Predicting Acceptance of Novel Technology from Social Network Data - An Agent-based Simulation-Approach

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Abstract
With digitization of production technology changes in technology infrastructure will become more frequent and more important for the competitiveness of organizations. Here, a crucial factor lies in the acceptance of such novel technology by users. Technology acceptance models aim to predict the adoption of new technology in an organization. They are however static in nature and fail to capture to dynamic process of adoption. To overcome this limitation, we utilize quantitative data from a small organization to understand both acceptance patterns and social structure of the organization. Both are used in an agent-based simulation to predict acceptance integrating social effects of diffusion over time. Our simulation achieves very similar results as the quantitative real-world data.

Keywords
Technology Acceptance; Social Network Analysis, Agent-Based Modelling, Adoption Prediction

1 INTRODUCTION

The integration of digitization in production technology has many different names: Industry 4.0, Internet of Things, Internet of Production. The common ground of these terms is the understanding that a key resource in production and manufacturing lies in the understanding of data that is generated in production processes. Utilization of such data in the form of data science, smart agents, decision support systems, smart logistics and AI-based automation promises the optimization of production processes by integrating various uncertainties. However, still many companies, especially SME are unprepared for total digitization. Both technological and social resources are missing to cope with the disruptive changes of the coming years. In today's rapidly changing technological environments, adapting to new technologies quickly is a crucial organizational skill both from a technological infrastructure perspective and from a human resources perspective. While the first is often addressed in research, the latter is far less understood.

Here, human resources required for total digitization in production refers to staff that has adequate attitudes, skills, etiquette, culture, and acceptance. Workers and engineers must approve of digitization strategies. They must have the technological capacities to implement or communicate necessary changes. Further, they must have a holistic understanding of the accompanying different work practices that are connected to digital processes (e.g., digital communication etiquette, sharing culture, privacy culture, etc.). Lastly, changes in working infrastructure and thus work processes must find acceptance in both workers and engineers. Without social acceptance of these novel technologies, introduction of said technologies will be silently sabotaged undermining objective performance measurement. The evaluation through KPIs ultimately yields only numbers masked by social practices and acceptance.

In this article we investigate social acceptance by trying to simulate the introduction process of novel software using an agent-based model. Based on one of the most popular and recent technology acceptance models the *Unified theory of acceptance of technology* (UTAUT) we measured psycho-social predictors of acceptance in a real working group. We then measured acceptance of a digital communication tool (i.e. Slack). Based on sociometric data of the working group (n = 20) we modelled social influence using a graph-based representation—the underlying social network. We then simulated the decision-making process in an agent-based model utilizing the previously established psycho-social predictors and underlying social-network structure. Lastly, we compared the individual simulated acceptance with the real-world measured acceptance and found very low deviance and similar acceptance patterns.

2 SIMULATING TECHNOLOGY ADOPTION

In order to understand the technology adoption process and establish a simulation model we first have to look at existing technology acceptance models. We then look identify various methods to establish the underlying social-network structure from different data source. Lastly, we need to establish a simulation approach that allows incorporating both inter-individual differences and social network information.

2.1 Technology acceptance models

Research on technology acceptance has had a long history in social psychology and the decision sciences. The earliest roots can be traced back to theories of understanding voter behavior in the 1960s in the theory of reasoned action [1]. The underlying assumption of this model is that both attitudes and norms play a role in accepting a social practice, a political candidate or a novel technology. Later models incorporate effects of behavioral control (e.g., theory of planned behavior [2]). More modern models specifically focus on the adoption of information systems and even formalize the diffusion of an innovation in society (theory of the diffusion of innovations [3]).

Nevertheless, these models formulate social processes by establishing user typologies and their characteristics. If the set of "early adopters" is convinced to use a product, the next phase in diffusion (majority adoption) is started and so on. This perfectly addresses large-scale social acceptance questions but misses to predict individual acceptance in individual organizations. Here the different revisions of the technology acceptance model (TAM [4]) triumph. By modelling individual psychosocial antecedents of social acceptance these models predict the behavioral intention of a user. They predict the answer to the question: Do I intend to use the software?

