NETWORK EFFECTS IN TECHNOLOGY ACCEPTANCE: LABORATORY EVIDENCE

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NETWORK EFFECTS IN TECHNOLOGY ACCEPTANCE: LABORATORY EVIDENCE

Les "network effects" dans l'acceptation technologique: preuves de laboratoire

Completed Research Paper

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Abstract

This research analyzes network effects in technology acceptance, on the hypothesis that the larger is user network, the more likely is technology acceptance. Still today, empirical measurement of network effects is challenging and there is a lack of experimental evidence, particularly in technology acceptance research. To overcome this limitation we reproduce a particular class of technology acceptance processes in a laboratory experiment, controlling for the user network size to verify if it can make a difference in user perceptions and, ultimately, in acceptance decisions. We measured user perceptions and analyzed the data set using standard technology acceptance models. The experiments confirm our working hypothesis, showing a significant role of network effects on key user perceptions influencing technology acceptance.

Keywords: Technology acceptance, network effects, network externalities, laboratory experiment.

Résumé

Cette recherche prend en considération les "network effects" dans l'acceptation technologique, avec une expérience de laboratoire. L'expérience montre qu'il est possible d'avoir une influence significative des "network effects" dans certains processes d'acceptation technologique.

Abstract in Italian

Questo lavoro prende in esame gli effetti rete nell'accettazione tecnologica, con un esperimento di laboratorio. L'esperimento mostra che è possibile avere una significativa influenza degli effetti rete in alcuni processi di accettazione tecnologica.

Introduction

In this empirical study we investigate the influence of network effects on technology acceptance. Network effects (or network externalities[1]) occur when users are directly or indirectly connected in a network of relationships, experiencing growing benefits as the number of connections in the network increases.

Technology acceptance is basically a choice among different candidate technologies/tools (like software applications or computer systems) to accomplish a user task. This fundamental choice was object of much research, often based on theory of technology acceptance (Davis et al. 1989; Venkatesh et al. 2003). However, the theory of technology acceptance does not explicitly take into account network effects.

This research work is based on the expectation that the candidate technology with a larger user network could be favoured in comparison with the candidate technology with a smaller user network, because users may experience growing benefits with an increasing user network size.

Until now, this issue has never been explicitly addressed in technology acceptance models for several reasons. 1) Technology acceptance models have been first proposed, in the late 1980s, when network technologies (and effects) were much less developed and recognized. 2) Network effects have been mainly investigated in Economics, at the macro-economic level, whereas technology acceptance processes have been investigated in Information Systems, at the individual level. The two aspects have never been integrated. 3) Empirical measurement of network effects is difficult and there is a lack of empirical evidence.

The investigation described here is based on data from laboratory experiments, reproducing the technology acceptance process under network effects of different intensity. The expected evidence of a significant role of network effects in user choice will actually be confirmed by the data, not without some unexpected outcomes.

This empirical study is resting on two main theoretical pillars: the theory of technology acceptance, and the studies on network effects/externalities.

Technology Acceptance Model (TAM)

Understanding why people accept or reject technologies has proven to be one of the most challenging issues in information systems (IS) research: along the last twenty years technology acceptance has been among the most investigated topics in information systems. The theory of technology acceptance was initiated in 1989, introducing

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[1] Network externalities are a particular type of network effect. The differences between network externalities and network effects, end their implications, are discussed in (Liebowitz and Margolis 1994). We are taking into account all kinds of network effects (not just network externalities), but an explicit discussion of this aspect is not relevant to our analysis.

the so-called "Technology Acceptance Model" (TAM: (Davis 1989; Davis et al. 1989)). As of April 2008, (Davis 1989) had collected 3578 citations according to Google Scholar. This makes (Davis 1989) the most cited paper on IS development and use since 1989, and probably one of the most widely cited contributions at all in Information Systems. There are even journals (like Information & Management) with a constant coverage of TAM-related literature. A meta-analysis of 88 empirical works based on TAM (King and He 2006) appeared recently, finally stating that TAM has become an established and robust model, with wide, and potentially wider, applicability.

Two aspects of the TAM-related theories and models are probably at the origin of their success in the academy: its simplicity and its potential (King and He 2006).

TAM is simple: TAM sheds some light on a complex phenomenon (technology acceptance) on the basis of just two fundamental factors: the perceived "ease of use" and "usefulness" of the system. A TAM investigation is natural and immediate: through standard questionnaires and statistical analysis tools, researchers can easily take rigorous measures of individual perceptions to build standard structural equation models.

TAM has a wide potential for application: a good model of technology acceptance may result in an invaluable help for making better systems, that would be more promptly and easily accepted by potential users. To recall Davis group's words, "computer systems cannot improve organizational performance if they aren't used" (Davis et al. 1989:982).

In (Lee et al. 2003) a general overview of the chronological progress of TAM research in the last twenty tears is provided. Four sequential phases are identified: 1) model introduction, from (Davis 1989) to (Taylor and Todd 1995); 2) model validation, from (Adams et al. 1992) to (Davis and Venkatesh 1996); 3) model extension, from (Straub 1994) to (Gefen et al. 2003); 4) model elaboration, from (Venkatesh and Davis 2000) to (Venkatesh et al. 2003). Along this way, several additions and extensions were included in the original model. In (King and He 2006) a simple depiction is proposed based on four main groups of additional factors, visualized here in Figure 1: Besides the original TAM core, (in the center), it is possible to distinguish 1) prior factors; 2) factors suggested from other theories; 3) contextual factors, and 4) consequent factors.

