

2008

Investigating the Buy-Side's Adoption Decision for Technology-Driven Execution Opportunities: An Extension of TAM for an Organizational Adoption Context

Bartholomäus Ende

Johann Wolfgang Goethe-University, ende@wiwi.uni-frankfurt.de

Markus Gsell

Johann Wolfgang Goethe-Universität Frankfurt am Main, markus.gsell@gmx.net

Follow this and additional works at: <http://aisel.aisnet.org/ecis2008>

Recommended Citation

Ende, Bartholomäus and Gsell, Markus, "Investigating the Buy-Side's Adoption Decision for Technology-Driven Execution Opportunities: An Extension of TAM for an Organizational Adoption Context" (2008). *ECIS 2008 Proceedings*. 158.
<http://aisel.aisnet.org/ecis2008/158>

This material is brought to you by the European Conference on Information Systems (ECIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ECIS 2008 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

INVESTIGATING THE BUY-SIDE'S ADOPTION DECISION FOR TECHNOLOGY-DRIVEN EXECUTION OPPORTUNITIES

An extension of TAM for an organizational adoption context

Ende, Bartholomäus, E-Finance Lab, Johann Wolfgang Goethe-University, Robert-Mayer-Straße 1, 60054 Frankfurt, Germany, ende@wiwi.uni-frankfurt.de

Gsell, Markus, Johann Wolfgang Goethe-University, Robert-Mayer-Straße 1, 60054 Frankfurt, Germany, gsell@wiwi.uni-frankfurt.de

Abstract

Within the securities trading industry recent technological innovations enable Institutional Investors to self-directed trading and thus lead to a reassessment of their intermediation relationships. This may yield to an in-sourcing of trading activities by buy-side organization. Scientific literature outlines advantages and disadvantages of some of them but no empirical investigations are reported concerning drivers for the adoption or refusal of such innovations. Against the background of the increasing market share of technologies, such as Algorithmic Trading, this conceptual paper introduces a model that aims at closing this gap, by identifying the drivers and inhibitors for the adoption of new technology-based execution opportunities. To account for the organizational context of the survey and the meta-character of the innovation, the model incorporates the following modifications of TAM: First, a generalization towards TRA and TPB in order to account for competitive pressure and inhibitors. Second, the integration of TTF, as it is said to exhibit better results for work-related tasks and thus enables the model to account for the fit between the technology and the given task requirements. Finally, a perceived risk construct is added, as in an organizational context the adoption of innovations is associated with risks.

Keywords: ADOPTION MODELS, INFORMATION SYSTEMS INNOVATION, ADOPTION AND DIFFUSION, ADOPTION.

1 INTRODUCTION

Increasing demands on promptness and cost efficiency along with technological advances lead to a dramatic revolution in the way trading is conducted on international securities markets. New technology-driven execution opportunities enabled buy-side¹ companies to perform self-directed trading and thus satisfy their demand for more execution control. Institutional Investors gain more independence from brokers, their traditional channels for order execution. Thus, a trend towards consolidation, new co-operation and co-opetition models as well as a refocus on value generation and innovation during trading activities has been initiated.

Typically buy-side companies trade large quantities and thus require suitable counterparties. 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. *Volume discovery*, i.e. to find a counterparty that wants to trade similar quantities, is therefore an important issue for Institutional Investors. In the past, orders were delegated to (human) brokers whose core competency is the handling of the buy-side's order flow. They then aimed at finding a suitable execution of the incoming orders. Alternatively, brokers also provide the opportunity of a principal bid where they grant full execution at a predefined price for a negotiated commission. Nowadays new trading developments expand the decision set for organizations which seek for more trading control in order to reduce their implicit trading costs. One alternative is provided by *Crossing Networks*, e.g. ITG's POSIT, which are non-transparent order book systems that match hidden orders at a price imported from a liquid and transparent reference market. Smart Order Routing technology allows to automatically search fragmented liquidity across multiple venues and to route suborders to the most appropriate venue combination. Algorithmic trading models provide yet another opportunity to bring large orders to transparent markets and to minimize the market impact at the same time, as they are slicing large orders into a multiplicity of smaller ones and time their individual submission. Based on mathematical models and considering historical and real-time market data, algorithmic trading models determine ex ante or continuously the optimum size of the (next) slice and its time of submission to the market. Such systems have been used internally by sell-side firms for years; recently they have become available to their buy-side customers. Based on the sell-side business model of a virtual *Direct Market Access* orders are not touched by brokers anymore but are forwarded directly to the markets. With the automation of the slicing and timing tasks, the speed of execution and the prompt availability of real-time market data become success factors.

For a decision whether the above mentioned trading technologies shall be adopted by an Institutional Investor it is also necessary to consider the investments for infrastructure as well as operational costs like potential membership fees and data subscriptions (Ende et al. 2007). The objective of this research is to identify factors that foster adoption or refusal of technological innovations, such as Algorithmic Trading Solutions and non-delegated order handling, which equals an in-sourcing of trading activities by buy-side organizations.

