new areas of study,

6.1.1 What problems and challenges exist?

1. Gathering extensive microscopic trading and market data, that isn't readily available at a professional trader level, in order to create the basis for examination and ultimately the formulation of new concepts and methods for creating the link between traders and *Assistive* trading tools
2. Utilizing this realtime data in order to formulate measurement methods and concepts to evaluate trader performance historically and in realtime
3. Interpreting data into meaningful trading actions that are influenced by *Assistive* trading tools
4. Creating the basis for realtime ongoing risk management surveillance of trading activity either directly from the *Assistive* trading tools or linked to a trader response

The thesis describes methods for capturing realtime data and analysing it and then the tools that could be created to assist the trader. In addition, the thesis suggests that the experiment results and findings could potentially influence future market microstructure design, perhaps removing the predominance of HFTs and introducing a more capable LFT supported by BITs. These findings pose a number of important questions, however:

1. Do humans trust machines enough to let them intervene in risky decisions regarding money?
2. How does working in a group or working with machines in risky decision-making situation change trading behaviour?
3. How does this change the way we look at markets and their purpose?
4. How does this influence our view of market ethics?
5. How does this influence market micro structure?
6. Does this bring back the human trader into the markets to compete more effectively with machines?

6.2 Summary

In the end, human traders will need to decide if they trust machines to make risky decisions on their behalf, or at least to nudge them in the right direction. Will the results show that human traders are happy to trust machines to enact direct decision-making behaviour? Perhaps this may be the case when there are small sums at stake and there is autonomous control over the ensuing outcome. If the machine makes a mistake, the human trader can intervene in the result of that mistake. The difficulty arises when the human trader has the option to rely on the machine in a relationship that is far from non-interventionist. There will be a need for an asymmetrical dual-dependence approach where both agents have lead-response initiative but only one can overrule the other at any time; the human can overrule the machine. Also there is a need for a continuously coordinated abstraction assessment of the trading environment (the CLOB) before decisions can be made so that trading decisions reflect the correct conditions of the time. This realtime assessment needs to be indisputable by both parties and thus must follow a structured format. The asymmetrical dual-dependency of human and machine, whereby the human trader has ultimate control in an outwardly autonomous relationship, enables intervention to take place in many instances including modifying orders once they have been placed (post-order variation) and reacting to the semantic content of information and news. The study of LFTs performing realtime in their ecological environment forms a new aspect of study that extends previous knowledge of behavioural decision-making theory into the realtime activity of expert financial operators. In the current study, trader's behavioural data is recorded and directly mapped to the price behavior of the futures instrument they are trading with millisecond accuracy. Research then prompts other questions to be asked including 'can the results of realtime trader activity in situ be compared effectively to trading in a simulated environment?' Of further interest is the research area of market microstructure. Interesting and useful observations have been made with regard to market microstructure with evidence that that bid–ask spreads and trading volume have a negative effect on transaction duration [72]. This suggests that wider bid-ask spreads and lower trading volume adversely impact on transaction duration while narrower bid-ask spreads and higher transaction volume impact positively. Additionally, evidence suggests that trades tend to form clusters over time and although this can form randomly, the intensity of the clusters forms particular interest. Another interesting order-related analysis involves the possibility of a ''house money'' effect and/or a ''break even'' effect [166] which assert that decision makers' risk taking is affected by past gains and losses. The ''house money'' effect asserts that risk taking is facilitated by previous gains. How these different aspects of market microstructure influence the behaviour of BITs will form an interesting future study. Further discussion and research could also focus on the way in which LFTs are susceptible to *success and failure clouding* at extremes of loss or profitability. For the industry, this research may form the basis of a new risk management tool based on the changing attitude of the trader to losses. What the exchange provides is not an uncertain risk, an equal bet. It provides clues as to how to reduce these risks and to benefit the trader. Through the research the following result can be clearly seen: LFTs who have higher risk tolerances and thresholds, are more likely to treat losses and profits in an equal way, as a cost of doing business, rather than risking losses and not profits. It is a central view that LFTs demonstrate, through time intervals between placing their trades, an increase or decrease in confidence and in their attitude to risk taking.

