Co-evolution of Knowledge Diffusion and Absorption: A Simulation-Based Analysis

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Abstract. The paper utilizes agent-based simulations to study diffusion and absorption of knowledge. The causal relation of diffusion on absorption is established in order. The process of diffusion and absorption of knowledge is governed by network structure and the dynamics of the recurring influence, conceptualized and modeled as legitimacy, credibility, and strategic complementarity; again a causal relation between the three in order. If not stationary, the agents can also move to acquire either random walk or profile-based mobility modes. Therefore, the co-evolution of network structure due to the mobility of the agents and the dynamics of the recurring influence of ever-changing neighborhood is also modeled. The simulation results reveal that – (i) higher thresholds for legitimacy and credibility determine slower, (ii) higher number of early adopters results into faster, and (iii) a scheduled and repeated mobility (the profile-based mobility) results in faster – absorption of knowledge.

Keywords: Knowledge diffusion · knowledge adoption · network structure · recurring influence · agent-based model.

1 Introduction

Humans tend to be similar to their peers and get influence from others [5]. In many contexts, such as innovation adoption [25] and collective action [22], these tendencies become decisive. For example, rapid diffusion of information is often associated with innovation adoption. However, a more thoughtful understanding of innovation adoption, for example, is heavily dependent on its underlying dynamics in terms of (i) the evolution of the underlying network and (ii) the modalities of interaction among peers [4]. These two factors are relevant to any scenario related to *social influence*, in general.

Social influence plays an important role in a range of behavioral phenomena observed around us [30]. However, there are ongoing challenges in quantifying social influence due to a number of reasons. For instance, people tend to engage in the same activities as their peers, thus making it difficult to identify who was influenced by whom temporally. Similarly, two persons may be influenced by the same source but in a spatially incremental way, thus, making it difficult to identify the exact source of information. Analysis of temporal and spatial causalities is an ongoing research area in social influence analysis [5].

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The research on understanding social influence revolves around the effectiveness of the mechanisms of diffusion and absorption, the impact of social structures and populations, the impact of dynamics of the structures, dynamics of interactions between the agents, and the impact of agents' mobility – all related to underlying information contents. However, not going into the academic discussion of how knowledge can be differentiated from information, in this paper, we have termed this content as knowledge – some novel thing or stream or data introduced into the network [12].

In the presence of many inter-dependent, overlaying, and overlapping aspects (as hinted in the paragraph above) the challenge of understating social influence is real. In addition to that, there are some general considerations stated below:

1. The increased availability of social networking and interaction data has resulted in an exponential growth in related domains of science, however, social network analysis in general and knowledge diffusion / absorption in particular, are comparatively new disciplines.
2. Social networks comprise of two parts, namely, the network structure, and the interaction between peers. The network not only influences the interactions but also gets influenced by the interactions. Social network dynamics, therefore, not only occur from network to interactions but also from the interactions towards the network. However, most of the studies on knowledge diffusion / absorption focus on one way dynamics, mostly, analyzing the impact of network structure on knowledge diffusion.
3. Knowledge absorption – a truer essence of knowledge diffusion – and knowledge diffusion are, most of the time, considered analogous, which is not the case. Therefore, the differentiation between diffusion and absorption of knowledge should be clearly marked when dealing with social influences.

Elaborating the last point further, it is of great importance to differentiate between diffusion and absorption of knowledge. The term diffusion is used to indicate the availability of knowledge. If a peer p comes to know about a new thing from its networked peers, the knowledge is said to be successfully diffused to p. It is, however, irrelevant whether p is affected by the disseminated knowledge or not. When p is influenced by the knowledge, the knowledge is said to be truly absorbed and thus able to lead towards subsequent actions.

With a focus on the argument that "diffusion should not be considered sufficient for the absorption of knowledge", in this paper, we have tackled important modalities of social influence namely (i) the evolution of social structures and populations, (ii) the evolution of friendship structures and interactions, and (iii) agents able to acquire various mobility modes. The underpinning of diffusion and absorption mechanism is based on factors of "strategic complementarity", "credibility" and "legitimacy", motivated from Centola et. al.'s model of complex contagion [9].

Using an agent-based model we have studied the conditions leading towards diffusion and absorption of knowledge. The main purpose of research is to see what emerges at a global scale due to localized interactions of the agents, while all these aspects were combined in a realistic and meaningful way. The simulation

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experiments revealed interesting results, which could not only validate a large body of domain-specific research results scattered all across social networking literature, but also provide an outlook of what to expect when looking at the things crossing across the borders.

