Agent-based Decision Support for Social Media Influence in Urban Planning

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Abstract. A variety of social media platforms have been recently used for citizen engagement in urban planning. However, social media generate large datasets and complex relations, making it difficult for planners and policymakers to understand the influential factors on the interactions and actions of various actors. Agent-based modelling (ABM) makes it possible to capture the complex interactions between actors. However, it does not come with a mature methodology to capture and measure social media influence. Besides, most of the existing studies are from the discipline of computer science and lack approaches to make it useful for participatory planning. Therefore, this research explores an agent-based approach for measuring and simulating social networking influence in urban planning to support informed decision making. It contributes to bridging the gaps between ABM research, social media studies, and planning literature.

Key words: agent-based modelling, decision support, social media influence, citizen engagement, urban planning

1 Introduction

Social media has changed the relations between individuals and organizations, and provided new ways of communication, and information sharing. In recent years, they have increasingly impacted planning practices and policymaking in many countries (Lin, 2022). On the one hand, governments employ them to support citizen participation to obtain information and improve transparency. On the other hand, citizens and civil society organizations use them as a new public sphere to let their voices be heard and establish large-scale networks for collective actions. However, social media have generated large datasets (including posts, messages and user interactions). The data is often noisy, distributed, unstructured, and dynamic; information is sorted in interconnected, heterogeneous sources (Ennaji et al., 2016). This makes it difficult for governments and planners to understand the key factors that influence the interactions and actions of various actors.

Agent-based modelling (ABM) offers the opportunity to understand and simulate the complex interactions between users on social media. Nevertheless, most of the existing studies on ABM for measuring information diffusion or social influence of social media are from computer science. There is a lack of studies to explore ABM for measuring and simulating social networking influence in participatory or collaborative planning. Although there is a growing body of literature on ABM as decision support systems (DSS) in urban planning, little research has been done to understand their relevance for supporting social media participation. ABM is often too complex for urban planners and policy makers to use in practice. It remains challenging to integrate planning knowledge into modeling, and transform complex data analysis and modeling into a user-friendly interface. Therefore, this research attempts to link the gap between computer science and urban planning. It explores the potential of ABM as decision support for social networking influence in urban planning. On the one hand, it reviews related literature on ABM, DSS and social media studies to identify the gaps and linkages between these three domains. On the other hand, it uses an experimentation case to illustrate a approach to connect planning knowledge and social media in an ABM decision support framework. This includes an innovative ABM model based on the SIR model and using Twitter data, with an interactive tool for visualization and communication.

2 Agent-based decision support systems

ABM is "a form of computational modeling whereby a phenomenon is modeled in terms of agents and their interactions" (Wilensky & Rand, 2015, p.1). It is a loosely coupled network of agents that work together to find answers to problems beyond each agent's capability or knowledge (Challenger & Vangheluwe, 2020). An agent is a system, individual or thing that can autonomously interact with its environment and perceive it, and thereby making informed decisions and taking actions (Jennings, 2001; Foster et al., 2005; Wilensky & Rand, 2015). The behavior of each agent is controlled by a set of rules, which are often simple at the agent level but when combined can capture complex emergent phenomenon (Gausen et al., 2022). It is a methodological instrument to develop micro-simulation tools that allow planners to visualize, analyze and forecast collective phenomena emerging from the interaction of individual behaviors of agents (Saarloos et at., 2008). ABM has been used in decision support systems (DSS) in many disciplines such as healthcare, business, operation, risk management, and urban planning (Sprague, 1980; Foster et al., 2005; Saarloos et at., 2008; Drakaki et al., 2018; Gupta et al., 2022). Sprague (1980, p.1) describes the characteristics of DSS as "interactive computer based systems, which help decision makers utilize data and models to solve unstructured problems". Zhai et al. (2020) define DSS as a human-computer system that utilizes multisource data, aiming at providing informed decision-making under different circumstances. But they indicate that DSS doesn't give direct instructions to users, since users are in the position of taking the final decision. Scholars develop many different frameworks of DSS to support various decision-making activities. For instance, Vahidov and Fazlollahi (2004) propose a framework for a pluralistic multi-agent DSS, which incorporates pluralistic agents that have diverse sets of views and values in approaching the problem and informing the decision. Boutkhoum et al. (2015) present a multi-agent model for DSS by combining multi-criteria decision analysis with online analytical processing. Chica and Rand (2017) develop an agent-based DSS for word-of-mouth (WOM) program that includes three steps and four guidelines: 1) involving stakeholders in a participatory model process, 2) analyzing available data to construct the DSS, 3) applying computation methods, and 4) minimizing number of parameters. Drakaki et al. (2018) propose an intelligent multi-agent-based DSS for refugee settlement siting. Gupta et al. (2022) review how artificial intelligence (AI) capabilities have been integrated into DSS to support decision-making in operation research. Although these studies are from different disciplines, they show a specific framework of agent-based DSS can be designed to meet the need of particular decision-making tasks. The framework often includes several interacted components, such as problem identification, data environment, an ABM architect (including a set of rules, and diverse agents with different functions, views or values), and various models/simulations. Some also engage stakeholders and have a user interface for communicating with stakeholders. But so far there is a lack of agent-based DSS for assisting social media participation in urban planning.