Definition 1: Algorithmic Trading

“Algorithmic Trading” emulates a broker’s core competence of slicing a big order into a multiplicity of smaller orders and of timing these orders to minimise market impact via electronic means (Gomber & Gsell, 2006, p.541). The term “Algorithmic Trading Solution” refers to sophisticated software

¹ Buy-side refers to investment management companies that are “buying” trading services from the sell-side, i.e. investment banks and brokers (Harris 2003).

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.

Definition 2: Non-delegated order handling

The term “non-delegated order handling” refers to order execution where a buy-side firm does not delegate execution responsibility to an intermediary but controls the choice of trading venue, order slicing and timing. This is achieved by a self-directed decision to apply technologies like Direct Market Access, Algorithmic Trading or Smart Order Routing.

To accomplish the aforementioned investigation purpose the rest of this conceptual paper is structured as follows: Section two provides a brief overview of related literature from domain specific as well as IS related literature. Then section three introduces the model that shall be utilized within the survey’s analysis. The subsections of the fourth section describe the latent constructs of the research model in more detail by outlining what they stand for, how they capture it and their supposed impact on other constructs. Finally, section five provides a brief outlook on upcoming research steps.

2 COMPARISON WITH EXISTING RESEARCH

Up to now, there is no extensive research concerning automated implementations of timing and slicing strategies. Barclay & Warner (1993) and Chakravarty (2001) address the strategic fragmentation of orders and the influence of trade sizes on price movements. Literature on the concept of Algorithmic Trading focuses on the investors’ perspective. Yang & Jiu (2006) propose a framework to help investors to choose the most suitable algorithm. These algorithms can be distinguished by their underlying benchmark, their trading style or aggressiveness (Kissell & Malamut 2006). Domowitz & Yegerman (2005) examine the execution quality of algorithms in comparison to traditional brokers’ offering. They conclude that e.g. VWAP algorithms on average have an underperformance of 2bps. Nevertheless, this underperformance can be overcompensated by the fact that algorithms can be offered at lower fees than human stealth trading. Morris & Kantor-Hendrick (2005) address some abstract factors that shall be regarded when deciding whether to build or buy an Algorithmic Trading Solution: trading style and frequency, the investment in technology infrastructure, regulatory obligations and the traders’ experience as well as technological proficiency. Further, surveys like Edhec-Risk (2005) and Financial Insights (2006) provide a descriptive perspective but do not identify drivers.

Schwartz & Steil (2002) as well as Steil & Perfumo (2003) indicate that unbundling of commissions and the usage of upcoming venues lead to significant decreases in trading costs. He et al. (2006) have shown that order preferencing exhibits negative effects on execution quality, which motivates the usage of non-delegated order handling. Furthermore, the results of Battalio et al. (2002) indicate that a strategic routing of orders, e.g. via smart order routing might improve execution quality. Although such trading innovations have been investigated from multiple viewpoints the focus of the academic investigations is set on individual advantages and disadvantages of trading innovations. An extensive literature review on these individual aspects can be found in Ende et al. (2007). Altogether, trading innovations offer a wide range of advantages for the buy-side but no causal model has been developed so far that tries to explain their adoption. Merely Khalifa & Davison (2006) investigate the adoption of electronic trading systems by the sell-side. But, for the cases of non-delegated order handling and Algorithmic Trading the buy-side’s adoption differs in several aspects: First, trading is traditionally outsourced to brokers so that the adoption corresponds to an insourcing by the means of new trading technologies which bears risks. Further, many buy-side companies are engaged in soft commissions that oblige them to trade via their brokers which constitutes contractual barriers. Finally it is necessary to assess whether these technologies are suitable as for the buy-side the adoption is not value-creating per se. Thus, some buy-side companies still rely exclusively on brokers for their trading task. Altogether, there is need for a scientific explanation of an organization’s decision to adopt or refuse such innovations.

In IS literature the investigation of technology adoption is a well established research area. One of the most prominent research models for this purpose is the Technology Acceptance Model (TAM) by Davis (1989). It focuses on the individual usage of innovations and has been successfully employed for multiple domains (Venkatesh et al. 2003, Legris et al. 2003). An extensive overview of the main drivers concerning innovation adoption is provided by Jeyaraj et al. (2006). Frambach et al. (2002) investigate drivers and inhibitors for organizational innovation adoption and identify further need to investigate especially the “*non-adoption of innovations*” (p.172), which is reflected in the research approach presented in section 3. Compared to traditional TAM research which lets individuals use an innovation and then tries via the help of their assessments to predict whether they will adopt it in the future (drivers for future user behavior), this research is distinct in the following aspects: First, it aims at identifying factors that have driven organizations in the past to adopt or refuse a technological innovation (drivers for past user behavior). Second, according to DiMaggio & Powell (1983) and Khalifa & Davison (2006) it incorporates different pressures that influence the organization’s adoption decision. As the adoption affects the core business, risk is included. Further, inhibitors like contractual barriers may prevent organizations from adoption and are therefore considered as well. Finally, our model addresses via Goodhue & Thompson’s (1995) theory of Task-Technology Fit (TTF) the fact that an innovation’s benefit depends on the organization’s demands.

