Algorithmic Trading Systems: A multifaceted view of adoption

David Bell
Department of Information Systems & Computing,
Brunel University,
London, UK.
david.bell@brunel.ac.uk

Laide Gana,
Department of Information Systems & Computing,
Brunel University,
London, UK.
laide.gana@brunel.ac.uk

Abstract

Algorithmic trading has been blamed for an increasing level of volatility in a number of financial markets. Adoption and deployment of algorithmic trading systems has increased and this is likely to continue, as regulation, competition and innovation drive the development of advanced technological tools. Expert and intelligent systems provide the mechanics for both reacting to and affecting a financial market that is now significantly faster and operating across multiple time zones and markets. Surprisingly, much of this innovation has escaped discussion within the Information Systems research community. This paper explores this growing arena by engaging with senior practitioners in the industry and using interviews and grounded theory (GT) analysis to uncover their adoption concerns. The paper generalises these issues within a framework and guidelines aimed at supporting algorithmic trading system adoption, deployment and development.

1. Introduction

Physical trading floors are starting to follow the predictions of Freund [12] with less reliance on human traders. The increasing volume of data flowing through financial markets is one cause. Technology has also played a role, leveling the field in securities trading (a trend that is likely to continue despite the current global economic slowdown). Electronic trading has significantly changed securities trading and the associated financial markets technology architecture, resulting in the blurring of boundaries between trading firms and helping to accelerate competition and efficiency within financial markets [2,4,23,28]. Coupled with new regulation, such as Regulation National Market System (RegNMS) and the Markets in Financial Instruments Directive (MIFID), a greater requirement for transparency and speed of execution on market participants is required. Technological innovations to support these evolving business trends are on the increase. Balarkas [3] and Domowitz & Yegerman [12] identify that some of the more visible effects of the changes in financial markets, the fragmentation of existing markets and the creation of new liquidity pools, which have in turn accelerated the urgency for technological driven innovations. Market pressures, driven in part by the need for increased transparency and speed of execution, has resulted in tighter profit margins. This is further compounded as technological transformations reshape the world's financial markets [11]. Furthermore, as global returns within financial markets show signs of weakening and market players are adjusting their growth forecasts in light of the recent credit crisis, executives are increasingly looking towards their technological assets as a core means of generating business value.

One innovation that has been gradually gaining prominence within the electronic trading arena is that of algorithmic trading. Algorithmic trading is defined as a system for conducting automated trading using computer programs operating within defined rules that respond in real-time to market data and news in order to make and execute trades across an increasing number of venues such as traditional electronic exchanges, Multilateral Trading Facilities (MTFs) and Electronic Communications Networks (ECNs) [15,18]. At a generic level, algorithmic trading can either be the trading strategy or programmed rules that govern the buying and selling activities of the trading entity. Alternatively, the approach can direct specific desks of a trading firm to execute its orders within a market in order to reduce market impact and enhance trading performance through the use of automated trading tools. Algorithmic trading has been referred to as black-box trading, computer trading, program trading, basket trading and enhanced execution [18]. It has been widely described as capable of providing significant benefits such as increased efficiency, transparency and capacity and most importantly cost reduction to the trade execution process [20]. These advantages realised by increasing the speed at which trades can be executed in the trading rooms, requiring intelligent

IEEE computer society

computers systems rather than humans to spot and exploit market imbalances that exists for very short timeframes. Although algorithmic trading adoption is on the increase, practitioners highlight that the core requirements for implementing successful algorithmic trading systems are: a fully integrated low latency infrastructure, data cleansing, risk management integration and performance measurement capabilities, a development and maintenance platform that is event-based and the ability to have the trade execution engine as an integrated component of this infrastructure. Hod [20] argues that performance and risk management should not be sacrificed in algorithmic system development. Bates et al. [6] highlights that one of the areas that the algorithmic trading community needs to focus on is in the use of algorithmic trading systems to meet regulatory and compliance requirements, in order to achieve this, algorithmic trading systems must not only be capable of achieving best execution but must also ensure that risk management and compliance rules are built in. Based on a global survey of financial markets operators, risk management and enhanced performance were identified as key drivers for the adoption of technology based innovations [11]. Focusing on risk management and performance, Dence et al. [11] and Hod [20] identify that capital market operators need to focus on risk assumption and management in the adoption of technological innovations in order to derive business value and the necessary take-up of algorithmic trading tools.

This paper takes an exploratory look at algorithmic trading from the perspective of technology personnel who deploy and manage such infrastructure. The paper starts with background coverage of electronic and algorithmic trading before describing the interviews and grounded theory research methods being utilized. A number of interviews (with senior financial community staff) are systematically analyzed using grounded theory techniques and resulting theories are proposed that address the adoption and associated implementation of such systems.