3 Agent-based models and social media

Different types of ABM models have been developed in social media studies. For instance, Ennaji et al. (2016) develop a framework for extracting and analyzing public opinion from social networks, including data extraction agent, data refinement agent, data analysis agent, database and analytical module. Yu et al. (2017) propose a multi-agent simulation model for understanding online opinion dissemination among four agents (cyber citizens, opinion leaders, the government and mass media) during emergencies in China. Aguado et al. (2020) design and implement a proposal that uses a software agent that performs sentiment analysis and another performing stress analysis on keystroke dynamics data. Among others, the susceptible-infected-recovered models (SIR) have been widely applied to measure information diffusion and model the spread of rumors or misinformation through social networking sites. It has a stochastic approach and was originally applied to epidemics: the probability of someone getting infected increases by the ratio of infected people in their network (van Maanen & van der Vecht, 2013). However, this model has been criticized for being oversimplified, because it assumes a homogenous population in a simple network with a constant probability of infection (Beskow & Carley, 2019). Zhao et al. (2012) extend the classical SIR rumor-spreading model by adding a direct link from ignorant to stiflers and a new kind of people-Hibernators. Beskow and Carley (2019) develop a twitter_sim model that includes the actions of the Twitter environment (tweet, reply, retweet, mention and follow) and heterogeneous behaviors such as varied rates of access, limited attention, dynamic network, and changed beliefs. Inspired by the SIR model, Gausen et al. (2022) develop an ABM of Twitter to compare newsfeed curation algorithms in terms of filter bubble formation and the spread of misinformation. Some studies have also been conducted to understand social networking influence on the behaviors of users. Van Maanen and van der Vecht (2013) develop a multi-agent behavior model, which contains the social network structure, individual behavior parameters and the scenario that are obtained from empirical data. They identify several influential factors, including: 1) individual factors, such as the number of followers and the user's age, 2) persuasion factors, such as liking, social proof, and consistency; and 3) external events, such as external events and user experiences. Li et al. (2018) propose an agent-based influence-diffusion model by defining the features and behaviors of micro-level individuals in social networks. Yet, this body literature is mainly from computer science, and there is little known about its relevance for the planning context. Li et al. (2020) research shows the positive impacts of civil society, personal interest, and social influence on citizens' motivation and participation intention in urban planning. Several recent studies have explored how citizens use social media to extend their networks and influence the planning process (Williamson & Ruming, 2020; Lin, 2022). They reflect the vital role of key agents such as civil society organizations, experts and elites in information flow, social influence, and the interaction between online debates and offline actions.

4 Experiment case

To fill the mentioned knowledge gaps, we propose an approach to link planning knowledge and ABM for measuring and simulating social networking influence on urban planning. We use Amelisweerd's planning controversy as an experiment case to study this approach. An urban plan has been made for widening the A27 highway in the Netherlands. However, widening the highway requires the demolishment of a substantial part of forests with many old trees and historical estates in Amelisweerd. This plan has caused many protests, demonstrations, and citizen activism. A lot of debate on the case study has taken place in social media platforms in the past few years. We design several steps to understand the problems, obtain and analyze social media data, and model and simulate the complex interactions.

4.1 Identify problems and stakeholders

To understand the nature of the case study, we first searched the case study's information from related websites, archives and policy documents. We identified a number of key stakeholders of the case, including public authorities from national, provincial and municipal governments, and several citizen initiatives. We then approached some of them and conducted semi-structured interviews to understand the problems and stakeholder relations. Through this qualitative research, we had three main findings that were helpful for the following data collection and modeling/simulation. First, we found several reasons for citizen activism, such as the concern on potential environmental impacts (e.g., noise, and pollution) of the plan, and the demolishment of the historical estate and old trees. Second, there were no formal channels for citizen participation at the early stages of the plan. Citizens have mainly participated in an informal way through social media platforms. Third, several citizen initiatives were set up in different periods of the project. They created their social media profiles and played a vital role in online debate and organizing offline events.

4.2 Social media data collection and preliminary analysis

Based on online information and interviews in step 1, we identified several hashtags of Twitter used for the case study. Through Twitter APIs, we scraped more than 21,000 tweets by using four key hashtags such as #StopDeVerbreding, and #amelisweerdnietgeasfalteerd, #a27, and #amelisweerd. Not all the tweets were related to the case study, so we used the tweets for the first two hashtags as well as tweets that had both of the third and fourth hashtags. This results in about five and a half thousand tweets in the model. The time period of the tweets is between 2010 and 2022. We analyzed the frequency of tweets on the topic plotted on a weekly basis and found the highest peaks ranged from November 2020 to March 2021 (Fig. 1.). We observed several events, including demonstrations, elections and petitions.