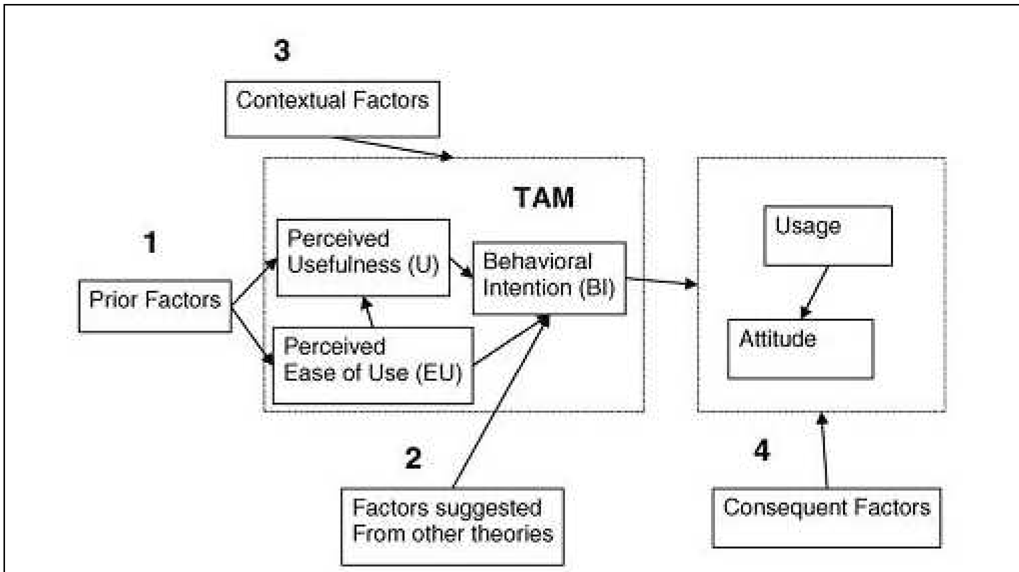

Figure 1. The original TAM model and 4 categories of modifications. Source: (King and He 2006:741).

All in all, TAM research covered quite a long way since its first introduction. Additional constructs for user perceptions, attitudes, and beliefs were proposed in order to better explain acceptance. The most significant contributions were recently integrated in a unified theory of acceptance, including constructs like "attitude towards technology", "social influence", "facilitating conditions", "self-efficacy", and "anxiety" (cf. (Venkatesh et al. 2003) and references therein).

Though widely used and investigated in the academy, there are strong concerns that TAM models (at the current state of the art) could realize their high potential, which is hampered by two major limitations: the lack of explanatory power and, most important, the limited practical value of current TAM applications.

Lack of generality in explanatory power

Recent meta-analyses evidenced that TAM studies in general are able to explain only around 40% (Legris et al. 2003) or 50% (King and He 2006) of the variance of technology acceptance. One of the most recent and credited extensions, the UTAUT model, reports an explained variance of use of 47% (Venkatesh et al. 2003).

Limited practical value of current TAM applications

A simple statement (given by a respondent to a recent survey on TAM among leading IS researchers) can easily express this point: "Imagine talking to a manager and saying that to be adopted technology must be useful and easy to use. I imagine the reaction would be « Duh! The more important questions are what makes technology useful and easy to use » " (Lee et al. 2003:766). A good model should not only predict acceptance well. It should also show ways to improve it: "If the models do not supply information that can guide development, they will not be useful to systems analysts, no matter how well they predict intention (to use a technology)" (Mathieson 1991:174).

In definitive, the strongest aspects of TAM –simplicity, generality and potential value for application- are also at the roots of its major weakness: the lack of good performances and useful indications for practice. TAM is easy to apply, but too general and shallow to be practically useful for predicting actual use and for designing better systems. Technology acceptance decision processes are complex and various: the richness and diversity of technology acceptance scenarios in terms of different users, systems, tasks, and goals poses serious challenges to any attempt of universal explanation into a single (and simple) model.

TAM for network effects: divide et impera

As pointed out by recent research on system usage (Burton-Jones and Straub Jr 2006), acceptance processes for particular class of systems/tasks/goals may be different. In consequence they may require different models. According to the thoughtful analysis by Andrew Burton-Jones and Detmar Straub, the nature of the task is actually one of the three fundamental dimensions characterizing system usage and acceptance: user, task, and system ((Burton-Jones and Straub Jr 2006:233), Table 1). One special category of acceptance processes could then be characterized by the existence of network effects affecting the user/task/system dimensions.

If different classes of systems, tasks and goals may lead to different acceptance decision processes, then a sensible research strategy could be based on distinguishing different models for different classes of processes, instead of aiming at a single universal TAM. Such a *divide et impera* research strategy could help improving the TAM approach, trading off generality for performance, but keeping the resulting specific models at the high level of simplicity typical of TAM. Actually, the idea that technology acceptance could vary in function of the user task has been already explored with the so called "Task-Technology Fit" (TTF: (Goodhue 1995; Goodhue and Thompson 1995)), a quite complex universal model trying to take into account general characteristics of systems and tasks. There is some evidence that technology acceptance may benefit from integration with TTF: see e.g. ((Dishaw and Strong 1999; Fang et al. 2006)). But approaches like TTF and TTF-TAM are actually rather difficult to implement in practice; moreover, the loss in simplicity is not compensated by a significant gain in explanatory and predictive performance. Instead, our *divide et impera* research strategy is aimed at taking into account the influence of different user tasks and goals keeping the model as simple as the original TAM.

In order to formulate a new specific TAM model focused only on the class of processes showing network effects, a brief analysis of extant literature on network effects is proposed in what follows.

Studies on Network Effects/Externalities

Network effects and network externalities have been widely debated and investigated: the most well known and comprehensive literature reviews published in the last 20 years in this area include (David and Greenstein 1990; Economides 1996; Farrell and Klemperer 2007; Stango 2004). As an indication of the richness of studies in this area (Farrell and Klemperer 2007) alone takes into account over 470 different contributions. One of the most influential early studies on network externalities is (Katz and Shapiro 1985). Their incipit is often quoted as a definition of network externality: "There are many products for which the utility that a user derives from consumption of the good increases with the number of other agents consuming the good" (p. 424). Katz and Shapiro propose a formal economic model of oligopolistic markets in presence of network externalities, showing two main results: 1) the role of consumer expectations for the selection of the dominant seller "if consumers expect a seller to be dominant, then consumers will be willing to pay more for the firm's product, and it will, in fact, be dominant" (p. 425); 2) the need for social incentives for achieving product compatibility "we find that in our model the firms' joint incentives for product compatibility are lower than the social incentives" (p. 425).

Another famous account of the economic issues related with network externalities is given in (Farrell and Saloner 1985). Many studies followed these two seminal papers. Network effects theories and related issues were popularized by the widely-cited account of Brian Arthur in Scientific American (Arthur 1990). More recently, (Katz and Shapiro 1994) took into account the so called "systems markets", involving products intimately related and working together, like hardware and software within a standard system architecture (e.g. PC vs Mac software). The success of a new product is actually bound to the success of the entire system/architecture, with network effects playing a strong role. In particular, three orders of decision are influenced by network effects: technology adoption decisions, product selection decisions and compatibility decisions. Again, the analysis is purely theoretical, based on existing studies and findings, but with no direct empirical support.