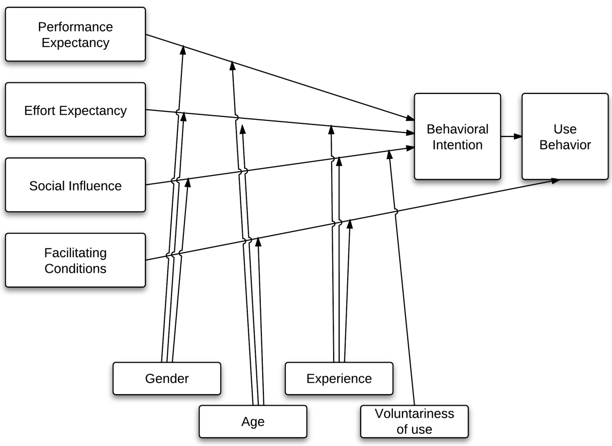

Figure 1 - UTAUT model visualization adapted from [5]

The most recent form of the model, the UTAUT [5] model (see **Fehler! Verweisquelle konnte nicht gefunden werden.**), predicts the behavioral intention from four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. *Performance expectancy* refers to the users evaluation of whether they believe that the system will improve their work performance—will it improve my work? *Effort expectancy* refers to the users belief about the required effort to work with the system—is it easy to use? *Social influence* refers to the perceived acceptance of the system by other people that are important (e.g., bosses, colleagues). It addresses the question: Will I be the only one using it? *Facilitating conditions* refers to the infrastructural support of the system—will I get help when I run into trouble?

These four factors determine the behavioral intention. Some of them are moderated by additional inter-individual differences (age, gender, experience, voluntariness). The UTAUT model is applied by measuring the antecedents of behavioral intention and then estimating the individual acceptance. This is achieved by using a hierarchical model of linear regressions (structural equation model). The coefficients of which have been established from extensive research in technology acceptance.

The drawback of this model is that the social influence for each individual is measured *only once* during the assessment. However, adoption is a dynamic process characterized by diffusion. Thus, social influence changes over time, when important persons in an organized change their individual acceptance over time (e.g., after training courses). This dynamic is insufficiently modelled in static acceptance models.

2.2 Measuring social network structures

In order to improve on the static nature of acceptance models, one core source of dynamics, the social infrastructure, can be modelled, integrated, and used in simulation models. Such simulation approaches should be able to predict shifts and changes in social acceptance in the social structure of an organization. But, how do we measure and access such structures. The science of sociometry is the study of relationships in groups by mapping individual perspectives of relationships onto self- and other-centric maps of social structure. Initially designed to understand dynamics in school classes, the method can has been extended to various other group dynamic processes [6]. The downside of sociometry is the extensive research effort required to measure adequate social structures. Often social relationships are asymmetrical—I like you, but you don't like me. Other relationships are unknown to the public. This requires extensive anonymization procedures to ensure trust towards the research procedure and the experimenters.

A different approach is to utilize proxy relationships to determine an image of the real social structure. Such proxy relationships can be collaborations in work projects, office co-occupation, attendance in meetings, etc. The proxy that we use in our research is the co-authorship on publications available to the public [7]. The benefit lies in the public availability of the data. The data does not necessarily capture to sole affective structure of the underlying social network—who likes whom. What it does, is capture a conjoint measurement of social coherence, organizational role, and organizational authority. All of which are factors typically relevant for social influence in the UTAUT model. From such data we can derive the structure of the underlying social network and even quantify the intensity of relationships from repeated co-authorships. Whether such data has sufficient quality for simulation modeling, is part of the research question in this article.

2.3 Agent-Based Modelling

Assessing both antecedents of acceptance and the underlying social network gets us only so far. Individual decision-making on acceptance and on observing the decisions made by colleagues are hard to formalize in closed-form representations or formulas. Technically, each individual conducts a set of matrix multiplications to derive the individual behavioral intention. However, these calculations have to be conducted iteratively multiple times until the state stabilizes. As soon as each individual incorporates a mental model of the opinion of others or starts learning, closed-form representations break down [8].

For such cases, agent-based models have been proven both successful in replicating real-world data and successful in communicating results to laymen [9]. The central idea of agent-based modeling lies in programmatically modeling the individual as a template or *agent* and letting the independent agents make their own decisions based on their perception of the environment. In our case agents each have individual perceptions of performance, effort and the facilitating conditions. The perception of social influence is generated from the environment—in our case the other agents and the underlying social network. From these perceptions they derive their own behavioral intention, possibly influencing the neighbors in the social network in the next iteration of the run. By analyzing the outcome of several of such simulations, probability of organizational acceptance can be derived.