3 GENERAL MODEL OVERVIEW

The research model (Figure 1) consists of the well-known blocks TAM, theory of reasoned action (TRA), theory of planned behavior (TPB) as well as TTF. These are complemented by a perceived risk construct.

TAM has been applied to a wide range of domains and has become an acknowledged tool in IS research. Starting in its initial domain, it has been used “*to predict information technology acceptance and usage on the job*” (Venkatesh et al. 2003, p.428). In recent years TAM has been applied in a more general context to a variety of (acceptance) decisions. E.g. Money (2004) applied TAM to a Knowledge Management System and Benamati & Rajkumar (2002) investigate the applicability of TAM in the context of an outsourcing decision. Venkatesh et al. (2003) give a broad overview of different theories and models that were applied in the context of user acceptance of IS. As their work generalizes different models and reveals the common roots of similar constructs we decided to stick to their terminology. Therefore, the TAM constructs ‘perceived usefulness’ and ‘perceived ease of use’ are termed ‘*Performance Expectancy*’ (Section 4.4) and ‘*Effort Expectancy*’ (Section 4.5) respectively in our model. Their definitions of the constructs have been generalized, as this work addresses an organizational decision process and not decisions made by individuals. These constructs affect the ‘*Attitude towards use*’ (Section 4.3) construct. Further, the influence of performance expectancy on ‘*Intention to Use*’ (Section 4.2) that shall finally predict the actual ‘*Usage*’ (Section 4.1) is mediated by attitude towards use.

TAM itself is “... *an adaptation of TRA (...) which is specifically meant to explain computer usage behavior*” (Davis et al. 1989, p.983). While TAM omitted the ‘subjective norm’ construct originally specified in TRA, it is re-introduced in our model. In the original TRA ‘subjective norm’ is defined as a person’s “*belief that important others think he should or should not perform a given behavior*” (Fishbein & Ajzen, 1975, p.401). As our research does not address individuals but organizations, the scope of this definition has been broadened to the perception of ‘*Pressure*’ (Section 4.6) to perform or not perform a given behavior exerted by important groups, i.e. competitors and customers. Ajzen (1991) extended the original TRA to TPB in order to break the “*original model’s limitations in dealing with behaviors over which people have incomplete volitional control.*” (p.181). Mathieson (1991) conducted a comparison of TAM and TPB and found that both models work well with slight empirical advantages for TAM. However, the comparison has been based on a survey among individuals so that TPB could not take advantage of its strengths. In contrast to Mathieson (1991) our model integrates both theories, as it has a TPB model that captures attitude/intention in the way TAM

does. In TPB the corresponding construct to measure volitional behavior is termed ‘perceived behavioral control’. In accordance with this extension (contractual) ‘Inhibitors’ (Section 4.7) are taken into account that might constrain the organization’s ability to decide unbiased about its behavior.

Although TAM is well established it has some limitations. E.g. Dishaw & Strong (1999) point out that it does not consider task characteristics and thus does not explicitly take into account whether a technology fits given tasks requirements. This issue is addressed by TTF theory. For the organizational level the requirement for such a fit seems also to prevail, as e.g. Weill & Olson (1989) reveal that within IS contingency research over 70% of the studies followed a model that assumes that the better the fit among contingency variables, the better the performance. On the other hand the TTF model lacks attitudes toward IT. Thus Dishaw & Strong (1999) integrate both models, which yields superior results for the adoption of software maintenance tools. Later, the validity of their combined model has been successfully extended by Klopping & McKinney (2004) to the domain of e-commerce. This integrated TAM-TTF approach is adapted here. From its TTF part the ‘Task Characteristics’ (Section 4.9) and ‘Task-Technology Fit’ (Section 4.8) constructs are taken without any modifications. As Algorithmic Trading and non-delegated order handling do not refer to concrete tool but instead to meta-technologies some adjustments have been conducted: First, the scope of the ‘Technology’ construct (Section 4.10) has been broadened and ‘tool experience’ has been generalized to ‘Technology Expertise’ (Section 4.11). Adopting innovations typically bears risks for organizations. Due to the fact that in our context risk affects the core business of the organizations – namely their trading performance – perceived risk is expect to be crucial for the decision to adopt or refuse Algorithmic Trading or non-delegated order handling. Therefore, ‘Perceived Risk’ (Section 4.12) is captured in a separate construct.

