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# TECHNOLOGICAL INNOVATIONS IN SECURITIES TRADING: THE ADOPTION OF ALGORITHMIC TRADING

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## Abstract

*Technological innovations currently alter the traditional value chain in securities trading. Investment companies that used to buy trading services from their brokers are now enabled by technology to emulate core competencies of their brokers themselves. To investigate the adoption decision regarding one of those new technologies – Algorithmic Trading – a survey among the top European buy-side institutions has been conducted. The proposed research model successfully integrates components from the Task-Technology Fit model with core constructs of the UTAUT model. The results presented in this paper reveal that the fit among the perceived capabilities of the technology and the companies' individual needs is a main driver for adoption. Further, the expected performance gains seem to excel the expected efforts perceived to be associated with the introduction of the technology, which further fuels the intention to make use of the new technology. Prior expertise about the technology characteristics shows to facilitate the adoption as it increases the expected performance and lowers the expected effort associated with the technology.*

Keywords: Adoption, Task-Technology Fit, Partial Least Squares, IT innovation.

# 1 INTRODUCTION

The context of this research is set in the securities trading industry where technological innovations are currently altering the traditional value chain. In the traditional value chain of securities trading investment companies utilize services offered by market intermediaries for their trading. Market participants are segmented in the so-called buy-side and sell-side according to their role in securities trading. Buy-side refers to investment companies that are ‘buying’ trading services from the sell-side, i.e. investment banks and brokers (Harris 2003).

Increasing demands on promptness and cost efficiency along with technological advances led to a revolution in the way trading is conducted on international securities markets. The roles of the so-called buy-side and sell-side are in a flux, as technology enables the buy-side to emulate some of the services traditionally offered by the sell-side. One of those traditional offerings is the handling of the buy-side’s order flow, especially the execution of large orders. On markets implementing an open order book approach, exposing a high intended trade volume to the market would result in an adverse price movement (market impact), i.e. the exposure of a large volume to buy would force market prices to rise. Vice versa market prices would fall when a high volume to sell is exposed to the other market participants. In the past, orders were delegated to (human) brokers whose core competency was to either find a suitable counterparty for the large order or to work the order with a minimal market impact by splitting it up and distributing the submission of the fragments over time. For plain-vanilla orders, i.e. orders in highly liquid securities this task can nowadays be automated by Algorithmic Trading solutions that emulate “a broker’s core competence of slicing a big order into a multiplicity of smaller orders and of timing these orders to minimize market impact via electronic means” (Gomber & Gsell 2006, p. 541). Such software solutions have been used internally by brokers for awhile to unburden their human traders and to enable them to concentrate on more sophisticated orders. Due to their increasing technological proficiency buy-side institutions have started to use Algorithmic Trading solutions on their own. They either use customizable or parametrizable solutions provided by their brokers, or use systems provided by independent software vendors or develop their own solutions. For the context of this research the term ‘Algorithmic Trading solution’ refers to sophisticated software which is used by buy-side trading desks to accomplish the aforementioned task regardless whether this software is offered by a broker, by an independent software vendor or has been self-developed. Such systems show to have an increasing stake in securities transactions as “Algorithmic Trading is the fastest growing source of order flow” (Preuss 2007, p.154). To attract this order flow market operators even charge lower trading fees or grant fee rebates for algorithmic orders (e.g. Deutsche Börse 2009a, p.11). Such incentives seem to work out as e.g. the German stock exchange recently reported the share of Algorithmic Trading to be at 43% in 2008 on its electronic trading system Xetra (Deutsche Börse 2009b, p.10).