Agent-based models are often designed in specialized software toolkits (e.g., Netlogo [10]). These toolkits simplify formulation of agent behavior and include interfaces for visualizing simulation states, interacting with simulation parameters, and exporting simulation results. As additional tools, they provide the means to run simulations in batches and to search for optimal parameter configurations using different optimization strategies such as genetic algorithms.

3 METHOD

In order to study the effectiveness of agent-based models for acceptance research, we first conducted a survey containing all UTAUT measurement variables in a scientific working group (n = 20). These measurements were directed at the use of the software "slack"[1]. The items of the UTAUT scale can be found in the original work by Venkatesh et al. (cite). All measurements were taken on a six-point Likert scale. From each individual response we derived an agent for our agent-based model (see Figure 2). The agent-based model was generated in Netlogo 6.0.1—an easy to use simulation

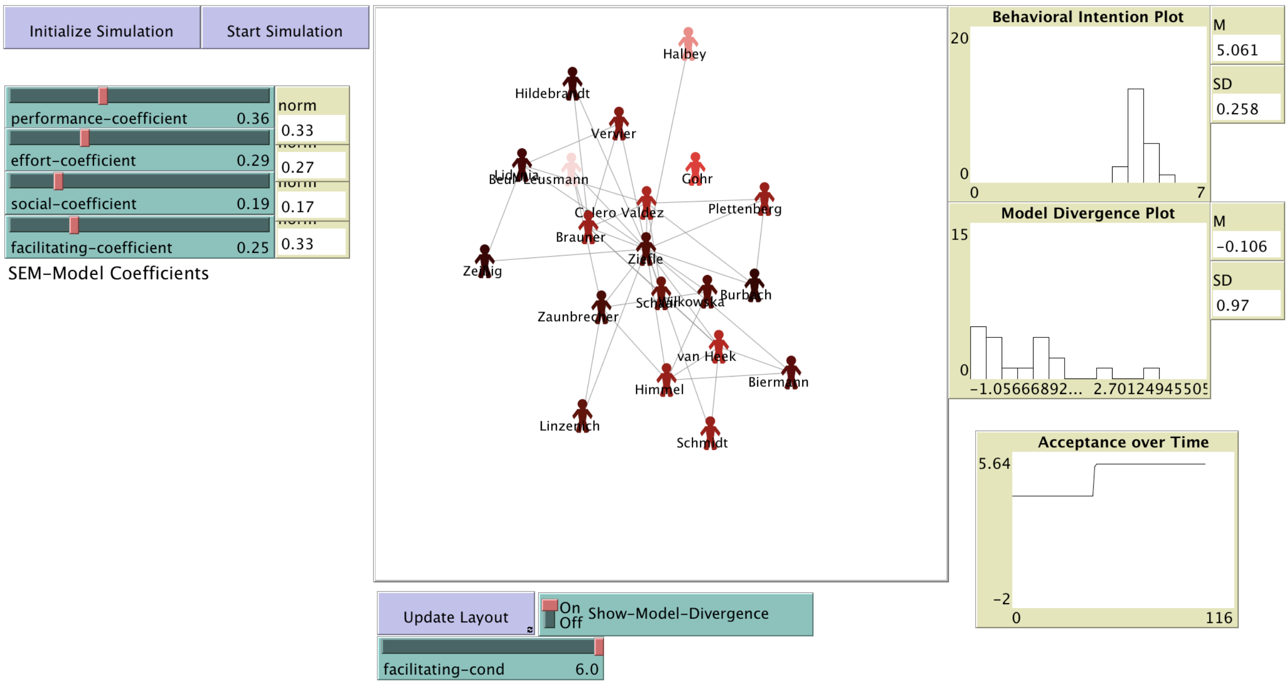

Figure 2 - Netlogo model used in this article. The left-hand side shows the coefficients used in the model, including a normalization. The center shows a graphical representation of the model. The right shows model evaluation parameters for an individual run.

software [10].

The survey was *not* anonymized to enable connecting the data with a social network structure. The social network structure was derived from the central publishing repository of the group, creating a connection between all agents, that were co-authors on any publication. Repeated co-authorship was not evaluated. All authors not present in the survey data were removed from the agent-based model. The target variable (i.e., behavioral intention) was modelled as the weighted sum of the variable's performance expectancy, effort expectancy, facilitating conditions, and social influence. While the first three were established from survey data, the social inclusion variable was determined as the averaged behavioral intention of all connected users. The behavioral intention of all agents was initialized as 3.5 which signifies a neutral stance.

