Comparison of Information Technology Adoption Rates across Laggards, Innovators and Others

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Abstract

It is important to predict and analyze user acceptance of information technology in order to address success and failures of technological products. The Theory of Reasoned Action (TRA) has been used for two decades in empirical studies to predict user acceptance of information technology. Agent-based modeling (ABM) is well suited for studying user acceptance of information technology, which is an instance of contingent behavior. In this paper we extend our research on ABM of the TRA by comparing technology adoption rates across varied sections of a population. We discuss intention variations among laggards, innovators and the undecided sections of employees in an organization. Our implementation is cost effective and easy to use in contrast to the empirical method. The results we produced corroborate the results obtained from the last few decades of empirical research in this field.

Keywords

User Acceptance of Information Technology, Theory of Reasoned Action, Technology Acceptance model, Laggards, Innovators

1. Introduction

Understanding why people accept or reject information technology (IT) products has received substantial research attention over the past two decades [1]. Much of this work has focused on identifying the key psychological determinants of peoples' intentions to use IT, drawing upon more general models of motivated human behavior from social psychology such as the Theory of Reasoned Action and the Theory of Planned Behavior, among others.

Over the last two decades, user acceptance of information technology has been modeled by introducing the system to a user and getting his /her opinion via a questionnaire. This process is repeated again a number of times (Typically about three times, once before the technology has been introduced to the user, then immediately after technology has been introduced to users and finally after the technology has been used for a few months). Then the empirical data is analyzed to check for any changes in the various parameters of human models of User Acceptance of Information Technology (UAIT). UAIT is inefficient and inflexible since analysis of the empirical data is discrete and not continuous. Changes that have occurred between these successive time cycles cannot be accounted for by the current empirical implementations. Also, the process of collecting user opinions through questionnaires is cumbersome and expensive.

Although there has been strong and steady progress in recent years towards understanding technology acceptance, we have passed a point of diminishing returns with the continued use of the traditional research methodologies of field studies, lab experiments, and qualitative case studies. It is increasingly difficult for researchers to identify additional variables that can increase the model's explanatory power. Nevertheless, there remain puzzling and unexplained patterns of technology acceptance or rejection that are not accounted for by the existing theories. Often, IT applications that would appear to an external observer to be useful and easy to use so often fail to garner the acceptance of target users [2]. Also, IT applications lacking true usefulness so often become widely accepted [3, 4]. Some promising IT applications gain initial adoption, only to fall by the wayside over time [5]. More generally, IT applications sometimes exhibit oscillating patterns of adoption [6]. Theorizing of UAIT models to date has been unable to resolve these puzzles.

We posit that there are several systemic limitations of current research toolbox that threaten to impede further progress towards clear and practically actionable insights about IT acceptance:

1. Causal models are inherently cross-sectional and static in nature. This temporal shortcoming masks important social dynamics among individuals, which prevents accurate trending analysis and aggregate-level predictions.
2. The individual reasoning models that capture concepts such as beliefs, desires and intentions do not fully account for external social influences bearing on the internal psychological motivation of the individual. This overly restricts the analytical focus to a relatively narrow span of the overall causal chain linking distal antecedents such as decisions to invest in new IT to distal consequences such as individual and organizational performance and quality of life.
3. The individual reasoning models do not adequately account for group decision making and team collaboration influences involved in acceptance of collective technology such as groupware. There is a difficulty in representing relevant antecedents or consequences of collective-level processes, because these involve linkages among phenomena that manifest at different levels of analysis such as individual, group and organization.

To overcome these limitations, we employ agent-based modeling (ABM) as an additional tool to investigate technology acceptance [7]. ABM allows for simulations that have varying time granularity as well as detailed dynamically interactive models of influence. Research on organizational adoption of such innovations as total quality management [8], quality circle [9], downsizing [10], and production technologies [11], have found ABM valuable in providing insights into the dynamics of adoption beyond those afforded by more traditional methods [12]. A major reason for these new insights is that ABM is well-suited to incorporate both rational and social forces within a common modeling paradigm. Rational and social explanations have often been regarded as competing accounts for technology adoption [13]. Although neither is able to single handedly explain technology discontinuance decisions, when combined they can account for fad-like waves of adoption and rejection [9]. These initial applications of ABM to the study of organizational adoption illustrate how the complex interplay of various social influences give rise to unintuitive emergent global behavior across a population of firms.