While many economic studies have been proposed for theoretical development, empirical evidence on network effects is much more scattered, and based on indirect approaches to measurement. (Schilling 2002), for example, by using survey data addressing multiple products and industries, showed that the installed base (among other factors like availability of complementary goods, a firm's learning orientation and timing of entry) can play a significant role in market success. This noticeable study was preceded by a few other empirical studies limited to a single product category, as noticed by the author herself: "owing to the difficulty of gathering suitable data, most of the empirical work on network externalities has focused on a single product category; Gandal's (1994) and Brynjolfsson & Kemerer's (1996) studies of spreadsheet software, Wade's (1995) study of microprocessors, and Shurmer's (1993) work on prepackaged PC software are examples" (Schilling 2002:388).

However, an accurate measurement of network effects would involve an accurate measurement of:

- the "installed base" (number of product users)
- some proxy for "consumer utility", or perceived user benefits.

None of the preceding studies could actually give a definitive solution to these two measurement issues: for example, (Schilling 2002) uses a 7-points Likert scale for installed base (ranging from 1=very large to 1=small installed base). She does not measure user benefits at all, giving just a raw indication of "product success/failure".

As another example, (Brynjolfsson and Kemerer 1996) investigate the relationship between market prices and installed base in the spreadsheet market, finding a significant, but only indirect empirical evidence of network effects: "our model suggests that the positive network externality effects [...] are approximately as important as any of the intrinsic product features" (p. 1644). Their measure of installed base is based on "unit sales", but as a proxy of "consumer utility" they can only find a very indirect (and potentially biased) estimate using product prices.

All in all, extant literature on network effects has a rich tradition of sophisticated economic models and simulations showing the theoretical relevance of user network size in the market diffusion of competing technologies and systems under various different assumptions and initial conditions. Such works are quite inspiring for the investigator interested in technology acceptance, suggesting that network effects could actually matter. To a certain degree, the "social influence" construct, present in some technology acceptance models (see e.g. (Venkatesh et al. 2003)), may partially contribute to explain acceptance due to an increased user network size. Nevertheless, it may be difficult to distinguish this largely unknown dimension of social influence from the most important dimensions due to behavioral expectations, power relationships and other organizational and social factors, which are not necessarily related with the user network size, but are the most theoretically prominent in previous studies.

Therefore, much space is left for further exploration of open issues on the following aspects:

- How to characterize and select the specific class of technology acceptance decision processes that are expected to show network effects, as opposed to different technology acceptance decision processes?
- How to operationalize and measure network effects?
- How to empirically test the influence of network effects on the selected class of technology acceptance decision processes?

The experimental design proposed in the following section is aimed at investigating these issues still left open by extant literature.

Research Design Strategy

For what discussed above, an investigation on network effects in technology acceptance should deal with the following aspects: 1) selecting the right class of technology acceptance processes 2) measuring network effects 3) empirically testing for network effects in technology acceptance.

Selecting a class of technology acceptance processes

The benefits due to a growing user network size could affect technology acceptance in different ways for different classes of systems/tasks/goals. One example of systems/tasks/goals associated with network effects is the choice of PC/Windows versus Apple Macintosh systems for personal computing, or the choice of eBay versus Yahoo auction systems: it is evident that, *ceteris paribus*, user acceptance choices are influenced in favor of the systems, like PC/Windows and eBay, with the biggest installed bases and user networks, because of the important benefits associated with the biggest "markets" like a wider potential software application portfolio or a higher probability to find a good buyer/seller at a convenient auction price.

On the other side, there are classes of systems/tasks/goals, in which the existence of a "market" associated with a user network is not necessarily relevant for user acceptance: for example the choice of using or rejecting a system internally developed in a factory, say, for controlling specific production machineries is going to be heavily influenced by the specific technical features of the system itself (like e.g. effects on productivity, quality, failure rate, etc.); conversely, in such a case the existence of a big network of external users is not probably going to play a decisive role for system choice.

Focusing on tasks/goals, and trying to generalize, it is possible to imagine various types of exemplary tasks/goals significantly influenced by network size:

- Transactional, market-exchange tasks, with benefits generated by availability of a growing market size for transactions (e.g. e-marketplaces, electronic commerce, electronic trading, banking etc.).
- Communication tasks, with benefits generated by growing number of actors and information available to communicate (like making telephone calls, sending fax messages, sending emails etc).
- Learning tasks where an exchange of knowledge is required, with benefits generated by wider availability of knowledge and learning opportunities (e.g. consulting within a community of practice/professionals).
- Secondary tasks where an exchange of goods/information/knowledge is often beneficiary as a complement to the main task, with benefits generated by opportunities for market transactions, communication, or learning (e.g. writing documents of spreadsheets and exchanging files with other users, using a computer systems with a wide third-party/software application market, etc.).

On the other side, user tasks and goals of different nature are not necessarily influenced by network effects, like for example simple, independent and well-known information processing tasks (e.g. math, accounting, computer graphics, application software development), not requiring communication/exchange with other users.

Extant literature is not much helpful for characterizing a general user task in terms of its "market degree". There is a long tradition of organizational studies on task analysis, especially with regard to task complexity (Campbell 1988; Wood 1986). Task complexity has been theoretically related to Group Support Systems (GSS) (Zigurs and Buckland 1998), showing how GSS may give different basic types of group support (communication, information processing, and process structuring) in correspondence with different categories of task complexity (simple tasks, problem tasks, decision tasks, judgment tasks, fuzzy tasks). Some studies as (Mennecke et al. 2000; Wageman 1995) are taking into account user and/or task interdependencies in a way potentially fruitful to our aim. But these concepts would require a much deeper theoretical elaboration, with multiple levels of analysis, possibly along the way pointed out by the enlightening and deep conceptualization recently proposed in (Burton-Jones 2005), (Burton-Jones and Gallivan 2007). Such an effort is here devoted to further research; in this contribution, the methodological choice of the laboratory experiment allows us to expressly design a few exemplar "market-like" tasks with some of the characteristics described here above.