2. Electronic Trading Background

Historically, trading was floor-based with traders meeting in a central location, typically called a stock exchange in order to transact business. The processes involved in trading spanned different parts of the financial organisation and not typically automated and integrated (see Figure 1 for a summary of these processes). To transact, a dealer had to move from pit to pit in order to obtain the best price and trading was

usually confined to the region in which the stock exchange was based. In recent times, advancing innovations in computing and communications technology has enabled a phenomenal growth in global electronic order routing, dissemination of quote and trade information, new methods of trading and new types of trading systems [7,14,21,22]. The adoption of newer technologies and continual innovation over the last three decades has resulted in disintermediation of particular segments of the capital markets and the birth of new types of market participant. Examples being systemic internalisers, ECNs and MTFs that now compete directly with traditional stock exchanges for order flow. They often use different trading mechanisms in order to match buy and sell orders with more differentiation in terms of execution price and speed.
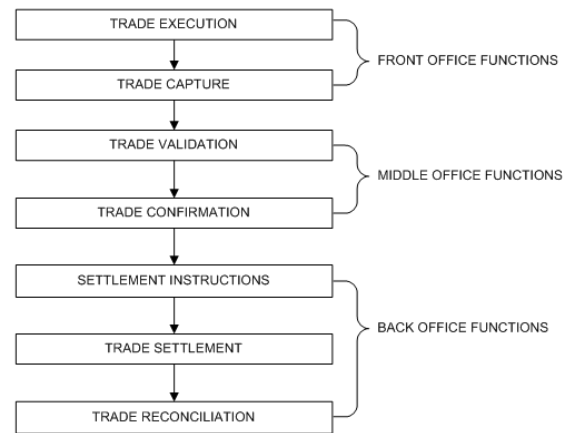

Figure 1. Trade Lifecycle Processes

Many argue that electronic trading has positively impacted market structure and efficiency by improving centralised market access and transparency; it has also enhanced the operational and information efficiencies of financial markets [4,17,23]. Automation in the financial markets has brought about opportunities where stock exchanges can evolve from non-profit to profit making organisations. In addition, new financial products development can occur at lower cost [17]. Empirical testing of a number of exchanges have shown cost reduction, increased efficiency, enhanced liquidity [8, 23].

Market microstructure is similarly concerned with the exchange of value within financial markets and a study of market microstructure helps to shed light on the working processes of a market, namely how these processes affects transaction costs, prices, volume and trading behaviour [35]. BIS [4] highlighted that electronic trading typically affects market structure

and associated architecture through centralisation - witnessed in the foreign exchange market. Hendershott [21] asserts that electronic trading systems impact market structure through the set of rules governing its trade execution mechanisms and the amount of price and quote data it releases. Handa et al. [19] mention that in assessing the value of a trading system, attention must be paid to its information aggregation procedures which includes order matching and trade execution. Irrespective of the market structure in place, modern electronic exchanges have to offer customers a unique combination of speed, quality, price and certainty of execution in order to remain competitive. Gramza [17] explains that electronic trading also provides other benefits such as reduced search, transaction and production costs, greater internal and market efficiency, improved price discovery and price transparency. Additional benefits are speed of execution improvements, capacity, efficiency, productivity, cost, improved security and audit trails, transparency, user friendliness and the general potential for democratizing the investment process and provision of a 24 hours market for some asset classes e.g. foreign exchange [24].

2.1. Next Generation of Trading Systems

Research into biological and natural sciences have also influenced solutions to the complex problems found in the financial markets [9,27,31,35]. These systems, typically of an evolutionary nature have been popular in solving problems of optimization and efficiency within financial markets. Lunga & Marwala [29] refer to the financial trading marketplace as a complex, evolutionary, and non-linear dynamic system, often characterised by data intensity, noise, non-stationary, unstructured, high degree of uncertainty and hidden relationships and correlations - all of which are influencing factors on the behaviour of financial markets. Turban et al. [40] observed that advanced intelligent computing methods can be combined to provide solutions that require speed, fault tolerance and adaptability. Srikanth [37] describes an intelligent trading system as a self-tuning adaptive system that is parametric, capable of operation at multiple risk tolerances and data frequencies and able to perform multi-criteria optimization across multiple asset classes and in line with changing market conditions. Using genetic algorithms and methodologies to develop algorithmic programs to trade the component stocks [30] generated superior returns in comparison to a passive investment strategy. Lunga & Marwala [29] utilize an improved incremental algorithm that functions by extracting new information from an additional dataset

that later becomes available without losing prior knowledge and provides evidence of improved learning, better forecasting and trading results.