As free parameters for the experiments the coefficients of the aforementioned weighted sum were selected. To ensure that the outcome variable stays within the original measurement range, all coefficients were normalized to add up to one. Coefficients can be chosen on a scale of 0 to 1 in 0.1 steps. As an additional free parameter, we let facilitating conditions be any integer on the scale of 1 to 6 to simulate different support conditions.

Using the *behavior space* simulation tool, we generated 161,051 parameter constellations with a ten-fold validation. This number is the number of unique *normalized* free form parameters from a total of 600,000 possible simulations. The random seed was uninitialized to allow for the influence of randomness in the model.

In each simulation run we measure the divergence of the simulated model from the real-world behavioral intention as measured in our survey. We do this for each individual agent and keep track of the mean model divergence and the standard deviation of the model divergence. For visual inspection, we implemented two visualizations, one to show the simulated behavioral intention, another to show the model divergence.

4 RESULTS

In order to see how the simulation results fare against the survey methodology we first look at the results of the survey and then compare the findings with the simulation results.

4.1 Survey Results

The survey of 20 participants, yielded 14 female and 6 male participants. The average age of participants was 32.7 years (*SD* = 7.6). The participants reported a high behavioral intention to use the software (*M* = 5.17, *SD* = 0.98). The software was seen as rather easy to use (*M* = 5.67, *SD* = 0.33) and was considered to be rather neutral with regard to increasing work performance (*M* = 3.91, *SD* = 0.67). The participants rated the social influence rather positively (*M* = 4.38, *SD* = 0.85) and found that the software was well supported (*M* = 5.35, *SD* = 0.52).

4.2 Simulation Results

Total simulation runtime was approximately 20 minutes. Each simulation reached the steady state in about 7 iterations. The output of the simulation extended to about 400Mb of comma separated values of free parameters and all tracked model

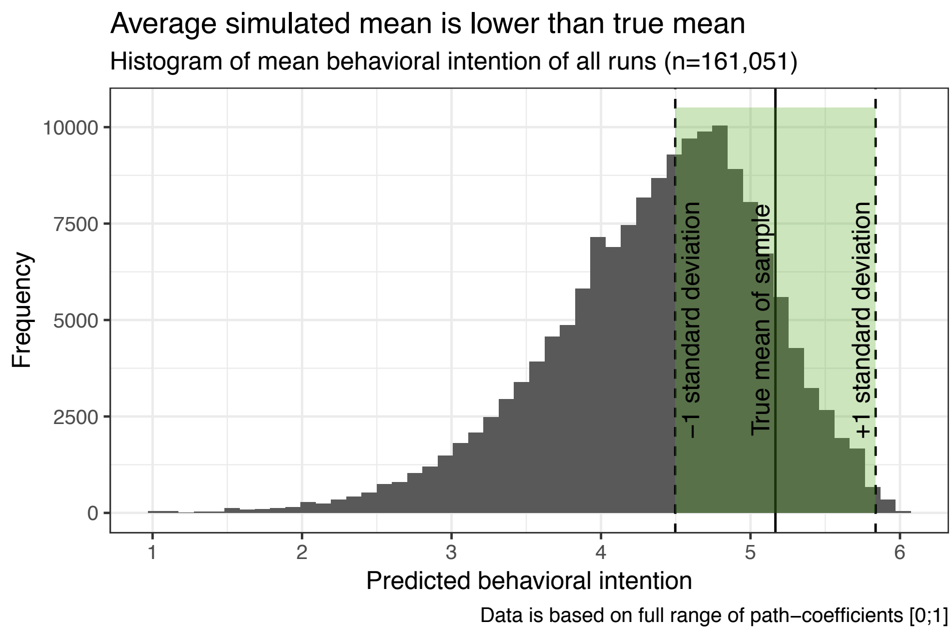

Figure 3 – Results distribution of all 161,051 simulations. The green area indicates the range of one standard deviation around the true mean of our sample.

parameters.

We use the software R to analyze the resulting data. Using multiple linear regression analyses, we find that from our simulation, effort expectancy and social influence are the most determining factors for this particular working group ($F(4, 161{,}046) = 1651$, $p < .001$, adj. $r^2 = .29$, see Table 1).

