# Socially Assistive Robots Diffusion in Elderly Care
# A Pre-Adoption Study by Agent-Based Modeling

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*This paper investigates socially assistive robots' acceptance and diffusion in eldercare from dependent-living seniors' perspective by combining data science with the agent-based model of cellular automata able to unveil the emergence of behavioural pattern in a complex system as the result of individual agent interactions. The ratio behind this methodology is that, while social dynamics are often underestimated, they are determinant for the success of an innovation, especially in a pre-market context, in which users do not know the product. In this way, by looking at how opinions are formed and Word of Mouth circulates among social agents, this paper identifies a cluster of enthusiastic seniors, which, if properly addressed, could behave as social hub and influence innovation success. At the same time, however, this work unveils the presence of extreme attitudes and Negative Word of Mouth (NWOM), which, in turn, can lead to innovation rejection.*

## INTRODUCTION

Since its beginning Marketing Science has struggled to understand human behavior on the marketplace. On an individual level, each case is, in fact, unique and its choices seem to be the result of a random set of circumstances impossible to predict. However, on a macro-level, it is possible to observe patterns of behavior: order or structures emerging from chaos. One of the most fascinating and relevant examples of such emerging patterns is innovation diffusion. Many products fail shortly after their market launch by getting a lower market share than expected [16], but, while many studies focus on modeling innovation diffusion after market entry, few address the pre-market phase, which, if properly managed, could lead to significant savings. Experiments like the studies on hybrid corn diffusion [34] have proved that social influence has a large impact on innovation adoption [16,19,31,32,34,38]. The market percolation phase transaction can be explained not only in terms of the number of buyers [1], but also by the network of connections and nature of interactions [17]. In this way, complex system theory and opinion dynamics offer an interesting framework for studying diffusion, especially in a pre-market setting. This paper defines complex systems as "systems composed of multiple individual elements interacting with each other, yet whose aggregate properties or behaviour is not predictable from the elements themselves" [47]. By describing the marketplace as a complex system, it becomes clear how each individual is embedded in the system and, therefore, subject to its rules, since, as the "butterfly effect" [29] reminds us, even a small change state could seriously affect the whole system in the long run. From individuals' interaction emergence i.e. "novel and coherent structures, patterns, and properties" [47] arise. In this way, the ultimate marketing goal is to study conditions under agent interaction within the marketplace. To this purpose, new modeling approaches arise, like Agent Based Modeling (ABM), which allows representing the world in a multiplicity of randomly distributed agents, subjected to certain rules, in order to unveil the mechanism behind behavioral patterns and drivers of change in the system. This paper combines a special class of ABM simulation methodologies, namely cellular automata (CA), with data science to investigate the chances of success and room for improvement of socially assistive robots' diffusion in institutionalised eldercare settings.

## SOCIALLY ASSISTIVE ROBOTS

### Overview

Over time, researchers, scientists and thinkers have wondered about the possibility of reproducing the flexibility of the human mind. However, the concept of intelligence has shifted over the years. Until the late 1980s problem-solving ability was its focal point and cognitive processes like playing chess were used as an exemplification of human intelligence, in order to build machines able to either simulate or exercise it. Soon, however, a new perspective arose: studying intelligence as the interaction between the subject and its environment. This shift from problem-solving mind to mind in the body [4] had significant implications for research in Artificial Intelligence (AI) by leading to the new paradigm of *behavioral-based AI* [42] and to robots able to interact with the environment and react to certain stimuli. By the mid-1990s this perspective evolved and researchers [4,5,6,7,8,9] underlined the importance of *social collective intelligence*, the cornerstone of researches in human-robot interaction [4]. This concept aims at emphasizing the social dimension in developing human intelligence: if primate intelligence evolves in adaptation to complexity [12,13,14,15], human-like intelligent machines should be able to adapt and interact with the environment by answering external stimuli. From this new perspective, social robots arise as one of the innovations with the highest potential and risk of our age. One particular category of social robots are Socially Assistive Robots (SAR) defined as intelligent machines created to provide assistance to users through social interaction and physical assistance. Nowadays, the interest in this category is growing in the light of Active Assisted Living (AAL) as a possible solution to social emergence like the aging issue.

### Social Impact

These SAR and AAL systems, in fact, can perform a variety of tasks by offering interesting opportunities in fields like physical rehabilitation, personal assistance and medical care. Particular literature identifies two relevant macro-tasks, i.e. emotional expression and daily-life support [17]. On this basis, it is possible to distinguish between companion robots keen on emotional stimuli and service robots, which offer daily-life support [49]. This paper mainly focuses on service robots due to their higher relevance for the chosen target, i.e. frail elderly people without cognitive disabilities.