2.2. Algorithmic Trading Systems Adoption

As trading becomes more electronic, the behaviour of the floor trader or human trader on the phone becomes easier and cheaper to replicate within a computer program and thereby achieving increased efficiency in the overall trading process [32]. To this end, market participants are increasingly replicating their investment strategies, whether long or short term, in algorithms that help determine the timing, price and quantity of orders; dynamically monitoring market conditions across different securities and trading venues; reducing market impact by optimally (and sometimes randomly) breaking large orders into smaller pieces, and closely tracking benchmarks such as volume-weighted average price (VWAP) over the execution interval [22]. McMahon & Nunlist [32] maintain that the requirement for speed in today's electronic markets falls on the software, hardware and network infrastructure that connects traders to the stock exchanges with trade execution speed now measured in the sub-milliseconds range.

Algorithmic trading adoption has been increasing as increases in liquidity occur - especially the equities and foreign exchange markets [22]. Kaenel & Brennan [25] have found that a third of trading volume now utilizes algorithmic trading tools for order and trade processes. Hendershott et al. [22] empirically tested the causal relationship between algorithmic trading and liquidity using a normalized measure of NYSE electronic message traffic as a proxy for algorithmic trading and discovered that algorithmic trading resulted in smaller trade sizes and promoted fragmentation of order sizes with its aim of reducing market impact. Although there is a level of secrecy amongst algorithmic traders and algorithm providers as to what kind of information algorithms observe, it is believed that algorithms monitor common factor price information within a stock and across the entire portfolio, as well as monitoring the presence of other algorithms in a bid to determine the order flow and information patterns that are generated by such algorithms. Algorithms are now been used to monitor information from news feeds and react instantly by adjusting trading patterns - regulators are also entering the debate by using algorithms to monitor trading patterns and trade data as part of their supervisory role [39]. Rostoker et al. [33] present core components of the algorithmic trading system – the underlying algorithms and mathematical models which are able to process and

analyse many thousands of high-frequency, multidimensional and heterogeneous time series data in real-time.

Using an algorithmic trading strategy that combined signals from multiple algorithmic strategies, Silaghi et al. [36] observed higher performance. Srikanth [37] also propose an integrated intelligent trading system framework that possesses learning, adaptation, flexibility, explanation and discovery capabilities using evolutionary programming models in solving optimization problems. Barbosa et al. [5] describe an infrastructure for implementing algorithmic trading agents for foreign exchange trading using a combination of case-based reasoning and rules based expert systems. Through the design and implementation of a real-time correlation and analysis system, Rostoker et al. [33] investigated the optimization of real-time stock market data analysis to aid algorithmic trading and knowledge discovery in high throughput electronic exchanges with the key finding supporting the view that the stock market when viewed as a complex system can be modelled as a network in which stocks act as nodes and relationships between the stocks can be viewed as links between the nodes. The work showed that algorithmic trading could provide the correlation analysis and clique-based clustering analysis between stocks in the market on a real-time basis.

Global electronic connectivity and extraordinary advances in data storage and computational power have enabled unparalleled flow of information and support the significant levels of processing capabilities witnessed in financial markets today (Lienbenberg 2002). Competition, innovation and the drive to reduce costs are compelling factors pushing financial markets to adopt electronic and algorithmic trading [7,24,41]. Although a number of studies have looked at the adoption of algorithmic trading from a trading perspective, few have considered the technological implementation issues.

3. Research Approach

An interpretive approach is used in order to uncover insights into the information systems and the associated processes in play [26]. A number of interview participants are chosen each providing a specific perspective on algorithmic trading. Two general questions are used to open the interviews and set the scene, namely; *why are trading firms adopting algorithmic trading? And what are the implications of algorithmic trading adoption on market structure*

and IS architecture? Further questions are designed to explore areas highlighted in the literature and help in the investigation and identification of generalized patterns of actions and behaviours amongst practitioners when adopting or considering algorithmic trading. The literature highlights a number of issues: the trading environment (from asset classes to performance), the technology (strategy, systems and innovation) and the cost (from staff to business optimisation). Areas of questioning are presented in Table 1 and are used to generate an open discussion around the issues above. It is envisaged that follow on questions will be used to extend the debate depending on the interviewee's prior responses.