Trading algorithms typically aim at achieving or beating a specified benchmark with their executions and may be distinguished by their underlying benchmark, their aggressiveness or trading style as well as their adaptation behavior (Kissell & Malamut 2006). For instance the volume-weighted average price (VWAP), which is calculated as the ratio of the value traded and the volume traded (number of shares) within a specified time horizon, commonly serves as a benchmark for (automated) trading. Empirical research found the execution quality of algorithms to be inferior to executions handled by a broker (Domowitz & Yegerman 2005). Nevertheless, this underperformance can be overcompensated by the fact that algorithms can be run at lower costs, as no (expensive) human traders are involved. Further, as mentioned above, some market operators charge lower trading fees for Algorithmic Trading. Due to the increased cost consciousness among market participants, algorithms hence have become an attractive alternative to delegating responsibility for order execution to a traditional broker. Though, buy-side institutions have to individually balance their realizable explicit cost savings and the perils potentially associated with the new technology. Such issues may arise from high costs associated with the setup or development of such a system as well as a lack of confidence in its

performance. An institution may doubt that an Algorithmic Trading solution, which is commonly implemented as a black-box, can fulfill the requirements of its particular trading task.

The aim of this research is to investigate the buy-side institutions' assessment of these perceived advantages and perils in the course of their decision on adoption or refusal of Algorithmic Trading as an additional execution channel for their order flow. The forces and factors driving adoption shall be identified. Therefore a causal model has been developed and a survey among persons responsible for the trading process at the top European buy-side institutions (in terms of assets under management) has been conducted. The rest of this paper is structured as follows: Section 2 will give an overview of related work on the adoption of technological innovations while the subsequent section describes the methodology utilized for this research. Section 4 presents the research model in greater detail. Afterwards section 5 will present the results obtained and finally section 6 concludes, gives an outlook on future research and contemplates the limitations of the research at hand.

## 2 RELATED WORK

Originating from social psychology, academic research has proposed numerous theories and models aiming to explain (human) behavior. One of the most influential is the Theory of Reasoned Action (TRA) (Fishbein & Ajzen 1975) which has been "... designed to explain virtually any human behavior" (Ajzen & Fishbein 1980, p.4). It posits that actual behavior is driven by intentions towards the behavior in question which in turn are determined by positive or negative attitudes towards the behavior as well as social norms defined as the perception of whether important others, i.e. the social environment of the individual, think the behavior should be performed or not. Ajzen (1991) extended the original TRA to the Theory of Planned Behavior (TPB) in order to break the "original model's limitations in dealing with behaviors over which people have incomplete volitional control" (p.181). As such generic models did not prove to be a panacea, academic research proposed more elaborate models to explain domain-specific behavior or particular types of behavior, e.g. the diffusion and acceptance of innovations. The domain-independent Diffusion of Innovation theory (DOI or IDT) proposed by Rogers (1983) aims at explaining why and how innovations are propagated within a particular social system. The actual adoption is said to be determined by the innovation's characteristics: 'relative advantage', 'compatibility', 'trialability', 'observability' and 'complexity'.

As particularly in the domain of information systems (IS) the explanation of acceptance or refusal of innovative technologies is of great interest, IS research provides various extensions or specializations of those models. Moore & Benbasat (1991) adapted DOI for the IS domain by slightly redefining the given set of innovation characteristics and expanding it by adding 'image' defined as the social approval associated with the adoption and 'voluntariness of use'. Davis (1989) proposed the Technology Acceptance Model (TAM) as a specialization of TRA to the context of IS adoption. It focuses on a user's perception of usefulness and ease of use associated with an innovation and their impact on attitudes and intentions towards usage as predictors of actual usage. Although Fishbein & Ajzen (1975) state that behavior is best predicted by an individual's attitude towards the behavior research has been equivocal about the role of attitude in TAM, as Davis et al. (1989) found that attitude does not fully mediate the role of perceived usefulness on intention. Thus, a parsimonious TAM that leaves out the attitude construct is also common in literature, e.g. Venkatesh & Davis (1996, 2000). Mathieson (1991) conducted a comparison of TAM and TPB and found that both models work well with slight empirical advantages for TAM. TAM has been successfully employed for multiple domains (Legris et al. 2003, Table 1) where in different research contexts various extensions to the core of TAM have been developed. Venkatesh & Davis (2000) proposed the external variables 'results demonstrability', 'output quality', 'job relevance', 'image' and 'subjective norm'. The latter being a construct that has been omitted when TRA has been specialized to TAM by Davis (1989). Featherman (2001) added a 'perceived risk' construct for his research. Mathieson et al. (2001) proposed a 'perceived resources' construct to measure the extent to which it is believed that there are sufficient skills, money, hardware, software, etc. to be able to utilize the innovation. Venkatesh & Davis (1996) added 'computer self-efficacy' as an external construct influencing the perceived ease of use.