SAR offer personal support through three main functions [36]:

- *Daily-life Assistance* to users in their daily activities through a *reminder function* (SAR help the users with time-planning and organization, they keep an updated schedule of users' activities and remind them of events, appointments, duties and deadlines) and a *fetch and carry ability* (capacity of moving or bringing objects, food, drinks)

- *Monitoring* physical conditions of users and their safety by warning, calling help in case of need.
- E*ntertainment* of users by socially communicating through voice, dialog, gesture, facial expression and by using a variety of media tools like videos, movies, games, music, telephone. To perform such functions effectively, it is necessary to work on the most relevant dimensions for human-robot interaction [18]
- *Design* (anthropomorphic, zoomorphic, caricatured or functional) impacts on the first impression, affects opinion formation and the way users will interact with the machine.
- *Personality* indicates "the set of distinctive qualities of an individual" [18] and impacts on opinions through emotions i.e. the ability of the machine to recognise emotional cues and to express them and intelligence i.e. ability of learning, as well as human-oriented perception and intentionality.
- *Language* i.e. the ability to communicate passively and actively through both verbal and para-verbal skills (body language, facial expression) has a great effect on robot perception and interaction possibilities.

However, the ethical impact of SAR has been largely debated [35,36,37,39,40,43,44]. While some consider these robots as the ultimate solution for elder welfare, others look at them as threats to eldercare quality. To briefly outline the complexity of such a debate, it is possible to identify 5 main dimensions relevant to assess SAR social impact:

1. autonomy and independence,
2. security,
3. privacy,
4. isolation,
5. dignity.

If these systems aim to make a significant contribution to elder care they must aid independence through a user-centred design without compromising safety / security and guarantee transparent data collection through informed consent. Furthermore, they cannot substitute human contact, since this would affect human dignity and increase loneliness which in turn can lead to diseases like Alzheimer [27].

## THEORETICAL BACKGROUND

### Social Percolation

Modeling innovation diffusion is one of the most relevant and fascinating issues in marketing studies. Over time, different approaches have been developed. In particular, we can underline three main streams of research [25]: firstly there are phenomenological models of diffusion, derived from Bass' work [1] able to reproduce sales dynamics through fitting of parameters secondly micro-modeling, which interprets innovation diffusion as results of individuals' rational decision making processes driven by the "interplay of expectations and maximization" [25]; finally, there are stochastic micro models, which look at collective phenomena (emergence) as consequence of individual decision making. These latter models, which constitute the focus of this paper, derive from the spatial stochastic process of percolation. Born from a physical phenomenon of fluid movement through porous matter, percolation is the diffusive process of deterministic movement through a random medium [19,31,38,48] in contrast with phenomenological models, which focus on innovation diffusion as random movement in a non-random medium. In other words, given a network of elements or "agents" with specific properties and initial status within a percolation regime the interaction, or connection, among agents is determined by a certain set of rules, which include both internal and external factors. While the agent's initial status is determined, the location and connection of the elements are randomly assigned by originating a random medium structure whereas in traditional models of diffusion like the Bass Model individuals' specifications are absent and there are no rules for agents' interactions at micro-level: the medium through which the innovation propagates presents, in this sense, a non-random structure. One of the main properties of the percolation regime is to be essentially “decentralized”: the global dynamic is not defined “a priori” but emerges as a result of agents’ interactions [2]. To sum it up, in contrast with the traditional phenomenological models, percolation does not adopt a mathematically-based approach but a computational one: instead of moving from utility functions or equations, percolation requires rethinking problems in terms of heuristics, rules and procedures, which agents use to make decisions [32]. In this way, Agent-Based Models, a form of computational modeling whereby a phenomenon is described in terms of agents’ interactions [47], is one of the best stochastic micro models to describe innovation diffusion as a percolation phenomenon.

**Percolation Versus Traditional Diffusion Model**

This paper approaches innovation spread as percolation and adopts Agent-Based Modeling instead of the more traditional Bass Model of diffusion. The structural difference between percolation as a deterministic movement through a random medium and traditional diffusion as random movement in a non-random medium has been depicted. However, before moving forward, it is necessary to better distinguish between these two approaches in order to make clearer the ratio behind this papers choice.

Firstly, we briefly remember that, while there are many studies on quantitative modeling of the time-profile of the diffusion process, this paper has a different focus: it aimsat investigating the starting phase of an innovation by looking at the moment in which the product is not yet on the market in order to analyze how people come to be aware of it. Therefore, the goal of this paper is to analyze the Word Of Mouth (WOM) dynamics in order to understand how information circulates in a social group and opinions are formed before the innovation actually enters the market.

By following Rogers’ diffusion theory (1962), the Bass Model emphasizes the role of two main sources of influence on the probability of adoption: external (e.g. advertising and mass media) and internal (e.g. WOM). In this way, through the conditional probability of adoption at time t diffusion is expressed as follows:

$$f(t)/[1 - F(t)] = p + qF(t)$$

In the formula, f(t) is the probability of adoption at time t, F(t) is the cumulative probability of adoption at time t, p represents the internal influence and q the external one. [1,19] The Bass Model is widely accepted, fits well many data and has its roots in the well-known innovation diffusion theory. Over time, the model has been extended to include for example marketing mix, competition, and repeated purchase [19]. However these aggregate models assume homogeneity in the communication behavior of adopters [19], specifications at individual level are absent and the impact of micro-level factors on macro-level phenomena remains unclear [10].