Measuring network effects

Measurement of network effects in technology acceptance lacks established metrics and research protocols. Without tested metrics and protocols, accounting for network effects in technology acceptance poses the problem of how to effectively detect user perceptions of benefits specifically due to the user network size within the complex web of user perceptions, attitudes and beliefs, avoiding any bias from contextual factors.

A straightforward strategy in the context of TAM would be to simply measure the user "utility" or "benefits" in terms of changes in "perceived usefulness" and "perceived ease of use", the two well developed and widely tested constructs in technology acceptance research.

Testing for network effects

Therefore, a simple strategy for producing and testing empirical evidence for network effects in technology acceptance could be based an testing whether, *ceteris paribus*, user benefits in terms of changes in "perceived usefulness" and "perceived ease of use" would be determined by a growing user network size.

To this aim, a laboratory experiment may be a powerful methodological choice to control for network effects and isolate them from contextual factors: the basic "ingredients" of system usage and technology acceptance (a user, a user task, different candidate systems/technologies (Burton-Jones and Straub Jr 2006:233)) can be carefully replicated with different user network sizes, in order to observe and study network effects.

Experimental Design: Task and System Description

The laboratory experiment is well known in IS research: see e.g. (Silver 1988), (Vance Wilson and Zigurs 1999). Also some TAM research was based on lab experiments: In a selection of 101 TAM studies, 86 were recently classified as field studies, 12 as laboratory experiments and 4 as qualitative studies (Lee et al. 2003). What is quite peculiar here is the reproduction of a technology with a "paper and pencil" system. In facts, to simplify the experimental setting, a decision was taken to build and compare very simple "paper and pencil" systems instead of traditional IT systems like word processing or spreadsheet software applications.

In facts in many cases, as observed above, the benefits of a growing user network are much more related to the nature of the user task than to the technicalities of the underlying system. For example, even the simplest system, like paper and pencil, may show quite important network effects if the underlying task requires a market exchange, like a boy having to exchange his double cards with friends: the dimension of his group of friends is relevant for the perceived benefits, more than the system (IT-based or not) used to negotiate and exchange his cards.

In consequence, the *rationale* for an experimental design is straightforward: one of the simplest possible "market-like" tasks could be just inspired by card games in which users have to exchange doubles with other users. A system where a (sub)task like "exchanging cards" is present could be a good basis to design an exemplary acceptance process including "market-like" tasks.

As noticed above, the basic "ingredients" of acceptance are a user, a user task, and different candidate technologies/systems. In our experiment, the user task consists of reconstructing an image by using different systems, i.e. different simple "mosaics".

System description: mosaic

Each "mosaic" had been prepared in advance, cutting a color image in 16 equal size, squared pieces (cards) within a regular 4x4 grid. During the experiment, the user task is to recompose individually the image by putting cards together on the grid. The initial 16-card user kit contains 8 missing cards and 8 repeated cards. In more detail, each kit is composed by 6 couples, 1 triple and 1 single card. In consequence, only 8 single cards can be directly used for image composition (12/2+3/3+1/1); the remaining 8 cards have to be exchanged. Users can exchange cards with other users, but one at a time. The "user network" is defined by the group of users who are allowed to exchange cards with each other. The missing cards in each kit are to be found in the other kits in the user network.

Task description: reconstructing an image using cards

The user has to get the 8 missing cards by exchanging the 8 multiples with other users in the network. Then, he has to position the available cards on the table grid. For each correctly positioned card, a few points are scored. The objective is to totalize the maximum score by a fully reconstructed image in the minimum time.

The task has two subtasks:

- locating and obtaining all the 16 necessary cards, by exchanging the 8 doubles with other users in the network;
- putting the 16 cards together to rebuild the original image.

Different type of mosaics, i.e. different technologies/systems, have been tested by users for comparative evaluation and final acceptance.

A simple feature, i.e. using numbered cards, (where card number indicates the correct card position on the table grid), may lower task complexity by making cards easier to distinguish/recognize, to name and find when exchanging, and to dispose on the table grid. The natural expectation is that a system based on numbered cards with a lower task complexity should be perceived as easier to use. On the other way, systems with higher scores for each card would improve the final user score, resulting in higher levels of expected perceived usefulness.

The choice of the task to be accomplished in the experiment was specifically done to control for network size: in facts, the need to exchange doubles with other users is much better fulfilled in a large user network than in a small one. The probability to find and get the right cards by exchanging doubles is proportional to the number of users available, i.e. to the size of the user network. In turn, the user benefit in terms of final scores is also growing with the probability of getting the right cards.

Designing "systems" with different expected levels of EASE OF USE

To obtain different levels of ease of use, we built two different versions of the experiment. One is based on an “easier" system (i.e. with lower task complexity), presenting a numbered grid to recompose the image, and a sequence number behind each card, in order to facilitate image composition by suggesting the correct card locations. The second version of the experiment is based on a “more difficult” system (i.e. with higher task complexity), with no numbers behind cards and on the grid.

Designing "systems" with different expected levels of USEFULNESS

In order to obtain different levels of usefulness, we used different scores: a more useful system attributed 5 points to each card (5x16=80 points), plus a bonus for the completed picture of 50 points, for a total maximum score of 130 points. A less useful system attributed only 4 points to each card (4x16=64 points) plus a 40 points bonus, for a total maximum score of 104 points.

The idea is that a typical user would associate a higher usefulness to the system enabling her to better accomplish her task, i.e. to maximize the final score.

Controlling the USER NETWORK SIZE

As discussed above, by design the task was highly influenced by network effects: at start, users were given 8 doubles. To be able to correctly recompose the original image, they had to exchange doubles with other users. We could control the user network size with two different configurations: a 20-nodes network vs four independent 5-nodes networks. In the first configuration all the 20 users were able to exchange cards with no limits in a fully connected network. In the second configuration the 20 users were divided in 4 independent sub-networks of 5 users each. In this case, each user could exchange doubles only with the 4 colleagues in his sub-network. Notice that the cards missing in each user kit (randomly assigned) are certainly present within the 20-nodes network, but after splitting the network, there is no guarantee for a user to find her missing cards in her own sub-network.