Follow-on Interview Questions
How has the adoption of algorithmic trading impacted on risk management processes and systems?
Do practitioners continue to use these systems during turbulent periods?
Are practitioners confident in these systems during times of market turbulence?
What criteria do practitioners use in evaluating the performance of algorithmic trading systems?
Are firms developing their own algorithmic trading systems in-house or buying externally?
Why are practitioners making the particular buy versus build choice?
What aspect of algorithmic trading systems do clients consider most important?
Is algorithmic trading suitable for multi-asset class and are practitioners utilizing these systems for portfolio trading?
What asset classes is algorithmic trading most suited for?

Table 1: Interview Questions

In order to address the identified areas of investigation and operationalize the research objectives, primary data is gathered during one hour in-depth interviews conducted with practitioners who have been selected based on their experience in securities trading and electronic systems development. The pre-prepared list of open ended questions was sent to each participant in advance in order to help give some structure and focus to the interview sessions. However, as the interviews progressed, additional areas arose as important and required further discussion. An additional benefit of the semi-structured interview approach was that it allowed for the exploration of these additional areas

that are important in gaining an understanding of algorithmic trading use within the industry.

Interviewee	Role Description	Organization
Participant 1	Head of IT, Financial Trading House	A major independent Forex, derivatives, equity and commodity trading house that operates globally.
Participant 2	Head of IT, Exchange Services	A leading pan-European equity multilateral trading facility (MTF)
Participant 3	Head, Direct Feed Products	A global market data and software provider that sells to the global financial industry

Table 2. Interviewee Profile

Grounded theory is used as a data analysis technique in this research. Building early theory is undertaken by breaking through biases and assumptions by a coding process driven by interviews [38]. The analysis is conducted is based on the work of Allan [1] who identifies five coding processes: (1) Micro-analysis coding, (b) Key point coding, (c) Conceptualizing, (d) Categorizing, and (e) Emerging theory respectively. Micro-analysis coding is done word-by-word and line-by-line of interview transcripts which was time consuming and could make confusion at times of coding [1]. The aim of coding is to identify, develop and relate the concepts that are the building blocks of theory.

Before starting to the coding process, the electronic interview records are first transcribed into interview transcripts. Coding [10,16,34,38] is used as a systematic method in the transformation of data into theory within grounded theory analysis. Semi-structured interviews were conducted with three participants that each represent different areas in the financial trading community, see table 2 for the profile of participants. The participants (each a senior member of their respective organisations with both strategic and operational scope) are chosen as they represent key stakeholder groups within financial markets and have first hand knowledge and experience of electronic and algorithmic trading systems. The interview transcripts are put through the coding processes that involved the identification, breakdown, and comparison of codes common in the data until clearly defined patterns are formed into concepts and then categories which gives insight into understanding the research questions posed.

The three interviews were recorded and transcribed, the coding and data analysis exercise was supported by the use of a well known computer aided qualitative data analysis software tools (CAQDAS) called MAXQDA and f4 software, see Figure 2 for screenshot of tool usage.
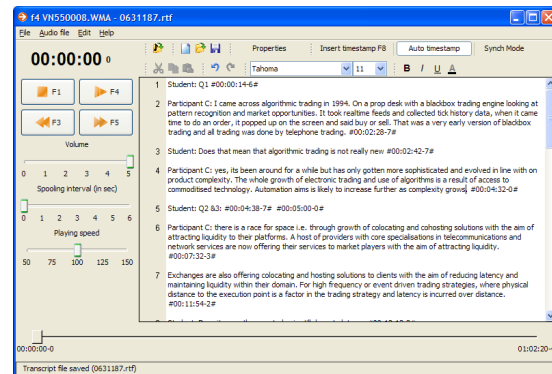

Figure 2: Screenshot of computer-aided qualitative analysis tools

With the interview data transcribed and the analysis tool chosen, the coding process started.

4. Grounded Theory Analysis

4.1. Coding

Analysis of the interview data after transcription was done using key point coding method [1]. This approach was preferred to the microanalysis method of Strauss and Corbin [38], as key point coding method was found to be more efficient for identifying key issues given the volume of transcribed interview data. The interview data was repeatedly analyzed with multiple pass-throughs in order to identify and validate key points.

The organized transcripts are analyzed line-by-line and question-by-question according. The key point coding is done interviewee-by-interview. Figure 3 shows examples of some of the key points and codes identified from the transcripts. Key points and code are referenced using a 'InQnLn' pattern where 'I' indicates Interviewee, 'Q' indicates specific Question, 'L' indicates Line in the transcript and 'n' indicates number of occurrences. This provides the opportunity to trace back to the actual sentences through the transcripts [1].

4.2. Interview Coding

A summary of the identified codes are presented in graphical form. The key point coding process for the first interview resulted in a list of key points and code (see table 3 examples).