In ABM within the percolation framework, agents are inserted into the network structure with a different number of connections [32], initial state (e.g. buy/not buy) and peculiarities, summarised in the variable “individual preferences” (pi) and are subjected to certain rules which govern the changes of state at micro-level [10]. In the model this paper deals with, each agent corresponds to an active or passive node in the network. Changes of state can happen only when there is a link between two nodes or, in other words, if there is an interaction between agents with a different state. In this case, the active node will communicate through WOM with the passive one, which, at that point, will choose to update its state or not: spread of information and the actual state change dependent on the social influence are, in fact, two different phenomena. It becomes clear that, in this approach, WOM is the privileged communication channel through which information propagates which is useful for research? In this way, this paper considers not only the Positive effect of the Word of Mouth (PWOM) but also the negative one (NWOM), which has been identified as more informative and stronger than the PWOM since it may be contagious and spread independently from the exposure to the product. [16]

Further advantages of this approach are that it provides an easy way to incorporate randomness in the model and therefore to represent complexity, it enables the construction of models in the absence of knowledge about global interdependencies of the system under research and it is easy to maintain since model refinements act on local interaction [2].

To conclude, ABM and percolation approach certainly have their limitations, like the computational complexity, the requirement of individual-based knowledge [33], the network structure, which is a discriminant choice for the final result. However, this methodology allows our work an extensive degree of heterogeneity at agent level, the possibility of building a very granular model of the social communication process topology [32] and the ability to look at the macro-effects of micro-behavior [19]. Such possibilities offer high potential for our work since it is our belief that in a pre-market setting for a social innovation with high impact on people's lives, like SAR, the comprehension of micro-behavior and WOM dynamics is fundamental to prevent not only market failure, but also an unethical introduction of the innovation, unable to consider final users' wants and expectations. Furthermore, it is interesting for us to examine the possibilities that ABM offers for innovation diffusion and marketing studies, since it is still uncommon for this research field.

### Applicability

There are six main factors for evaluating the applicability of ABM [33]:

- *Medium Number of Agents* [3]: ABM works better when there is a number of agents "big enough that no agent determines the system final outcome but small enough that a group of population can significantly affect the outcome" [33]. In this way, ABM enables monitoring of every agent in the system.
- *Complex but local interactions:* ABM is not useful when all actions are the same or have the same global impact. It is, however, valuable when dealing with complex local interactions which can be history or property dependent. Information, anyway, is not transmitted outside the network.
- *Heterogeneity:* as discussed above, this is one of the main features of ABM; agents are not all the same, they have specific properties and different ways of interacting.
- *Temporal aspects:* all agent-based models feature time, looking at how agents take decision over time in a dynamic and changing environment. It is not a sufficient condition but it is necessary for ABM models.
- *Adaptability:* an agent is adapting if, when confronted with the same circumstances experienced in the past, he/she takes different actions based on learning. It is a powerful ability to incorporate in a model and in presence of such conditions opting for ABM modeling becomes almost necessary.
- *Rich Environment:* ABM offers many possibilities for representing environment, the agents'-habitat. For example agents may be located in an abstract social network but also in a real geographical space, which could even have its own rules.

## THE MODEL

### Opinion Formation

The user is the starting point for agent-based modeling. In this way, the first step to build a model of opinion dynamics has been to identify drivers of social robots' acceptance from seniors' perspective. This process has been adopted in order to derive a behavioral equation behind the binary decision of adoption (pro/contra). To this purpose, acceptance factors have been identified from literature [22,23,24] and adapted to our case in order to study opinion formation.

**TABLE 1**
**ACCEPTANCE FACTORS**

| Code | Description | Construction |
| --- | --- | --- |
| ANX | Anxious or Negative emotional reactions to the system | I am afraid of robots making mistakes<br>I am afraid of robots making me dependent<br>I am afraid of robots affecting my privacy<br>I find robots scaring<br>I find robots annoying<br>I think only young people can understand this technology |
| ATT | Personal attitude towards the technology | I am interested in this technology<br>I like to be innovative |
| PEOU | The degree to which users believe a system is easy to use | I think I can use robots with a good manual<br>I think I can use robots without support |
| PENJ | Perception that the system could be enjoyable | I think robots are enjoyable<br>I think robots are nice<br>robots seem to be alive<br>I think robotsare sociable |
| PU | The feeling the system could be useful, adaptable and reliable | I think robots are useful for me<br>I think robots conform to my needs<br>I think robots are reliable |
| SI | The degree to which others affect the decision about technology | I would use robots if my friends/family suggested it<br>I would use robots if my doctors/carers suggested it<br>I would use robots if experts suggest it<br>I would use robots if someone using them before suggested it |
| TRUST_SOURCE | The trust in the source of information about the technology | I trust my friends/family<br>I trust my doctors/carers<br>I trust experts<br>I trust people already using the technology |
| TRUST_MESSAGE | The trust in the message received about the technology | I think the information is clear<br>I think the information is reliable<br>I think the information is relevant |
| WOM | The attitude to spread Word of Mouth | I like to talk with my friends about new products<br>I often suggest new products to my friends |