In an extensive review of IS innovation adoption models Jeyaraj et al. (2006) identified 135 independent variables used as predictors for adoption. However, as Venkatesh et al. (2003) pointed out most acceptance models are based on similar root constructs. Therefore they proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) which generalizes the definition of similar constructs used in the different models to emphasize their common roots. They identified four main determinants of intention or actual usage: ‘performance expectancy’, ‘effort expectancy’, ‘social influence’ and ‘facilitating conditions’, which are expected to be moderated by ‘gender’, ‘age’, ‘experience’ and ‘voluntariness of use’.

Another approach to explain utilization of new technology – that has explicitly not been included in UTAUT – is the Task-Technology Fit (TTF) model (Goodhue & Thompson 1995) which emphasizes that an innovation’s benefit depends on the adopter’s demands. It focuses on the extent to which the capabilities of an innovative technology fit to a user’s portfolio of given tasks. A high degree of fit is assumed to have a positive impact on the performance and utilization of the respective technology and is said to lower the expected effort to make use of the innovation. Dishaw & Strong (1999) and Klopffing & McKinney (2004) successfully integrated TAM and TTF components within one model.

As technological innovations are currently altering the traditional value chain in securities trading, it is of interest to investigate why they are adopted by market participants as well as what their impact on the securities markets is. For the latter empirical studies highlight differences in the algorithmic and non-algorithmic order flow (Prix et al 2007, Gsell & Gomber 2009). However, although trading innovations offer a wide range of advantages in particular to buy-side institutions no causal model has been developed so far that tries to explain their adoption. Merely Khalifa & Davison (2006) investigated the adoption of electronic trading systems by the sell-side and Lucas & Spitler (1999) investigated the adoption of broker workstations. The former found coercive, mimetic and normative pressures to impact the adoption decision in an organizational context, while for the latter the variables used for TAM did not prove to be significant.

### **3 METHODOLOGY**

As the technology of Algorithmic Trading is expected to feature strong economies of scale, the survey has been conducted among the largest organizations, i.e. the top institutions in terms of assets under management. The sample has been constructed based on data retrieved via ‘Thomson ONE Banker Web’. The sample has been selected by constraining the population to European buy-side investment managers, excluding strategic investors and governments to ensure substantial trading activity. The remaining population has been further restricted to the top 500 in terms of assets under management. The restricted sample still covers 95.4% of the total assets under management. Within each institution the person responsible for the trading process (process owner) has been contacted by phone to check whether they are interested in participating in the survey. If they were willing to participate the questionnaire was sent to them which could either be filled out paper-based and returned via mail or could be filled out online. Unfortunately many contacted persons argued that their company has the policy to generally not participate in surveys. Finally 41 responses were retrieved out of which 39 could be used to evaluate the research model. Those 39 returned questionnaires (7.8% response rate) still cover about 28% of the total assets under management in the sample.

Each construct of the proposed research model is represented by a set of indicators that correspond to the questionnaire used for the survey (see Table 2). Whenever applicable, existing measures from prior empirical studies have been adapted. For all questions a 7-point Likert scale has been applied: “completely disagree – mostly disagree – slightly disagree – indifferent – slightly agree – mostly agree – completely agree”. For two of the usage questions a 7-point percentage scale has been applied which was developed during independent pre-tests: “none – <10% – 11-25% – 26-50% – 51-75% – 76-90% – >90%”. Based on the insights gained during pre-tests the questionnaire has been modified. The model has been analyzed applying the Partial Least Squares (PLS) method (Chin 1998) using the software SmartPLS (Ringle et al. 2005), as PLS provides the ability to have both reflective and formative measures within the research model and has minimal requirements on sample size. Chin (1998, p.311) states the sample size requirement to be at least the larger of either a) 10 times the block

with largest number of formative indicators or b) 10 times the number of independent latent variable impacting the most complex dependent latent variable. For the model applied for this research this rule of thumb would require a minimum sample size of 40. Therefore, the number of responses retrieved is at the edge of acceptability. However, one has to be aware of an ongoing discussion regarding these minimum sample size requirements (Goodhue et al. 2006). Nevertheless, Goodhue et al. (2006, p.9) conclude that there is no evidence that statistically significant results on small sample sizes are false positives and that merely if no significant results are found for relationships it is invalid to conclude – based on a small sample size – that no such relationship exists.

