USING SOCIAL NETWORK DATA TO PREDICT TECHNOLOGY ACCEPTANCE

Research-in-Progress

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Abstract

In contrast to popular literature on technology acceptance, this research-in-progress paper does not intend to build an explanatory model of technology acceptance but a predictive model so as to predict whether a specific person is likely to accept some technology. We show that the constructs that were identified in the classic UTAUT (such as performance expectancy, effort expectancy and social influence) can be used in a predictive model but that better predictions of system use can be made using knowledge about social networks that exist between people. Both social influence and social selection data are valuable to make predictions. Our approach is tested in the context of a video system which is part of an online learning platform, using a sample of 133 interconnected students.

Keywords: Adoption, UTAUT, Predictive modeling
Introduction

The UTAUT (Unified Theory of Acceptance and Use of Technology, (Venkatesh et al. 2003) and UTAUT2 models (Venkatesh et al. 2012) have been developed to get insight into factors related to technology acceptance. Such explanatory models are often used in the end to make predictions about technology acceptance. This is inappropriate as testing a predictive model actually requires taking a holdout of the dataset (see below). Still, it is important for technology vendors and IT departments to predict technology usage. In this paper we turn to the predictive research paradigm. We show that the antecedents of the intent to use a system in the state-of-the-art UTAUT explanatory model are valuable to make predictions about usage but that significantly better usage predictions can be achieved by going deeper into the social influence construct. We notice tests of the UTAUT (e.g. (Venkatesh et al. 2003)) often do not show a significant direct effect of social influence on behavioral intention, and the interaction terms involving social influence are largely insignificant as well. Our research shows there is a more valuable way we can use knowledge about social influence in technology acceptance research.

In this research project we step away from explanatory models, which have been dominating IS research in top journals (Shmueli et al. 2011), and we move to predictive models. A predictive modeling approach can be beneficial for empirical and theoretical testing (Shmueli 2010; Shmueli et al. 2011). Predictive models do not only aim to fit to known samples, but also intend to predict the value of a dependent variable for new entities. For example, one could try to predict whether a specific person is likely to buy augmented reality glasses or would accept online buying practices, given the behavior of other people in that focal person’s network. Our approach is tested in the context of the student acceptance of watching course videos using an online learning platform (OLP). Our research results show it is possible to achieve relatively high accuracy in predicting technology usage using data about one’s social ties.

In what follows we first present related work and the theoretical background. We shortly come back to the UTAUT model, we explain the difference between predictive modeling and explanatory modeling, and we discuss social network effects in human behavior. Subsequently, we explain the research method in terms of data collection, analysis and modeling details. Next we report the results and finally we discuss the results and specify our contribution.

Related work

UTAUT model and extension

The UTAUT explains user intentions of information systems utilization. The four key elements of performance expectancy, effort expectancy, social influence, and facilitating conditions are considered to be relevant antecedents to usage intention and use behavior. Meanwhile demographical information about gender, age, as well as other characteristics such as experience and voluntariness are also considered to be relevant. There are various extensions of the original UTAUT model (Cody-Allen et al. 2006; Venkatesh et al. 2012; Zhou et al. 2010), which attempted to get a better explanatory model to assess causal relations. Often no significant direct relation is found between social influence and behavioral intention. A few significant effects were noted with complex multi-way interaction terms, which are difficult to interpret and control.

In this paper we will use the UTAUT to test whether our case is similar to other cases in the sense that Social Influence seems insignificant as an antecedent of behavioral intention. Once we have shown that, we will move from explanatory modeling to predictive modeling.

Explanatory modeling versus predictive modeling

Prior works (Shmueli 2010; Shmueli et al. 2011) define explanatory modeling and predictive modeling as follows. Explanatory modeling assumes causality at theoretical level and tests causal hypotheses using association-type models, e.g. regression and structural models. Such modeling evaluates the goodness of fit of the model using criteria such as adjusted $R^2$. Predictive modeling (such as data mining) is designed
for predicting new observations or scenarios and therefore uses a holdout. These two types of models compensate for each other’s shortcomings since predictive models are built based on the distribution of the data but are weak in terms of explanatory power. Explanatory models contain causal associations between the response (user intention and behavior in our case) and the constructs, but overestimate the model fit since it builds and evaluates the model using the same sample (i.e., there is no hold-out). Explanatory models and predictive models can go hand in hand for example in the sense that explanatory models can tell predictive model builders what variables could be considered to make predictions. A literature review of MISQ and ISR articles showed that predictive modeling is scarce in mainstream IS research (Shmueli et al. 2011) and that sometimes explanatory modeling was used to reach a predictive goal, which is inappropriate given the fact that no holdout is used. Still, predictive modeling was said to be valuable for both rigorous theory-building and for achieving practical relevance (Shmueli et al. 2011).