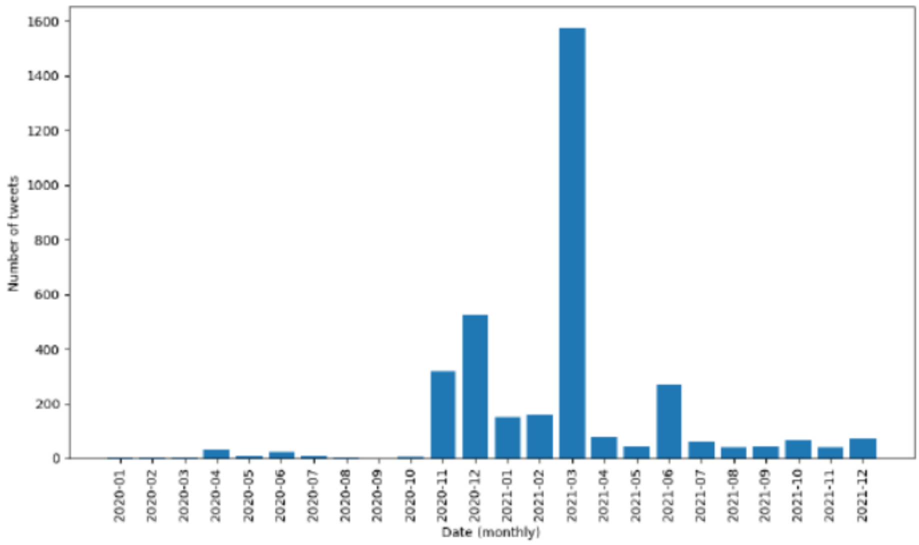

Fig. 1. Frequency of tweets on topic plotted for each year

4.3 Agents and actions

From Step 1, we identified citizens and citizen initiatives as two key types of agents in online activism. But they have different actions. For citizens, there are three types of actions on social media: 1) tweetOnTopic - post about the topic, 2) tweetOffTopic - post about something unrelated to the topic, and 3) doNothing – not post on the topic for some time. However, the behavior of social media users can be strongly influenced by the behavior of the users they follow or their neighbor agents. We thus hypothesize that the more followers of an agent tweet on the topic, the more likely the agent is to tweet about the topic. For citizen initiatives, we expect that the posts on social media are all related to the topic, because their social media profiles were established based on the case study. Hence, they only have two actions: tweetOnTopic and doNothing. They have also organized offline events such as protests and demonstrations. These offline events could be external factors that lead to increased tweets on the topic.

4.4 The SIR-Twitter model

We develop an innovative Infection Tweet model for analyzing and simulating social networking influence on urban planning (Fig. 2.).