6.3 Contributions

O'Hara [2] fired a broadside across the boughs of the financial markets stating that market microstructure conditions had changed for the worse and asking for a new way to research markets and their participants. This thesis proposes a range of suggested new methods and tools for helping human traders to compete in a high-frequency trading environment in answer to this challenge. Under the current conditions, human traders have difficulty trading against predatory algorithms and the thesis proposes methods that support the creation of *Assistive* tools that can help them to compete profitably. It also develops further understanding of classical decision-making theory in a realtime trading context demonstrating that human traders improve decision-making biases when linked together in groups or with an assistive machine.

As described in the thesis human traders are monitored, and their data is captured, in realtime and in situ using unique tools designed for the purpose. The trading performance and behavioural characteristics of the traders are studied in this context in order to determine if they can be positively modified. The thesis presents a new model for studying human trading behaviour in realtime and in situ using the unique RTDS software. It also describes the basis for the development of a range of *Interventionist* and *Assistive* tools that are designed to augment trading performance. The approach put forward is unique in its application. It also provides evidence that human traders are willing to allow machines to augment their trading decisions.

Other contributions of this thesis are that it overcomes the problem of assessing human trader risk-taking behaviour in realtime and in situ, it makes sense of human trading behaviour at realtime speeds and then it shows that, with new approaches to human-machine collaboration, trading performance improves and traditional classic decision-making biases are reduced.

Lastly, this thesis provides the basis through new models, methods, tools and approaches for a re-think leading of the effectiveness, and, to some degree, the fairness of the following areas by developing methods for realtime work using tools to observe, positively modify and intervene in market trading activity:

1. Risky Decision-making

2. Psychology and behavioural finance
3. Market Microstructure
4. Ethics in Financial markets
5. Booms and bust cycles
6. Trading technology
7. Research
8. Financial Education: Learning through trading

6.4 Future opportunities

This thesis describes and promotes a new level of human trader understanding through the access to rich realtime data sets, in context and in situ. Although part of the future reach of the research in this thesis, the findings significantly broaden the scope to create new study methods and models for behavioural analysis at realtime speeds and brings into play some new ideas with regard to improving financial markets design including market microstructure, HFT and market regulation. In future following the findings detailed in this thesis, there is merit in the possible modification to financial market transaction architectures, in particular, the industry reliance on realtime transactions and micro-second trading speeds. This may extend the reach of the research into GUI design and trading system configuration.

6.4.1 Extending classical theory of risky decision-taking

This thesis describes how these innovations extend the classical view of some of the elements of risky decision making and seeks to extend the three cornerstones of economic risky decision-making namely *Loss aversion*, *Disposition effect* and *Overconfidence in predictions* by assessing them in relation to BITs and to observing changes to the ways in which human traders use them. The thesis describes experiments that extend classical theory into the realtime context.

6.5 New areas of research

The thesis opens up new suggestions on areas of study, concepts and methods for the implementation of these activity links between human traders and machines by looking at the traditional measures of trader realtime-decision making psychology and applying them to a structured collaborative environment with other traders and machines. By using a range of metrics to interpret trader behaviour in situ and in realtime, this thesis breaks new ground in analyzing and researching trader behaviour. This thesis also suggests that LFTs use of *Assistive* trading tools in the form of BITs that encourage profitable/reasonable/ethical trading behavior begin to remove damaging behavioural inconsistencies and biases by improving trading behaviour and reducing market risk. These tools reduce the impact of inefficient traders and reduce the opportunity for herd instinct and ultimately, longer term booms and busts. Once methods and processes have been designed to take these observations and analysis to a higher level, traders in situ and in realtime can work directly with tools that can be created that intervene in a positive way in the critical point activity of the traders. The results have far reaching implications for studying and interpreting human-machine interaction and extend the field of study in this area. For example, it was observed that human traders were comfortable working collaboratively with each other and with machines in a high-risk environment. This is not common practice presently as most LFTs trade independently of each other even though their risk is assessed by risk managers as a group in most cases. Markets should seek to serve all participants rather than make a proportion of them their victims.

References

[1] Bodek, H., 2012, The Problem of HFT, Collected Writings on High Frequency Trading & Stock Market Structure Reform. Decimus Capital Markets.