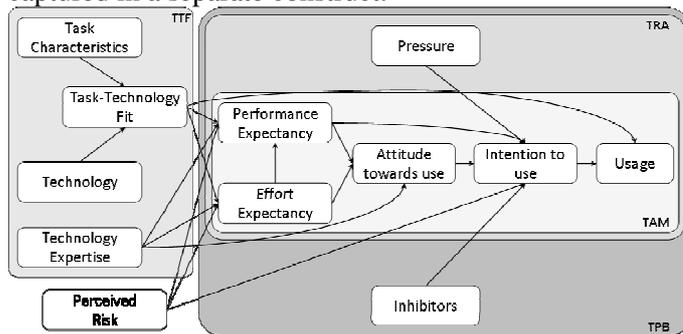


Figure 1. Research Model

4 LATENT CONSTRUCTS

4.1 Usage

The construct usage measures the actual utilization of the system along three dimensions derived from Thompson et al. (1991). They include *intensity* defined as the share of workload for which the system is used, *frequency* to reflect the regularity of usage of the system and finally *diversity* which captures the variety of system types used to cover the multitude of tasks.

4.2 Intention to use

Intentions in our model are in accordance with existing literature on TAM, TRA and TPB, as they “...are assumed to capture the motivational factors that influence a behavior; 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 behavior”(Ajzen 1991, p.181). The intention to use construct shall measure the determination of a subject to act in a certain way. In the context of this survey the intention of an

investment firm to make use of a new technology – non-delegated order handling or Algorithmic Trading – is regarded. To evaluate the construct four dimensions are used, namely the intended intensity, the intended frequency, the intention to use in the near future and the determination of the intention. Intentions are expected to possess a positive impact on the actual usage (Ajzen 1991).

4.3 Attitude towards use

“Attitude toward using technology is defined as an individual’s overall affective reaction to using a system” (Venkatesh et al. 2003, p. 455). 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. Davis et al. (1989) find that attitude does not fully mediate the role of perceived usefulness on intention. Thus, they suggest a parsimonious TAM that removes the attitude construct and is common in literature (e.g. Venkatesh et al. 2003). As more recent research finds the effect of attitude on intention to be quite important (Dishaw & Strong 1999, Mathieson et al. 2001) we incorporate attitude to our TAM part. For its operationalization items from Mathieson (1991) and Mathieson et al. (2001) are used. Attitude is expected to possess a positive impact on the intention to use (Mathieson et al. 2001).

4.4 Performance Expectancy

The performance expectancy construct is defined as the degree to which an organization expects that using the system will enhance its performance. It measures the performance improvements that are expected to be realized by non-delegated order handling or Algorithmic Trading. The name performance expectancy has been adopted from Venkatesh et al. (2003), as it better suits the context of this survey. However, it corresponds to the perceived usefulness construct of TAM. It shall be evaluated along the following three dimensions:

- Perceived Usefulness: The degree to which an organization believes that a particular system will increase its task performance
- Extrinsic Motivation: The degree to which an activity is performed by an organization *“because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself”* (Venkatesh et al. 2003, p. 448)
- Relative Advantage: *“The degree to which using an innovation is perceived as being better than using its precursor”* (Moore & Benbasat 1991, p. 195)

Due to previous results performance expectancy is supposed to be the strongest predictor for the attitude towards use construct (e.g. Mathieson et al. 2001, Venkatesh et al. 2003). The better the expected performance of the technology is, the more distinct the attitude towards use and the more the intention to use will be. This positive influence is confronted with the effort expectancy construct defined in the following section. Balancing those two beliefs is at the core of TAM.

4.5 Effort Expectancy

Equivalent to the cognitive cost/benefit framework (e.g. Christensen-Szalanski 1978) the effort expectancy construct constitutes the effort component. Therefore, it is designed to measure *“the degree of ease associated with the use of the system”* (Venkatesh et al. 2003, p. 450). To meet the requirements of the model’s organizational context, this construct is designed to capture not only the ongoing effort associated with the use, but also the initial one-off effort of adopting the system. One-off effort accounts for the requirements to setup the respective knowledge, infrastructure and resources in terms of staff. For similar reasons as for the performance expectancy the name of the construct has been adopted from Venkatesh et al. (2003), although it corresponds to TAM’s ease of use. It shall be evaluated along the following three dimensions:

- Information Provision: The degree to which information about the advantages and disadvantages of the innovation in question is perceived as difficult to obtain

- Implementation Complexity²: The degree to which an innovation is perceived as difficult to setup
- Ease of use: *“The degree to which using an innovation is perceived as being difficult to use”* (Moore & Benbasat 1991, p. 195)

Previous research has shown that ‘effort expectancy’ negatively impacts ‘performance expectancy’ (e.g. Davis et al. 1989) as well as the ‘attitude towards use’ (e.g. Mathieson et al. 2001). Although this influence is significant it is said to decrease with deepening experience with the technology (Venkatesh et al. 2003, Klopping & McKinney 2004).

4.6 Pressure

In TRA subjective norm refers to perceived social pressure to either conduct or not conduct a certain behavior. In an organizational context, there are three isomorphic pressures (DiMaggio & Powell, 1983): mimetic, coercive and normative pressure. The indicator mimetic pressure shall measure how strong organizations are pushed *“... to conform with the industry practices of their significant competitors”* (Khalifa & Davison 2006, p. 279). Coercive pressure shall measure the pressure *“...exerted on organizations by other organizations upon which they are dependent”* (DiMaggio & Powell 1983, p. 150), i.e. in our context the organization’s customers demanding adoption of the innovation. Normative pressure is not applicable in our context, as customers or suppliers can not adopt the innovation. Further, pressure caused by a competitive environment is supposed to positively influence the intention to use an innovation which provides a competitive advantage (Robertson & Gatignon 1986, Frambach et al. 1998).