Tag	Key Point	Code
I1Q8L6n1	Latency reduction is not the main challenge or issue in algorithmic trading system development or adoption	Latency is not an issue for everyone
I1Q8L23n1	A key concern is how to deal with the ever increasing volumes that will grow as we rollout technology to the retail end of the market	Data management is a key challenge
I1Q10L4n2	With the adoption of algorithmic trading, the profile of people on the trading floor will also change	Change in skill set

Increase in quant know-how |

Table 3. Key Point Coding Example

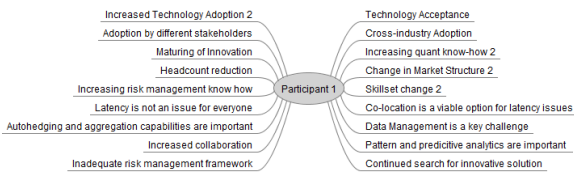Analysis of interview 1 resulted in the following codes (Figure 3).

Figure 3. Resulting codes (Participant 1)

Figures 3 to 5 present the codes derived from each of the interview sessions, an identifier is attached to each code and the codes are then further analyzed and combined.
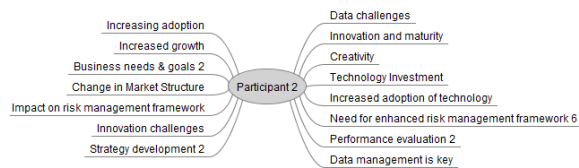

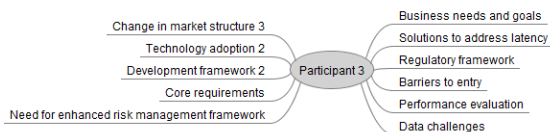Figure 4. Resulting codes (Participant 2)

Figure 5. Resulting codes (Participant 3)

4.3. Emergent Concepts and Categories

Conceptualizing and categorizing involves the merging of common codes and subsequent grouping under categories. Initially, grouping into related themes of key word codes, and resulting in a single concept. Identified codes from the three interviews were grouped together and combined based on common themes in order to arrive at the core concepts that the researcher identifies as recurring themes in the data. This constant comparison technique was utilized when comparing the concepts from each case study with each other in order to fully refine the recurring themes from the data. The concepts are created manually as tree nodes grouped and hierarchically structured (Hoover & Koerber, 2009). The codes that have related theme are moved into concepts that indicate they were mentioned more in the interview.

Concepts that have related themes are grouped into a category. Finally, categories then emerge in participant transcript analysis – for example *'Suitability in Use of IT'* and *'Skills and staffing'*. The concepts that fall under similar themes were then categorized together and a repeat pass of the interview data carried out. This iterative process resulted in the identification of additional codes and concepts and was continued until the researcher was satisfied that code generation from the interview data was fully saturated. The concepts were further reviewed and then compared with each other for common themes and the following categories subsequently evolved from the data, see Table 4.

CONCEPTS AND <CONTRIBUTING CODES>	CATEGORIES
Increasing adoption in the industry <KP1; KP2;KP24>	
Competitive necessity for all firms <KP1;KP2;KP24;KP43;KP45>	Stability in Use of Innovation/technology
Market wide acceptance and usage <KP2;KP3;KP17;KP18>	
Ongoing drive for innovative solutions <KP7;KP14;KP17;KP21;KP22;KP23;KP24>	Market structure changes
Industry drivers <KP14;KP15;KP20;KP21;KP39>	
Headcount reduction <KP5;KP6;KP10;KP11;KP16>	Skills and Staffing
Changes in skillset of staff <KP3;KP5;KP6>	
Provision of portfolio risk and performance tools and metric <KP6;KP9;KP15;KP24;KP25;KP28;KP29;KP30;KP31;KP34;KP35>	Risk Management enhancements
Enhanced risk management framework <KP35; KP49>	
Provision of data management and analytics tool <KP9;KP12;KP13;KP37>	Data management Challenges
Access to historical data <KP37; KP48; KP50>	
Robust trading and investment strategies <KP12;KP13;KP14;KP19;KP22;KP30;KP31;KP32;KP33;KP34;KP36>	Algorithms/Strategy development
Requirements for complex event processing capabilities <KP25;KP27>	
Integration of data and information across multiple areas <KP11;KP14>	Knowledge Management goals
Latency is not an issue for everyone <KP8;KP39>	Performance Goals

Performance standards |
Ability to autohedge and liquidity aggregation is key <KP12;KP32>	
Collaborative approach across highly skilled teams and disciplines <KP10;KP11, KP14>	Algorithmic trading system development lifecycle
Rapid application development framework <KP45; KP48>	