[2] O'Hara, M., 2015. High Frequency Market Microstructure, Journal of Financial Economics, 116, 257-270.

[3] O'Hara, M., 2013. CFA Institute Financial Analysts Seminar, held in Chicago on 22–25 July ("To survive, LFTs must avoid being detected by predatory algorithms of HFTs").

[4] Hou, D., Skeie. D., 2014, LIBOR: Origins, Economics, Crisis, Scandal, and Reform, Federal Reserve Bank of New York Staff Reports, no. 667 JEL classification: G01, G12, G15, G18, G21, E43.

[5] O'Hara, M., 2011. What is a quote? Journal of Trading 5 (2), 10-26.

[6] O'Hara, M., Yao, C. and Ye, M. (2014), What's Not There: Odd Lots and Market Data. The Journal of Finance, 69: 2199–2236. doi:10.1111/jofi.12185.

[7] Koo, S.G.M., 2010, Human Machine Interaction in Ubiquitous Application Design

[8] Kumiega, A., Van Vliet, B. E., 2012 Automated Finance: The Assumptions and Behavioral Aspects of Algorithmic Trading, Journal of Behavioral Finance, 13:1, 51-55, DOI: 10.1080/15427560.2012.654924.

[9] Brogaard, J. A. (2011). High frequency trading and its impact on market liquidity. Working Paper.

[10] Brogaard, J. A. (2011). High frequency trading and Volatility. University of Washington.

[11] Camerer, C., Loewenstein, G., Prelec, D., 2005 Neuroeconomics: How Neuroscience Can Inform Economics. Journal of Economic Literature Vol. XLIII (March 2005), pp. 9–64.

[12] Salehie, M., Tahvildari, L., 2005 Autonomic computing: emerging trends and open problems., DEAS '05 Proceedings of the 2005 workshop on Design and evolution of autonomic application software, 1-7.

[13] Blue, J., Andoh-Baidoo, F.K, 2010, Directive Decision Devices: Extending the Reach of Automation into the Finance Doman, Expert Systems with Applications 37, 45–54.

[14] Tversky, A. and Kahneman D., 1991**,** Loss Aversion in Riskless Choice: A Reference-Dependent Model, The Quarterly Journal of Economics 106 (4): 1039-1061.doi: 10.2307/2937956.

[15] Tversky, A. and Kahneman D., 1974, *Judgment Under Uncertainty: Heuristics and Biases,* Science, New Series, Vol. 185, No. 4157. (Sep.27, 1974), pp. 1124-1131.

[16] Kahneman, D., & Tversky, A. 1979, Prospect theory: An analysis of decisions under risk. Econometrica, 47(2), 263–292.

[17] Shefrin, H., and Statman., M., 1985, The Disposition to Sell Winners too Early and To Ride Losers Too long: Theory and Evidence., Journal of Finance Vol. XL, No 3.

[18] Benos, A.V., 1998, Aggressiveness and Survival of Overconfident Traders, Journal of Finance Markets 1(3–4), pp. 353–83.

[19] Odean, T.,1998 Volume, Volatility, Price, and Profit When All Traders Are Above Average. Journal of Finance, December 1998a, 53(6), pp. 1887–934.

[20] McAndrew, C., & Gore, J., 2013. Understanding preferences in experience-based choice: A study of cognition in the "wild". Journal of Cognitive Engineering and Decision Making, 7(2), 179-197.

[21] Smith, A., 1790, The Theory of Moral Sentiments. 1790., Library of Economics and Liberty.

[22] Bentham, J., 1789, Introduction to the Principles of Morals and Legislation., Library of Economics and Liberty.

[23] Homo Economicus; 'The Economic Man'.

[24] John Maynard Keynes, The General Theory of Employment, Interest and Money (London: Macmillan, 1936), p. 383.

[25] Fisher, Irving. The Theory of Interest. New York: The Macmillan Co. 1930.

[26] Fama, E. F., Random Walks in Stock Market Prices, Institutional Investor (1968).

[27] *Fama*, E.F., *Efficient Capital Markets*: A Review of Theory and Empirical Work. Journal of Finance, *1970*, vol. 25, issue 2, pages 383-417.