**Opinion Dynamics**

This paper applies a particular class of ABM namely Cellular Automata CA for investigating SAR percolation chances. There are some basic principles or assumptions distinguishing cellular automata:

- *Spatial Structure* "Cellular World": agents are positioned in a specific structure, commonly a checkerboard, in which every cell corresponds to a specific location.
- *Specific* meaning for *local interactions*: individuals can only interact with others at close distance. There are many different ways for representing neighborhoods, the most common being Von Neumann with four neighbors per cell and Moore Neighbours with eight per cell.
- *Initial State and Opinion Dynamics*: agents have a state (Si) corresponding to specific opinions or features, which can change according to the neighbors' opinions (Sj).
- *Time is discrete*: time moves in steps or rounds; in some models, each agent changes his/her status simultaneously, in others agent update opinions one at a time.

The ratio behind this model involves different social phenomena like Gabriel Tarde's imitation principle "do as the others do" [41], which is based on two phenomena [45]:

- *Bounded rationality*: in many situations agents lack objective information about a phenomenon and therefore decide to imitate others. In this sense conformity and social influence also may be ascribed to the imitation phenomenon.
- *Externalities*: following the majority might have its advantages.

Initially the system was set with the classic assumptions of cellular automata:

- Agents are positioned in a social system with a Von Neumann neighborhood (each agent is located in a cell with four neighbors).
- The social system is represented by a four lattice structure 50x50.
- Information can be passed on only when there is a link between two agents.
- The spread of information and the social dynamics are two different phenomena.
- Agents have an initial status/opinion (Si) which may vary according to neighbors' opinions.
- At t1 all agents update their status at the same time.

In order to determine opinion dynamics, it is necessary to unveil the rules behind state changes of the agent. Such a change is dependent on the state of neighbors at the previous time step and on the probability of the agent choosing adoption.

In order to compute such a probability a binary logistic regression based on the determinant of adoption was used by applying the following formula:

$$P= 1/1+e^{-(a+b_1x_1+b_2x_2+\ldots b_nx_n)}$$

Before moving on we summarise the hypotheses concerning opinion formation tested by the study:

***H1*** *Initial opinion configuration is heterogeneous*

***H2*** *Attitude (ATT) and Social Influence (SI) are expected to be the main determinants on preference of agent pi*

***H3*** *Anxiety, Perceived Usefulness, Perceived Enjoyment and Perceived Ease of Use are expected to impact on Attitude toward SAR innovation*

***H4*** *Tendency to spread WOM, Trust in the source and Content of Information, Education are expected to impact on SI*

## THE EXPERIMENT

### Selection of Participants

The experiment was conducted through an on-field study. In particular study sessions were organised in 11 homes for the elderly belonging to two Austrian networks: Kuratorium Wiener Pensionisten-Wohnhäuser (9 homes) and Alten-.und Pflegeheime der Kreuzschwestern (2 homes). The sessions were organized following specific criteria. The study was conducted on based on a convenience sample of 131 respondents aged 60 years and older living dependently in Austrian homes for the elderly. In order to collect realistic opinions voluntarily expressed by participants, three conditions were given to management staff to select participants:

- Absence of drastic physical impairments: selection of participants able to provide to the most basic needs like bathing dressing, using the toilet, eating, drinking and walking ( tools for support were allowed)
- Absence of severe cognitive impairments: selection of participants in full possession of their faculties.
- Consensus to take part in the study: participants were informed in advance about the study topic and agreed to collaborate.

**Robot Selection**

For the study, the robot Care-O-Bot 4©, developed by the German research institute IPA of Fraunhofer Gesellschaft, was selected as an example. The robot's aesthetic and functional design, its imminent market launch in 2018 and the geographical proximity between the German and Austrian market were decisive for this choice. The profile and key abilities of Care-O-Bot 4 © are summarised below.

**TABLE 2**
**CARE-O-BOT 4© PROFILE**

| Design | Technical Schedule | Technical features |
|---|---|---|
|  | **Height**: 158 cm<br><br>**Weight**: 140 kg<br><br>**Max Speed**: 1.1 m/s<br><br>**Interface**: 7'' Touch Screen<br><br>**Degrees of Freedom**: 29 | **Movement**: autonomously moving and charging, obstacles recognition, bowing down<br>**Commandos**: vocal and gesture recognition, touch-screen<br>**Functions**<br>- Assisting: taking and bringing objects -<br>Monitoring: reminder function, calling help in case of emergency -<br>Entertaining: interactive communication, multi-media access (video, pictures, games) |

**Material Selection**

Images and video material were selected from the Fraunhofer Gesellschaft IPA website with their consent. The video material was more emotional than explicative, but being merely used as an introduction, it was considered adequate for our purpose. Functionalities were then illustrated. In the survey, questions about video reliability, credibility and relevance were inserted.