Much IS research concerns technology acceptance but that is typically exploratory research, leading to many papers with minor extensions of the important models (TAM & UTAUT). In this paper we work on a parallel path, using predictive models in IS acceptance research. The UTAUT (an explanatory model) is used as the theoretical foundation (Shmueli et al. 2011) for selecting variables to be used to empirically test a model to predict technology acceptance. The rich theoretical foundation in UTAUT and its explanatory power provide interpretability for the predictive modeling process. Hence the predictive model will be built with the explanatory model constructs and will empirically test whether these constructs do provide a good estimate on the potential IS usage. We will also build alternative predictive models to compare the predictive performance.

**Social network analysis**

As is clear from the theory behind the UTAUT model, people in a social network may influence each other and thus change each other’s behavior. This ‘social influence’ is, however, not the only reason why knowledge about a social network could be valuable to guess the behavior of people in a network. In a social network one often observes correlation between certain characteristics. This is often referred to with the term homophily (McPherson et al. 2001). Common ground for understanding such a phenomenon is that people with similar behavior are clustered selectively. In order to predict the user’s acceptance of an information system, not only ‘social influence’ but also ‘social selection’ is worth investigating. Social selection is the phenomenon where social ties grow between people with similar behavior (Mercken et al. 2007). It should be noted that, while social influence could be impacting technology adoption, one cannot say there is a causal relation between social selection and use behavior (Aral et al. 2009; Sun et al. 2011). Therefore, social selection is not a variable that could be used in causal explanatory research, but it can be used in predictive research and may allow making better usage predictions than information about social influence relations.

We can now obtain different viewpoints on social networks. First, one could consider ‘influence’ relationships in the sense that one person is said to influence the technology acceptance of another person. Alternatively, one could study more general social ties such as friendship which could encompass social selection and social influence elements. Both above observations imply the potential interdependency (Jensen et al. 2003) between IS usage among different people connected with social ties. We intend to capture such interdependency in our predictive model and contrast with the classical social influence construct as measured in the UTAUT in terms of the predictive performance. Hence, a new social influence measure exploring the social network structure will be used as the alternative to the classical construct.

In this paper we deal with the following research questions:

1. Can social network information be useful to predict technology acceptance?
2. Which view on social ties (influence/friendship) is most powerful to consider for prediction?
3. Can a better prediction be realized by combining different views on social ties?
Research setup

Data collection

Data has been collected through a survey conducted at a European business school. The sample was composed of 3rd year bachelor students participating in a “management information systems” course. In this course, students were supposed to watch online theory videos at home before each offline session. In total it concerned 6 videos, each ranging from 20 to 40 minutes. At the end of the semester students were asked about different UTAUT constructs such as performance expectancy, effort expectancy, social influence and facilitating conditions as well as others such as gender. Questions to measure the classical social influence construct are designed to capture the influence from faculty, staff, and other students with good grades in the same course as well as other influential people. The voluntariness of use was measured by asking if respondents perceived it as mandatory to watch the videos. For behavioral intention students needed to specify their willingness to use the system on an ordinal scale. All these measures were adapted from prior work (Venkatesh et al. 2003). For use behavior the actual total duration of watching all videos together was recorded. For our predictive model, we choose the use behavior as the dependent variable, as one is usually more interested to predict a user’s behavior than to predict the user’s intent to do something. Furthermore use behavior such as usage can be obtained from historical data in practice, without explicitly asking customers about their intention. The availability of use behavior records makes it more attractive for data-driven research in predictive modeling.

In addition to these regular UTAUT questions, the survey also asked questions to uncover the social network between students. The social network data was collected in a “free recall” manner (Wasserman et al. 1994) where respondents specify the list of people they know and the intensity. Two views on the social network were asked:

1. the social network specifying the friendship-relations in the school at large (rather than just in the same class) with intensity expressed in terms of how often students meet during a week: together most of the day, we meet several times per day,...,

2. the degree of influence from peers for watching videos using the Online Learning Platform (OLP) with intensity levels ranging from major influence to minor influence.

