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MODELING THE ACCEPTANCE AND USE OF TELECENTERS IN BRAZIL

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Abstract

This article describes the modeling of factors that affect the adoption and use of Information and Communication Technologies (ICT) in Telecenters context. For such, some conceptual dimensions are used, such as a potential demand model (PDM), which aims at characterizing processes that determine the technological acceptance, and an acceptance dynamics model (ADM). Together, PDM and ADM constitute a simulation combined model based on agents that allow the analysis of the effect of different aspects related to Telecenters and the users's individual profile, according to the target audience behavior. This modeling approach intends to constitute an analysis tool that is able to help formulate digital inclusion public policies.

Keywords: digital inclusion, telecenters, social networks, TAM, ABMS.

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Introduction

Digital divide is the latest social gap that characterizes developing societies, especially in Latin America. It is the consequence of other gaps, such as the excessive income concentration among the most affluent individuals and the resulting incapability of the poor to acquire technological innovations or paying for communication services. It is also the result of the lack of infrastructures, such as electric power, telephone, among others that are required for the use of technology. However, digital divide is often the main cause for other gaps, since the digitally excluded ones are unable to access citizenship services offered via Internet, and have less access to information, knowledge, and working opportunities.

Among the government policies and initiatives to minimize the digital divide for their citizens, the most common is the installation of public facilities for computer and Internet access, also known as Telecenters. As these facilities are free, they can serve the low-income individuals, overcoming one of the principal barriers to inclusion: the cost. However, as a means to digital inclusion, the Telecenters have many other benefits that, if appropriately explored, can be extremely useful to arouse the interest of potential users that otherwise would face social, psychological or cognitive barriers when using unfamiliar equipment, such as a computer. Therefore, the Telecenters can support new users, by diminishing these initial barriers. Telecenters can also offer additional services, such as courses and training that stimulate new users' acceptance.

However, the telecenters can also have some disadvantages such as being located in an inconvenient place, cause the formation of queues and have a limited use time as the computers are shared among users. They can also create a discouraging factor as related to its location, due to the distance from the user place to the Telecenter, as well as the "social distance" perceived by the potential user when he/she does not consider the telecenter as belonging to his/her community.

By considering such advantages and disadvantages and the fact that they depend on factors that may be controlled by the public administrator, it is desirable to develop an analysis model capable of simulating alternate Telecenter dimensioning and positioning scenarios for a given locality. This analysis can predict the most significant factors in the adoption of these public facilities by a community, by showing the best combination of features for each context. Therefore, the administrators can optimize the results expected from the telecenters by reducing the most detrimental aspects to their popularization and thus preventing the waste of resources.

Therefore, this paper describes an analytical and simulation model that supports the study of the Telecenter adoption process by the population it is meant to serve. The model considers facts such as spatial location, quantity of equipment, and availability of support services, and correlates these factors to the user profiles and their perception of the Telecenter. As this is a complex environment, the simulation model requires an interdisciplinary treatment with a systemic approach, and technique and method diversity. Thus, the modeling process described herein uses technological acceptance and innovativeness models, and statistics and agent-based simulation methods (ABMS) in order to computationally test the different scenarios for the Telecenter configuration.

This modeling aims at identifying the individuals' preferences related to what the Telecenters can offer, extending the knowledge base about the impacts of an innovation and use of Information and Communications Technologies (ICT) in public context. Additionally, the scenario simulation and subsequent impact analysis will allow gathering information related to the formulation of public policies for digital inclusion, and to the Telecenter structuring according to the needs of the community to be served.

This study is one of the activities conducted in the scope of a telecommunication solution project for digital inclusion, whose general guidelines are presented in (Holanda & Dall'Antonia, 2006).

ICT Acceptance: Modeling Conceptual Aspects.

Adopting new technologies is a subject that has been widely studied in several research areas. Its importance in predicting income, resource allocation flow and in planning the introduction of a new technology in the market draws the researchers' attention to the proposition of novel adoption prospecting techniques.

The study of technology adoption can be divided into two parts. The first one addresses the potential demand, i.e., the number of individuals that will adopt the technology during its lifecycle (potential users). The other deals with the moment when each adoption will occur. Their combination produces a technology diffusion curve along its lifecycle. This curve has an 'S' shape, which saturates when 100% of the potential users become users.

Bass (1969) proposed a diffusion model based on a linear relationship between the acceptances in a given period ('t') and the sum of the acceptance within other periods up to 't'. In this diffusion curve, two parameters are used: one of them is exogenous (innovation effect), and the other is endogenous (imitation or word-of-mouth effect). In this way, the larger the number of effective users of the new technology is, the larger the number of potential users who get to know it, and become effective users. Other researchers have extended the Bass' diffusion model – see, for example, (Sterman, 2000; Talukdar *et al*., 2002; Gupta *et al*., 1999). These models have become useful for predicting diffusion of new technology, provided that external factors do not significantly affect its behavior (Bonadia *et al*., 2006).

However, approaches that evaluate the aggregated behavior (top-down) do not consider emerging events that can affect the average diffusion behavior. These events can have significant impacts on innovation diffusion, and its analysis helps predict risk mitigation strategies. For this reason, this modeling can be included into a system dynamic context – see (Forrester, 1989) –, with a bottom-up orientation. According to this approach, the global behavior is defined by the ensemble of the individual behaviors. The bottom-up approach is used to analyze evolutionary systems and in environments where the decisions are made as a result of the interaction among individuals. A typical example is the game theory, which deals with optimal behavior selection when the costs and benefits of each option depend on the decisions made by other individuals – see (Neumann and Morgensten, 1944).