Tuning and initial testing

A first set of experiments was directed to the tuning and validation of the experimental design. In a correctly designed experiment, user perceptions for usefulness and ease of use should be in line with what expected "by design" for the different systems. The tuning and initial testing experiments confirmed our expectations: the results are not shown here, due to space limitations; for more details see (Pontiggia and Virili 2005). In this phase also an appropriate standard time interval for the execution of all the experiments was defined.

Research Hypotheses

In order to empirically test for network effects in technology acceptance, we formulated a set of research hypotheses in line with the *divide et impera* strategy discussed above. No universal claim on technology acceptance is advanced here. We are not going to show that network effects always matter in technology acceptance. We are going to test whether networks effects could matter for some acceptance processes, involving "market-like" tasks. Therefore, the hypotheses are formulated using a "can be" formula:

Hypothesis 1. *Some technology acceptance processes can be influenced by network effects.*

Network effects may also have a positive impact on perceived usefulness:

Hypothesis 2. *Perceived USEFULNESS can be positively influenced by network effects.*

The influence on perceived ease of use could be positive. Sometimes in facts a big user community can help and facilitate system adoption and usage in many ways, including more effective learning and knowledge sharing. On the other side, when a system is used in interaction with a large network of users, actual system usage could be more complex and difficult, due to transaction costs including interaction, search, negotiation and similar activities. In this regard, a negative influence of network effects on perceived system ease of use could be expected. The overall influence is therefore uncertain. We advance here that the prevailing pattern would be positive:

Hypothesis 3. *Perceived EASE OF USE can be positively influenced by network effects.*

Finally, network effects may also positively influence the behavioral intention to use the system:

Hypothesis 4. *BEHAVIORAL INTENTION of acceptance can be positively influenced by network effects.*

Data Collection

Experiments were organized for groups of 20 users. Users were students who volunteered at different locations (University of Cassino, both in Cassino and in Terracina; University of Lugano). We measured and collected user perceptions using standard TAM (Davis et al. 1989) and UTAUT (Venkatesh et al. 2003) questionnaires.

In particular, in a preliminary set of experiments, we used the whole 31-items questionnaire of the "Unified Theory of Acceptance and Use of Technology" (UTAUT) as from (Venkatesh et al. 2003:460).

In the following set of experiments, to facilitate user comparison of different systems, we reduced the number of items in the questionnaire from 31 to 11. Each item of the standard TAM questionnaire was duplicated in two columns side-by-side, in order to allow an easy comparative evaluation of the same system with different levels of network effects. The measurement scale was the same adopted in the original sources: a Likert scale with numeric values ranging from 1 (strong agreement) to 7 (strong disagreement). The questionnaires are available at request from the authors. To measure the influence of network effects, the same card system was tested by the same 20 users for two consecutive times. The 20 users were disposed in a room, in 4 rows of 5 users, with tables and chairs. Each user was given a user kit with a mosaic and 16 cards. Everybody could move and talk around the room. In the first round, all the 20 users could freely exchange doubles with all the other ones, in a fully connected 20-node network. In the second round, each user could exchange doubles only with the other four colleagues in his row. The original user network was now split in four smaller 5-node networks.

The two rounds, during a few minutes each, were executed in sequence. At the end of the second round, each of the 20 users filled the questionnaire, introducing comparative evaluations for the "systems" tested in the first round and in the second round. We accepted the risk of introducing some bias in the experiment by allowing each user to play two times in sequence, because we wanted to explicitly model the acceptance choice as a comparative evaluation between alternative systems for accomplishing a given task. This aspect, quite novel in TAM research, is more elaborated in the discussion. The meaning of the evaluation was briefly explained to the users before distributing the questionnaires. With the first 8 question items they had to evaluate usefulness and ease of use of the two alternative "ways" to accomplish their task (maximizing scores) experienced in the two rounds. In the last three question items they had to formulate an intention of acceptance for each of the two "systems". We clearly explained what had to be intended in the TAM questionnaire with "system" and "task" with reference to the experiment. We did not suggest any specific meaning for "usefulness" and "ease of use".

In the preliminary set of experiments we used three different systems: P1, P2, and F (see (Pontiggia and Virili 2005) for details). For each system we made in this stage three experiments with high network effects (a single 20-node user network). We collected 56 (out of 60=20*3) valid questionnaires for F and P1, 55 for P2. We then conducted an additional experiment with system F and low network effects (four 5-node user networks), resulting in 56 valid questionnaires. In total we collected 56*3+55 = 223 valid questionnaires in the preliminary phase. We collected 40 valid questionnaires in the second set of experiments with system F and high network effects, and 39 additional valid cases with low network effects, for a grand total of (223+79) = 302 valid cases.

Data Analysis and Results

Expected results are that different levels of network effects could influence user perceptions and their behavioral intention of acceptance. As explained above in more detail, each user had to test the same "system" (mosaic) for two times: a first time with the possibility to freely exchange doubles within a network of 20 users (high network effects). A second time, the exchange was limited to 4 separate “sub-networks" of only 5 users each. (low network effects). After two successive rounds of experiments, each user could express in the comparative TAM questionnaire the perceived values of "usefulness" and "ease of use" for the two alternative "systems" and formulate an intention of acceptance for each one. The collected data were then checked and analyzed according to well established statistical methods based on structural equation models (SEM). In our case the two structural equation models were built and analyzed using the commercial software package AMOS rel. 4 (Arbuckle 1999).

A first strategy to check for the influence of network effects was to build two separate TAMs and compare the outcome. To this aim we could use 56 valid questionnaires from the first set of experiments and 39 from the second set, for a total sample of 95 observations for each TAM[2].

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[2] For this particular hypothesis testing, the number of available observations (95) is actually much lower than the minimum usually suggested in structural equation modelling (around 15 observations per variable = 15*(4+4+3) = 165). Therefore, the results should be considered with some caution. In presence of such a small sample, the two models were particularly sensible to perturbations in the sample distributions; it was also necessary to take into account a certain (abnormal) degree of correlation between "usefulness" and "ease_of_use" (shown in the models with an arrow connecting the two latent variables). In any case, statistical tests for relative fit were quite good (RMSEA = 0.03 and Tucker-Lewis Index = 0.99 for both the models).

In the two rounds, at a few minutes distance, no "traditional" condition of acceptance had presumably changed: users, tasks, and "systems", were exactly the same. All the context factors were eliminated and could not alter the outcome. The only changing condition was the dimension of the two users networks, a factor not explicitly accounted for in theory of technology acceptance. If the second TAM changed, this should be necessary due to network effects, confirming H1: *Some technology acceptance processes can be influenced by network effects*.