The rest of the paper is structured as follows. Next section is about the background and motivation for this work. It not only introduces the diffusion and absorption models but also enlists the contribution of this work. In the following section, the conceptual model of the proposed work is presented, proceeded by a detailed description of the agent-based model. Then the simulation results are provided. The last section concludes the paper.

2 Background and Motivation

Research done on social influence particularly in terms of social networking can easily be divided into research which is performed on social structures and interaction dynamics and research on the models of diffusion and absorption of the knowledge. We present related work in both domains. In this section, the terms information and innovation should be considered synonym to knowledge. Similarly, the differentiation between dissemination and diffusion should be considered a synonym to the differentiation between adoption and absorption.

2.1 Networking Structure and Interactions

Social networking [15] is considered as one of the best means of knowledge dissemination these days and considered as the best platform to investigate the mechanisms of information and innovation diffusion. One of the most important factor in this regards is networking structure [9]. One important networking features in this context is the nature of ties in the network. The understanding about "the strength of weak ties" is an established fact now, given by Granovetter [14] as: "whatever is to be diffused can reach a larger number of people, and traverse a greater social distance, when passed through weak ties rather than strong". Conversely, the notion of "the weakness of strong ties" is also true resulting in localization of information diffusion, due to propagation of information only in a closely knit network. It means that strong relational ties are structurally weak, and vice versa, where relational ties are individual social ties and a structural tie represents its ability of propagating information. Consequently, information spreads more rapidly in a small-world network structure in which a few long ties augment mostly tightly-knit local communities [30]. Also, people who interact more often have greater tendency to influence each other [16]. On the other hand, people who interact infrequently could have more diverse social networks, resulting in providing novel information [8].

Contrarily, with a more broader focus, authors in [24] defined "knowledge network", and emphasized that social relationships and the network relationships play a vital role in knowledge creation, diffusion, and absorption. Furthermore, authors in [20] argued that strong interpersonal ties are more effective than weak ties to enhance knowledge transfer and learning. Their thesis is that strong ties help to establish trust, which increases awareness to access each other's

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knowledge. When it comes to knowledge creation, weak ties allows access to disconnected or distinct partners, and results in diverse information and have a positive effect on creativity [23]. Authors in [13] discuss how strong ties relate to job finding on Facebook's social network. Several other examples of research on the influence of tie strength on information dissemination can be listed [28] [29] [17] [26] [6].

Another important network structure is that a network having a power-law structure is most conducive for information dissemination. If the network is following the power-law structure, the authors in [21] have proved that it would result in disseminating information to "a large number of nodes in a small amount of time is possible". Also in such networks, "large scale dissemination can be achieved with simple resend rules (i.e, they do not require sophisticated centralized planning)". Moreover, node centrality has been seen as pivotal to maximize the information dissemination in a social network [18]. But this is typically true for social networks which are generally scale-free networks. Also, there are noted aberrations to these basic principles. For example, authors in [27] discuss that not the centre but the periphery of the network have a decisive role in spontaneous collective action. This example separates purely network-based dissemination from physical activity, thus, evidencing the fact that mere dissemination / diffusion cannot guarantee innovation adoption / absorption.

From the above related work, we conclude that social influence is directly related to contagion diffusion and absorption. In terms of network structure, social influence is mostly about type and modality of connectivity. However, there are contradictory views on that. In one case, a special kind of network such as a scale-free network supports quick diffusion due to central nodes. In the second case, even in a scale-free network, peripheral nodes are more important, indicating the importance of real-life implications [31] when the knowledge is *absorbed*. As we have already mentioned that knowledge diffusion should be differentiated from knowledge absorption. Therefore, we opted to use a regular network (for the diffusion of knowledge) to handle this confusion. Further, in our model, the knowledge absorption mechanism builds on diffused knowledge and considers tie strength as a decision parameter.

2.2 Diffusion and absorption of knowledge

Knowledge dissemination happens through diffusion models. At a very basic level, it can be a Susceptible-Infectious (SI) model [3]. SI and extended models use a threshold-based mechanism where a node becomes infected if a designated fraction of the neighborhood (the threshold) is already infected. We have used this basic principle to enrich our diffusion model.