Although Bass's dynamic model has essentially aroused from a top-down approach, the idea that the technology diffusion is considerably influenced by the imitation (word-of-mouth) effect is also appropriate to the bottom-up approach. Hence, the concepts represented by innovation and imitation parameters are used in our approach as decision rules so that, when interacting, the individuals create the aggregated behavior of the diffusion. The individuals are classified according to their innovativeness level and tendency to imitation.

The parameter related to the "innovation" effect is used as a factor that makes individuals adopt the technology regardless of other people's attitudes. The parameter related to the "imitation" effect is adopted to account for the number of effective users needed in the social network of a given individual to make him/her adopt the technology. The classification according to the innovation and imitation level follows Rogers's terminology (1983), which defines the user profile according to how long it takes him/her to adopt a technology from the moment it is released. Therefore, as there are some individuals that demonstrate a clear tendency to search for new products, technologies and services, there are also some others that resist to everything that is new, and behave in a conservative and reserved manner – see also (Moore, 1991).

The profile division results from a parametric association with the Normal curve (,) – derived from an S-shaped curve – where the users are classified in a time line according to their innovativeness profile (and corresponding adoption delay). Then, the first three categories represent the individuals who adopt a given innovation earlier than the average adoption time: the 2.5% fastest adopters are called "innovators"; the following 13.5 % are the "early adopters", while the next 34% are the "early majority". The second half of the population is divided into "late majority" (34%) and "laggards" (16%), which are the last ones to adopt the innovation.

Therefore, in order to simulate an acceptance dynamics of a Telecenter, one should consider Bass innovation and imitation effect concepts through a bottom-up approach, and Rogers's classification for the innovativeness profile of the individuals.

However, the models for adoption dynamics do not provide an estimate of the potential demand, i.e., the number of potential users is exogenous to the models. These models estimate the adoption speed, regardless of the total number of potential and effective users. Thus, it is necessary to use tools to estimate the service potential demand so as to allow sizing the Telecenter, and planning its upgrade.

Studies related to behavioral aspects aim at understanding an individual's relation to technology in order to analyze her/his attitude towards it and estimate its adoption. This approach considers the individual, rather than the aggregated behavior. The most influential model (although not generally accepted) among those that attempt to explain ICT adoption and use is the Technological Acceptance Model – TAM, which focuses on computer use. For proposing this method, Davis (1989) adopted the Rational Action Theory – formulated by Fishbein and Ajzen (1975) – and replaced the determining factors of TRA attitude with two distinct variables: perceived usefulness, and perceived ease of use. The first one refers to the use motivated by the belief that technology will improve user performance; the second one refers to the perception of usage effort as an attenuator of the benefits that a given application can bring to its users.

However, cultural and social influences are not considered in the first technological acceptance models, which arouse new discussions related to this subject – see, for example, (Malhotra and Galletta, 1999; Hofstede, 1980 and 1991; Venkatesh and Davis, 2000; Veiga *et al.* 2001 and Walshan, 2002).

Another factor that is not directly related to either one of TAM's key variables is the individual's social profile. This fact can be considered when building-up a single model for the potential demand so that it can, when combined with the adoption dynamics model, simulate emerging phenomena, predict the diffusion of Telecenter use and provide a better sizing during the entire telecenter lifecycle. Considering this aspect, ABMS appears as the appropriate modeling to combine both adoption aspects for a technological service or innovation, besides being considered a bottom-up tool, as discussed above.

Furthermore, ABMS is one of the branches of Distributed Artificial Intelligence (DAI) that, according to Costa (1997), aims at developing methods and techniques to solve complex problems through the collective intelligence metaphor. In this case, collective intelligence can be classified in separate units, called agents, or emerge from their interaction. While the classic Artificial Intelligence (AI) is based on individual human behavior, DAI emphasizes social behavior in conjunction with the ideas of the game theory, mentioned above.

According to Costa (1997), one of the most accepted definitions of "agent" is given by Ferber & Gasser (1991): "an entity that is able to act by itself and on the environment and to communicate with other agents, and whose behavior is the result of its observations, understanding and interactions with other agents".

The contamination models, on the other hand, including those with an *ex ante* nature, are based on the understanding of the underlying communicative process of an innovation diffusion as a result of socially transferred information through word-of-mouth dissemination. Each adoption within the agent population locally changes the user and non-user ratio, and modifies the social influences on this neighborhood. Therefore, by using ABMS, the diffusion of the Telecenter use in the social network can be simulated as in a real world communication process.

An Empiric-Analytical Method

Considering the sides of the potential demand estimate and the acceptance dynamics, a single simulation model is designed to allow evaluating the impacts on the demand and on the adoption dynamics, due to the population profile scenarios and the Telecenter sizing.

Thus, an estimate model is initially presented for the potential demand of the Telecenter use. Then, considerations for the Telecenter acceptance dynamics model are taken, and the combination for both partial models in one simulation model is proposed based on agents, which are assigned here as a simulation combined model.