Both networks were recorded using an ordinal scale from 1 to 4 with 4 indicating the strongest relationship. This resulted in a network with 133 respondents with 578 edges in terms of friendship and 269 edges in terms of OLP use influence, as shown in Table 1.

Data analysis

Explanatory modeling

We first run an explanatory model to test the similarity between our dataset and other published cases in terms of the significance of social influence as an antecedent of user intention and behavior. The hypotheses are then in line with the UTAUT model of (Venkatesh et al. 2003), but we do not include the age and experience moderators as all students in the sample have similar age and experience and we do not consider the complexity of all the interaction terms in the UTAUT model. We first run the model with the Social Influence construct measured in the classic way and next we run the model using a new approach to measure Social Influence. We then use knowledge about the ‘neighbors’ in the social network (i.e. the nodes to which a focal node is connected in the network representation). The social influence score then becomes a weighted sum of the student’s neighbors’ response values on the dependent variable. In line with previous work (and to allow comparison with previous work), we applied PLS-SEM (Venkatesh et al. 2003).

Predictive modeling

In predictive research, typically data mining techniques are used such as decision trees, random forest
and support vector machines (Vapnik 1999). These techniques are aimed mostly at non-relational data, and make predictions based on a record’s individual attributes. Network based classification attracted much attention in recent years with larger amounts of data provided by online platforms such as social media. Such techniques are capable of capturing network structures in the data and utilize network information with or without any additional information concerning the nodes of the network. Most relational learning methods are designed based on the homophily assumption that instances (such as users of a certain platform) are connected because they are similar to each other.

With predictive modeling we want to assess whether we can predict node attributes such as use behavior. Furthermore we want to find out if a network only model can outperform the model using UTAUT constructs. Much literature involving technology acceptance pointed out, the intent to use is usually a strong predictor of actual usage (Kim et al. 2008; Pavlou et al. 2006). In line with this, explanatory researchers have predicted that the system usage will be higher if the system is easier to use, if the system is more useful, etc. Therefore, in this paper we will test whether the UTAUT antecedents of behavioral intention can indeed be used for predicting actual usage.

(In contrast to what is happening in explanatory research) a cross validation or holdout is needed to avoid bias and over-fitting in predictive models. We use AUC (Fawcett 2006) (area under the receiver operating curve) to assess the accuracy of our prediction result. We can say that the predictive model performs better than a random guess as soon as the AUC is significantly higher than 50%. All prediction tests have been conducted with a 30% hold out and 100 trials.

We retrieved the log files from the OLP with the time students had been watching the videos. We label nodes as ‘1’ if students watched more than 40 minutes of the videos in total and ‘0’ otherwise. We use such a binary variable as in practice we are rarely interested in predicting the actual number of minutes one is going to watch videos. Rather, we are interested to determine whether students are likely to watch them for a sufficient part. Moreover, by using such a binary variable our research approach can be easily transferred to other domains where prediction is valuable (e.g. whether a person will buy some new technology or whether a person will use online/offline media to buy something).

### Table 1. Descriptive statistics for predictive modeling

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
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<tbody>
<tr>
<td>Number of nodes</td>
<td>133</td>
</tr>
<tr>
<td>Label distribution</td>
<td>29(1) 21.8%</td>
</tr>
<tr>
<td></td>
<td>104(0) 78.2%</td>
</tr>
<tr>
<td>Number of edges for friendship network</td>
<td>578</td>
</tr>
<tr>
<td>Number of edges for influence network</td>
<td>269</td>
</tr>
<tr>
<td>Total number of edges</td>
<td>847</td>
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</table>

A so-called ‘local model’ is learned using a traditional data mining technique: random forests (Breiman 2001) with the basic UTAUT constructs including performance expectancy, effort expectancy, facilitating conditions, behavioral intention, classical social influence (without social network structure data), voluntariness and the gender. In the UTAUT, variables such as voluntariness are directly linked to use behavior and others are not. In order to consider the impact of that hierarchical structure in the UTAUT model, we tested three different sets of variables to predict use behavior. First, we took into account all UTAUT’s direct and indirect antecedents of use behavior mentioned above. The AUC of the local model was then 0.67 (with a standard deviation of 0.08). Secondly we predicted use behavior using only UTAUT’s antecedents of behavioral intention (0.65±0.08). Thirdly we ran tests only using UTAUT’s direct antecedents of use behavior (0.56±0.08). We can conclude that the constructs that are identified in the explanatory UTAUT model can be used in a predictive model to make a prediction for new cases and that the antecedents of behavioral intention in the UTAUT allow making better predictions of the actual usage.