**Session Organisation**

For the study, a group session was organised in each home for the elderly. It was structured by a brief presentation (20 to/30 minutes) of project goals, survey rules and interface presentation through visual support (images and video) followed by a Q&A panel and the distribution of the survey. In order to guarantee attention and support for the survey, the number of participants was limited to between 10 and 20 and the maximal duration scheduled was two hours.

## Data Processing

This paper mainly follows a quantitative approach based on a 5 point-scale survey printed out and handed to senior citizens living in 11 Austrian homes for the elderly. The survey showed secondary and primary data generated by problem-centred interviews with four experts (a robot researcher, a carer at a home for the elderly, a director of a home for the elderly and a town councillor) addressing general expert experience, the relationship between eldercare and technology in Austria, impressions of socially assistive robots and Care-O-Bot4©, chances of being accepted. The data were then analysed with SPSS statistical software, in particular after descriptive statistics and Cronbach's alpha reliability test was executed on constructs identified as possible determinants for willingness to adopt. In a second step correlation and regression analysis were performed in order to identify a behavioral equation for our Specific Interest Group (SIG). Such an equation was then adapted to include heterogeneity: the presence of different opinions was confirmed by cluster analysis from which the opinion dynamics model was then derived. Finally, a computer-based simulation was run using LSD simulation software.

# RESULTS

## Descriptive and Reliability Test

74% of 131 dependent-living senior citizens without cognitive disabilities, were women. 56% of the 131 respondents were over 80 years old, and 44% between 65 and 80 years old. Moreover, half of the participants in the survey had physical impairments and an average education level. 63% neither owned, nor used a computer. The reliability test was then executed and all constructs were proven to be meaningful with a Cronbach's Alpha over 0.7.

**TABLE 3**
**CRONBACH'S ALPHA**

| Code | Cronbach's Alpha |
|---|---|
| ANX | 0,715 |
| ATT | 0,745 |
| PENJ | 0,762 |
| SI | 0,905 |
| TRUST_SOURCE | 0,795 |
| TRUST_MESSAGE | 0,835 |
| WOM | 0,767 |
| PU | 0,786 |
| PEOU | 0,736 |

## Configuration of Initial Opinions

The model tests different Hypotheses: The first hypothesis that the social system under consideration is heterogeneous in beliefs, opinions and experiences. Furthermore, extreme behaviour is likely to occur. In order to test this hypothesis and capture such heterogeneity, a cluster analysis was performed on the ten drivers mentioned above (Anxiety. Perceived Enjoyment, Social Influence, Attitude towards Technology, Perceived Usefulness, Perceived Adaptability, Trust in Information, Perceived Ease of Use, Perceived Sociability, Social Presence).

The clustering was performed using a hierarchical method in order to determine the number of Clusters. This is used as basis for a k-means classification. The resulting factors were significant for the segmentation (p-value < 0.05). From the analysis four clusters of opinions emerged as described in final cluster centre Table IV. The peculiarities of these opinion groups can be summarised as follows:

- ***Enthusiasts*** *(14%):* This cluster's members perceived Care-O-Bot 4© as easy to use and useful. They had a positive attitude toward technology and were genuinely interested in Care-

O-Bot 4© which they saw as enjoyable. They did not fear to become dependent or lose privacy or that the robot could make mistakes. Furthermore. they were sensitive to social influence when forming opinions on this topic.

- ***Skeptics** (51%):* This group was not confident neither of the reliability of information about Care-O-Bot 4© or its ability to fit their needs. However, they valued it as easy to use and generally as useful. Furthermore, these respondents had a positive technological attitude and perceived the robot as enjoyable. A positive factor for acceptance is the low value of anxiety.
- ***Worriers** (23%):* This group had an instinctive negative reaction towards the robot concept: fear outweighed attraction. They perceived the robot as a threat for safety, privacy and independence. For this group the technology was hostile and difficult to use.
- ***Opponents** (12%):* This cluster strongly rejected the very idea of robots, which were not attractive or interesting or useful to them. They perceived Care-O-Bot 4© as difficult to use, have a negative attitude toward technology and hardly changed their opinions because of social influence.

The analysis confirmed the occurrence of extreme behavior. Furthermore it appears that these four groups can be linked to three different initial states the "Enthusiasts" cluster was mainly pro-SAR adoption and identifiable with the initial state Si=1, while the "Opponents" cluster which was clearly against-SAR adoption with the initial state Si=-1. "Skeptics" and "Worriers" were between the two extreme opinions and were identified with an initial opinion Si=0.

**TABLE 4**
**FINAL CLUSTER CENTER**

| Cluster | Skeptics | Enthusiasts | Opponents | Worriers |
|---|---|---|---|---|
| PEOU | 0.23 | 1.05 | -1.11 | -0.55 |
| PU | 0.20 | 1.33 | -1.44 | -0.48 |
| SI | 0.15 | 1.46 | -1.29 | -0.52 |
| ATT | 0.07 | 1.13 | -1.35 | -0.11 |
| ANX | -0.13 | -0.55 | -0.04 | 0.63 |
| PENJ | 0.27 | 1.31 | -1.48 | -0.61 |
| TRUST | -0.02 | 1.35 | -1.23 | -0.11 |

**Opinion Dynamics**

Correlation and regression analyses were performed with the purpose of determining opinion dynamics to identify opinion drivers and derive a possible behavioural equation (Table V).