Potential Demand Model (PDM)

The potential demand estimate is performed by considering the analysis of factors that can be related to the Telecenter service acceptance decision. Therefore, the theoretical framework presented in the previous section is used in this step to select the variables that are more probable to respond to the Telecenter acceptance.

TAM studies show that there is a relation between, on one hand, the attitude regarding acceptance and, on the other hand, the use of a technology and two factors perceived by the user: “ease of use” and “usefulness”. However, other aspects can be related to the Telecenter effective adoption. This means that besides the factors considered in TAM, the individual’s profile is also considered (in terms of educational background, age, etc.). Additionally, the social network influences, and their effects on the individual decisions, can also be related to the adoption. Another part is the cultural influence, which can be responsible for regional differences. Considering the different factors that can explain the adoption of a technology, the next step is to obtain a set of key variables that can be responsible to explain statistically the Telecenter adoption behavior.

Thus, the logistics regression model (LRM) is used to select the variables that can explain the Telecenter adoption more appropriately. As a response, the model results in the probability of an individual with certain characteristics to be a potential user. The logistics regression model aims at identifying the determining factors for the Telecenter adoption according to the individual’s characteristics, provided that these characteristics are significant and are selected to compose a final regression model. In other words, the LRM describes how the Telecenter adoption (response variable) can be explained by other variables (explanatory) introduced to the model, and, therefore, estimates the probability of an individual to go to the Telecenter, which would characterize him/her as a potential user or non-user. This way, LRM has two main benefits (see Hosmer and Lemeshow, 1989): descriptive power, when defining the relationship nature between the response (i.e. the probability of Telecenter adoption) and one or more explanatory variables, and predictive power, when predicting if a person tends to adopt the use of Telecenter in the future.

The LRM curve adjustment method allows selecting a set of explanatory variables (ease of use, perceived usefulness, individual profile, social networks and cultural influence variables) that can better explain the different response variables (potential user or non-user). Therefore, the resulting LRM is shown in equation (1).

$$\ln\left(\frac{p_{adoção}}{1-p_{adoção}}\right)=\sum_{j=0}^{L} b_j v_j \qquad (1)$$

Where

- $p_{adoption}$ is the probability of the Telecenter adoption;
- b_j (j = 0,..., L) are the regression coefficients estimated for the model, and
- v_j is the selected set of explanatory variables for the model ($v_0 = 1$).

The resulting LRM is obtained from actual data collected in the field. In order to evaluate the predictive power of LRM, a validation sample consisting of part of the collected answers should be used. These answers are not included in the adjustment initial process. LRM resulting equation is the potential demand model itself, which is incorporated into the simulation combined model introduced further in this document.

Adoption Dynamics Model (ADM)

The diffusion and the appropriation of an innovation by the members of a social system result from a communication process among them. The networks that constitute this social system allow for analyzing how individual behaviors towards a technological innovation can affect the population global behavior. Particularly, bottom-up modeling enables the analysis of the phenomena related to contamination and diffusion processes. It helps to understand how subjective aspects (that affect individual behaviors) influence the final result of a diffusion process. This way, the time necessary to the diffusion of a specific technology is the result of the communication process among individuals and their social networks until the effective adoption of a technology.

ADM comprehends two parts that are directly related. The first one is the allocation of individuals in subsequent categories (according to the terminology used in Rogers’s innovativeness profile) that refer to the required number of effective users belonging to the social network of a potential user so that he/she can also become an effective user. The second part refers to the estimated pace in which the information exchange (or interaction among the individuals from the social network) occurs in each of the subsequent categories. This part is responsible for the speed at which an individual's social network affects his/her decision of becoming an effective user. Table 1 shows the relationships between Rogers's profile, the number of influencers required and the influence pace.

Table 1:

Relationships among Rogers's profiles, number of influencers, and influence pace

Rogers's Profiles	Number of Influencers	Influence Pace
Innovation-prone	0	$F(T_1 – T_0); (T_1 > T_0)$
Early Adopters	N_1 $(N_1 > 0)$	$F(T_2 – T_0); (T_2 > T_1)$
Early Majority	N_2 $(N_2 > N_1)$	$F(T_3 – T_0); (T_3 > T_2)$
Late Majority	N_3 $(N_3 > N_2)$	$F(T_4 – T_0); (T_4 > T_3)$
Laggards	N_4 $(N_4 > N_3)$	$F(T_5 – T_0); (T_5 > T_4)$

ADM is included in the combined model to complement the information on the potential demand model. However, in this case, it determines the moment when potential users are likely to adopt the Telecenter.

Simulation Combined Model

The information resulting from the partial models is inputted to a model that tests the social relationships among the individuals from a given network, and thus simulates the social influence dynamics. The combined model is programmed in a simulation software based on agents (ABMS). To get this, a grid is built with 10,000 agents representing a social network where each agent represents an individual in the society and his/her acceptance behavior depends on the rules and conditions imposed. Each agent has eight immediate neighbors whom they interact with and who influence the decision process (according to "Moore neighborhood"). In addition to these immediate neighbors, each agent in the model has some neighbors, referred to as remote neighbors, with whom they have mutual influence relationships. The selection of remote neighbors for a given agent is random and aims at reproducing the real-world social relationships where, as described in (Milgram, 1967; Watts, 1999), we can notice the "small world" effect, as the existence of remote relationships among non-contiguous agents make the information diffusion or contamination process faster than if there were only local relationships (see also Holanda *et al*. 2003). Figure 1 shows the influence network configuration in the simulation grid.