The AUC of this UTAUT based model can now be used as the baseline criterion to compare the predictive power of the network model which is built based on social network data only. In what follows we will only use the network structure without any other UTAUT constructs to build a relational learning model for predicting use behavior.

For relational learning with our social network we define a graph $G = (V,E)$ containing edges $E$ and
vertices (i.e. nodes) $V$. The relationships between nodes are summarized in an adjacency matrix $W$, where $W_{ij}$ denotes the strength of the relationship from node i to j. $W_{ij} = 0$ indicates disconnected nodes. For an unweighted graph, $W_{ij}$ are either 0 or 1. For an undirected graph, $W_{ij} = W_{ji}$. The target categorical label of the nodes we intend to identify is denoted as $L = (l_1, l_2, l_3, \ldots, l_n)$ where $n$ is the total number of nodes. We classify the nodes by computing $P(l_i = c|N_i)$, the probability a node belongs to a label of certain class $c$, given its neighbor information $N_i$. We summarize the definition in Table 2. Among many choices we have, we will mainly report the results of the Class-distribution relational neighbor algorithm (Macskassy et al. 2007) in this paper. Prior work (Macskassy et al. 2007) provides a systematic overview of network classification methods. We refer readers to their work on node-centric classification in network data for more details on other algorithms.

<table>
<thead>
<tr>
<th>Table 2. Definition of symbols</th>
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<tbody>
<tr>
<td><strong>Graph</strong></td>
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<tr>
<td><strong>Adjacency matrix</strong></td>
</tr>
<tr>
<td><strong>Edge</strong></td>
</tr>
<tr>
<td><strong>Vertices</strong></td>
</tr>
<tr>
<td><strong>Node attribute</strong></td>
</tr>
<tr>
<td><strong>Neighbors of node i</strong></td>
</tr>
<tr>
<td><strong>Probability a node belongs to class c</strong></td>
</tr>
</tbody>
</table>

CDRN works as follows:

$$CV(v_i)_c = \sum_{j \in N_i} w_{ij} \cdot P(l_i = c|N_j), \quad (1)$$

$$RV(c) = \frac{1}{Z} \sum_{v \in V} CV(v)_c. \quad (2)$$

$$P(l_i = c|N_i) = \text{sim}(CV(v_i), RV(c)). \quad (3)$$

where the label $l_i$ of a node $i$ is determined by the weighted sum of its neighbors’ label information. The term $Z$ is used to normalize the weighted sum to a scale between 0 and 1. CV is the class vector for every node $v_i$, it is a weighted sum of its neighbor belonging to the same class. More specifically, if the label of a node is either 1 or 0, CV contains two columns; the weighted sum of neighbors belonging to 1 and belonging to 0. RV is the reference vector that is the global overall description of the CV of all nodes. The probability of a node belonging to a certain class is the cosine similarity of a node’s CV compared with the global RV. The classifier assumes homophily, meaning neighboring nodes behave similarly.

The social ties can be considered either directional or unidirectional. CDRN is designed for undirected networks. Therefore, we took the maximum value of social tie strength between $W_{ij}$ and $W_{ji}$. The reader should be aware of the fact that sometimes such tie treatment might lead to a loss of information. We therefore also applied predictive models which do consider the direction of social ties (Wang et al. 2010), and essentially the ties treatment brings a better classification result. Therefore, we neglect the effect of direction of ties in this short paper.
Research results

Assessment of the explanatory model

We tested the applicability of the basic UTAUT to our dataset. Using the PLS SEM (partial least square structural equation model) implemented in SmartPLS 2.0 we obtain the results shown in Table 3. Behavioral intention is used as the dependent variable. We first tested the UTAUT with the classic measure for Social Influence (asking scores on statements such as ‘people who are important to me think that I should use the system’). We then tested the UTAUT using the information about the ‘influence’ social network that exists between students (‘new SI measure’ in the table).