**TABLE 5**
**BINARY LOGISTIC REGRESSION ON WILLINGNESS TO ACCEPT (A)**

| Dependent | Independent | Regression Sig. (p-value<0.05) | Regression Beta | Regression Exp. Beta | Cox's R2 |
|---|---|---|---|---|---|
| Willingness to Accept | PENJ | 0.643 | 0.225 | 1.252 | 0.483 |
| | SI | 0.000 | 2.624 | 13.797 | |
| | ATT | 0.011 | 1.105 | 3.020 | |
| | PU | 0.877 | 0.075 | 0.927 | |
| | TRUST | 0.888 | 0.054 | 1.055 | |
| | PEOU | 0.533 | 0.213 | 1.237 | |
| | Constant | 0.000 | -11.709 | 0.000 | |

While correlation analyses confirmed the hypothesis, binary logistic regression emphasized only two determinants of opinion formation: social influence and personal attitude.

A multiple linear regression on these two elements allowed finding their determinants (Table VI).

**TABLE 6**
**MULTIPLE LINEAR REGRESSIONS ON ATT AND SI**

| Dependent | Independent | R2 | Beta | T | Sig. (p value <0.10) |
|---|---|---|---|---|---|
| ATT | PU | 0.368 | 0.596 | 2.807 | 0.006 |
| | PENJ | | 0.250 | 1.341 | 0.102 |
| | PEOU | | 0.578 | 2.994 | 0.030 |
| | Constant | | 3.753 | 4.553 | 0.000 |
| SI | Trust_Information | 0.537 | 0. 954 | 7.831 | 0.000 |
| | WOM | | 0. 523 | 3.432 | 0.001 |
| | ANX | | -0.110 | -1.746 | 0.083 |
| | Constant | | -1.343 | -0.739 | 0.461 |

As a result personal Attitude toward technology seems to be determined by Perceived Usefulness (as a construct of reliability, usefulness and robot adaptability to users' needs) Perceived Ease of Use and Perceived Enjoyment (a construct of social presence and perceived sociability of the robot). Social Influence, on the contrary, seems to be influenced by Trust in the information (as a construct of trust in the content and the source of information), Word of Mouth tendency and to a lesser degree by anxiety (as a construct of evaluation of possible mistakes, privacy invasion, possible dependence and risk of substitution of human contact).

Anxiety has a negative effect on social influence and the two variables are negatively correlated thus meaning that the higher anxiety the lower the chances of changing opinion about the robot. At this point the binary logistic regression was performed again with only the two significant factors. in order to determine a behavioural equation.

**TABLE 7**
**BINARY LOGISTIC REGRESSION ON WILLINGNESS TO ACCEPT (B)**

| Variables in the Equation | | B | Sign. | Exp(B) |
|---|---|---|---|---|
| Phase1[a] | Attitude | 0.974 | 0.004 | 2.649 |
| | SI | 2.188 | 0.000 | 8.920 |
| | Constant | -0.272 | 0.282 | 0.762 |

In this way we can compute the probability of robot adoption ($P_{pro}$) according to (1).

$$P_{pro} = [1/1+e^{-(-11.412+0.596SI+0.582ATT)}] \quad (1)$$

We can better describe this equation by adding Social Influence and Attitude determinants as described in formulas

$$SI = 0.954\ Trust\_Info + 0.523\ WOM - 0.110\ ANX \quad (2)$$

$$Att = 0.596\ PU + 0.578\ PEOU + 0.250\ PENJ \quad (3)$$

By adapting this equation to the average values obtained through cluster analysis it was possible to derive the probability that members of the two undecided clusters (Skepticals and Worriers) would switch their opinion toward the two extreme positions "pro robot" and "against robot" under the social influence of neighbors belonging to the Enthusiasts and Opponents clusters.

By inserting the average values for social influence and personal attitude, we obtain the transition probabilities:

- P Skepticals → enthusiast= 0.53
- P Skepticals → against = 0.47
- P Worriers → enthusiast= 0. 32
- P Worriers → Opponents= 0.68

**TABLE 8**
**RESULT OF HYPOTHESIS TEST**

| | | |
|---|---|---|
| H1: Heterogeneity in users' opinions | Confirmed | Four different opinion clusters were identified |
| H2: Social influence and attitude are the main determinants of willingness to adopt? | Confirmed | The analysis confirmed the hypothesis |
| H3: Perceived utility. perceived ease of use. perceived enjoyment. anxiety impact on attitude | Partially confirmed | Anxiety did not appear as a determinant of individual attitude toward SAR |
| H4: Trust. WOM attitude. education | Partially confirmed | Education did not appear correlated. On the contrary ANX appeared as a determinant negative factor for SI: the higher the fear of technology the lower the readiness to change one's opinion |

**Computer-based Simulation**

To the initial CA assumptions described in the model section. another condition was added:

- The initial status (Si) of the agents at t0 could be of three types i.e. "1" (agents willing to adopt the robot); "0" (agents unsure if to adopt the technology); "-1" (agents strongly against adopting). The number of agents for each status was established from the data and the model set their distribution randomly. These are so called "seeds".