The Theory of Reasoned Action (TRA) model predicts human behavior. The *intention* of an individual in a particular manner is a function of two determinants, one the person's nature and the other the social influence on that person. A person's positive or negative view to perform a particular behavior is known as his /her *attitude* [14]. The social pressure to perform a particular behavior put on him/her by the society of which he/she is a part of is known as *subjective norm*.

The TRA is used in empirical social simulations like predicting and understanding women's occupational orientations, weight loss, family planning behaviors, consumer behavior []and voting in British elections. In the remainder of this paper, we will discuss our agent-based implementation of the TRA with respect to user acceptance of information technology. Furthermore, we compare the technology adoption rates across laggards, innovators and others.

2. Agent Based Modeling

Agent-based modeling (ABM) is a computer simulation technique in which autonomous individual "agents" are programmed based on a set of explicit assumptions. Agents are able to influence each other's behavior either directly or indirectly via the environment. Agents can mimic the behavior of individuals, groups, and even countries [15] ABM has been used for sometime within biology and political science [15], as well as combat simulations for the military. ABM is becoming more widely used by business and management researchers [16, 17, 18].

ABM is well matched to the present research because it forces the researchers to make their assumptions explicit, enables them to selectively put detail where they would get high fidelity without a loss of generality, and provides a way around the researcher's limited cognitive ability to mentally simulate the consequences of all of the assumptions and mechanisms. Compared to traditional research methodologies involving empirical surveys or experimentation, ABM is better aligned with the aim of the current research to isolate and understand the non-linear dynamics surrounding a specific motive while implicitly holding other motives constant. ABM can overcome the linear and static limitations of traditional empirical research methods.

3. Agent Based Implementation of the TRA to model User Acceptance of Information Technology

Lack of user acceptance has always been an obstacle to the success of new information technologies. Determining user acceptance is very important as it enables us to predict and analyze user behaviors. It answers problems related to failure and success of technologies, and explains abnormal behaviors.

We have designed a basic computational model of the TRA that targets user acceptance of information

technology. Much richer models of TRA are available like the Technology Acceptance Model (TAM). However, our agent-based implementation omits complex parameters found in non computational TAM models.

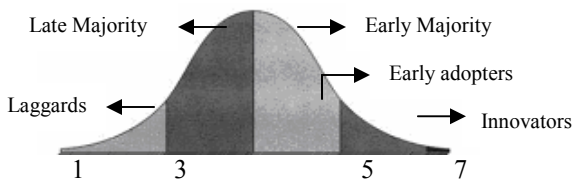

Figure 1: Bell curve representing attitudes of a population towards accepting a new technology.

Assumptions

- *Attitudes* of the entire population are represented using a bell curve because *"technology is absorbed into any given community in stages corresponding to the psychological and social profiles of various segments within that community" [19]*
- As shown in Figure 1, *attitudes* of entire population range from 1-7 wherein innovators have a high *attitude* range of 5-7 and laggards have a very low *attitude* range of 1-3. Majority of the agent population falls in the early and late majority categories with an attitude ranging from 3-5
- *Subjective norm* and *behavioral intention* range on a scale of 1 to 7 similar to the options given in questionnaires. (7 represents maximum *intention* to use the new information technology and 1 represents the minimum *intention* to use the technology)
- Initially, all the agents have a *subjective norm* of 1.
- Every agent is assigned an independent error in his or her *intention*. We assign the error to agents in the range of -1 to +1 resembling a bell curve (as in figure 1) with most of them having an error of zero. This error term accounts for the inaccuracies across individuals.

We compute the *behavioral intention* of an agent by multiplying the *attitude* and *subjective norm* with the respective weights and then taking a sum of their products and the error term, i.e.