## 4 RESEARCH MODEL

At the core of the causal model proposed for this research there are constructs whose terminologies as well as their hypothesized effects are based on Venkatesh et al.'s (2003) UTAUT model. However, due to the context not all constructs theorized in UTAUT are applied, as e.g. 'gender' and 'age' were omitted. Further the definitions of some constructs slightly vary. Analogue to the integration of TTF and TAM by Dishaw & Strong (1999) and Klopping & McKinney (2004) Task-Technology Fit is integrated with the UTAUT core. Therefore the definition of UTAUT's 'facilitating conditions' and 'experience' and their hypothesized causal effects have been altered. In the following the scope of each construct will be defined and their causal effects hypothesized.

As Diamantopoulos & Sigauw (2006, p.274) point out, "the choice of measurement perspective (...) does matter from a practical point of view". Though, an "almost automatic acceptance of reflective indicators" has been observed by Diamantopoulos & Winklhofer (2001, p.274) which is supported by the findings of Jarvis et al. (2003) who found about a third of investigated studies to be subject to misspecification of the measurement model. Therefore all constructs have been reviewed according to the guidelines provided by Jarvis et al. (2003, Table 1). Except for one (Task-Technology Fit), all constructs have been measured reflectively.

### 4.1 Usage

Usage is defined as the extent to which a buy-side institution makes use of Algorithmic Trading in terms of frequency and intensity of usage. Frequency refers to how regularly the innovation Algorithmic Trading is used and intensity of usage refers to the relative share of orders and the relative share of transaction value for which Algorithmic Trading is used.

### 4.2 Intention to use

Intentions in the model are in accordance with existing literature on TAM, TRA and TPB, as they "... are assumed to capture the motivational factors that influence a behaviour; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behaviour" (Ajzen 1991, p.181). The intention to use construct shall measure the determination of a subject to act in a certain way, i.e. to make use of Algorithmic Trading, the intended frequency of usage and intended intensity of usage. In line with prior research intentions are expected to exert a positive impact on usage.

**Hypothesis H1:** Intention to use is positively related to usage.

### 4.3 Performance Expectancy

Performance Expectancy is defined as the degree to which it is believed that using the system enhances job performance. In the context of this research this refers to reducing costs or increasing the quality of execution. Further, the expected performance may be fueled by an extrinsic motivation "because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself" (Venkatesh et al 2003, p. 448). E.g. using Algorithmic Trading may be seen as

providing a competitive advantage to the adopter. Following previous findings, Performance Expectancy is supposed to be the strongest predictor for the Intention to use construct (Venkatesh et al. 2003, p.447).

**Hypothesis H2:** Performance Expectancy positively impacts the intention to use.

#### 4.4 Effort Expectancy

The Effort Expectancy construct is defined as the degree to which it is perceived to be difficult to setup and make use of an Algorithmic Trading solution. The difficulties may rise from the complexity of setting up the system itself as well as setting up the technological infrastructure needed. The system needs to be integrated in the existing trading processes and software environment, i.e. the order management system used by the institution. Further it has to be ensured that input data needed by the algorithms, i.e. historical and real-time market data, is available in the required quality in terms of latency and reliability. Additional effort may rise from setting up adequate staff resources as well as from the need to learn how to use the system.

As the perceived effort associated with the adoption of Algorithmic Trading might be prohibitively high, it is hypothesized to have a negative effect on the intention to use.