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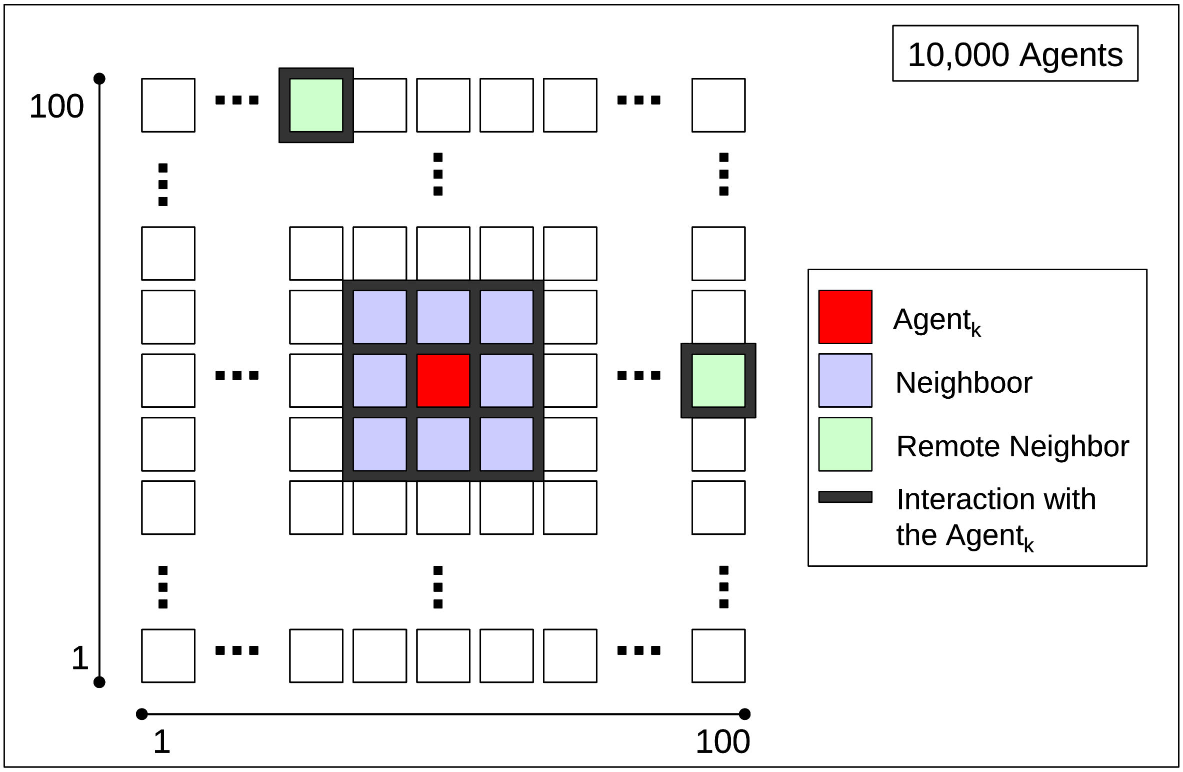

Figure 1: Agent neighborhood configuration in the grid

In ABMS, each agent presents one of several possible feature combinations. These characteristics essentially depend on the potential demand models (PDM) and on the adoption dynamics model (ADM). First, each agent receives a set of characteristics that are relevant to the demand model and to his/her innovativeness profile information. Then, these characteristics are validated by the partial models (PDM and ADM). As a result, the agent is "marked" as a potential user or a potential non-user. If the agent is qualified as a potential user, ADM allocates the result from the total number of influencers that interact with the agent, and the interaction pace that his/her acceptance can occur in a "t" period, and due to the environment conditions in each iteration of the combined model.

In the model described herein, each agent is in a given social context defined by his/her location in the grid (and by his/her neighborhood) and by the distance from the test units (existing Telecenters in the location).

Unlike top-down simulations, which work with uniform population aggregates, the agent simulation allows for detecting counter-intuitive behaviors that only occur when each agent can make decisions individually. This permits to anticipate social dynamics in the technological acceptance process and to verify the sensitivity of different variables.

Thus, in addition to the neighborhood configuration, the combined model also has characteristics of the environment where the service exists and of its conditions. An individual's attitude regarding a service or technology does not depend only on impressions that are constant and stable overtime, but also on occasional and dynamic aspects, such as certain conditions that dynamically affect the users' experience: increasing the number of users implies longer waiting time in queues, or can reduce the usage time, according to the internal policies of a Telecenter. Hence, the random allocation of testing units (Telecenter simulation in the combined model environment) defines part of the environment and affects agents' behavior depending on their location (among other factors) in relation to the testing units. Similarly, the features that vary overtime, according to the agents' behavior towards the moment condition, also modify the characterization of the agents in every iteration. Figure 2 shows the interaction and decision diagram for the combined model.