4.7 Inhibitors

Similar to the perceived behavioral control construct of TPB, inhibitors shall capture all factors that constrain the organization in their volitional behavior. As Ajzen (1991) states, most behavior depends *“at least to some degree on such non-motivational factors as availability of requisite opportunities and resources”* (p. 182). It is measured by contractual inhibitors, lack of top management support, lack of standardization and unavailability of staff resources. Empirical confirmation for contractual inhibitors can be found e.g. in Schwartz & Steil (2002). They identify, that 14% of portfolio managers actually predefine the broker to be used and 64% reward a broker’s research by choosing the broker for execution, which limits the actual choice of execution venues. Top management support is said to be one of the best predictors for innovation adoption (Jeyaraj et al. 2006, Lucas 1981, Cervený & Sanders 1986). Innovation diffusion literature points out that a lack of standardization inhibits innovation adoption (Robertson & Gatignon 1986). Inhibitors restrict volitional behavior and therefore are supposed to have a negative impact on the intention to use (Ajzen 1991).

4.8 Task-Technology Fit

For work-related tasks the concept of TTF is said to be more effective than TAM (Dishaw & Strong 1999). It 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 (Gebauer & Ginsburg 2006, Dishaw & Strong 1998). Unfortunately, items which 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). Their proposed interaction term for fit is not feasible for our domain, as it requires well established models for the task

² Based on Rogers & Schoemaker’s (1971) concept of complexity

and technology in question. To our knowledge these do not exist for the domain of securities trading. Thus, similar to Goodhue (1995) a separate fit construct is defined. It consists of three indicators: First, compatibility reflects how well the innovation is matching the individual difficulties of the task. This corresponds to the technical perspective of Tornatzky & Klein's (1982) interpretation of Rogers & Schoemaker's (1971) definition of compatibility as "*the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters*". Second, flexibility captures the fit concerning the variety of tasks. Finally, control relates to the degree of fit concerning the requirements for trading control.

TTF is expected to directly positively affect the actual usage and indirectly affect it via the TAM variables of performance and effort expectancy. The first is positively and the later negatively affected (Dishaw & Strong 1999).

4.9 Task Characteristics

As each technological trading innovation leads only for specific order characteristics to superior results (Ende et al. 2007) and the task characteristics are key for the definition of fit, it is necessary to identify the most prominent requirements of the task. Thus, this construct shall reflect the most relevant order characteristics. Trading, i.e. the implementation of an Institutional Investor's investment decision consists of six steps: First, within a pre-trade analysis information is gathered to be used in the second step which determines an appropriate execution strategy. For Algorithmic Trading the former incorporates the choice of an algorithm. Then a suitable execution venue is selected. In the fourth step a suitable communication channel to the venue is chosen. The fifth step monitors the order execution to enable appropriate reactions. Finally, within a post-trade analysis the outcomes will be evaluated. In each step the objective is to identify the option that optimally suits the individual order's specific characteristics.

Fry & Slocum (1984) propose a task characterization along the three dimensions of difficulty, variety and interdependence which is commonly employed (e.g. Goodhue 1995, Goodhue & Thompson 1995). Non-routine orders lead to higher costs (Bikker et al. 2004, Keim & Madhavan 1998) concerning the identification of liquidity, i.e. finding adequate counterparties (Schwartz & Francioni 2004). To capture the difficulty of the order flow, four aspects are considered: order size, urgency demands, sensitivity concerning information leakage as well as the distribution among capitalization classes. The variety dimension is intended to capture the workload's predictability. Therefore, it aims at outlining the heterogeneity of the order flow among assets classes, different investment strategies as well as the aforementioned order difficulty aspects. The interdependence dimension has been proposed to measure whether "*...one or more discrete operations has consequences for the completion of others*" (Fry & Slocum 1984, p. 225). In our context it is to capture whether the order flow contains trades whose outcomes might influence each others (e.g. basket trades) and hence requires a high level of control concerning order execution. Due to this broader focus it is renamed to control.

As common in TTF literature, task characteristics are expected to have an effect on task-technology fit (e.g. Goodhue 1995, Dishaw & Strong 1999). For Algorithmic Trading this effect is expect to be negative, as Domowitz & Yegerman (2005) have shown that the overall cost savings from the omitted broker intermediation diminish for increasing order sizes. For non-delegated order handling expectations are ambiguous. On the one hand Transaction Cost Economics (Williamson 1975) suggests that the more specific the task, the more suitable it is to be not delegated to a third party. On the other hand, trading is the core competency of brokers and because of their expertise in identifying suitable counterparties the toughest orders should be delegated to them.