**Hypothesis H3:** Effort Expectancy negatively impacts the intention to use.

#### 4.5 Task-Technology Fit

In UTAUT ‘facilitating conditions’ are conceptualized to embody among others DOI’s innovation characteristic ‘compatibility’, which is defined as “the degree to which the innovation is perceived as consistent with the existing values, past experiences, and needs of the potential adopter.” (Rogers 1983, p.223). This is in line with the concept of TTF which assumes that “... a better fit between technology functionalities, task requirements and individual abilities will lead to better performance” (Goodhue 1995, p. 1828). Although strategy research outlines different ways for the conceptualization of fit (Venkatraman 1989, Iivari 1992), only little guidance concerning its application is available and thus fit is difficult to operationalize. Items that aim at capturing a broader field of tasks and IT technologies lose their ability to capture the specific notions of fit, which deteriorates their explanatory power. Thus, Dishaw & Strong (1998) state that “new measures of fit must be developed for each application to a different task or technology” (p. 108).

The task relevant for this research is the buy-side institutions’ orders that have to be executed – their so-called order flow. Main characteristics of the order flow are the frequency of trading (large or small number of orders), the intensity of trading (large or small order sizes) and in which securities (blue-chip or small-cap, liquid or illiquid) the institution is predominantly trading. An Algorithmic Trading solution should also comply with the investment strategy pursued by the institution, i.e. the rules and procedures of trading designed to achieve the respective investment goals. Further, Algorithmic Trading solutions must avoid that their behavior can be detected and forecasted due to a predictable way of slicing and timing the order submissions, as this leaked information could be exploited by other market participants to their advantage (Brunnermeier & Pedersen 2005). Therefore an Algorithmic Trading solution should also meet the anonymity requirements set out by the institutions, i.e. adopters have to trust the Algorithmic Trading solutions referring this regard. As the extent to which Algorithmic Trading may satisfy these independent facets of fit does not necessarily correlate and as these facets themselves constitute the overall extent of fit between the technology and the task, the TTF construct has been operationalized in formative mode.

Following the direct effect of facilitating conditions in UTAUT, a strong fit between the perceived abilities of Algorithmic Trading and the trading task is expected to have a positive impact on the actual usage of Algorithmic Trading.

**Hypothesis H4:** Task-Technology Fit is positively related to usage.

Following the direct effects in Dishaw & Strong (1999) and Klopping & McKinney (2004), a strong fit is further expected to increase Performance Expectancy and to lower the Effort Expectancy.

**Hypothesis H5:** Task-Technology Fit is positively related to Performance Expectancy.

**Hypothesis H6:** Task-Technology Fit is negatively related to Effort Expectancy.

#### 4.6 Technology Expertise

As in this research no specific tool but a technology is investigated the TTF theory's 'tool experience' construct has been altered to a more general Technology Expertise construct which also replaces UTAUT's 'experience'. It is important to include expertise in the model as it facilitates the interpretation of performance and effort expectancies. Only a process owner that has knowledge about the technology's characteristics can have sound expectancies about the effort associated with setting up the technology and about the performance that can be achieved with it. The characteristics of expertise are measured on two levels: First, as a generalization of Goodhue's (1995) task literacy, innovation literacy is supposed to measure whether the respondent is familiar with the innovation and has already considered its adoption. For the second level, self-efficacy shall measure whether the respondent is confident to adopt the technology without external expertise concerning IT or trading issues as it deems itself to have sufficient skills. The more distinct the Technology Expertise is, the lower the expected effort is supposed to be, as knowledge about the technology and sufficient skills will ease the setup and integration of the Algorithmic Trading solution.

**Hypothesis H7:** Technology Expertise negatively impacts Effort Expectancy.

Alike the precise knowledge about the technology will have an impact on its expected performance. However, ex ante it is impossible to generally suppose whether this knowledge will favor the technology, i.e. its advantages would outweigh the disadvantages, or not. Moreover this assessment might vary for different institutions. Therefore no direction of the direct effect towards Performance Expectancy can be hypothesized. Hence, the significance of this path will have to be evaluated using a two-sided test.

**Hypothesis H8:** Technology Expertise has a direct effect on Performance Expectancy.

## 5 RESULTS

### 5.1 Quality criteria of the measurement model

As up to now no general measure for the goodness-of-fit of a PLS model is available, the quality of the model has to be assessed by a multitude of criteria. As furthermore reflective and formative latent variables substantially differ, different methods for their validation have to be applied.