Table 4: Emergent concepts and categories

All interviewees were concerned with risk, both internal to their organizations and external market

risk, resulting in the associated codes and category *Risk Management Enhancements*. Example comments include:

"Risk management systems and processes still lag behind as current systems cannot measure or calculate risk in real time" (Participant 1)

"Risk management systems must be developed to cater for correlation between complex events" (Participant 2)

The technology personnel and assets were seen as the drivers of algorithmic trading strategy – with *Algorithm Development* and associate *cycle* identified as categories:

"Technology has been the mobilizer of new and innovative strategies" (Participant 3)

As a consequence of a more technology centric trading platform the trading floor staffing requirements will change (combining technical and market knowledge and skill sets):

"With the adoption of algorithmic trading, the profile of the people on the trading floor will change" (Participant 1)

5. Adoption Framework

Increased adoption of algorithmic trading has been driven by a combination of factors, key amongst these are regulation, competition, quest by market practitioners for efficiency in the trade process and availability of commoditized technology that supports the innovation (see Figure 6). The drivers resulted from a synthesis of literature with GT coding. In spite of the fears in some quarters that technology would be capable of replacing humans on the trading floor, this research has in part shown that this very unlikely to be the case. One significant change however on the skills spectrum is that the trading floor is likely to become more quantitative and highly specialized going forward. The interviews have clearly shown that technology is an enabler of change (and not the change in itself). A common misconception even amongst those in industry is that technology has been the driver of business needs and goals; we have attempted through this research to engage with practitioners and shown that the use of technology is actually driven by business needs/goals. This reality is further highlighted by the fact that only technologies that aid strategic business

goals, i.e. algorithmic trading systems are the ones gaining the required investments in the marketplace.

Algorithmic trading has provided a means of replicating traders' behaviors and functions and has also aided the development of trading strategies using advanced artificial intelligence models. These tools now represent the norm within financial markets with widespread adoption by both buy- and sell- side practitioners with the potential of this innovation becoming mainstream within the retail end of the market outside of foreign exchange. However, it does appear that there exist a number of risks and issues in-spite of the enormous performance gains that the electronic trading evolution is bringing to the market place. There appears to be a real need for the definition of both regulatory and industry based standards.
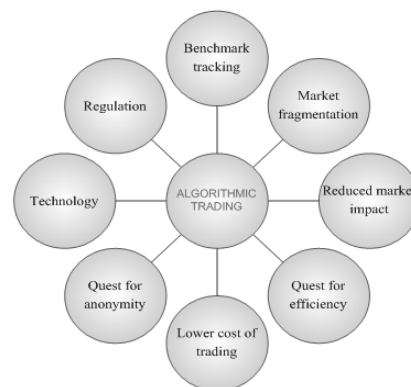

Figure 6. Literature Derived Adoption drivers

When considering the adoption of algorithmic trading solutions it is clear from the analysis that a number key concerns exist. The technology itself – it's capability in both use and under development, as well at the performance, is a core concern. The ability to deploy such technology into dynamic market environments and support its evolution with the correct operational and strategic guidance (staff capability) poses a critical challenge, that of mapping the technological issues to the people and environment (market) in which it will operate. This is shown graphically in Figure 7. The bolder line represents the need to appropriately combine technology provision with environmental and human constraints. A second mapping is required (dashed line), between the companies capability and the infrastructure connecting to the market.

This need for two dimensional mapping emerges from the in-context categories identified. *Market structure* and *Skills and Staffing* are two category

examples. Categories easily fit within segments, with underlying codes providing dependencies.

Technology Capability		Technology Performance
Staff Capability		Environment

Figure 7. Algorithmic Trading Adoption Matrix

5.1 Recommendations for action

One issue that was repeatedly mentioned is that the development and deployment of algorithmic trading systems often lacks an adequate risk management framework that supports both pre-trade and post-trade analysis. Risk management tools and techniques can be analyzed in all segments of the adoption matrix, including the mapping between the risk management required in a particular environment to the technology capability to undertake a particular approach. With the potential of algorithmic trading tools becoming available to the retail end of the market in other asset classes outside of foreign exchange, this paper proposes a number of recommendations in Table 5 to practitioners and regulators when evaluating decisions on whether to adopt and develop algorithmic trading strategies. If these requirements are incorporated into the algorithmic trading architecture, the authors believes that risk assumptions and mitigation will be further enhanced as the innovation and speed to market moves beyond the confines of Wall St. and the City of London. Again, the implementation recommendations in Table 5 originate from both literature and interview analysis and are also able to help the implementation team understand the functionalities required from a successful algorithmic trading platform. They can also be addressed in a more general sense within the wider adoption matrix in Figure 7.