4.10 Technology

To calculate the task-technology-fit the technology construct complements the task characteristics (Goodhue 1995). It captures the specific capabilities (advantages/disadvantages) of the technology. To

accordingly reflect the dimensions of the task characteristics the utilized measures are functionality, flexibility and controllability. Functionality aims at capturing the abilities of the technology concerning the task difficulties. The technology's flexibility is to address the capabilities of handling the variety of tasks, i.e. the heterogeneity of the order flow. The controllability refers to the level of control provided by the technology. In addition to the aforementioned aspects, trialability and visibility are added. Trialability is defined as the "... *degree to which an innovation may be experimented with on a limited basis*" (Rogers & Shoemaker 1971, p.155). Due to the option of utilizing systems offered by brokers, Algorithmic Trading exhibits this characteristic. As non-delegated order handling requires technical infrastructure and skilled staff, it bears one-off costs which limit its trialability. Theoretically this is said to lower its expected rate and speed of adoption (Tornatzky & Klein 1982, p.38). Visibility shall capture the extent to which the effects of applying the technology are visible to the adopting organization. The technology construct is expected to have a positive effect on task-technology fit (e.g. Goodhue 1995, Dishaw & Strong 1999).

4.11 Technology Expertise

As in this research no specific tool is investigated the TTF's tool experience construct has been changed to a more general technology expertise construct. Similar to e.g. Dishaw & Strong (1999) it has been extended by abilities specific to the organization. Overall, it now accounts for the organization's experiences as well as general aversion or affection concerning technology. These factors are measured on three increasing levels of expertise: First, as generalization of Goodhue's (1995) task literacy, innovation literacy is supposed to measure whether the organization is familiar with the innovation and has already considered its adoption. For the next higher level the concept of computer self-efficacy (Compeau & Higgins 1995, Compeau et al. 1999) has been considered. Here, self-efficacy shall measure whether the organization is confident to adopt the technology without external expertise concerning IT or trading issues. The third and highest level of expertise is based on computer/tool experience by Goodhue & Thompson (1995) and Smith et al. (1999). It shall capture the present IT as well as the trading experience within an organization. The larger the experience with and affection for technology is, the smaller the expected effort and the larger the expected performance is supposed to be (Strong et al. 2006, Jeyaraj et al. 2006). Further, experience is supposed to possess a positive impact on attitude (Mathieson et al. 2001).

4.12 Perceived Risk

As in the organizational context of this research risk affects the organizations' core business – namely their trading performance – perceived risk is expected to be crucial for the adoption. In line with Gewald et al. (2006) risk is generally defined as "...*the potential for an undesired outcome due to uncertainty about future developments*" (p. 81). From Featherman & Pavlou (2003) the following three risk facets have been adopted: First, performance risk, which refers to the risk that the advantages expected, will not materialize. Second, financial risk captures that the actual costs may exceed the planned/budgeted costs. Third, overall risk accounts for the organizations' general risk perception. Like Gewald et al. (2006) a strategic risk facet capturing the risk of lock-in situations is employed. The perceived risk construct shall express the expectation that perceived risks associated with the adoption have strong influences on the intention to use, as well as the performance expectancy (Lee et al. 2001, Featherman 2001) and effort expectancy (Johnson 2005).

5 FUTURE RESEARCH STEPS

This conceptual paper introduces a model that aims at identifying the drivers and inhibitors for the adoption of new technology-based execution opportunities. As the survey shall be conducted in an organizational rather than individual context, the model incorporates some modifications to TAM: First, to account for competitive pressure and inhibitors a generalization towards TRA as well as TPB

has been performed. Second, TTF has been integrated to the model as it is said to exhibit better results for work-related tasks. This overcomes the lack of TAM to account for the fit between the technology and the given task requirements. Third, as in an organizational context the adoption of innovations is associated with risks the model is extended by a perceived risk construct. Finally, on the construct level further generalizations have been employed in order to reflect the meta-character of the innovations in question.

As the benefits of adopting non-delegated order handling or Algorithmic Trading are subject to economies of scale, the largest European buy-side companies will form the target group. Within a contact data base, that has been provided by Thompson Financial GmbH, the top 500 buy-side institutions in terms of asset under management cover more than 96% of the assets managed in Europe. Thus this group forms the survey sample. In late 2007 pretests based on the recommendations of Yin (1994) were conducted with selected companies from the target group in order to ensure the comprehensiveness and completeness of the questionnaire. Currently the actual survey is conducted with support from the European Fund and Asset Management Association (EFAMA). For the organizational perspective within each company one of the following persons is addressed: the Head of Trading, Chief Investment Officer, Portfolio Manager or a Trader.

Acknowledgment

We thankfully acknowledge the support of the E-Finance Lab, Frankfurt for this work.

