A Network Agent-Based Model for Moroccan Inbound Tourism: Incorporating Social Influence in the Decision-Making Process

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Tourism plays a critical role in Morocco's economy, supported by its rich cultural heritage and diverse attractions. Understanding the decision-making processes of inbound tourists is essential for enhancing destination appeal and promoting sustainable growth. This paper proposes a network agent-based model for Moroccan inbound tourism, incorporating social factors into tourist decision-making processes. By simulating interactions within a network of agents, the model highlights the role of social influence in shaping tourist behaviors. It provides a comprehensive framework for examining how individual decisions emerge from the interplay between personal preferences and social environments.

The paper also explores various scenarios to evaluate the effects of social influence, the promotion of lesser-known destinations and the repercussions of negative reviews. The simulation results offer valuable insights into strategies for sustainable tourism development, emphasizing the importance of leveraging social dynamics to optimize tourism policies and enhance the visitor experience.

Keywords: Moroccan tourism; social influence; social network; tourist decision-making; agent-based model

1. Introduction

Tourism is a major economic driver for many nations, including Morocco, which is renowned for its rich cultural heritage, diverse landscapes and vibrant traditions. Understanding the decision-making processes of tourists is critical for fostering sustainable tourism

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growth and enhancing destination appeal. Traditionally, destinations have been conceptualized as well-defined geographical areas such as countries, towns or islands [1, 2]. Destinations provide an amalgamation of tourism products and services, which together create a unique branded experience for visitors. Leiper [3] describes destinations as places where individuals travel and temporarily stay to experience specific features or attractions. Cooper et al. [4] further emphasize that destinations serve as focal points for facilities and services tailored to meet the needs of tourists.

Tourist decision-making is inherently complex and influenced by a combination of push and pull factors, which shape their choice of destination. The push factors are internal to individuals and install a desire for people to want to travel. The pull factors are external to individuals and affect where, when and how people travel, given the initial desire to travel [5–7]. While traditional models in tourism research emphasize intrinsic motivations and the appeal of destination attributes, they often overlook the significant role of social dynamics. Peer recommendations, online reviews and social networks play an increasingly important role in shaping tourists' perceptions and decisions in the modern digital age.

Social influence can be better understood through the lens of complex networks, which describe patterns of connections in social, biological and technological systems [8]. Key network structures, such as small-world (SW) and scale-free networks, are particularly relevant in the tourism context. SW networks exhibit high clustering and short path lengths, facilitating rapid dissemination of information. In contrast, scale-free networks are dominated by a few highly influential nodes, such as prominent social media users or opinion leaders, who disproportionately shape public perceptions [9, 10].

To better represent such complex systems, agent-based modeling (ABM) offers a solution. ABM is considered an accurate tool for studying tourism due to its ability to capture the dynamic interactions between tourists and the destinations. ABM simulations can also be useful for the description and development of scenarios. They allow us to explore the dynamics of a real process where empirical experiments are often impossible due to scale, cost and ethical considerations [11]. Tourists exhibit distinct preferences, behaviors and decision-making processes, and ABM excels in representing this heterogeneity. Furthermore, it is adept at incorporating spatial dimensions, providing insights into how tourists move through various destinations [12].

To address these complexities, this paper proposes a network agent-based model for Moroccan inbound tourism, integrating social influence into the tourist decision-making process by simulating interactions within a network of agents [13]. This approach allows for the exploration of how individual behaviors emerge from the interplay of personal preferences and social influences. Specifically, the model examines scenarios such as the impact of promoting lesser-known destinations, the consequences of negative reviews and the role of social networks in shaping tourist choices.

By incorporating the dynamic interplay of push and pull factors alongside the influence of complex social networks, this paper offers a novel framework for understanding tourist behavior. The findings provide actionable insights for destination managers and policymakers, enabling them to design strategies that enhance Morocco's competitiveness in the global tourism market while supporting sustainable tourism development.

The structure of this paper is organized as follows: Section 2 presents the background information. Section 3 introduces the model, providing a detailed explanation of its components and development process. Section 4 discusses the results of the simulations and analysis, emphasizing the key findings and insights. Finally, Section 5 draws conclusions based on the results.

2. Background

2.1 Agent-Based Modeling

ABM is a computational modeling technique that has gained significant popularity in various disciplines including economics, ecology, social sciences and epidemiology. It is particularly well suited for studying complex systems where individual agents interact with each other and their environment, giving rise to emergent behavior. The core idea of ABM is that, instead of merely describing the overall, global phenomenon, this phenomenon can rather be generated from the actions and interactions of agents. This bottom-up nature is the most important feature of ABM [14]. Thus, ABM is particularly suitable for the analysis of complex adaptive systems and emergent phenomena [15–18]. In general, an agent-based model has three elements [19–21]:

- A set of agents, their attributes and behaviors.
- A set of agent relationships and interaction methods: an underlying topology of connectivity defines how and with whom agents interact.
- Agent environment: agents interact with their environment in addition to other agents.

ABM has emerged as a powerful tool for understanding the complex dynamics of tourism systems. By simulating the behavior of individual agents and their interactions within a given environment, ABM offers researchers and practitioners a unique perspective on how tourism destinations evolve, how tourists make decisions, and how various factors influence the sustainability and resilience of tourism systems.