<table>
<thead>
<tr>
<th></th>
<th>UTAUT with classic SI measure (R²=0.52)</th>
<th>UTAUT with new SI measure (R²=0.514)</th>
</tr>
</thead>
<tbody>
<tr>
<td>gender</td>
<td>2.4263 **</td>
<td>2.3976 **</td>
</tr>
<tr>
<td>Performance Expectancy</td>
<td>2.6252 **</td>
<td>3.3982 ***</td>
</tr>
<tr>
<td>Effort Expectancy</td>
<td>2.8058 **</td>
<td>3.0346 ***</td>
</tr>
<tr>
<td>Voluntariness</td>
<td>2.5511 **</td>
<td>3.0411 ***</td>
</tr>
<tr>
<td>Social influence (classic)</td>
<td>1.2794</td>
<td></td>
</tr>
<tr>
<td>Social influence (new)</td>
<td></td>
<td>0.7092</td>
</tr>
</tbody>
</table>

When applying the standard UTAUT model to our dataset, the social influence construct cannot be shown to be a significant antecedent of behavioral intention, what seems consistent with most applications of the UTAUT. The new social influence measure (based on knowledge of the ‘influence’ social network) is not a significant antecedent of behavioral intention either.

Assessment of the predictive model

In terms of predictive modeling, we implemented all predictive models using MATLAB 2012b. A first set of tests has been done using only one type of network edges: the social influence relations. The AUC of this model was 0.62±0.06 (standard deviation). In a second test, the friendship network was used, resulting in an AUC of 0.73±0.06. The prediction results of the friends’ network are also better than those achieved with the UTAUT components. These results immediately answer research questions 1 and 2: (1) social network information is useful to predict technology acceptance and (2) knowledge on a friendship network seems more powerful than knowledge on perceived social influence relations.

It is possible to build more sophisticated research models for better prediction results. However, as shown by the research questions above, in this paper we focus on the relevance of different data, not on different modeling techniques. The CDRN model used here already outperforms the local model, supporting our statement that social network information is relevant.

We now turn to research question 3: we investigate whether a better prediction can be made by combining information about both social networks. As mentioned above, using a standalone influence network does not give a very good result. A stacking network model is used to present the network by adding edges from the ‘influence’ network to the ‘friendship’ network to check whether this additional information can be translated into a better prediction. Two different approaches have been used:

Cascade influence: if node i and j have an influence score mentioned, form an edge between i and j based on the influence score, overwriting possible friendship edges that were present.
No Cascade influence: if node i and j have an influence score mentioned, form an edge between i and j, with an intensity based on the influence score only if no friendship edge existed yet.

The results of the stacking model tests are shown in Table 4. A network model with no cascade provides a relatively better prediction than with cascade.

<table>
<thead>
<tr>
<th>Table 4. Result of predicting use behavior</th>
<th>AUC+stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>UTAUT constructs</td>
<td></td>
</tr>
<tr>
<td>All direct and indirect UTAUT antecedents of use behavior</td>
<td>0.67±0.08</td>
</tr>
<tr>
<td>UTAUT direct antecedents of behavioral intention</td>
<td>0.65±0.08</td>
</tr>
<tr>
<td>UTAUT direct antecedents of use behavior</td>
<td>0.56±0.08</td>
</tr>
<tr>
<td>Friendship network</td>
<td>0.73±0.08</td>
</tr>
<tr>
<td>Influence network</td>
<td>0.62±0.06</td>
</tr>
<tr>
<td>Friendship network with cascade influence</td>
<td>0.74±0.06</td>
</tr>
<tr>
<td>Friendship network with no cascade influence</td>
<td>0.76±0.07</td>
</tr>
</tbody>
</table>

Discussion

Our test result of the classic explanatory UTAUT model suggests that our research setting is similar to the setting used in other technology acceptance research (Venkatesh et al. 2003) in that we don’t find a significant direct relation between social influence and behavioral intention. Also, replacing the classic measure of social influence with our new measure has no impact on the results of the UTAUT model test. Consequently, it is interesting to see that social network knowledge can be used to predict system acceptance, while it does not seem to explain system acceptance. Our results show that the AUC of the social network model is higher than the AUC achieved with the classic UTAUT constructs, so that a better prediction can be made with social network knowledge. This is also interesting in light of the fact that the PLS-SEM tests of our model, as reported in Table 4, give an $R^2$ of about 52%, which is considerably higher than the $R^2$ of the comparable model in the original UTAUT paper of about 41%. That is, the antecedents of Behavioral Intention in our dataset are better at explaining the variability in Behavioral Intention than in the original dataset of Venkatesh et al. (2003). It may quite well be that the performance of a predictive model using the UTAUT constructs with the Venkatesh et al. (2003) dataset would be lower than the AUC we found and that the prediction using the social network data would be even more appreciated in that light. Still, we should be cautious: the fact that the social influence construct is insignificant in our dataset just as well as in Venkatesh et al. (2003) does not mean that the social selection will be valuable in all contexts. Further research, especially in a worker setting, is needed to confirm this.