[28] Regnault, J., 1863, Calcul des chances et philosophie de la bourse, Paris: Mallet-Bachelier and Castel.

[28] Malkiel, Burton G.,1973., A Random Walk Down Wall Street, Penguin Books.

[29] Neisser, U., 1967., Cognitive Psychology, Appleton-Century-Croft.s

[30] Shefrin, H., 2002., Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology, Oxford University Press.

[31] Samuelson, W. and R. Zeckhauser, 1987., Status Quo Bias in Decision Making, Journal of Risk and Uncertainty, 1, pp.7-59.

[32] Miller, D; Michael R., 1975, "Self-serving Biases in the Attribution of Causality: Fact or Fiction?". Psychological Bulletin 82 (2): 213–225.

[33] Kahneman, D., & Tversky, A.,1981, The Framing of Decisions and the Psychology of Choice, Science, New Series, Vol. 211, No. 4481 (Jan. 30, 1981), pp. 453-458.

[34] Shiller, Robert J., 2000, Irrational Exuberance. Princeton University Press. pp. 149–153.

[35] Hilton, Denis J., 2001, The Psychology of Financial Decision-Making: Applications to Trading, Dealing, and Investment Analysis, The Institute of Psychology and Markets.

[36] Nicolosi, G. et al., 2008, Do Individual Investors Learn from their Trading Experience*?* Journal of Financial Markets 12, 317–336.

[37] Seru, Shumway and Stoffman., 2006, Learning by Trading, University of Michigan.

[38] Jacoby, J., Et Al., 2001, Training Novices to become more expert: The Role of Information Accessing Strategy, The Journal of Psychology and Financial Markets, Vol.2, No. 2, pp69-79.

[39] Sutherland, N.S., 1992, Irrationality: The enemy within. Harmondsworth, Penguin.

[40] Wilson, D.W., 1983 The False Consensus Bias: Extending Normal Biases to the Abnormal, University of Mississippi.

[41] Stoner, J.A.F., 1968, Risky and Cautious Shifts in Group Decisions: The influence of widely held Values, Journal of Experimental Psychology, 4, 442-459.

[42] Coval, J. D & Shumway, T., 2005, *"*Do Behavioural Biases Affect Prices*?* The Journal of Finance, Vol LX no.1.

[43] Braas, A., Bralver, C. A., 2001, Stock Volatility and Program Trading; Theory and Evidence. Journal of Applied Corporate Finance, pp 91-96.

[44] Steenbarger, Dr. Brett N., The Psychology of Trading, John Wiley and Sons, (2003).

[45] Lo, Andrew W., and Dmitry V. Repin, The Psychophysiology of Real-Time Financial Risk Processing, NBER Working Paper No. 8508, October 2001, JEL No. G10, G14, C91, C93.

[46] Lo, Andrew W., A Non-Random Walk Down Wall Street, Princeton University Press, (2001).

[47] Norman, D. J., 2004., Critical Point Activity, Managing Technology Change., IIT Lecture series, Chicago Mercantile Exchange.
[48] Stuart, Thomas. A., Think with your Gut, Business 2.0, November 2002, p.99-104.
[49] Klein, G., 1999 Sources of Power. How People Make decisions. MIT Press; New Ed edition (31 Mar. 1999).
[50] Shiv, B., Loewenstein, G., Bechara, A., Damasio, H., Damasio,H., Investment behaviour and the Negative Side of Emotion, Psychological Science June 2005 vol. 16 no. 6 435-439.
[51] Peterson, R.L., 2005, The neuroscience of investing: fMRI of the reward system., 15;67(5):391-7. Epub 2005 Jul 19.
[52] Biais, Hilton, Mazurier and Pouget*:* 2002., Psychological Dispositions and Trading Behaviour.
[53] Shliefer, A, Summers, L.H., 1990, The Noise Trader Approach to Finance., Journal of Economic Perspectives, Vol.4 No.2, pp19-33.
[54] Lifson, L.E., Geist, R.A., 1999, The Psychology of Investing, J. Wiley & Sons.
[55] Jacoby, J., Et Al. Training Novices to become more expert: The Role of Information Accessing Strategy, The Journal of Psychology and Financial Markets, (2001), Vol.2, No. 2, pp69-79.
[56] Ericsson, K. A., & Smith, J. (Eds.) 1991, Toward a general theory of expertise: Prospects and limits, Cambridge: Cambridge University Press.
[57] Locke, P. R. & Mann, S. C., 2009. Daily income target effects: Evidence from a large sample of professional commodities traders, Journal of Financial Markets, Elsevier, vol. 12(4), pages 814-831.
[58] Lo, Andrew W., Repin, V, Dmitry, Steenbarger, N Brett., 2001, Fear and Greed in Financial Markets: A Clinical Study of Day Traders, Journal of Cognitive Neuroscientific Foundations of Economic Behavior, *vol* 95, No 2.
[59] Andersson, R., Tour, R., 2005, How to sample behaviour and emotions of traders: A psychological approach and an empirical example.
[60] Cooksey, R.W., 1996, The Methodology of Social Judgement Theory, Thinking and Reasoning 2, (2/3) pp.141-173.
[61] Van Boening, M. V., Williams, A. W. and LaMaster, S.: 1993, Price bubbles and crashes in experimental call markets, Economics Letters 41, 179–185.