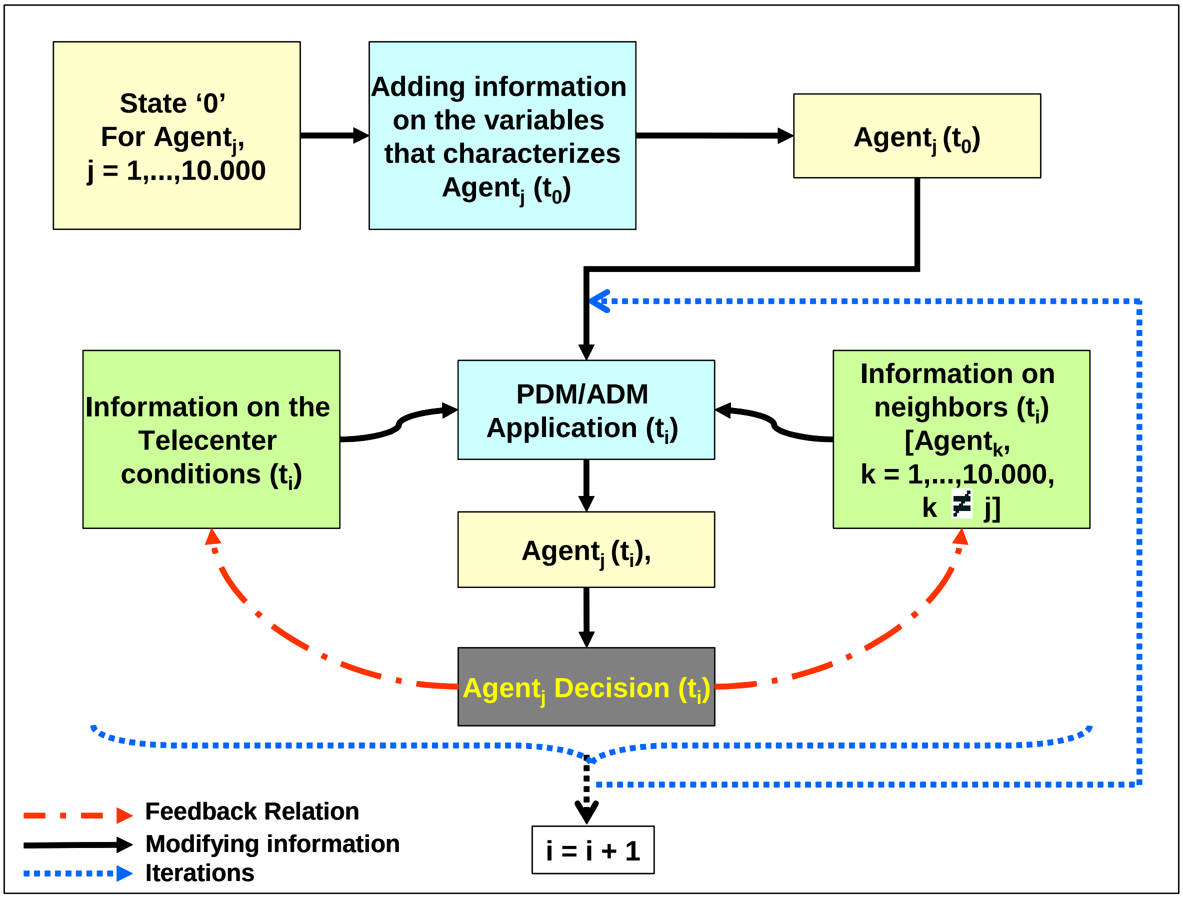

Figure 2: Interaction and decision diagram

As shown in Figure 2, for each *i* iteration in the simulation, the information that supports the decision regarding the Telecenter use changes, as the environment is dynamic. Agent$_j$, in the initial state (t_0), is characterized by the information on the variables related to ease of use, perceived usefulness and profile. With this information, PDM and ADM are applied, constituting Agent$_j$ state in iteration *i* (t_i), and his/her decision on the acceptance is made. The decisions made by each agent modify the information. New decisions are made, and constitute the diffusion curve for the Telecenter use at the end of the simulation (i.e., the number of iterations defined *a priori*). These curves are object of sensitivity analysis, considering different profile, environment and sizing for the Telecenter.

Simulation Scenarios

In order to build-up simulation scenarios, we consider the main system variation factors, which are divided into three types: (i) for dynamics, (ii) for eventuality, and (iii) for reality.

The dynamics variation sources are the ones that cause broader unpredictability in the diffusion process, given the feedback effects in the agents' behavior. Factors such as the increase in the waiting time for use, the decrease in the access quality or dispute for the monitor attention promote a cascade effect, as they positive or negatively affect the information transfer among individuals in the social network (neighbors) modifying, at each iteration, the diffusion behavior.

The modeling of this variation source is performed by checking, in every iteration, the momentary conditions, and analyzing whether they are favorable or not to the adoption by the agent, according to the PDM result (whenever the variables are significant to explain the adoption). Thus, even if in the initial state the agent is allocated as a potential user, the values in the potential demand model can be changed in the following iteration, so the agent's features are dynamic. Figure 3 shows the algorithm for such variation factor, which occurs in the PDM application step, with the waiting time as example.