Quantifying the timing of interaction and recurrence [10] is another important aspect of knowledge diffusion. For example, authors [2] provide a general discussion on the impact of social networks on human behavior. According to [4], "the propagation of adoption depends on several factors from the frequency of contacts to burstiness and timing correlations of contact sequences. More specifically, burstiness is seen to suppress cascades sizes when compared to randomised contact timings, while timing correlations between contacts on adjacent

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links facilitate cascades." Similarly, authors in [19] credit two factors, 1) When did someone in your friends adopted an innovation and 2) The number of exposures, but they discredit personal traits, such as number of friends (followers) and date of joining the network.

However, knowledge diffusion alone is not enough to make people act and bring a change – the situation termed as absorption. Taking knowledge absorption as an extension of diffusion, we enrich our diffusion model based on findings reported in [4]: "what drives the adoption of a node is the number of recent contacts from adopted individuals, such that multiple contacts from the same adopted individual have the same effect as the same number of contacts from multiple adopted sources.".

Like the above, the absorption of knowledge is considered as an extension of diffusion in most cases, but it can be considered as a mechanism having its own dynamics. For example, a thesis advocating it and in other words contradicting the notion of the "strength of weak / long ties" differentiates between mere dissemination and potentially a more demanding collective action. The seminal work is from Centola and Macy [9]. The authors postulate that "network structures that are highly efficient for the rapid dissemination of information are often not conducive to the diffusion of collective action based on the information". Authors in [9] also provide a more discrete specification capturing the soul of the argument as: "The "strength of weak ties" applies to the spread of information and disease but not too many types of social diffusion which depend on influence from prior adopters, such as participation in collective action, the use of costly innovations, or compliance with emergent norms. For these contagions, we contend that long ties are not strong in either of Granovetters meanings, relational or structural."

Information and diseases are simple contagions requiring only one source to spread. Complex contagions require two or more sources of activation. According to Centola and Macy [9], four factors contribute to a complex contagion: (i) late adopters waiting for early adopters, termed as *strategic complementarity*, (ii) *credibility* provided by neighbors who have already adopted an innovation, (iii) *legitimacy* provided by close friends who have already adopted an innovation, and (iv) "expressive and symbolic impulses in human behavior that can be communicated and amplified in spatially and socially concentrated gatherings" [11] termed as *emotional contagion*. Further, they define "a contagion as *uncontested* if activation depends solely on the number of neighbors who are activated, without regard to the number who are not activated." Whereas, a contagion is *contested* if it also depends on persons who are not activated. The implications of this, according to them, are: in case of uncontested contagions, "The larger the number of neighbors, the greater the chance of becoming activated", and in case of contested contagions, "the more neighbors an actor has, the lower the susceptibility to activation". Examples of complex contagion are the spread of participation in collective action and norms and social movements. Naturally, these usually fall into the category of contested contagions. We adopt

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this model (with some refinements) as our basic absorption model typically in an uncontested environment.

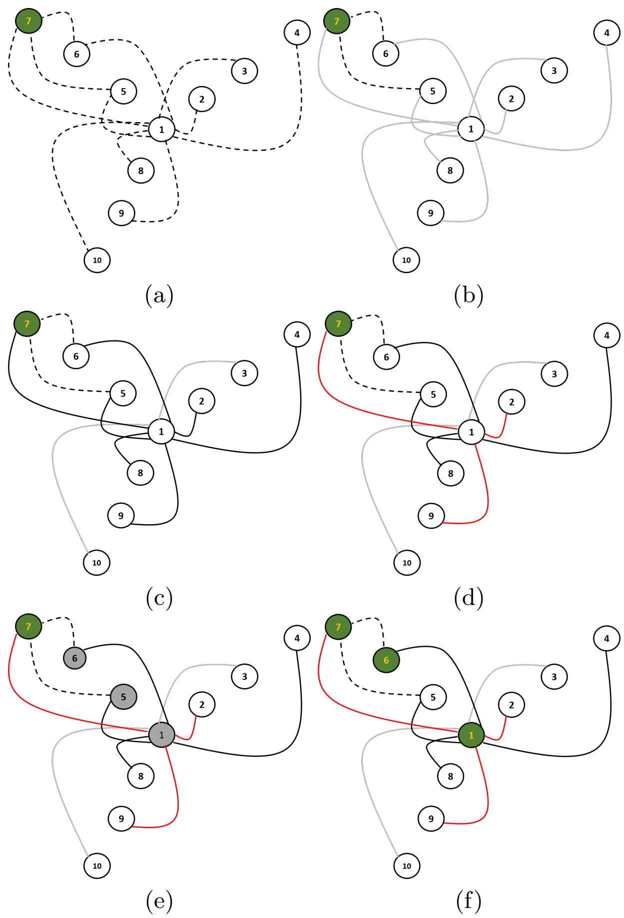

Fig. 1. An overview of the proposed model.