[62] Bruguier, Antoine Jean and Quartz, Steven R. and Bossaerts, Peter, 2010, Exploring the Nature of 'Trader Intuition' (January 1, 2010). Journal of Finance, Forthcoming; Swiss Finance Institute Research Paper No. 10-02.

[63] Baghestanian, S., Walker, T.B., 2015, Anchoring in experimental asset markets. Journal of Economic Behaviour and Organisation. 116, pp 15-25.

[64] Mirowski, P.,2002., Machine Dreams: Economics Becomes a Cyborg Science. Cambridge, 670 p.

[65] Frino, A., Grant, J. & Johnstone, D. (2008). The house money effect and local traders on the Sydney Futures Exchange. Pacific-Basin Finance Journal, 16 (1-2).

[66] Masry, S., 2013, Event-based microscopic analysis of the FX market.

[67] Anderson and Dyl, A., Market Structure and Trading Volume," (with Edward A. Dyl), Journal of Financial Research, Spring 2005, Volume 28, 115-131.

[68] Smith (1962) An Experimental Study of Competitive Market Behaviour. Journal of Political Economics, 70, 111-137.

[69] Spinelli, E., Counselling Psychology: a hesitant hybrid or a tantalizing innovation, Counselling Psychology Review, (2001).

[70] Azencott, R., Beri,A., et al, Real-time market microstructure analysis: online transaction cost analysis, Department of Mathematics , University of Houston , Houston.

[71] Sato, AH., Time interval in successive trading in Foreign Currency Market (2004).

[72] Taylor, N., 2002, Trading Intensity, Volatility and Arbitrage activity, Journal of Banking & Finance 28 (2004) 1137–1162.

[73] Tenenbaum, J. B. et al., 2006, Theory-based Bayesian models of inductive learning and reasoning, Trends in Cognitive Sciences, Volume 10, Issue 7, 309 – 318.

[74] M. Lattimer Wright, M. W. Green, G. Fiegl, and P. F. Cross, An expert system for real-time control, IEEE Software, 3 (2), 1986, 16-24. 7.

[75] Van Dujin, M., 2011 The Biocognitive Spectrum, Biological Cognition as Variations on Sensorimotor Coordination.

[76] Kermer, D.A., Driver-Linn, E., Wilson, T, D., Gilbert, D.T., 2006, Loss Aversion Is an Affective Forecasting Error, University of Virginia and Harvard University.

[77] Gal, D., 2006, A Psychological Law of Inertia and the Illusion of Loss Aversion. Judgment and Decision Making, Vol. 1, pp. 23-32.

[78] Harinck, F., Van Dijk, E., Van Beest, I. and Mersmann,P. 2007. When Gains Loom Larger than Losses: Reversed Loss Aversion for Small Amounts of Money.

[79] List, J A., 2003, "Does Market Experience Eliminate Market Anomalies? The Quarterly Journal of Economics, 41.