For any agent i,

$$\textit{Behavioral intention}_i = \textit{Weight on Attitude}_i * \textit{Attitude}_i + \textit{Weight on Subjective Norm}_i * \textit{Subjective Norm}_i + \textit{Error}_i \quad (1)$$

If the computed *behavioral intention* is greater than the threshold specified then update the *subjective norm* using the equation below.

$$\textit{Subjective Norm}_i = (6*(\textit{Total number of users/population size})) + 1; \quad (2)$$

The TRA model of our implementation is shown in figure 2. As shown in the figure, the *behavioral intention* influences the number of users of the technology, which in turn influences the *subjective norm*.

An agent whose *behavioral intention* is greater than the threshold set at runtime is considered as a new user of the technology.

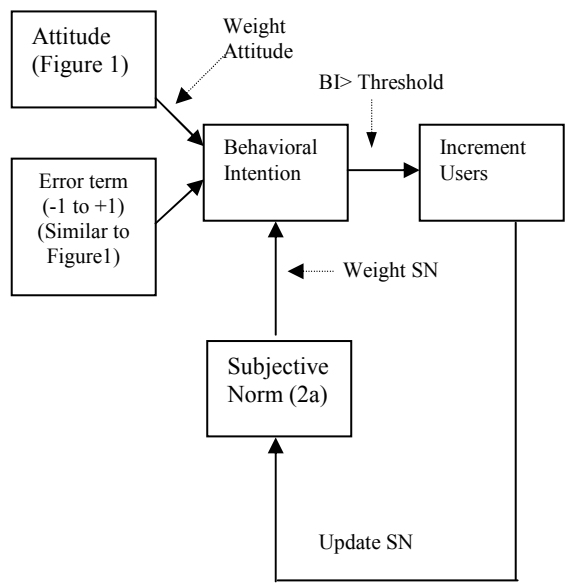

Figure 2: TRA Model

The algorithm developed for this implementation is given below:

```
Instantiate all parameters (Population size, Attitude,
Subjective Norm, their corresponding weights and
Behavioral Intention Threshold)
  For every time cycle
      For each agent n
        If the agent is not a user
          Compute its Behavioral Intention using
          equation (1);
            If the Behavioral Intention is greater than
            the threshold then
              Increment the number of users;
                Update subjective norm using equation
                (2a);
            End If
        End If
      End Loop
  End Loop
```

In the next section, we explain the results of the experiments conducted and our future work.

4. Experimental Results

We conducted numerous experiments by varying the parameters such as the relative importance of the *attitude* and *subjective norm* components, population size and threshold values. This relative importance given to the attitude and the subjective norm is called beta weights in the IT industry. Generally, in the traditional method of handing out questionnaires to a population, the beta weights are obtained after statistical analysis of the feedback obtained from the population. But in ABM, reverse engineering plays a very important role. We start with the beta weights and analyze the technology adoption rate of a product.

We assume the number of employees working in an organization is limited to 100.The population is divided into three categories based on their attitudes(figure) The first group called laggards have an attitude range of 1-3.The second group called undecided have an attitude range of 3-5.The final group called innovators have an attitude range of 5-7.

We are modeling varying dispositions of populations toward adoption by changing values of BI. High values of BI threshold (e.g. BI threshold 5 reflects an eagerness and ease of adoption where as, low BI threshold (e.g. BI threshold 1) reflects a reluctance to adopt. Other values of BI threshold reflect an indecisive disposition toward adoption.

The GUI of our implementation is shown in Figure 3.