	Recommendations
1	The ability to re-aggregate fragmented liquidity through solutions such as Smart Order Routing technology
2	Auto-hedging capabilities must be provided at both individual security and portfolio levels
3	Ability to back-test on historical and real-time data streams
4	Real-time risk exposure tracking between the front and back office (Real-time STP processing)
5	Availability of pre-trade analytics and tools- to enhance predictiveness at a security or portfolio level
6	Ability to measure performance of an algorithmic strategy in real-time over the execution horizon.
7	Adoption of common standards for measuring and reporting on performance of algorithmic trading systems.

Table 5. Implementation recommendations

6. Conclusion

Algorithmic trading tools are now a competitive necessity and the research presented in this paper focuses on engaging with senior stakeholders in the marketplace. The paper explores algorithmic trading from a technological perspective in order to understand the issues around adoption and the implications of using such tools on performance and risk management. Analysis of the interview data using grounded theory techniques are presented as concepts and themes that emerge from the data. The application of grounded theory to coding is fully explored in a process of identifying issues facing the industry as well as areas that practitioners should focus on when deploying algorithmic trading systems. The key drivers for algorithmic trading are summarised, along with an adoption matrix and number of implementation recommendations. As mentioned, the research is exploratory and much work is still required if this elusive business domain is to be better understood.

7. References

1. G. Allan, "A critique of using grounded theory as a research method". Electronic Journal of Business Research Methods, 2003, Volume 2, Issue 1 pp 1-10.

2. H. Allen, J. Hawkins and S. Sato, "Electronic trading and its implications for financial systems". Bank of International Settlements (BIS), 2008, Papers No 7.

3. R. Balarkas, "Algorithmic Trading: From Pilot To Auto-pilot - As Market Structures Change, Only The Largest Brokers Will Be Able To Justify Maintaining The Complex Platforms Needed For The Electronic And Algorithmic Trading Systems That Are Redefining The Relationship". The Banker, ABI/INFORM Research, 2006.

4. Bank of International Settlements (BIS), "The implications of electronic trading in financial markets". Report by a working group established by

the Committee on the Global Financial System of the central banks of the G10 countries.

5. R.P. Barbosa and O. Belo, "Autonomous forex trading agents", Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2008, Volume 5077 LNAI.

6. J. Bates, "Algorithmic Trading". Dr. Dobb's Journal: The World of Software Development, 2007, Volume 32(4), pp. 18(4). ISSN/ISBN: 1044789X

7. S. Boisvert, and C. Gaa, "Innovation and Competition in Canadian Equity Markets". Bank of Canada Review, 2001, Volume 2001, pp 15-30.

8. A. Chaboud and S. Weinberg, "Foreign exchange markets in the 1990s: intraday market volatility and the growth of electronic trading". Bank of International Settlements *(BIS)*, 2005, Papers No 12, part 8.

9. S. Chen and N. Navet, "Pretests for genetic-programming evolved trading programs: zero-intelligence strategies and lottery trading", Lecture Notes in Computer Science, 4234 LNCS, 2006.

10. G. Coleman, and R. O'Connor, "Software Process in Practice: A grounded theory of the Irish Software Industry". Springer, Lecture Notes in Computer Science. 2006, Volume 4257, pp 28-39.

11. S. Dence, D. Lattimore and J. White, J. "The trader is dead, long live the trader!A financial markets renaissance". IBM Institute for Business Value, 2006.

12. I. Domowitz and H. Yegerman, 'The Cost of Algorithmic Trading: A first look at comparative performance", Institutional Investor Journal, Spring 2005, Vol. 2005, No. 1: pp. 30-40.

13. W.C. Freund, 'Trading Stock Around the Clock: The Future Growth of Global Electronic Markets'. California Management Review. 1991, Volume 34(1) p 87- 102.

14. M. Fan., J. Stallaert and A.B. Whinston, "The Internet and the future of financial markets". Communications of the ACM. 2000, Volume 43 (11), pp 82-88.

15. G. Giddings, "Humans vs Computers: Differences in their ability to absorb and process information for business decision purposes and the implications for the future". Business Information Review. 2008, Volume 25(32) pp 32-39.

16. R. Goede and C. Villiers, "The Applicability of Grounded Theory as Research Methodology in studies on the use of Methodologies in IS Practices". Proceedings of SAICSIT, 2003, pp 208-217.