[80] Novemsky, N., Kahneman, D., 2005. The Boundaries of Loss Aversion. Journal of Marketing Research: May 2005, Vol. 42, No. 2.

[81] Pratt J.W., 1964, Risk Aversion in the Small and in the Large, 1964, and Arrow. K., "The Theory of Risk Aversion", 1965.

[82] Hens, T., Vlcek, M., Does prospect theory explain the disposition effect? Journal of Behavioral Finance, Vol. 12 (No. 3), p. 141-157, 2011.

[83] Cheng., P.Y.K., 2007, The Trader Interaction Effect on the Impact of Overconfidence on Trading Performance: An Empirical Study, Journal of Behavioural Finance, Volume 8, Issue 2, pp.56-69.

[84] Ericsson, K. A. (2006). In K. A. Ericsson & N. Charness & P. J. Feltovich & R. R. Hoffman (Eds.), The Cambridge Handbook of Expertise and Expert Performance, 1st ed.: 3-20. Cambridge: Cambridge University Press.

[85] Kahneman, D. & A. Tversky (1989). Prospect theory: an analysis of decision under risk. Econometrica, 47(2): pp. 263–91.

[86] Foucault, T., Order flow composition and trading costs in a dynamic limit order market1. Journal of Financial Markets, 1999, vol. 2, issue 2, pages 99.

[87] Hoffman, E. Chiang and P. Wrightson, 2012., Rapporteurs; Board on Global Science and Technology; Policy and Global Affairs; National Research Council.

[88] Biais, Bruno & Foucault, Thierry & Moinas, Sophie, 2013. "Equilibrium Fast Trading," TSE Working Papers 13-387, Toulouse School of Economics (TSE).

[89] Baghestanian, S; Walker, T, B. 2015., Anchoring in experimental asset markets," Journal of Economic Behavior.

[90] Davis, M., Kumiega, A., Van Vliet, B., 2012, Ethics, Finance, and Automation, A Preliminary Survey of Problems in High Frequency Trading, Science and Engineering ethics, pp.1-33.

[91] Miller, R.M., 2008., Don't let your robots grow up to be traders: Artificial intelligence, human intelligence, and asset-market bubbles, Journal of Economic Behavior & Organization 68 (2008) 153–166

[92] Horvitz, E., 2000, 'Foundations of Augmented Cognition', ISAT Group, Defense Advanced Research Projects Agency. Meeting at the National Academy of Sciences

[93] Sutherland, J. W., 2007). 'Directive Decision Devices: Reversing the Locus of Authority in Human-Computer Associations,' Department of Information Systems, Virginia Commonwealth University,

[94] Broy., M., 2004., Time, Abstraction, Causality, and Modularity in Interactive Systems Extended Institut fur¨ Informatik, Technische Universit¨at Munchen ¨ D-80290 Munchen,

[95] J. Blue, F.K. Andoh-Baidoo, 2010., Expert Systems with Applications 37 (2010) 45–54

[96] Bayes, Thomas, and Price, Richard (1763). "An Essay towards solving a Problem in the Doctrine of Chance. By the late Rev. Mr. Bayes, communicated by Mr. Price, in a letter to John Canton, A. M. F. R. S." Philosophical Transactions of the Royal Society of London 53 (0): 370–418

[97] Thaler, Richard H. and Johnson, Eric J., 1990., Gambling with the House Money to Break Even: The Effects of Prior Outcomes on Risky Choice

[98] Klein, G. A., Calderwood, R., & Clinton-Cirocco, A. (1986). Rapid decision making on the fireground. Proceedings of the Human Factors and Ergonomics Society 30th Annual Meeting, 1, 576–580.

[99] Klein, G. A. (1989). Recognition-primed decisions. In W. B. Rouse (Ed.), Advances in man-machine systems research (Vol. 5, pp. 47–92). Greenwich, CT: JAI Press.

[100] Pearl, J., Bayesianism and Causality. Or Why I am only Half a Bayesian. In D. Corfield and J. Williamson (Eds) *Foundations of Bayesianism*, Kluwer Applied Logic series, Kluwer Academic Publsihers, Vol.24, 19-36, 2001.