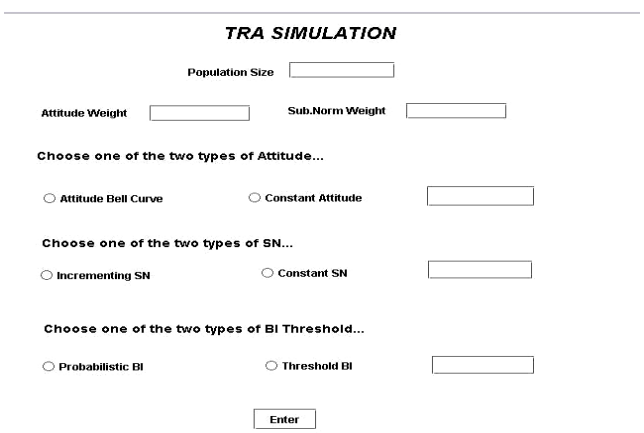

Fig 3: GUI of the simulation

4.1 Case 1: Technology appealing to all categories of the population leads to rapid adoption rates

In the simulation, the threshold value is set to 1 and any employee whose behavioral intention value is greater than 1 adopts the technology. In the global perspective, all the employees of the organization adopt the technology in the first few time cycles which indicates that the product adopted is immensely popular among all the categories of the population and also has a low risk factor associated with it.

Fig 4 indicates the observed adoption rates with the behavioral intention threshold set as 1. With a low threshold value, we observed immediate maximum adoption rates.

Figure 4: Technology Adoption rate for threshold=1

Fig 5 shows the average behavioral intention values across group 1 (Laggards). Each line in the graph represents the average intention value for a specific value of the beta weights of Attitude and Subjective Norm. For example, 0.2/0.4 means a 0.2 weight to the Attitude and a 0.4 weight to the subjective norm. The slope of the graph is constant because all the users adopt the technology in the first time cycle and maintain their intentions throughout the course of this simulation. Higher weights given to the core components of this model leads to a higher intention value.

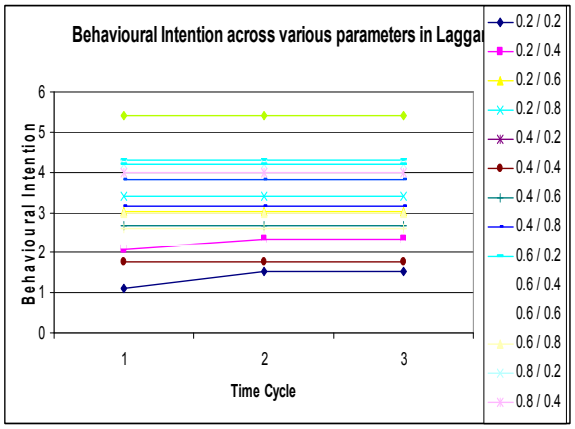

Figure 5: Average Intention values for group 1 (laggards) with threshold=1

At the agent level, first the innovators become users and this triggers a diffusion effect where in the next time cycle, a combination of innovators and undecided employees become users and finally the laggards adopt the technology. This reinforces the fact that some members are opinion leaders, and other members of the population tend to follow their footsteps. These patterns of relationships mean that once opinion leaders successfully adopt a new technology, the rate of adoption increases. Increase in number of users results in ease of adoption. Accelerating adoption rates means that successful technologies will be picked up ever more quickly, and so will also be harder for competitors to displace. Conversely, the steepening of the adoption curve highlights the time-sensitive nature of technology markets. The graphs for the innovators and the undecided are similar with higher intention values.

4.2 Case 2: Technology appealing to a small section of the population leads only the innovators to adopt the technology

A product which is intended to be used by only a portion of the population will cause only the innovators to adopt the technology and not cascade the effect to the other categories of the population. In this simulation, the behavioral intention threshold was set to 5.

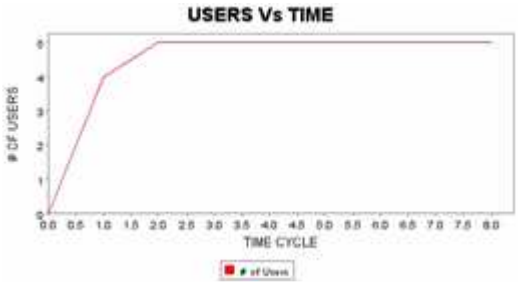

Fig 6: Technology Adoption rate for threshold=5

Fig 6 shows a small fraction of the population adopting the technology and not all the opinion leaders adopted the technology. This fortifies the fact that a product with limited appeal will not succeed in the information technology world.

Fig 7 shows the average intention values across group 3(Innovators). The intention values of the innovators who adopted the technology remain constant during the course of this simulation. For a couple of cases, we observed some innovators waiting a time cycle and then adopting the technology indicating the low appeal or probably a high risk associated with the product.