#### 5.1.1 Reflective constructs

Quality criteria for the reflective constructs have been evaluated along the dimensions of convergent validity, construct reliability and discriminant validity to ensure on the one hand that all measurement items strongly correlate to their respective theoretical construct and on the other hand correlate only weakly with the other constructs. Convergent validity has been checked in terms of the indicator reliability which recommends all indicators' loading to be above 0.707. All reflective indicators lie above this threshold and are significant at the 0.001 level (Table 2). To test for significance bootstrapping with 1000 samples was applied. The construct reliability has been checked according to composite reliability. For each construct in the proposed model the composite reliability is above its required threshold of 0.7. Further Cronbach's  $\alpha$  (Cronbach 1951) was determined which also lies above its recommended value of 0.7 for all reflective constructs (see Figure 1). Further the average variance extracted (AVE) for all reflective constructs is given in Table 1 (diagonal) which lays above the recommended value of 0.5 for all constructs. Discriminant validity is assessed by examining the



indicator's cross-loadings. As for all reflective indicators the loading upon their respective construct is higher than for any other construct discriminant validity is given. Further the Fornell-Larcker criterion recommends that the AVE of each latent variable should be larger than the squared correlation of this variable with any other latent variable (Fornell & Larcker 1981, p.46). This criterion is maintained by all reflective constructs of the model presented (see Table 1).

	Usage	Intention	Performance Expectancy	Effort Expectancy	Technology Expertise
Usage	<b>0.83</b>				
Intention	0.43	<b>0.95</b>			
Performance Expectancy	0.47	0.60	<b>0.78</b>		
Effort Expectancy	0.11	0.27	0.10	<b>0.83</b>	
Technology Expertise	0.49	0.59	0.44	0.29	<b>0.80</b>

Table 1. Squared correlations among constructs and AVE (diagonal)

### 5.1.2 Formative construct

As Task-Technology Fit has been operationalized in formative mode it needs a special evaluation. For formative constructs there are by far less quality criteria for validation. A problem for the validation of formative measures may rise from multicollinearity in the data. The calculation of the variance inflation factors (VIF) enables to determine potential problems with multicollinearity. Within the academic literature  $VIF > 10$  is commonly accepted as a cut-off point for VIF values. Due to the size of the sample available for this research it was decided to stick with a stricter threshold, i.e. a threshold of  $VIF > 5$  has been applied. However, the VIF values obtained all lay below this threshold.

Purifying formative constructs is not that straight-forward as each indicator is a facet that causes the construct. Therefore the deletion of an indicator may alter the meaning of the construct. Although one of the formative indicators (anonymity demands) showed only a minor weight and did not prove to be significant it was retained in the model as it constitutes an important facet of the fit construct. By removing this indicator the construct would not have covered all aspects of fit anymore and content validity would no longer be preserved (Bollen & Lennox 1991).

Within the Task-Technology Fit construct the indicator concerning the fit with the investment strategy proved to be the one with the highest weight and significance (see Table 2), followed by the fit to the order flow.

## 5.2 Quality criteria of the structural model

The main results of the PLS algorithm are depicted in Figure 1, which shows that 48.5% of the variance in Usage can be explained by the proposed model. For Usage as well as Performance ( $R^2=62.8\%$ ) and Effort Expectancy ( $R^2=34.1\%$ ) the model shows moderate explanatory power, while for Intention to use there is substantial explanatory power ( $R^2=69.0\%$ ) according to the values proposed by Chin (1998, p.323). All path coefficients in the model are above the recommended 0.2 level. In order to test the path coefficients for significance bootstrapping with 1000 samples was conducted. The thereby determined significance levels are shown in Figure 1.