References

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50 (2), 179-211.
- Barclay, M. and Warner, J. (1993). Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics*, 34 (3), 281-305.
- Battalio, R.; Greene, J.; Hatch, B. and Jennings, R. (2002). Does the Limit Order Routing Decision Matter? *The Review of Financial Studies*, 15 (1), 159-194.
- Benamati, J. and Rajkumar, T.M. (2002). A Design of an Empirical Study of the Applicability of the Technology Acceptance Model to Outsourcing Decisions. *Proc. of the 2002 ACM SIGCPR conference on Computer personnel research*, 52-57.
- Bikker, J.A.; Spierdijk, L. and van der Sluis, P.J. (2004). The Implementation Shortfall of Institutional Equity Trades. *EFA 2004 Maastricht Meetings Paper No. 1813*.
- Cerveny, R. P. and Sanders, G. L. (1986). Implementation and structural variables. *Information and Management*, 11 (4), 191-198.
- Chakravarty, S. (2001). Stealth Trading: Which traders' trades move prices? *Journal of Financial Economics*, 61 (2), 289-307.
- Christensen-Szalanski, J. J. J. (1978). Problem Solving Strategies: A Selection Mechanism, Some Implications, and Some Data. *Organizational Behavior and Human Performance*, 22 (2), 107-122.
- Compeau, D.R. and Higgins, C.A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS Quarterly*, 19 (2), 189-211.
- Compeau, D.; Higgins, C.A. and Huff, S. (1999). Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study. *MIS Quarterly*, 23 (2), 145-158.
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13 (3), 319-340.
- Davis, F.D.; Bagozzi, R.P. and Warshaw, P.R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, 35 (8), 982-1003.
- Di Maggio P.J. and Powell, W. W. (1983). The iron cage revisited. *Institutional Isomorphism and Collective Rationality in Organizational Fields*. *American Sociological Review*, 48 (2), 147-160.
- Dishaw, M.T. and Strong, D.M. (1998). Supporting software maintenance with software engineering tools: A Computed task-technology fit analysis. *Journal of Systems and Software*, 44 (2), 107-120.

- Dishaw, M.T. and Strong, D.M. (1999). Extending the technology acceptance with task-technology fit constructs. *Information and Management*, 36 (1), 9-21.
- Domowitz, I. and Yegerman, H. (2005). The Cost of Algorithmic Trading – A First Look at Comparative Performance, In Brian R. Bruce (Ed). *Algorithmic Trading: Precision, Control, Execution*, Institutional Investor Inc. 30-40.
- EdHec-Risk Advisory (2005). European Buy-Side survey – A step into the 21st century.
- Ende, B.; Gomber, P. and Wranik, A. (2007). An Order-Channel Management Framework for Institutional Investors. *Proc. of the 8. Internationale Tagung WI 2007*, Vol. 2, 705-722.
- Featherman, M.S. (2001). Extending the Technology Acceptance Model by Inclusion of Perceived Risk. In *Proc. AMCIS*, 758-760.
- Featherman, M.S. and Pavlou, P.A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59 (4), 451-474.
- Financial Insights (2006): *Marching Up the Learning Curve: The Second Buy Side Algorithmic Trading Survey*, Financial Insights Special Report, December 2006.
- Fishbein, M. and Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior. An Introduction to Theory and Research*, Addison-Wesley - Reading, Mass..
- Frambach, R.T.; Barkema, H.G.; Nooteboom, B. and Wedel, M. (1998). Adoption of a Service Innovation in the Business Market An Empirical Test of Supply-Side Variables. *Journal of Business Research*, 41 (2), 161-174.
- Frambach, R.T. and Schillewaert, N. (2002). Organizational innovation adoption – A multi-level framework of determinants and opportunities for future research. *Journal of Business Research*, 55 (2), 163-176.
- Fry, L.W. and Slocum, J.W. (1984). Technology, Structure, and Workgroup Effectiveness: A Test of a Contingency Model. *Academy of Management Journal*, 27 (2), 221-246.
- Gebauer, J. and Ginsburg, M. (2006). Exploring the Black Box of Task-Technology Fit: The Case of Mobile Information Systems, Working Paper 06-0120, University of Illinois, College of Business, Access Date: 03/28/2007, http://www.business.uiuc.edu/Working_Papers/papers/06-0120.pdf
- Gewald, H.; Wüllenweber, K. and Weitzel, T. (2006). The Influence of Perceived Risks on Banking Managers' Intention to Outsource Business Processes - A Study of the German Banking and Finance Industry. *Journal of Electronic Commerce Research (JECR)*, 7 (2), 78-96.
- Gomber, P. and Gsell, M. (2006). Catching up with technology – The impact of regulatory changes on ECNS/MTFs and the trading venue landscape. *Competition and Regulation in Network Industries*, 1 (4), 535-557.
- Goodhue, D.L. (1995). Understanding User Evaluations of Information Systems. *Management Science*, 41 (12), 1827-1844.
- Goodhue, D.L. and Thompson, R.L (1995). Task-technology fit and individual performance. *MIS Quarterly*, 19 (2), 213-236.
- Harris, L. (2003). *Trading and Exchanges: Market Microstructure for Practitioners*. Oxford University Press, New York.
- He, C.; Odders-White, E. and Ready, M.J. (2006). The impact of preferencing on ecution quality. *Journal of Financial Markets*, 9 (3), 246–273.
- Iivari, J. (1992). The organizational fit of information systems. *Journal of Information Systems*, 2 (1), 3-29.
- Jeyaraj, A.; Rottman, J.W. and Lacity, M.C. (2006). A review of the predictors, linkages, and biases in IT innovation adoption research. *Journal of Information Technology*, 21(1), 1-23.
- Johnson, A. (2005). The Technology Acceptance Model and the Decision to Invest in Information Security. *Proc. of the 2005 Southern Association of Information Systems Conference*, 114-118.
- Keim, D. and Madhavan, A. (1998). The Cost of Institutional Equity Trades. *Financial Analysts Journal*, 54 (4), 50-69.
- Khalifa, M. and Davison, R.M. (2006): SME Adoption of IT: The Case of Electronic Trading Systems. *IEEE Transactions on Engineering Management*, 53 (2), 275-284.
- Kissell, R. and Malamut, R. (2006). Algorithmic Decision-Making Framework. *Journal of Trading*, 1 (1), 12-21.