2.3 Contribution of the paper

Most of the models detailed above are analytical in nature. However, there is a lot of potential in analyzing the models using a bottom-up approach, thus, providing an opportunity to have a behavioral-based implementation at an individual level. Agent-Based Modeling (ABM) [7] provides an approach to model a population at an individual level, with detailed temporal and spatial resolution, including the stochasticity of interactions and mobility. Therefore, through this work, we

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intend to enrich a relatively thin body of research done in knowledge diffusion and absorption modeling in ABM domain.

In our earlier work [1], we have shown that the late absorbents are affected by the early absorbents, but only when the mobility model is closer to human mobility (a planned, scheduled, and repeated mobility). Early absorbents do not affect late absorbents if all agents are stationary or acquiring random walk mobility. Also, with an increase in the percentage of early absorbents, the number of final absorbents increases. All the other varying factors, such as interaction radius, threshold values, etc. do not have a substantial impact.

But this work is different from our earlier work. In our earlier model, the phases of diffusion and absorption were not distinct. In fact, knowledge diffused to an agent was considered sufficient for comparison. In this paper, we have introduced a formal mechanism of knowledge diffusion, which was lacking before. Hence, we can differentiate between diffusion and absorption quantitatively. More specifically, in this paper, we provide a thorough study about conditions leading to knowledge diffusion and absorption in a proximity-based regular network of agents. The study also intends to quantify the relationship between credibility with legitimacy in time and spatial domains and its relationship to early vs. late adopters. Lastly, and most importantly, knowledge diffusion and absorption in an environment of dynamically evolving tie strengths due to agents' mobility is also studied.

3 Conceptual Model

The model is constituted by four sequential phases, followed by an optional mobility phase. The conceptual model for this work is explained using a regular network of 10 nodes shown in Figure 1. It explains the interaction, consolidation, diffusion, and absorption phases, thus providing a conceptual outlook of the dynamically changing network structure due to continuous interactions. The interaction and consolidation imitate the strength of ties, where the friends are the strongest, contacts being the weak while mere connectivity means no tie. Then, subsequent processes of diffusion followed by absorption (based on principles of complex contagion) are conceptualized.

We use nodes labelled from one (1) to ten (10). Dotted lines are representing the connections between the nodes. Green color nodes are the nodes that have absorbed the knowledge. The initial setup is presented in Figure 1(a), in which only node seven (7) has absorbed the knowledge. All the nodes, in parallel, invoke interaction, consolidation, diffusion and absorption processes in order.

Interact: Taking the example of node one (1), Figure 1(b) illustrates the interaction process, which allows a node to interact with all its neighboring nodes. For example, node one (1) has nine (9) neighbors to interact with (gray color lines represent this).

Consolidate: The consolidate process is split into two parts namely, determining the *contact* nodes among the interacting nodes and then determining the *friend* nodes among those who have become contact nodes. These two steps use 'k' and 'm' thresholds to determine the contact and friend nodes respectively,

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where 'k' and 'm' relate tie strengths to the frequency of interactions. For example, six (6) out of nine (9) neighbors for node one (1) become contact nodes (represented using dark lines), as illustrated in Figure 1(c). Finally, Figure 1(d) shows that three (3) out of six (6) contact nodes became friends (represented as red lines).

Diffuse: Figure 1(e) shows the number of nodes that receive the knowledge diffused. In this example, suppose to three nodes named one(1), five (5), and six (6), the knowledge has been diffused.

Absorb: The knowledge absorption depends on the credibility and legitimacy of the connected nodes. Credibility is concerned with all the connected nodes and legitimacy is concerned with the friends only. Both thresholds should be fulfilled in order for knowledge to be absorbed. In this example, the thresholds of credibility and legitimacy are 1/9 and 1/3 correspondingly. That is why two nodes (namely one (1) and six (6)) absorbed the knowledge, as shown in Figure 1(f).