Appendix

7.1 Metrics used in Calculations in RTDS

1. Winner Count
2. Loser Count
3. Scratch Count
4. Long Winners
5. Long Losers
6. Long Scratches
7. Short Winners
8. Short Losers
9. Short Scratches
10. P/L per Contract Traded
11. Average P/L per Winning Contract Traded
12. Average P/L per Losing Contract Traded
13. Average Time in Trade
14. Average Time in Winner
15. Average Time in Loser
16. Average Time in Scratch
17. Average Time Since Last Trade Winner
18. Average Time Since Last Trade Loser

19. Average Time Since Last Trade Scratch

20. Average Time Since Last Trade

21. Max Loser

22. Max Winner

23. Average Winner PL

24. Average Loser PL

25. Average Trade PL

26. Standard Deviation of Times in Trade

27. Standard Deviation of Times in Winners

28. Standard Deviation of Times in Losers

29. Standard Deviation of Times in Scratches

30. Standard Deviation of Times Since Last Trade

31. Standard Deviation of Times Since Last Trade Winner

32. Standard Deviation of Times Since Last Trade Loser

33. Standard Deviation of Times Since Last Trade Scratches

34. Average Time in Trade (W)

35. Average Time in Trade (L)

36. Average Time Since Last Trade (W)

37. Average Time Since Last Trade (L)

38. Average PL (W)

39. Average PL (L)

40. Range P/L per Trade (W)

41. Range P/L per Trade (L)

42. Max Trade P/L (W)

43. Max Trade P/L (L)

44. Use of Time in All Trades

45. Average Trade Theta (W)

46. Average Trade Theta (L)

47. Total Time in Trade (W)

48. Total Time in Trade (L)

49. Average P/L per Contract Traded

50. Average P/L per Spread Traded

51. Spread Traded Range (W)

52. Spread Traded Range (L)

53. Use of Time in Winners

54. Use of Time in Losers

55. Consistency in Winners

56. Consistency in Losers

57. Erratic Behavior in Winners

58. Erratic Behavior in Losers

59. Clouding in Winners

60. Clouding in Losers

61. Pyramiding in Winners

62. Averaging in Losers

63. Gunning

64. Sharpe Ratio

65. Total Trade PL (W/L)

66. Average Trade Size

67. Average Winner Size

68. Average Loser Size

69. Average Scratch Size

70. Average Number of Trades (W)

71. Average Number of Trades (L)

72. Pattern Recognition Score

73. Performance Taper (W)

74. Performance Taper (L)

75. Average Positive Drift

76. Average Negative Drift

77. Maximum Positive Drift

78. Maximum Negative Drift

79. Average Drift Ratio

80. Max Drift Ratio

81. Average Drift (W/L)

82. Average Missed Positive Drift

83. Average Missed Negative Drift

84. Missed Opportunity (W)

85. Missed Opportunity (L)

86. Loss to Profit Momentum

87. Profit to Loss Momentum

88. Market Class Recognition
89. Number of Trades in Sideways
90. Number of Trades in Breakout
91. Number of Trades in Trending
92. Number of Trades in Reversal
93. Number of Winners in Sideways
94. Number of Winners in Breakout
95. Number of Winners in Trending
96. Number of Winners in Reversal
97. Number of Losers in Sideways
98. Number of Losers in Breakout
99. Number of Losers in Trending
100. Number of Losers in Reversal
101. Profit Restoration
102. Repeat Trade(W)
103. Repeat Trade (L)
104. P/L in Sideways
105. P/L in Breakout
106. P/L in Trending
107. P/L in Reversal
108. Avg P/L in Sideways
109. Avg P/L in Breakout
110. Avg P/L in Trending

111. Average P/L in Reversal
112. Sideways Score
113. Breakout Score
114. Trending Score
115. Reversal Score
116. Time in Trade Range Score (W)
117. Time in Trade Range Score (L)
118. Risk Return Score (W)
119. Risk Return Score (L)
120. Trade Class Score (W)
121. Trade Class Score (L)
122. Trade Class Score (Sideways)
123. Trade Class Score (Trending)
124. Trade Class Score (Reversal)
125. Trade Class Score (Breakout)
126. Trade Trigger Reaction Time (W)
127. Trade Trigger Reaction Time (L)