In order to run the simulation, it was necessary to define mathematically the interactive mechanism among agents. From our results illustrated in the previous section the rules of interaction were set as follows:

As far as "active agents" were concerned:

- Agents with Si "1" or Si "-1" at time t0. remained with Si "1" or Si "-1" respectively at time t1

- Both groups of agents with state Si "1" or state Si "-1" communicated actively through WOM but the former spread Positive Word of Mouth (PWOM) and the latter a Negative one (NWOM).

As far as "passive agents" were concerned

a. If the majority of their neighbors were of the opinion Si "1"
   - 51% of agents with Si "0" at t0. will update their state to Si=1 at t1 with a probability = 0.53
   - 23% of agents with Si "0" at t0. will update their state to Si=1 at t1 with a probability=0.32

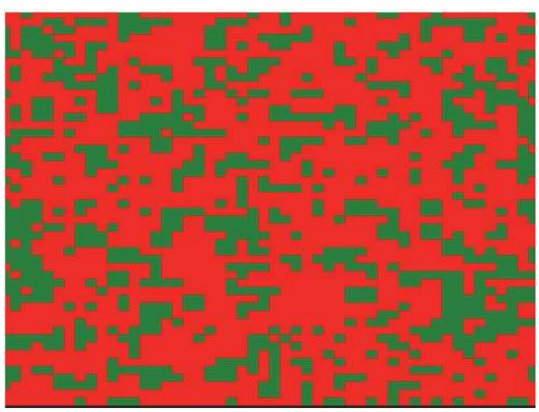
b. If the majority of their neighbors were of the opinion Si "-1"
   - 51% of agents with Si "0" at t0. will update their state to Si "-1" at t1with a probability=0.32
   - 23% of agents with Si "0" at t0. will update their stateto Si "-1" at t1 with a probability=0.68

c. If the number of neighbors with opinion Si "-1" = number of neighbors with opinion Si="1"
   - 51% of agents with Si "0" at t0 will update their state in Si=1 to t1 with a probability=0.53
   - 23% of agents with Si "0" at t0 will update their state to Si "-1" at t1 with a probability=0.68

The model tests the result of this interaction with a simulation in many time steps. At each time step the state of any agent was defined as a function of the state of neighbors in the previous time step and the probability that the agent has to adopt is given by its characteristics derived from the data analysis.

The simulation was run in 1000 time-steps on a 50x50 lattice. The software used was the LSD. Laboratory for Simulation Development based on C++. LSD is an online source for developing discrete-time simulations and specifically designed for economically oriented simulations [50].

**FIGURE 1**
**CA SIMULATION RUN ON A 50x50 LATTICE WITH LCD SOFTWARE**



As a result it was clear that the NWOM prevailed by blocking the percolation of innovation and creating a strong rejection in the social system. The green dots represent agents adopting the innovation while the red ones represent agents rejecting it. Only 32.8% of all cells are at state "1" at the final simulation step.

## DISCUSSION

This study addresses innovation diffusion by looking at a pre-market phase in which a technology is not on the market yet and by exploring how Positive but also Negative WOM contributes to form a market open to the technology or against it. In particular it looks at the acceptance of a socially assistive robot namely Care-O-Bot 4© by senior citizens living dependently in Austrian retirement homes. In doing this, the work aims to link the microscopic behavior of final users with the macroscopic phenomena of adoption through cellular automata model and percolation theory. Few marketing studies take into account social percolation and even fewer consider a Negative Word of Mouth effect. Still many scientific studies are needed to validate results. Our analysis has some interesting implications:

**Research Implication**

- Percolation approach is useful in a pre-market analysis since WOM dynamics affect the market readiness for innovation acceptance. There is still little attention given to the emergent effect of customer interaction in potential markets [16]. This paper tries to look at customer interaction through data science and ABM to find determinants of social influence and individual attitude able to influence the adoption and investigating how individual interaction generates macro-patterns of behavior. Even if much more research is needed. This paper suggests a behavioral equation as a first step towards achieving a better comprehension of social dynamics and their impact on innovation diffusion.
- Negative Word of Mouth has a strong impact and prejudices against SAR innovation are able to block the innovation entry in the market since NWOM is perceived as more informative and reliable [16] even if it is spread independently from the actual product trial like in our study. The effect of NWOM is not usually taken into account in innovation diffusion studies. However this paper shows that it is a relevant obstacle, which should be considered to prevent product failure.