Both Intention to use (H1) and Task-Technology Fit (H4) have a significant positive impact on Usage. Performance Expectancy showed to be the strongest predictor for Intention to use (H2) with a highly significant path weight of 0.677, which is in line with prior research (Venkatesh et al. 2003, p.447). Performance Expectancy itself is highly significantly impacted by the Task-Technology Fit (H5). The expected effort associated with the setup of Algorithmic Trading exerts a highly significant negative impact on the intention to use (H3) and is itself significantly negatively influenced by both Task-Technology Fit (H6) and Technology Expertise (H7). The significance of hypothesis H7 points out

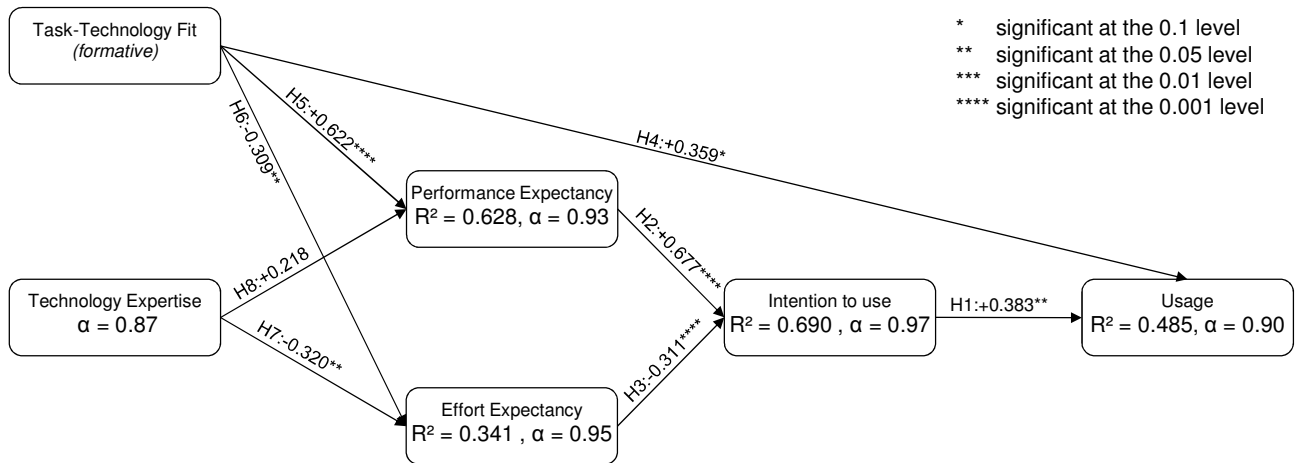


Figure 1. Results of the structural model

Usage	Loading	t-value
For what percentage of your orders (number of orders) do you use Algorithmic Trading at all?	0.946	52.522
For what percentage of your transaction value do you use Algorithmic Trading at all?	0.926	37.143
We regularly use Algorithmic Trading.	0.856	21.423
Intention	Loading	t-value
We intend to use Algorithmic Trading.	0.961	32.009
We intend to use Algorithmic Trading as often as suitable.	0.984	117.687
To the extent possible, we would use Algorithmic Trading frequently.	0.980	71.768
Performance Expectancy	Loading	t-value
Using Algorithmic Trading allows reducing overall trading costs.	0.908	32.799
Using Algorithmic Trading enables our trading desk to be more successful.	0.869	17.653
Using Algorithmic Trading preserves portfolio alpha.	0.854	14.972
Using Algorithmic Trading increases quality of execution.	0.819	12.543
Using Algorithmic Trading gives (will give) us a competitive advantage.	0.956	86.013
Effort Expectancy	Loading	t-value
Setting up an Algorithmic Trading Solution is so complex, that it is not worth the effort.	0.931	23.196
Setting up the staff resources for Algorithmic Trading is so costly, that it is not worth the effort.	0.921	29.769
Setting up the technological infrastructure for Algorithmic Trading is so costly, that it is not worth the effort.	0.948	33.317
It takes too long to setup an Algorithmic Trading Solution to make it worth the effort.	0.928	33.602
It takes too long to learn how to use Algorithmic Trading to make it worth the effort.	0.816	17.443
Technology Expertise	Loading	t-value
We are familiar with Algorithmic Trading.	0.962	50.050
We are aware of the advantages and disadvantages of Algorithmic Trading.	0.944	33.214
We have the skills to use Algorithmic Trading.	0.765	4.685
Task-Technology Fit (formative)	Weight	t-value
Algorithmic Trading is suitable for the characteristics of our order flow.	0.320	2.072
Algorithmic Trading satisfies our requirements concerning high anonymity demands.	0.137	0.905
Algorithmic Trading satisfies the requirements of our investment strategy(s).	0.536	2.896
Algorithmic Trading satisfies our requirements for more trading control.	0.320	1.861