This is, however, a static view of the proceeding, not truly capturing the dynamics of the model. In the case of mobility, some connectivity may not transform into a tie. However, some ties may become strong and vice versa. The model runs at each iteration and for all the agents.

4 Agent-Based Model

The ABM of the above conceptual model operates in a 2D space comprising a grid of cells. The agents reside on top of the cells and can move on the grid (if required). The simulation runs in discrete time, each time unit termed as an iteration. At each iteration, each agent in a population of agents acts according to the model specification given below. Agents perform calculations and act in a sequence, where the order of the sequence is randomly shuffled for each iteration, thus, maintaining fairness between agents. We distribute the model into four sequential procedures.

Interact Within a radius **r**, an agent updates its neighborhood; the *neighbor_list*. In case of no mobility (stationary case), nothing would change in the data associated with a neighbor; its identity, and its corresponding discovery frequency. But, if the agents are moving (random walk or profile-based mobility cases), the discovery frequency serves as a number to distinguish between more frequent and less frequent neighbors. The agents which were neighbors of an agent at time $t-1$ and are not neighbors anymore (at current time t) remain in the list of neighbors and do not get deleted. In this way, we have complete interaction history of all the agents.

Consolidate A fraction k of agents which are in *neighbor_list* and *still* neighbors of an agent would be added into a *contact_list* of an agent. Along with contact identity, the associated data stored is contact-making time (current time). Again, the old contacts still remain and we do not delete them. Thus we have a list of contacts, the latest identifiable by time at which they were converted from neighbors to contacts.

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A fraction m of agents which are in the *contact_list* and *still* neighbors of an agent would be added to the *friend_list* of an agent. Along with the identity of a friend, the associated data stored is friend-making time (current time). Yet again, the old friends still remain and we do not delete them. Thus we have a list of friends, the latest identifiable by time at which they were converted from contacts into friends.

Diffusion An agent is considered *wobbling* if it has received new knowledge. If an agent is not wobbling, the new knowledge is not diffused to it. Hence, with probability p, the agent which is not wobbling would start wobbling based on the following equation:

$$p = c \times N \times \tau \times (W_t/N) \times ((N - W_t)/N)) \tag{1}$$

where N is the count of neighbors of an agent and W_t is the count of agents in the neighborhood of an agents who are wobbling. And c and τ are two constants acting as sensitivity parameters (both set to 0.5). With a probability of p (equal to 0.5 again) – if a random float is less than the value of p – the current agent starts wobbling itself. Wobbling equates to diffused influence, which does not guarantee knowledge absorption.

Absorption This applies to all the agents who did not absorb yet but are able to wobble. The measure of *credibility* is calculated as:

$$credibility = N_A/N \tag{2}$$

where N_A is the count of the agents in the neighborhood who have already absorbed the knowledge and N is the total number of neighborhood agents. Next, the friends who have already absorbed the knowledge are counted, designated by F_A. Then the measure *legitimacy* is calculated as:

$$legitimacy = F_A/N_F \tag{3}$$

where N_F is the total number of friends. Finally, if *credibility* and *legitimacy* is greater than $th1$ and $th2$ respectively, the agent is considered to have absorbed the knowledge.

Mobility There are three **mobility** modes under which the whole mechanism operates.

1. Mobility 1: No mobility – all agents are stationary.
2. Mobility 2: Random walk – agents choose a direction to move randomly at each iteration.
3. Mobility 3: Profile-based walk – agents build some random locations to move to, and they move from one location to another. This equates to a planned, scheduled, and repeated mobility.

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5 Simulation

5.1 Simulation Setup

The simulation world consists of a grid of size 100×100. This equals 10000 cells, each having a unique xy-coordinate. An agent population equal to $x\%$ was generated for a simulation run, for example, if $x = 25\%$, the population equals 2500 agents. An initial population of $y\%$ of these agents is considered to have absorbed the knowledge already – referred to as *early adopters*. If $y = 5\%$, 125 agents out of 2500 would be early adopters.

Towards the analysis of the simulation model, we have focused on three parameters:

1. **threshold 1 (th1):** the threshold (the percentage of agents in the contact list) to measure the credibility of the information being disseminated. Values are 0.1 (10%), 0.2 (20%), and 0.3 (30%).
2. **threshold 2 (th2):** the threshold (the percentage of agents in the friend list) to measure the legitimacy of the information being disseminated. Values are 0.1 (10%), 0.2 (20%) and 0.3 (30%).
3. **mobility mode:** stationary, random walk, and profile-based walk.