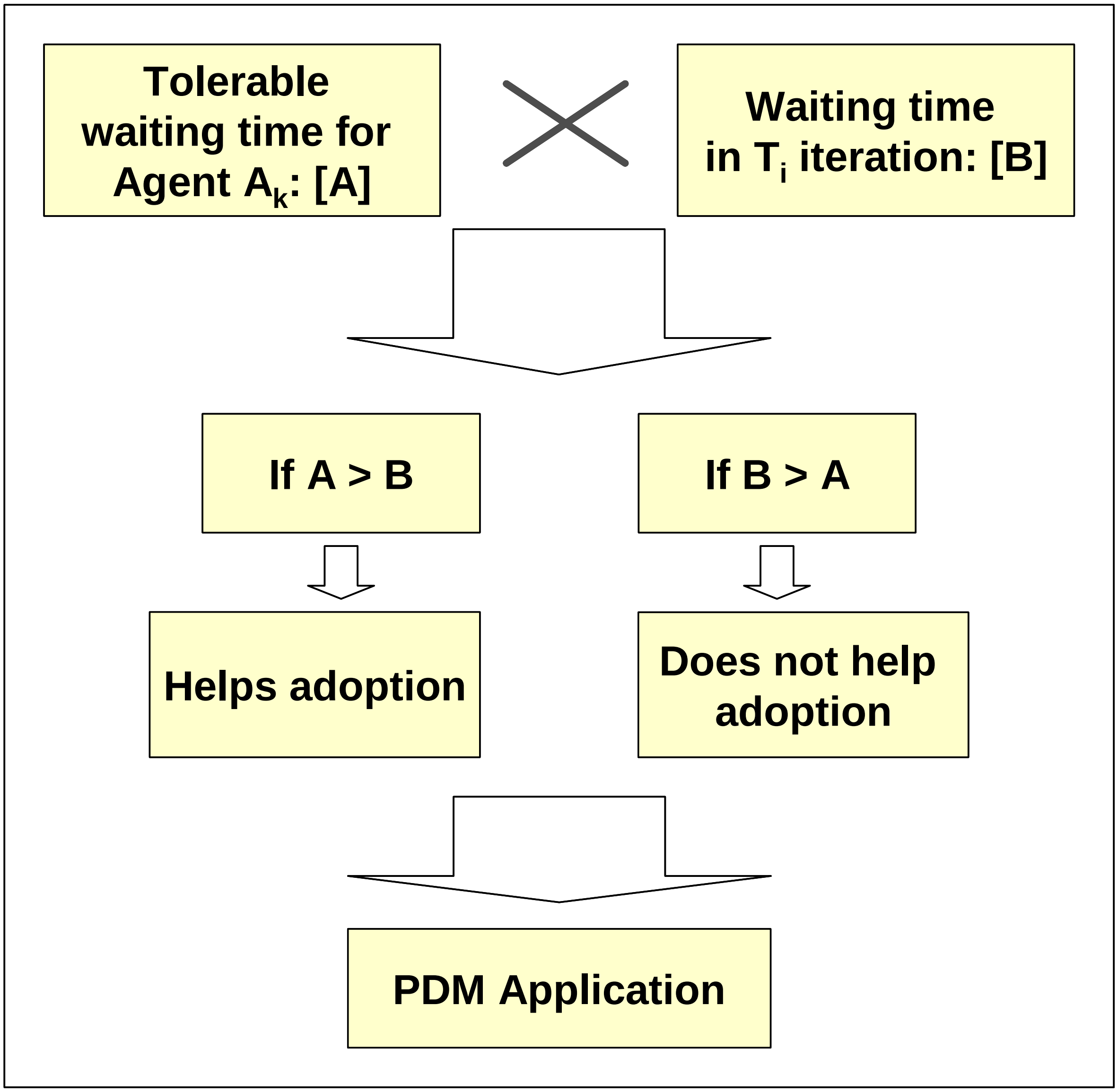

Figure 3: Algorithm for the dynamics variation source

This variation factor is the main responsible for following up the telecenter size evolution, by showing the need and time for new investments in order to increase the number of computers, monitors, access bandwidth, etc. If, for example, the waiting time increases due to a higher demand and the number of computers remains the same, the usage diffusion tends to stagnate. In this case, the offering of new computers redefines the parameters and allows for the continuation of the diffusion among potential users.

The eventuality variation factor occurs due to the random allocation of agents and telecenters in the ABMS grid. Factors related to the distance from the individual's location to the telecenter can determine, to a certain extent, the likelihood that he/she is a potential user. This might occur when the RLM parameter related to this variable apears to be significant (greater than zero) to explain part of the telecenter adoption probability. Considering the initial location of the telecenter in the grid, it does not change during the iterations, however, each agent is at a different distance, an also has as a particular perception of this distance.

The modeling of this variation factor is performed at the model initial state (t_0) when the actual distance from the agent to the testing unit is calculated and compared to the distance that this agent perceives as not too far. Figure 4 shows the algorithm for this variation factor, considering the "distance" variable.