- Klopping, I. and McKinney, E. (2004). Extending the Technology Acceptance Model and the Task-Technology Fit Model to Consumer E-Commerce. *Information Technology, Learning, and Performance Journal*, 22 (1), 35-48.
- Lee, D.; Park, J. and Ahn, J. (2001). On the explanation of factors affecting e-Commerce adoption. *Proc. of the Twenty-Second International Conference on Information Systems*, 109-120.
- Legris, P.; Ingham, J. and Colletette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management*, 40 (3), 191-204.
- Lucas, H. C. (1981). *Implementation: The key to successful information systems*, McGraw-Hill, NY.
- Mathieson, K. (1991). Predicting User Intentions: Comparing the Technology Acceptance Model with the Theory of Planned Behavior. *Information Systems Research*, 2 (3), 173-191.
- Mathieson, K.; Peacock, E. and Chin W. W. (2001). Extending the Technology Acceptance Model: The Influence of Perceived User Resources. *ACM SIGMIS Database*, 32 (3), 86-112 .
- Money, W. (2004). Application of the Technology Acceptance Model to a Knowledge Management System, *Proc. of the 37th HICSS*.
- Moore, G.C. and Benbasat, I. (1991). Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Information Systems Research*, 2 (3), 192-222.
- Morris, D. and Kantor-Hendrick, L. (2005). Key Considerations in Selecting an Algorithmic Trading Provider. In Brian R. Bruce (Ed.). *Algorithmic Trading: Precision, Control, Execution*, Institutional Investor Inc, 20-28.
- Robertson, T. S. and Gatignon, H. (1986). Competitive Effects on Technology Diffusion. *Journal of Marketing*, 50 (3), 1-12.
- Rogers, E.M. and Shoemaker, F. (1971). *Communication of Innovations*, The Free Press, New York.
- Schwartz, R.A. and Francioni, R. (2004). *Equity Markets in Action: The Fundamentals of Liquidity, Market Structure & Trading*. Wiley Trading, New Jersey.
- Schwartz, R.A. and Steil, B. (2002). Controlling institutional trading costs: We have met the enemy, and they are us. *Journal of Portfolio Management*, 28, 39-49..
- Smith, B.; Caputi, P.; Crittenden, N.; Jayasuriya, R. and Rawstorne, P. (1999). A review of the construct of computer experience. *Computers in Human Behavior*, 15 (2), 227-242.
- Steil, B. and Perfumo, D. (2003). *The Economics of Soft Dollar Trading*, Efficient Frontiers, NY.
- Strong, D.M.; Dishaw, M.T. and Bandy, D.B. (2006). Extending task technology fit with computer self-efficacy. *SIGMIS Database* 37(2-3), 96-107.
- Thompson, R.L.; Higgins, C.A. and Howell, J.M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly*, 15 (1), 124-143.
- Tornatzky, L. and Klein, K. (1982). Innovation Characteristics and Innovation Adoption Implementation: A Meta-Analysis of Findings. *IEEE Transactions on Engineering Management*, 29 (1), 28-43.
- Venkatesh, V.; Morris, M.G.; Davis, G.B. and Davis, F.D. (2003). User Acceptance of Information Technology: Towards a unified view. *MIS Quarterly*, 27 (3), 425-478.
- Venkatraman, N. (1989). The Concept of Fit in Strategy Research: Toward Verbal and Statistical Correspondence. *The Academy of Management Review*, 14 (3), 423-444.
- Weill, P. and Olson, M.H. (1989). An assessment of the contingency theory of management information systems. *Journal of Management Information Systems*, 6 (1), 59-85.
- Williamson, O.E. (1975). *Markets and Hierarchies: Analysis and Antitrust Implications*. The Free Press, New York.
- Yang, J. and Jiu, B. (2006). Algorithm Selection: A Quantitative Approach. In Brian R. Bruce (Ed.). *Algorithmic Trading II: Precision, Control, Execution*, Institutional Investor Inc, 26-34.
- Yin, R. (1994). *Case study research: Design and methods* 2nd Edition. Thousand Oaks, CA, Sage Publishing.