All this reveals the need for a new stream of IS acceptance research, focusing on prediction. We found that information about a person’s friends is valuable to predict the adoption beyond what is possible with knowledge about social influence relations. Students may just be friends with other people that are behaving in the same way by nature, without having real social influence.

From theoretical perspective, this work has shown an alternative method to measure social influence in IS acceptance. Prior IS research that focused on social networks (such as (Sykes et al. 2009)) use network statistics such as centrality and density. These social network features are “static” in a sense that they do not depend on other attributes of the individual observations in the network. The approach in this paper is different as we demonstrated with our prediction result that there is statistical interdependency among certain attributes (use behavior) between different observations. The predictive model is able to confirm the statistical interdependency and utilize it for prediction. The recent developments in social software and other information technology make huge amounts of data available for business and research. There are great challenges and opportunities in exploring large amounts of social network data that are available nowadays for new research paradigms (Sundararajan et al. 2012). This paper is our initial attempt
towards IS research incorporating new social network analysis methods. Classical technology acceptance models provide a comprehensible view and obtain some predictive power. This paper has shown it is possible to achieve better prediction considering other alternative modeling techniques. The empirical results we obtain show that knowledge about a friendship network gives a better prediction result than knowledge about a reported influence network. This is an interesting phenomenon since the friendship network is a longer term and more stable network than the particular influence network for OLP course videos. It is in line with prior research (Freeman et al. 1988; Hammer 1985; Wasserman et al. 1994) that a sample from a long term network gives a better estimation of “true structure” of interaction. This implies information about a long term general social network might be more desired than a network sampled from particular interactions of the IS usage context as it describes the underlying network structure more accurately.

The practical relevance of our research is that it suggests that social ties may be useful to predict user acceptance of many digital products (such as tablets) and services (such as online buying). Given the quantity of publicly available social network data, different marketing strategies can be inferred. Identifying influencers and/or focusing on similar profiles of customers can be helpful to promote certain products. In contrast to classic marketing approaches, grouping those ‘similar profiles’ does not require knowledge about people in terms of gender, age, etcetera. Rather, network connections are used to identify people that are likely to behave similarly. We obtain a relatively good prediction in terms of use behavior (and a better prediction than what is achieved using the UTAUT constructs, including gender).

Our future research will include several different areas of work:

1. This paper showed the UTAUT constructs are predictive as well (AUC = 0.67). It will be interesting to further investigate how to build predictive models where i.i.d (independent, identically distributed) constructs and social network data could work cohesively.
2. We are limited to a specific context with a small sample on students watching course videos on an OLP. It will be interesting to investigate the acceptance of different technologies, such as digital products, and the acceptance of different practices, such as online buying. In these case studies there are many different decision models (Choudhury et al. 2008; George 2004; Kim et al. 2008; Pavlou et al. 2006) proposed that are domain-specific than UTAUT.
3. Longitudinal studies, where social networks evolve over time, could be used to investigate the extent to which social influence and social selection are taking place in the context of technology acceptance (Aral et al. 2012). The interaction between social network and continued usage over time could be an interesting topic (Ortiz de Guinea et al. 2009).

Conclusion

The contribution of this paper is that we really build predictive models to predict technology usage, rather than using on explanatory method to make predictions. We show that the constructs that were identified in the classic UTAUT can be used in a predictive model but that better predictions can be made using social network information. Social network data are valuable to make predictions. We found a theoretical limitation on existing technology acceptance papers assuming i.i.d by contrasting explanatory and predictive models. We provided an alternative to the predictive aspect of the IS technology acceptance modeling paradigm with a different survey design to capture social influence relations and social networks in general. We identify statistical interdependency among IS usage which was not captured by previous IS research models but would be beneficial for new IS research paradigms.

Acknowledgement

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