Data seem to suggest that this is what actually happened. Figure 2 here below shows the results obtained with the two TAMs. The first TAM, visible on the left side, is referred to the experiments with 4 small separated groups of 5 users freely exchanging doubles. All the regression weights have correct sign, and they are all statistically significant at the 0.05 level, with the exception of the relationship between "ease_of_use" and "behav_intention", displayed with a dotted line because non significant (p value = 0,16). Given the small sample, (see note 2) and the fact that the non- significant value is close to the 10% level, this outcome might be regarded as substantially in accord with acceptance theory. The second TAM, visible on the right side, is referred to the experiments with a fully connected network of 20 users freely exchanging doubles. The regression weights have correct sign, but their values are changed, in comparison with the previous TAM. Particularly evident are the statistical relationships between the constructs "usefulness" and "behav_intention" and between the constructs "ease_of_use" and "behav_intention": both the weights are now closer to 0 (0.13 and 0.11 respectively) and highly non-significant (p values of 0.4 and 0.5). The key statistical relationship linking user behavioral intention with the two fundamental TAM constructs for user perceptions is here now contradicted by data. Therefore, *H1 is CONFIRMED*.

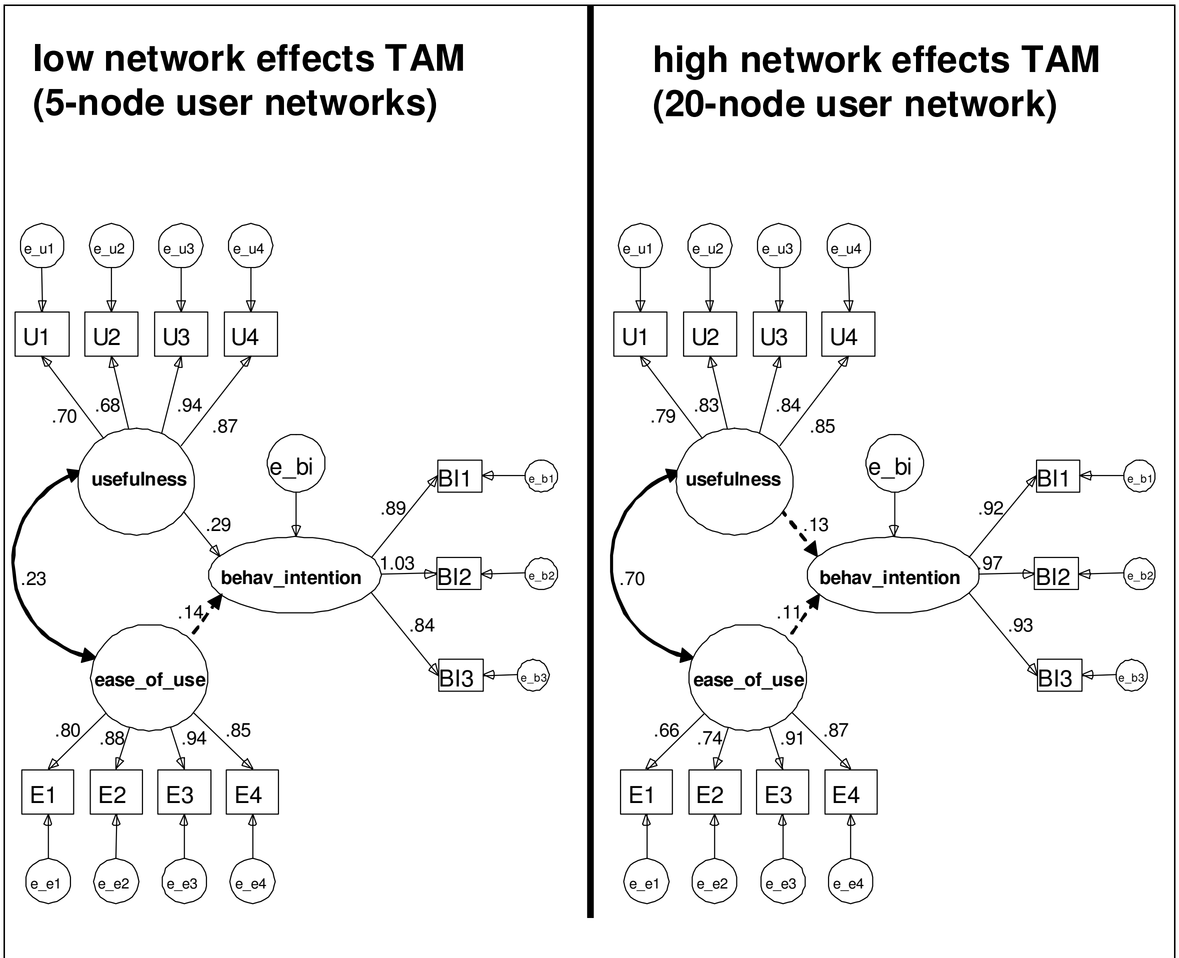

Figure 2. Structural equation models of the two technology acceptance experiments, including the main regression weights (standardized values). At left, low network effects (four 5-node user networks); at right, high network effects (a single 20-node user network).

According to the data, network effects seem to heavily influence the acceptance process. Even with the necessary caution, suggested by the small sample size, it is quite evident from figure 2 that in presence of higher network effects (larger user network: right side TAM), and in absence of any other change, the usual determinants of the behavioral intention of acceptance are somehow perturbed. How? An answer can be obtained by testing for hypotheses H2-H4.

Testing for hypotheses 2-4

A second strategy to get a deeper understanding of network effects' influence is to introduce network effects as a moderator in the TAM and check for its statistical relationships with the main constructs. Therefore, we added to the data set a new dummy variable called "net_effects", scaled to the same range of all the other variables. We used now the whole available data set collected during several sessions of experiments with 3 different system types, both in presence and in absence of network effects, accounting for 303 valid cases, a statistical sample now over the minimum typically required. A new TAM was computed using this data set, including the moderator "net_effect". The statistical relationships of "net_effects" with the three main constructs of the TAM were estimated and tested, according to hypotheses H2-H4.