All of the above three parameters are permuted to form different cases representing all possible combinations. Each of these cases is executed under two "aggregation" strategies. In the **basic** strategy, the two thresholds (stated above) are used without any change. Whereas, in the **local** strategy, both thresholds are normalized according to their relative difference. The other parameters such as radius (range of influence of an agent), population size and density, the percentage of early adopters, and values like k and m are kept constant.

5.2 Simulation Results

Lower threshold values provide less resistance to adoption as a result of the achievement of credibility and legitimacy easily. For example, if both th1 and th2 are set to 0.1, it only requires 10% of the contacts and 10% of the friends who have adopted for an adoption to occur. It should be possible in all cases and should not take that much time. This is what is apparent in Figure 2 (a). The adoption occurs almost right after diffusion (wobbling) and it happens very early in the simulation. Further, it is noted that changing mobility mode does not affect this pattern at all. That is also valid for adoption strategies. So, the graph shown in Figure 2 (a) is for all possible mobility modes and for both "aggregation for adoption" strategies. Further, it only takes a few iterations before the whole population of agents has adopted. A simulation view representing this is shown in Figure 3 (I) in the case of random walk mobility and basic adoption strategy.

As the value of th1 increases, the resistance to adoption increases, typically to gain credibility. However, if the value of th1 still supports credibility, the adoption would most certainly happen (in many initial configurations), however, it will be delayed. This is what is apparent in Figure 2 (b). The adoption occurs but late. however, it is not that late if th1 values are increased further, that is

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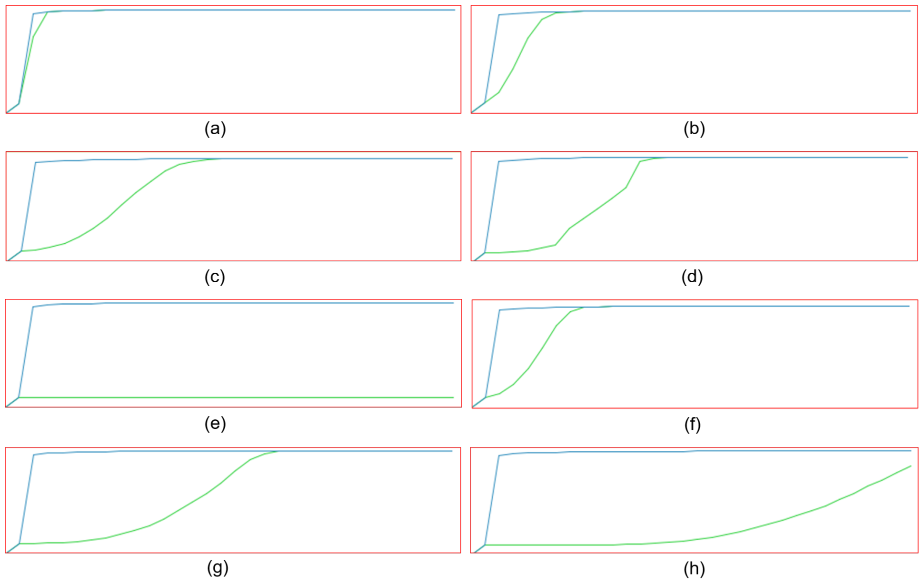

Fig. 2. x-axis of the graph shows time (simulation iteration) and y-axis shows the number of agents. Blue line represents the wobbling agents and green line represents agents who have adopted.