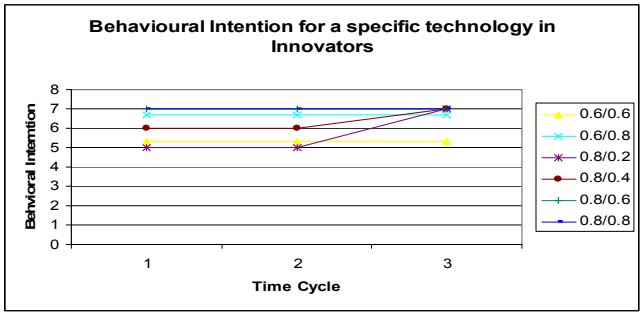

Figure 7: Average Intention values for group 3 (Innovators) with threshold=5

The intention values of the group 1 and group 2 categories were much less than the threshold.

4.3 Case 3: Technology appealing to a majority of the employees of an organization leads to a technology adoption rate lying between the previous two cases

In the simulation, the threshold is set to 3 and any agent with an intention value greater than 3 adopts the technology. The rate of adoption of a product, which appeals to a majority of the population, typically plots as an "s-shape" reflecting a slow beginning as only a few innovators adopt, followed by a rapid spread throughout the class and finally by a leveling off as full diffusion is reached. This technology may not have a 100% adoption rate. Due to a slow beginning, competitors can have a distinct advantage in selling a similar technology and this also highlights the time sensitive adoption cycle in the IT industry.

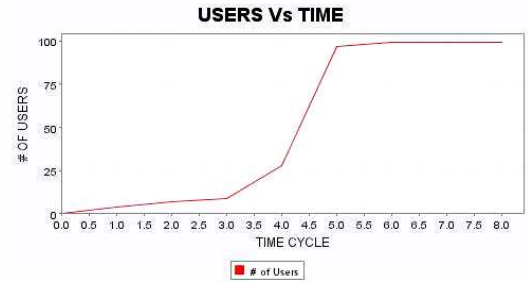

Fig 8: Technology Adoption rate for threshold=3

Fig 8 shows a small fraction of the population adopting the technology in the first few time cycles, which triggers a steep diffusion effect through the remainder of the population and finally levels off as maximal diffusion is reached. The adoption rates of a product in this category lie between 80% and 100%.

A typical result of the behavioral intention across the three populations is given in Fig 9. The figure shows the group 2 populations, who adopt the technology at a later stage have more intention of using the product

than the innovators. This is followed by the group 1 population having more intention of adopting the technology compared to the other two groups. The intentions of the opinion leaders remain constant whereas for the other two categories, there is a steep increase in the intentions in their third cycles.

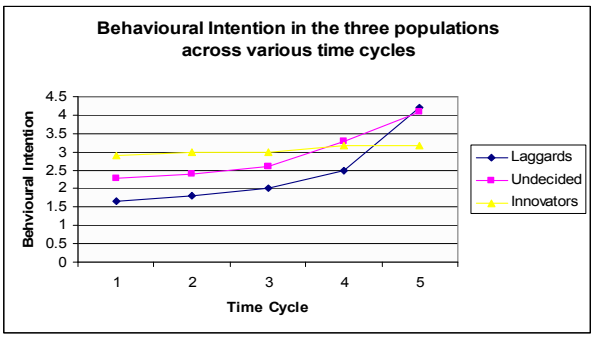

Figure 9: Intention values across the three populations

5. Conclusion and Further Work

In this paper we discussed varying intentions among different sections of employees in an organization. We observed that for high intention values there is a steep increase in the rate of adoption of the given technology in most cases resulting in 100% adoption of a technology. Low values of intention resulted in only a fraction of the population adopting the technology.

We do not, however, claim that this will always be the case, as there will be situations in which agents may not accept the technology in spite of favorable conditions.

The next stage in this research is to conduct experiments involving numerous technology acceptance models that implement the concept of dynamic social networks. This will enable us to specify relationships between the artificial agents representing the employees of any given organization.

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