Table 1 – Multiple linear regression result table from simulation results

Coefficient	Estimate	SE	*t*-value	*p*
(intercept)	3.47	0.19	18.63	<.001
PE	0.30	0.19	1.6	.11
FC	-0.25	0.19	-1.347	.18
EE	2.64	0.19	14.12	<.001
SI	0.91	0.19	4.86	<.001

PE=Performance Expectancy, FC=Facilitating Conditions, EE=Effort expectancy, SI=Social Influence

When we look at the attained behavioral intention from all simulation runs, we see that the achieved behavioral intention is on average slightly lower than the true sample mean, which was measured by the survey (see Figure 3). This means that independent of the coefficients of the model behavioral intention is strongly determined by the perceived low effort expectancy in this group. The mean model divergence was -0.79 (SD = 0.73).

When we limit the free parameters of the model to the established parameters from literature (±0.1), we get a better fit of results (see Figure 4). Mean model divergence from the data now only yields $M = -0.37$ ($SD = 0.28$). This indicates that the parameters established by Venkatesh et al. [5] in conjunction with our agent-based simulation help predict acceptance of novel software solutions.

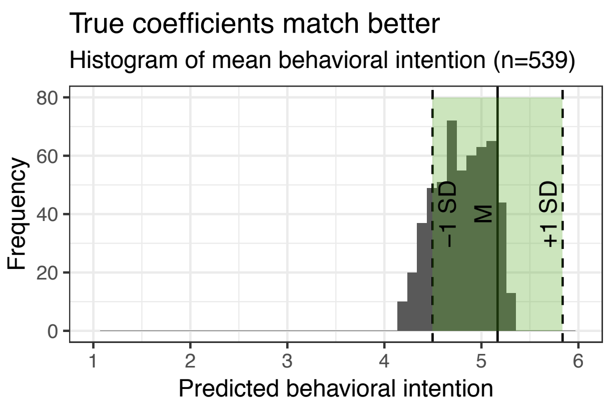

Figure 4 – Resulting simulations when the model coefficients are used from data

5 DISCUSSION AND LIMITATIONS

In this paper, we have simulated human decision making on the basis of the relatively simple UTAUT model. We surveyed twenty employees of a research group and modelled their virtual twins based on their survey results. We further used public co-authorship information to infer the underlying social network structure in the work group. The simulation of the acceptance of a collaboration software suite yielded similar results as the quantitative assessment of acceptance.

These results indicate that the agent-based model was able to *generate a similar prediction* as the structural equation-based approach. What was most interesting was that when looking at the individual network visualizations one could see that the users who reported the lowest behavioral intention still showed the lowest behavioral intention. The idiosyncrasies of the network were retained. Our approach was computationally not very challenging as the network was rather small in size.

The real-world data that we collected was a static snapshot of a long adoption process of two years. Since we did not collect this information regularly across time, we are unable to verify whether the adoption diffusion progressed similarly in the model as in the real world. Future research could try to *validate longitudinal* data—inherently available in the simulation—from simulation and the real-world.

The standard deviation of model divergence in some simulation runs was still rather large (between 0.9 and 1.1). It would be interesting to see, *who is responsible for these deviations*. Are individual users badly simulated or do some parameter constellations lead to overall bad results. Here, more detailed analyses would help in understanding where this simulation error can be attributed to.

So far, our model does not include a mental model for the individual agents. Thus, the *agents are unaware of trends*, or do not change their social network structure. Future research could investigate whether a model of trustworthy colleagues, whose social influence would then matter more, is able to predict adoption even better.

Our approach can, in theory, also be used to predict acceptance of novel technology in large organizations, given that a proxy for the social structure is available. Future research will have to *validate the simulation in larger organizational settings*.

6 CONCLUSION

Overall, we were able to simulate the diffusion process of acceptance in a small organization. The final outcome was relatively close to the observed real-world data. Our simulation was able to integrate dynamic behavior into a static model of technology acceptance. Applying such models can be useful in determining neuralgic users that are well connected and could drastically shift long-term adoption one way or the other. Understanding their motivation, will help in designing a support structure to persuade these key-users and gatekeepers, allowing organizations to adapt to the required changes of digitization more rapidly.

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9 BIOGRAPHY

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