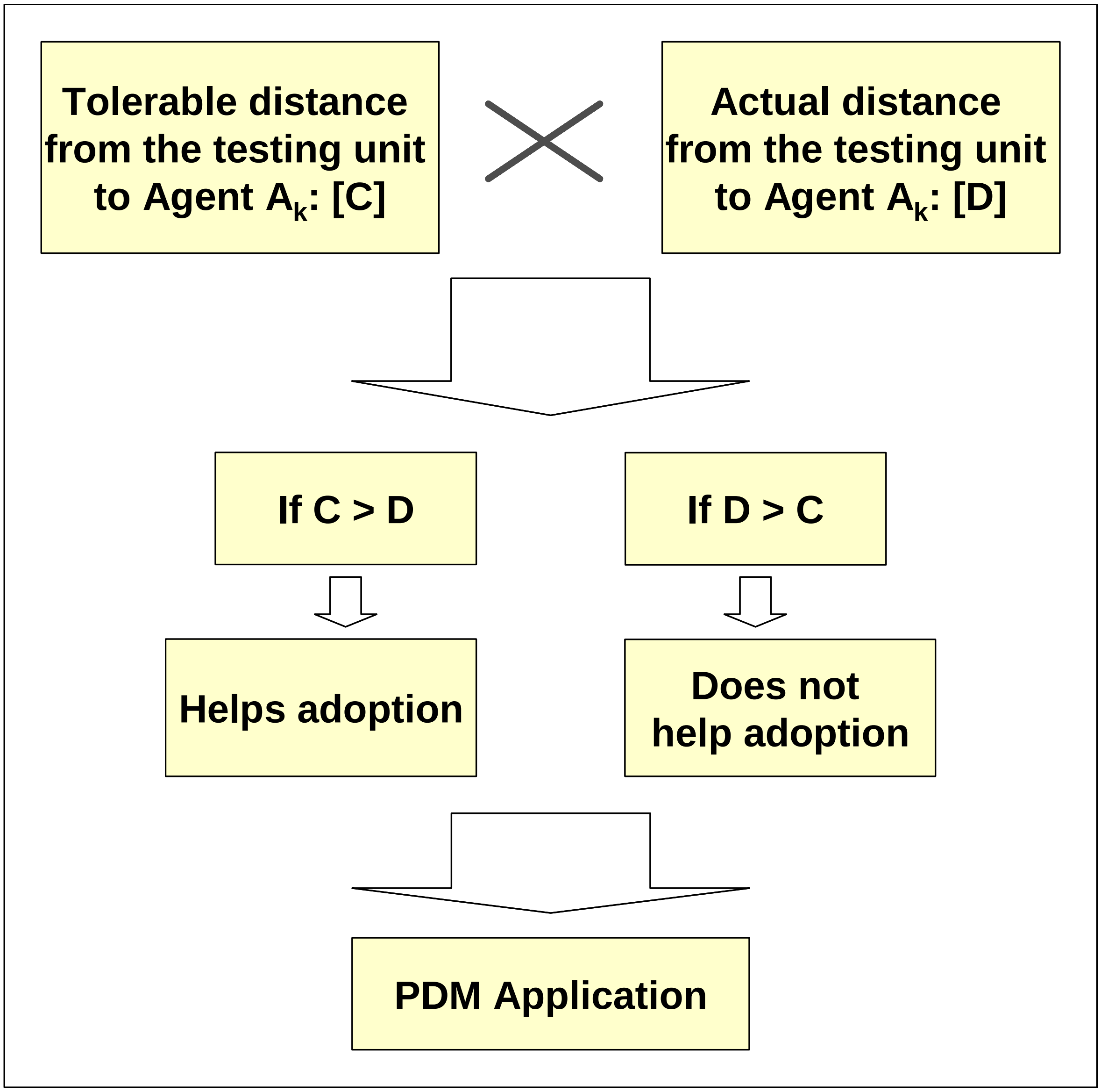

Figure 4: Algorithm for the eventuality variation source

In a real environment, although the telecenter location is not random, it is not reasonable to suppose that the agent profiles that are most likely to adopt are also situated in the shorter distance to the telecenter. However, field surveys can find data regarding the most appropriate location for the telecenters. Some scenario simulations provide relevant information on the diffusion in terms of the impacts of different distances due to the resource allocation in more than one location so as to serve a larger number of users.

The reality variation factors are those on which the public administrator can not have any kind of direct influence. This variation factor is related to the combination of population profiles and how they respond to the telecenters. On one hand, some profiles can be more inclined to use the telecenter; on the other hand, the number of individuals with such profiles can vary depending on the region. The variability of profiles that tend to adopt can be smaller than the variability of the number of individuals per profile in different regions. However, this information must be obtained from field surveys.

But, regardless of specific surveys in the region where the telecenter is to be installed, the scenario simulation provides a sensitivity analysis considering these two real-world variables, aiming at pointing out the impact of these differences on the diffusion of telecenter use. These factors are entries for PDM and ADM and do not change according to the environment. Some examples are: educational level, distance and waiting time perception, age group, among others, in terms of their distribution among the population.

The impact analysis for these three types of variation factors allows the creation of strategies for the deployment and sizing of telecenters in Brazilian cities. Figure 5 shows the results of a simulation in a test case where "distance" and "waiting time" parameters are significant in PDM, and affect the diffusion.