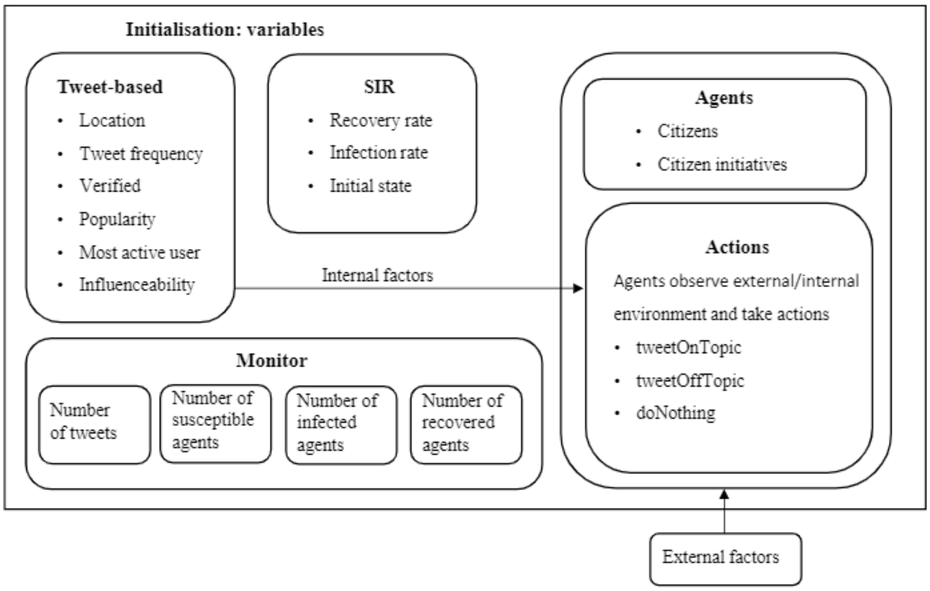

Fig. 2. The SIR-Twitter model

Variables: Our proposed model merges the traditional SIR model and the Tweet-based model. In the SIR model, an agent can be in one of three states: Susceptible, Infected, or Recovered. We use *initial state* variable to determine which agents start the simulation in an Infected state. At each step of the simulation, Infected agents infect agents in Susceptible state with a predefined *infection rate.* The agents that are in Infected state recover with a *recovery rate* and move to Recovered State. However, we observe on Twitter that not everyone propagates information equally; some users who are more active or have more followers would have more effect on how information spreads. To mimic this, we create a persona for each agent such that each agent represents one Twitter user online. The persona has variables such as *location (i.e., whether the user is in Utrecht), tweet frequency (i.e., how often she tweets), verified (i.e., whether her account is verified),* and *number of followers.* This persona is then used to determine how much one agent infects another agent. We also keep track of what percentage of her tweets are on the hashtags we are interested in. The agents that have verified accounts, have more followers, and tweets mostly on the topic are more likely to infect others.

Actions and influential factors: There are three actions of citizens: tweetOnTopic, tweetOffTopic and doNothing (see step 3). But citizen initiatives only have the actions of tweetOnTopic and doNothing. The influential factors include internal factors and external factors. First, internal factors are related to the influence of the neighbors on the behavior of agents. We take the average probability of the neighbors to post on the topic of neighbors, not post on the topic, or do nothing. The agent observes their own scores for these values. Influenceability is thus the degree of the own score of the agent and the environmental variables. A high score of influenceability would result in a high influence of the environmental variables, while a low value would result in a high influence of the internal values. Second, external factors include two large events that took place between November 2020 to March 2021. They include a large demonstration and a large petition in which a video has been shared. A recovery time of the event is included. After an event, the number of posts will be higher but will slowly decrease. Citizen initiatives are the key agents organizing these offline events. Their events may also be influenced by other factors such as budget.

Monitor: it monitors the number of tweets and the different states of agents: 1) an agent is seen to be susceptible if an agent has not tweeted on the topic; 2) an agent is infected if agents tweeted at least once on the topic; 3) an agent is recovered when an agent was infected but has not tweeted on the topic anymore. We can also see the number of tweets sent at each time.

4.5 User interface: an interactive tool

To test the influence of various influential factors, an interactive tool is developed for different what-if scenarios (Fig.3). It uses the Python package Mesa. There are several buttons, such as read-world network-based, number of agents, influenceability, citizen initiative included, verified accounts excluded, local excluded, excluded user with most followers, etc. It is an interactive tool enabling hypothesis testing in which users can try and observe different values or include/exclude different variables. We identified multiple hypotheses to examine the role of factors such as location, authority, population and consistency. Furthermore, we test the influence of citizen initiatives by considering the year of establishment, included/excluded, or with/without budget. Besides, we test different hypotheses including removing certain actors and enabling temporal modifications. We have observed that having citizen initiatives in the simulation increases the tweet exchange between citizens. Citizen initiatives that join in recently are more active and thus increase this exchange more than others. Moreover, it is important to account for the external factors, such as offline protests. Including these creates more realistic simulations that are in line with real-life data. Producing such validations with real-life data enables the simulation to answer questions for future decision-support situations soundly.

Fig. 3. An interactive tool to understand how information related to planning propagates on social media and to test hypothesis

5 Conclusion

This research explores an agent-based approach to measure and simulate social networking influence to support decision-making in urban planning. It attempts to bridge the gap between ABM research, social media studies, and planning literature. In the experimental case, we develop several steps to understand planning problems, obtain and analyze social media data, and identify key agents, actions and influential factors. Based on these, we develop a SIR-Twitter model to analyze and simulate the complex interactions, and an interactive tool for different what-if scenarios. The main challenges include difficulties to develop a simulation that is close to the reality. We run several simulations and finally identify the one with external factors (offline events: a large demonstration and a large petition) as the closest to the reality, since this model can mimic the actual data closely. However, there are several limitations for this research. First, it only uses a case study, in which citizens and civil societies use social media against an urban plan. More case studies should be examined to test the validity of the approach. Second, although it integrates planning knowledge through interviews with stakeholders, it remains unknown whether the tool can help decision-makers in practice. In planning literature, several studies show potential issues of modeling or systems, such as mismatches between tool outputs and local interests, and difficulties for users to understand, use, and accept them (Pan et al., 2022). To solve the mentioned issues, it requires engaging stakeholders in the lifecycle of the tool development. It should also pay attention to privacy concerns by using social media data (Lin, 2022).

More research is required to explore a collaborative, integrated and feasible approach for developing ABM-based decision support systems to support social media participation in urban planning.

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