Table 2. Items used

that knowledge and skills concerning the technology significantly lower the complexity and the associated costs of introducing the Algorithmic Trading solution. Further this knowledge exhibits a positive impact on the Performance Expectancy. However, as no direction had been hypothesized for this impact (H8) a two-sided test has to be applied which slightly fails to determine significance ( $p=0.125$ ). If the direction of the effect could have been hypothesized the path would have been significant at the 10% level.

The Stone-Geisser criterion for prognostic relevance  $Q^2$  gives a measure of how well the empirically retrieved manifest variables can be explained by the determined model (Stone 1974, Geisser 1974). A good prognostic relevance requires  $Q^2 > 0$ , which is given for all constructs of the model. Further the effect size  $f^2$  proved to be well for all hypothesized paths according to the values recommended by Cohen (1988, p.413/4) who suggested 0.02, 0.15, and 0.35 as definitions of small, medium and large effect sizes. H5 and H2 showed to have a large effect size, H3 a medium effect size while all others showed small effect sizes.

## 6 CONCLUSION

In the context of a technology-driven change currently happening to the value chain in securities trading, this survey among the process owners of the top European buy-side institution was designed to explain their adoption decision concerning the IT innovation of Algorithmic Trading taking into account their appraisal of the potential performance gains and efforts associated with the adoption. The underlying causal model successfully integrated components of the Task-Technology Fit model with core constructs of the Unified Theory of Acceptance and Use of Technology. This might be a fruitful proposal for further research, as all but one hypothesized effect proved to be significant.

In particular the fit between the technology of Algorithmic Trading and the task to be fulfilled by the buy-side institutions, i.e. their order flow, proved to be a very important construct in directly or indirectly explaining the actual use of Algorithmic Trading solutions. On the one hand its significant direct impact on usage shows a similar strength as the intention to use construct. On the other hand it also shows strong indirect effects on usage, as it exerts strong and significant impact both on Performance Expectancy as well as Effort Expectancy. In particular the very strong effect on the Performance Expectancy is of interest as this construct in turn also exhibits a very strong and significant effect on the intention to use. The expectations concerning improved performance are primarily grounded on potential cost savings which are also seen to provide a competitive advantage. Although also the Effort Expectancy strongly and significantly impacts the intention, the even stronger effect of Performance Expectancy seems to be the main driver for the Intention to use. This indicates that for the respective process owners the perceived performance gains by far outweigh the perceived potential effort associated with the adoption. Further the construct Technology Expertise showed good effects on both Performance and Effort Expectancy. Process owners that are familiar with the concepts of Algorithmic Trading and deem themselves to have sufficient skills to make use of it have a lower Effort Expectancy. As no direction for the effect of Technology Expertise on Performance Expectancy was hypothesized this path coefficient could not prove to be significant. Following the conclusion of Goodhue et al. (2006) it would be incorrect to conclude that no such effect exists. Due to the small sample size the power of the test is too low to significantly detect weak effects.

There may be other constructs that may affect the adoption of innovative technology in the field of securities trading, such as Algorithmic Trading. Therefore future research might incorporate further variables into the research model. As particularly the expected effort associated with the adoption of Algorithmic Trading solutions could only be partially explained, it became obvious that there have to be additional factors that exert an impact on the perceived effort. Such factors might be different facets of risk perceived to be associated with the adoption of Algorithmic Trading solutions.

## Limitations

The low number of responses, which is due to institutions' policy to not participate in surveys, might have an impact on the results obtained. Following the conclusion of Goodhue et al. (2006) it is not valid to conclude from the non-significant path from Technology Expertise to Performance Expectancy that such an effect does not exist.

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