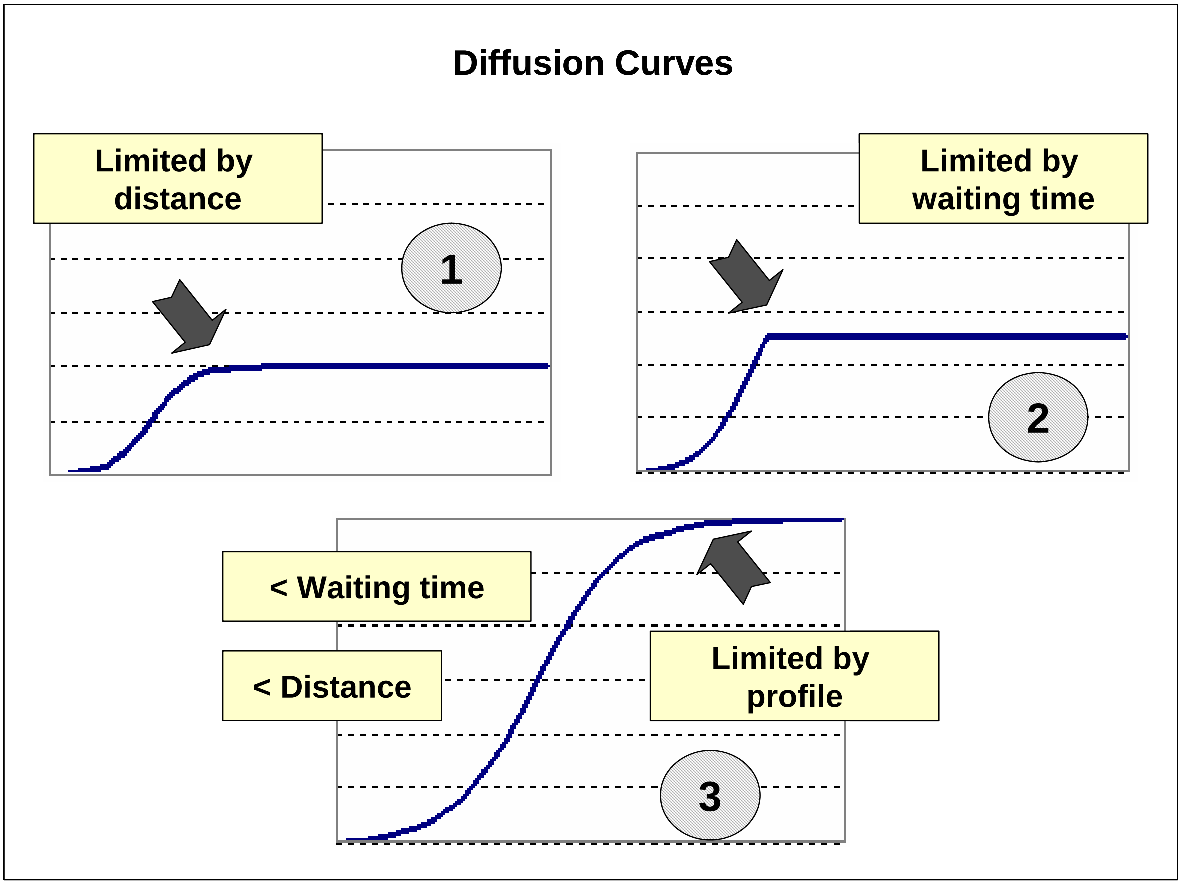

Figure 5: Examples of possible results in the scenario simulation

In Graphic 1, the diffusion is limited by the average distance between the inhabitants of a given locality and the telecenter installed there, reducing the efficiency of that facility in favoring the digital inclusion. In Graphic 2, the demand for the telecenter is higher than the offer of access points (computers connected), so the digital inclusion probability is limited to a given condition. In Graph 3, the deployment of other strategically allocated telecenters is considered in order to decrease the average distance from the inhabitants to the closest site and to offer a larger number of terminals. In such case, all the resources have been allocated to optimize the digital inclusion; however, it is limited by the population profile itself, a factor that can not be controlled by the public administrators. To raise the public interest in using ICTs and spreading the perception of their importance, social, psychological and cognitive barriers should be overcome. With such aim, long term policies are required, mainly in the educational field.

Discussion

The results of the modeling process and the analysis of technological adoption of telecenters will help identify relevant factors and replicate them in an ABMS environment, supporting the decision process for the best ICT offering strategy in public facilities, in order to bridge the digital divide. In this sense, it is crucial to collect primary data among the population to be served. Thus, a field survey has been performed in three Brazilian cities in different regions. Each city had at least one telecenter functioning for more than two years. Once the primary survey data is available, the sensitivity analysis will provide elements to optimize the resource allocation, what, by considering the target population profile, will increase the success probability of a digital inclusion policy.

The sensitivity analysis in ABMS environment will also allow to identify the aspects that can create *lock-ins*, i.e., restrict the adoption process in specific locations, preventing the adoption by new users. This will make possible to foresee the requirements in every context, and, by means of simple actions such as advertising strategies or physical adaptation of the facilities, will minimize the risks associated with the uncertainties in resource allocation.

It is also expected that the learning process, resulting from the application of the combined model of technology diffusion, will allow the qualitative replication of this model in different combinations of individual profiles and their preferences regarding the features of a telecenters or a specific ICT. Although the field research estimates can not quantitatively represent the behavior of the population as a whole regarding the adoption of a telecenter, the sensitivity analysis, in a general way, will provide elements for a qualitative evaluation and for the expansion of the knowledge about the human dimension of new technologies. By applying the data collected in three cities in the potential demand model, we expect to highlight the profile differences in the demand behavior of each one of these profiles. However, the challenge is how feasible is the identification of the variables and the determination of the reasons that really influence the telecenter attractivity and the user's usage preferences.

These results will help the macro-analysis of nation-wide application of medium- and long term public policies, supporting the resource allocation and the establishment of strategies and initiatives for digital inclusion.

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