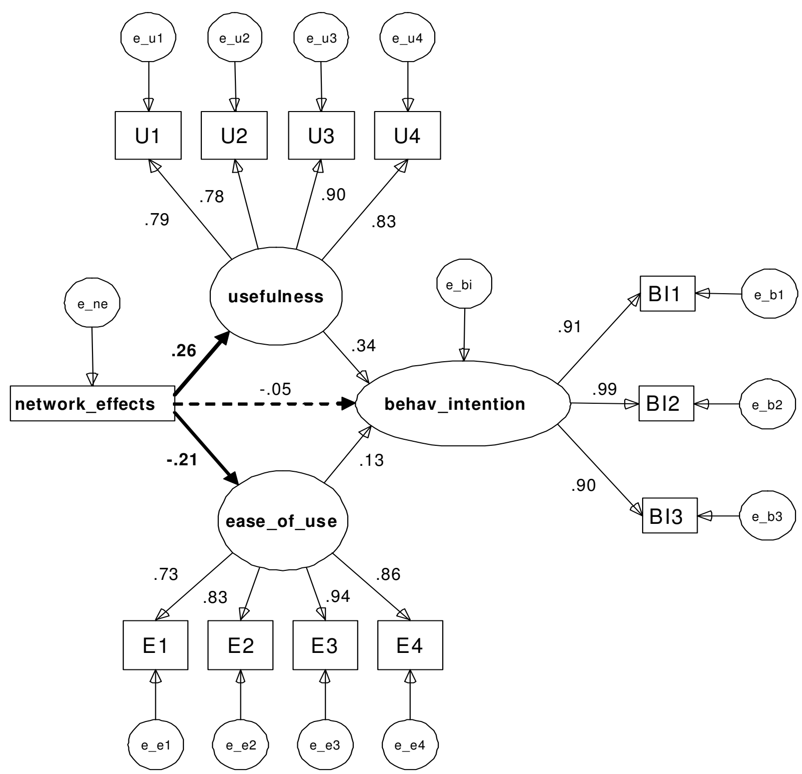

Figure 3. TAM with moderator "network_effects", including the main regression weights (standardized values).

Table 1 here below shows the main regression weights with the respective statistics. All the traditional TAM relationships are significant and have correct sign. Though with a low absolute value and a quite high standard error, also the path coefficient between "ease_of_use" and "behav_intention" is now highly significant ($p = 0.03$). The relationship between "network_effects" and "behav_intention" has a coefficient close to 0 (-0.05) and non significant ($p= 0.4$). All the other path coefficients and factor loadings are highly significant ($p < 0.01$). The relative standard errors are extremely low in absolute value (< 7%) for all the factor loadings, and around or below 25% for all the significant path coefficients. The model fits data quite well, as confirmed by the Squared Multiple Correlations (S.M.C.), (the statistic similar to the R2 in linear regression), showing a high portion of variance explained by the main variables of TAM.

Table 1. Regression weights (std) and statistics, including SMC, p values, standard errors and Relative Standard Error (R.S.E.), the ratio between standard error and the estimate

			Weight	S.M.C.	P value	S.E.	R.S.E.
Usefulness	→	behav_intention	0.34	-	0.00	0.08	17.67%
ease_of_use	→	behav_intention	0.13	-	0.03	0.08	45.16%
network_effects	→	Usefulness	0.26		0.00	0.15	24.10%
network_effects	→	ease_of_use	-0.21		0.00	0.16	-27.54%
network_effects	→	behav_intention	-0.05	0.11	0.40	0.11	-118.09%
E1	←	ease_of_use	0.73	0.55	(constraint)		
E2	←	ease_of_use	0.83	0.69	0.00	0.08	6.82%
E3	←	ease_of_use	0.94	0.89	0.00	0.08	6.07%
E4	←	ease_of_use	0.86	0.74	0.00	0.07	6.62%
U1	←	Usefulness	0.79	0.62	(constraint)		
U2	←	Usefulness	0.78	0.60	0.00	0.07	6.98%
U3	←	Usefulness	0.90	0.80	0.00	0.07	5.89%
U4	←	Usefulness	0.83	0.70	0.00	0.07	6.34%
B1	←	behav_intention	0.91	0.82	(constraint)		
B2	←	behav_intention	0.99	0.99	0.00	0.03	3.04%
B3	←	behav_intention	0.90	0.80	0.00	0.04	3.97%

If the model is correctly specified, the regression weights and their statistics can be used to verify the research hypotheses.

Hypothesis 2. Perceived USEFULNESS can be positively influenced by network effects

The regression coefficient for the relationship between the moderator "network_effects" and the latent variable "usefulness" is positive (0.26) and strongly significant ($p < 0.01$), suggesting that *H2 is CONFIRMED*.

Hypothesis 3. Perceived EASE OF USE can be positively influenced by network effects

The regression coefficient for the relationship between the moderator "network_effects" and the latent variable "ease_of_use" is negative (-0.21) and strongly significant ($p < 0.01$), suggesting that *H3 is NOT CONFIRMED*: a relationship is actually suggested by the estimates, but it is negative. User perceptions of ease of use appear to be negatively influenced by network effects. Finally,

Hypothesis 4. BEHAVIORAL INTENTION of acceptance can be positively influenced by network effects

H4 is not confirmed by data, given the regression coefficient close to 0 (-0.05) and highly non-significant ($p = 0.4$). Therefore, *H4 is NOT CONFIRMED*: the statistical model does not suggest any direct influence of network effects on behavioral intention of acceptance.

Testing for correct model specification and good fit

In order to test for the correct model specification, a number of test statistics were estimated, selected according the indications given in (Gefen et al. 2000) for covariance-based SEM. The model, with 50 degrees of freedom and a complex structure of statistical relationships, could easily suffer from misspecification, failing to correctly identify the underlying relationships fitting with the data set.

Table2 here below shows some selected statistics for model fit, commonly used in structural equation modeling. For a discussion on SEM fit statistics, cf. also (Hu and Bentler 1998).