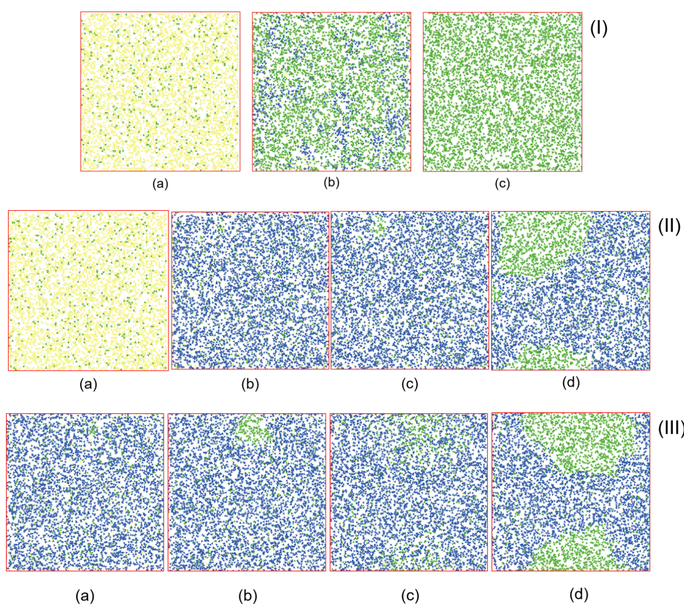

Fig. 3. Blue agents represent the wobbling agents and green agents represent agents who have adopted. (I) at t= 0, (b) at t= 1, and (c) at t= 2. (II) at t= 0, (b) at t= 1, (c) at t= 2, and at t = 10. (III)) at t= 1, (b) at t= 3, (c) at t= 5, and (d) at t = 7.

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to 0.3 (compare Figure 2 (b) with Figure 2 (c)). Again, changing mobility and adoption strategy do not affect this pattern at all. A simulation view representing this is shown in Figure 3 (II) in the case of random walk mobility and basic adoption strategy (th1 = 0.3, th2 = 0.1).

In case of th1 = 0.3 and th2 = 0.1, and in profile-based mobility, a very different pattern emerges. Analyzing Figure 2 (d), it is apparent that the adoption happens in phases. A simulation view representing this is shown in Figure 3 (III). Also, the adoption depends on the relative positioning of the early adopters. In many random simulation setting, the adoption would not happen at all if th1 = 0.2 or more (see graph shown in Figure 3 (III)) . But, instead of applying quantitative analysis, we applied qualitative analysis unless we have an educated knowledge of where to put the early adopters and what should be their relative positioning, which remains as future work.

These results show that just wobbling (diffusion) in fact happens very quickly in all the cases. However, the absorption may happen late or never, based on the values of thresholds for achieving credibility and legitimacy. Hence, there is a clear-cut difference between diffusion and absorption (although related) and these two aspects should not be treated equally. A lower threshold for legitimacy (th2) would let the agents acquire the absorption sooner or later depending on the threshold for credibility (th2) – lower threshold, sooner, and higher threshold, later. Stationary and random walk behave exactly the same, whereas, profile-based mobility (typically with high th1) produces absorption in phases of increasing intensity.

As th2 is increased, the resistance to absorb would increase, and generally, it would take more time to absorb. A comparison between Figure 2 (b) (th1 = 0.2, th2 = 0.1) and 2 (f) (th1 = 0.2, th2 = 0.2), and Figure 2 (e) (th1 = 0.3, th2 = 0.1) and 2 (g) (th1 = 0.2, th2 = 0.3) is sufficient to establish this fact. Finally, another case is when both th1 and th2 are quite high. Occasionally, it would generate absorption as shown in Figure 2 (h), but most of the time, there would be no absorption, similar to the graph shown in Figure 2 (e).

6 Conclusion

This paper presents a framework integrating the models for information dissemination/diffusion and adoption/absorption using an agent-based modeling paradigm. In particular, we provide an application of the Centola and Macy's information / innovation dissemination and adoption model [9] in a realistic setting. Sub-models of discrete spatial configuration (a grid of cells) and of proximity-based networking are integrated with an agent-based specification of the innovation adoption. Consequently, a thorough study about conditions leading to innovation dissemination and adoption is presented. Additionally, we quantify the relationship of late vs. early adopters in different conditions. The study also intends to quantify the relationship between credibility with legitimacy in time and spatial domains. Lastly, and most importantly, innovation dissemination in different mobility modes is studied in a proximity-based regular network.

The study revealed the following qualitative results:

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- The proximity and strong ties between people in a proximity-based regular networks play an important role in dissemination and ultimate adoption of information.
- This dictates that the social interactions among individuals are a key factor for the disseminating and adaptation of information in a society.
- It was witnessed that as the number of early adopters was increased, it convinced more late adopters to adopt information.
- To start with less number of adopters, it will take more time to disseminate and ultimately convince people to adopt an innovation.
- Late adopters are, however, influenced by early adopters only when the latter category people had planned, scheduled, and repeated interaction with the former category.

Comparison with real experiments on social group and evaluation with real datasets such as social networks, which could greatly improve the proposed work, will be taken up as future work .

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