17. D. Gramza, "Electrification of markets", Futures: News, Analysis & Strategies for Futures, Options & Derivatives Traders, 2008, Volume 37(11), pp. 52-55. ISSN/ISBN: 07462468

18. T. GRIFFO, "Algo Trading and CTAs- perfect together". Futures, ABI/INFORM Research, 2007, Volume 36 (13) pp 64-67.

19. P. Handa, R. A. Schwartz and A. Tiwari, "A tale of two trading venues: electronically delivered orders vs. floor brokered orders on the American stock exchange", HICSS-32: Proceedings of the 32nd Annual Hawaii International Conference on System Sciences, 1999, Volume 7 pp 7.

20. Z. Hod, "Algorithms for financial markets, when speed isn't enough". IBM Global Business Services, 2006.

21. T. Hendershott, "Electronic trading in financial markets", IT Professional, 2003, Volume 5(4), pp. 10-14.

22. T. Hendershott, C.M. Jones and A.J. Menkveld, "Does Algorithmic Trading Improve Liquidity", Journal of Finance, 2011, Vol 6(1), Blackwell Publishing Inc.

23. G. Jiang, N. Tang and E. Law, "Electronic trading in Hong Kong and its impact on market functioning". Bank of International Settlements (BIS), 2005, Papers No 12, part 7.

24. M. Khalifa and M. Davison,"SME adoption of IT: the case of electronic trading systems", IEEE Transactions on Engineering Management, 2006,, Volume 53(2), pp. 275-284. ISSN/ISBN:0018-9391

25. M.L.V Kaenel and B. Brenman, Algorithmic trading's journey, where performance is the destination, http://www.mondovisione.com, Accesssed: 2006.

26. H.K. Klein. and M.D. Myers, "A set of principles for conducting and evaluating interpretive field studies in information systems", MIS Quarterly, 1999, Volume 23(1), pp. 67. ISSN/ISBN: 02767783

27. C.S. Lee. and X. Yang, "Development and Test of an artificial-Immune-Abnormal-Trading Detection system for financial markets". 2005, LNCS 3644, pp 410-419.

28. D. Leinweber, "If You Had Everything Computationally . . . : Where Would You Put It, Financially?', The Journal of Portfolio Management Fall 2005, Vol. 32, No. 1: pp. 61-75

29. D. Lunga, and T. Marwala, "Online forecasting of stock market movement direction using the improved incremental algorithm", Lecture Notes in Computer, 2006, Volume 4234 LNCS – III.

30. D. Mallick, V.C. Lee and Yew Soon Ong.,"An empirical study of Genetic Programming generated trading rules in computerized stock trading service system", International Conference on Service Systems and Service Management, 2008,pp 1-6.

31. P. Marrow, "Nature-inspired computing technology and applications", BT Technology Journal, 2000, Volume 18(4), pp. 13-23.

32. C. Mcmahon, and T. Nunlist, "The new arms race and the coming revolution', Futures: News, Analysis & Strategies for Futures, Options & Derivatives Traders, 2008, Volume 37(12), pp. 70-72. ISSN/ISBN: 07462468

33. C. Rostoker, A. Wagner and H. Hoos, "A Parallel Workflow for Real-time Correlation and Clustering of High-Frequency Stock Market Data", IEEE International Parallel and Distributed Processing Symposium, 2007, pp 1(10).

34. S. Sarker, F. Lau and S, Sahay, "Using an adapted grounded theory approach for inductive theory building about virtual team development", Data Base for Advances in Information Systems, 2001, Volume 32(1), pp. 38-55.

35. M.V. Sewell and Y. Wei, "Ultra high frequency financial data", Conference Proceedings of the 10th Annual Conference on Genetic and Evolutionary Computation (GECCO'08), 2008, pp 1847-1849.

36. G.C. Silaghi and V. Robu, "An agent strategy for automated stock market trading combining price and order book information", ICSC Congress on Computational Intelligence Methods and Applications, Volume 2005.

37. V. Srikanth, "Intelligent trading systems: a multi-agent hybrid architecture", Conference Proceedings of the IEEE/IAFE on Computational Intelligence for Financial Engineering (CIFEr),1999, pp 64.

38. A.L. Strauss and J. Corbin, Basics of Qualitative Research Techniques and Procedures for Developing Grounded Theory. Sage Publications Inc, London, 1998.

39. The Economist. "Ahead of the tape", Economist, 2007 Volume 383 (8534), pp. 85. ISSN/ISBN: 00130613

40. E. Turban, J.E. Aronson and T.P Liang, Decision support systems and intelligent systems, Pearson Prentice Hall, USA. 2005, Chapters 1-2, 10-13.

41. B.W. Weber, "Transparency and bypass in electronic financial markets", Proceedings of the Twenty-Seventh Hawaii International Conference on Collaboration Technology Organizational Systems and Technology, 1994, Volume 4 pp 865