Table 2. Fit statistics	
Fit statistic	Value
chi-square test	155.70
degrees of freedom (df)	50.00
p value	0.00
chi-square/df	3.11
root mean square residual (RMR)	0.39
goodness of fit index (GFI)	0.93
adjusted GFI	0.88
normed fit index (NFI)	0.94
relative fit index (RFI)	0.93
incremental fit index (IFI)	0.96
Tucker-Lewis index (TLI)	0.95
comparative fit index (CFI)	0.96

The basic chi-square test of model fit is not passed: the p value, shown in the third row of Table2 should be >= 0.05. Failing this test is actually quite common in structural equation models, because the test works correctly in presence of "good" data sets, but it suffers particularly from problems like non-normal distributions, small sample size and in presence of complex relationships with a high number of parameters. The ratio chi-square/df around the value of 3 is usual for correctly specified model in such conditions. The RMR index of 0.39 shows a quite contained residual variance: it should be lower than 0.8. The good values of the GFI and AGFI indexes (respectively, above 0.9 and above 0.8) confirm the previous indications of quite good model fitting. NFI is the normed fit index, which varies from 0 to 1, with 1 = perfect fit. By convention, NFI values below.90 indicate a need to respecify the model. RFI is the relative fit index. RFI close to 1 indicates a good fit. IFI is the incremental fit index. IFI close to 1 indicates a good fit and values above 0.90 an acceptable fit. TLI is the Tucker-Lewis coefficient. TLI above 0.95 indicates an acceptable fit. CFI is the comparative fit index. CFI close to 1 indicates a very good fit, and values above 0.90 an acceptable fit. All in all, therefore, the statistics suggest a correct model specification with a quite good fit of the data set.

Discussion

The results obtained with the laboratory experiments confirm our initial expectations of a strong influence of network effects on technology acceptance. Though no direct influence of network effects on behavioral intention was evidenced in the model (H4: not confirmed), strong and significant statistical relationships were evidenced, linking network effects with both usefulness (path coefficient 0.26) and "ease_of_use" (path coefficient -0.21).

Surprisingly, while network effects are positively correlated with usefulness (H2: confirmed), they are negatively correlated with ease of use (H3: not confirmed). Such outcome requires some interpretation. First of all, the comparison of the models in figure 2 with the model in figure 3 could show if the introduction of the moderator helps to better explain data. The two models are actually based on rather different samples, therefore any indication from this exercise should be taken with prudence and subject to further investigation. It appears that both the most important determinants of "behav_intention" according the acceptance theory have stronger path coefficients in the model of Figure 3 (explicitly including the influence of the moderator for network effects) than in the two previous ones. In particular, the relationship of "behav_intention" with "ease_of_use" is much stronger and clearly significant in figure 3, compared with figure 2. This would mean that the TAM basic relationships "work better" if accounting for network effects. When accounting for net effects, the perception of usefulness is more strongly and positively related to the intention of acceptance. Moreover, when network effects are more intense (larger user network), the perception of usefulness is higher and so is the intention to accept the system.

On the other side, the perception of ease of use is lower in presence of higher network effects. This could be explained by a learning effects bias: in 5 different sessions , each of 5 different 20-user groups had to experience the same mosaic twice. The first time it was always with high network effects (20 users freely exchanging doubles). The second time, after a few minutes, it was always with low network effects (free exchanges only within four separate small subgroups of five people). Given the fact that the user task was the same, doing it for the second time could be perceived as easier, because users had already experienced it for the first time, and they already knew how it worked. In other words, they had already learnt how to play the game. The perception of higher ease of use could be associated with a learning effect bias due to the fact that the lower network effects session was always executed after the higher network effects session. Such a bias may be detected and perhaps addressed by altering the order of execution of the experiments. Another sensible alternative could be a two group randomized experimental design. In this case each user would not make a comparative evaluation of the same system under network effects of different intensity, but only a single evaluation of just one system. But the choice of an experimental design based on comparative evaluation is here the result of a specific design strategy, motivated by the idea (still quite unexplored in TAM research) that acceptance choices are actually comparative choices. When a technology is discarded, there is typically an alternative option to accomplish the same task. Making the alternative options explicit may result in a better understanding of user choices.

The lower perceived ease of use associated with larger user networks could also be associated with the nature of the task: exchanging doubles could be perceived as a harder task within a 20-node network than within a 5-node network. In the 5-node case, users were just a few and very close to each other, so it was easier to check and negotiate the five double cards. In the 20-node case, users had to go around in the room, find the right person(s) among many, and convince her to negotiate, all in very short time. The larger network offered more opportunities for exchange (reflected by a higher perceived usefulness), but also more competition and higher complexity in settling negotiations. Therefore, in line with what briefly discussed during hypothesis formulation, a candidate technology with a larger user network could also sometimes generate negative network effects affecting the perceived ease of use of the system under evaluation. This aspect looks potentially interesting and it would deserve further investigation.

In synthesis, according to the results of our experiments, in user choice the candidate technology with a larger user network is favored for its higher perceived usefulness, but unfavored for its lower perceived ease of use. Globally, in the model of Figure 3, the combined effect is towards acceptance, because the positive network effect (through enhanced usefulness) is about three times stronger than the negative network effect (through lowered ease of use).

Concluding Remarks

In conclusion, our laboratory investigation may be regarded as a first step towards showing that in some cases network effects may play a significant role in technology acceptance, pushing users towards accepting a system that could otherwise be discarded. Several famous case studies in the IT markets could be read as acceptance stories influenced by network effects, like the Microsoft Windows case (Liebowitz and Margolis 1999). The possibility to isolate the acceptance process from the contextual factors, controlling the dimensions (and even the topography) of the user network, makes this research design strategy quite appealing. This is certainly not to pretend that all the other multifaceted factors that may be relevant in a network of user relationships, like e.g. power, communication, trust, identity, and knowledge, could be easily ignored: further studies could depart from here in order to enrich and widen this perspective. In facts, a deeper understanding of network effects in technology acceptance may help researchers and managers to better predict user choice and to design more successful products and services. This contribution is just one of the first steps in this direction. Some of the limitations of this work could actually suggest directions for further research, exploring the influence of network effects not only on the initial user choice, but in the second phase of the acceptance process leading to the actual systems usage. There are fascinating and complex issues related to this research territory, recently object of inspiringly new pieces of work (Burton-Jones and Gallivan 2007). In an optimistic view, a more comprehensive and ambitious long-range research program may actually depart from here, aiming at a comprehensive reframing of acceptance theories with multi-dimensional and multi-level investigations, taking into account the rich and challenging complexity of IT system choices in organizational settings.

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