**Managerial Implications**

- Innovation acceptance/rejection depends on personal attitude and social influence especially in a social context like retirement homes.
- Attitude is not only influenced by Perceived Usefulness and Perceived Ease of Use but also by the construct Perceived Enjoyment to the extent to which the robot is perceived "sociable" "friendly" "alive?" "human-oriented" and "caring". This construct deals with the dimensions of Social Presence (i.e. how much the robot has presence thanks to its particular personality i.e. emotion and intelligence) and Perceived Sociability (i.e. how much the robot is able to socially interact with its users). This dimension is hardly ever measured in a pre-adoption analysis and needs to be further investigated with a robot prototype. However, the impact of this dimension on individual attitude confirms the importance of social interaction skills and social intelligence in future AI developments.
- Social Influence is related to "Trust in Information", to the tendency to share information with others and also to the degree of anxiety: the higher the fear due to mistrust in technology (possibility of mistakes), privacy issues (the robot is perceived as an invasive presence in the environment, it is seen as a guardian more than a helper) need for human contact (the robot is perceived not as an aid but as a substitute for humans in an unethical way) the lower the tendency to switch toward acceptance under social influence. In the context of high uncertainty like innovation introduction it is easy for NWOM to spread and block the innovation.
- The innovation does not percolate in the system because of NWOM. However, in the overall sample heterogeneous positions and mixed feelings appear. This creates the opportunity to identify a foothold market and to implement strategies of market entry.

Starting from the analysis of the four groups identified it is possible to suggest some guidelines for proper communication and positioning of the technology as summarized in Table IX.

**TABLE 9**
**POSSIBLE STRATEGIES**

| Cluster | Problems | | Actions |
|---|---|---|---|
| **Enthusiasts** | -Targeting them in the first phase of entry<br><br>-Satisfying their needs | **Communicating**: Involving experts in robot deployment. offering assistance and group sessions in which the first adopters can share their experiences | **Positioning:**<br>Promoting and explaining the assisting functions by underlining robots security and autonomy.<br><br>**Robot development:**<br>Working for creating products efficient before the market test |
| **Skeptics** | - Lack of trust in the robot and diffident about the conformity/ of the robot of satisfying their needs | **Communicating**: Working together with carer in dealing with the robot. and stimulating confrontation between them and the "Enthusiasts" | **Positioning:** Promoting the monitoring function by providing transparent and clear information about data storage. processing and protection in order to enhance trust and perceived adaptability. Also entertaining function is appreciated<br>**Robot development:** Working for guaranteeing the privacy and improving technical capabilities for monitoring. |
| **Worriers** | -Worried about ethical concerns. rejection of the concept of robot | **Communicating**: stimulating confrontation with other elderly people. suggesting trials with carer's support | **Positioning:** Promoting security and working on aesthetic design and entertaining functions to improve unconscious acceptance of robots. Strongly underlining that robots cannot substitute humans but only support them in their daily lives<br>**Robot development:** increase capabilities associated with assisting function and social skills. |
| **Opponents** | -Technology rejection. robots are seen as evil machines. dangerous or useless | **Communicating**<br>Starting an honest dialogue with them to better understand their apprehension. Trying to stimulate their interest in technologies in general before that in robots through games, activities, wworkshops | **Positioning**<br>They will access robots only if the product has reached technological maturity in terms of technical capabilities so that they will be extremely easy to use. Improvement in robotic aesthetic design and social presence may stimulate unconscious acceptance and promote a better image of robots. |

## LIMITATIONS AND FINAL CONSIDERATIONS

Starting from social percolation and a complex system theory, this research combines data science and agent-based modeling to look at opinion formation and dynamics and conduct a pre-market analysis of one of the most revolutionary and disruptive technologies of our time: socially assistive robots. However this paper is not without its limitations: a larger sample could increase the results' accuracy especially on regression analysis. A demographic stratification could give a better insight into the impact of demographic variables, the cellular automata model's fixed structure could influence results and the absence of a real robot prototype might bias perception. Nevertheless the value of this paper lies in suggesting an innovative approach to innovation diffusion modeling.

To this purpose, influential drivers of socially assistive robots' acceptance have been selected from literature and investigated with statements rated by dependent-living senior citizens on a five-point Likert-scale. As a result a cluster analysis underlines the respondents' heterogeneous opinions. Thus way two extreme clusters: Enthusiasts and Opponents and two moderate clusters: Skeptics and Worriers emerge. From this starting point an initial configuration of opinions was set. A regression analysis then emphasized the role of two drivers, Social Influence (dependent on trustworthiness of the message and source of information and attitude towards sharing Word of Mouth) and Personal Attitude (dependent on Perceived Enjoyment, Perceived Adaptability and Perceived Ease of Use) towards innovation acceptance. From this consideration an equation was defined with the purpose of deriving probabilities of opinion changes for the two moderate clusters. Thus a computer-based simulation was set up and run.

As a result the socially assistive innovation success seems to be threatened by the strength of negative opinions mainly due to physical, psychological, ethical and social barriers that SAR needs to overcome to achieve success. The study of social impact dynamics and the correspondence between users' needs and robot abilities and the proper communication of the new technology appear as key factors for the socially assistive robots' future.

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