2.2 Social Influence

Decision-making has been transformed by the growing trend of online shopping, which has changed how consumers gather and evaluate information. Modern consumers face a vast array of information from numerous sources, particularly when making travel decisions. Researchers have employed various theoretical frameworks to explain the impact of online reviews. Several studies indicate that traveler reviews function as a form of social influence. This influence is arguably more pronounced in today's interconnected society, where online reviews and social media offer near-constant access to peer opinions. Social influence theories suggest that individuals are affected by the opinions, beliefs and attitudes of others [22]. Social influence occurs when an actor adapts his behavior, attitude or belief to the behaviors, attitudes or beliefs of other actors in the social system [23]. Peng [24] summarized the basic understanding of social influence as follows:

- It arises from the interaction between two entities, where one entity (influencer) influences the other entity (influencee) to perform an action.
- It is a function of uncertainty. If the influencer is certain about the influencee's action, influence is complete. Conversely, if uncertainty is high, the influence is minimal or absent.
- Its level can be measured by a continuous real number, and also be represented with uncertainty (e.g., stronger, strong, weak, weaker, etc.).
- It is not necessarily symmetrical: the influencer may exert different levels of influence on the same influencee for the same action.

2.3 Social Network

A complex network is a structure made up of nodes connected by one or more specific types of interdependency. Nodes represent individuals, groups or organizations, while connections (links, edges or ties) represent relations such as friendship, economic deals, internet connections, neuron connections, protein interactions and others [8].

Networks with a complex topology and unknown organizing principles often appear random; thus random-graph theory is regularly used in the study of complex networks. The theory of random graphs was introduced by Paul Erdös and Alfred Rényi [25–27]. In their classic first article on random graphs, Erdös and Rényi define a random graph as N labeled nodes connected by n edges, which are chosen randomly from the $N(N-1)/2$ possible edges [25].

The scientific research on complex networks has become very active, inspired by the empirical study of real-world networks from different perspectives. In fact, most social, biological and technological networks present interesting topological features, with patterns of connection that are neither purely regular nor purely random [8].

Two well-known and representative classes of complex networks are SW networks [9] and scale-free networks [10]. Both topologies are characterized by structural features like a high clustering for the SW network, short path lengths in both cases and power-law degree distributions for the scale-free case.

In an SW network [9] all nodes are not direct neighbors, but most of them can be reached from every other by a small number of links. These networks present the SW phenomenon, in which nodes have small neighborhoods, but yet it is possible to reach any other node in a small number of hops. The most popular manifestation of small worlds is the "six degrees of separation" concept, uncovered by the social psychologist Stanley Milgram [28], who concluded that there was a path of acquaintances with a typical length of about six between most pairs of people in the United States. Two major properties of SW networks: high average clustering coefficient, short average shortest path length. A wide variety of real-world networks such as the World Wide Web, gene networks, social networks, electric power grids, brain neuron connections and the metabolic network also exhibit these properties [8].

Scale-free (SF) networks [10] follow a power law concerning degree distribution, at least asymptotically. These networks are characterized by having a few nodes acting as highly connected hubs, while the rest of them have a low connectivity degree. SF networks show characteristics present in many real-world networks, like the presence of hubs connecting almost disconnected subnetworks. Their degree distributions are heavy tailed, and follow a power law [8]. The origin of the power-law degree distribution in networks was first explained by Barabási and Albert in 1999 [10]. They proposed that the scale-free nature of real networks is due to two common mechanisms found in many networks (growth and preferential attachment) [29]. Although many real-world networks are considered scale free, a few examples of such networks include social networks, various types of computer networks (including the internet), protein-protein interaction networks, semantic networks and airline networks.

To imitate the real world, as seen in social media and travel review platforms, where popular influencers attract more attention and connections, the Barabási–Albert (BA) model's preferential attachment mechanism can be applied effectively. This mechanism is suitable for modeling the dynamics of influence and popularity in social networks. Using the BA model, new nodes (representing tourists) preferentially attach to existing nodes with higher degrees (representing popular influencers).

3. Model

3.1 Description of the Study Area

In recent years, understanding tourist behavior has become increasingly important for destination management and marketing, particularly in culturally rich regions like Morocco. Located in the northwestern region of Africa, Morocco is a country known for its diverse landscapes, rich cultural heritage and vibrant tourism sector. It is bordered by the Atlantic Ocean and the Mediterranean Sea, offering a unique blend of coastal, mountainous and desert environments.

This paper employs ABM to explore how social influence impacts the destination choices of inbound tourists in Morocco. This approach models tourists as autonomous agents, each making decisions based on personal preferences, social interactions and environmental factors [13, 30–34]. The Moroccan international tourism network depicted in Figure 1 includes 11 destinations, each interconnected by highways, trunk roads or direct flights [35]. The size of the nodes indicates the number of tourists visiting each destination, while the thickness of the connections represents the volume of tourist traffic along those routes [30].

According to the 2016 reports from the Moroccan Tourism Observatory [35], each destination is defined by its annual arrival rates and level of attractiveness, as detailed in Table 1, derived from their analysis of tourist demand.

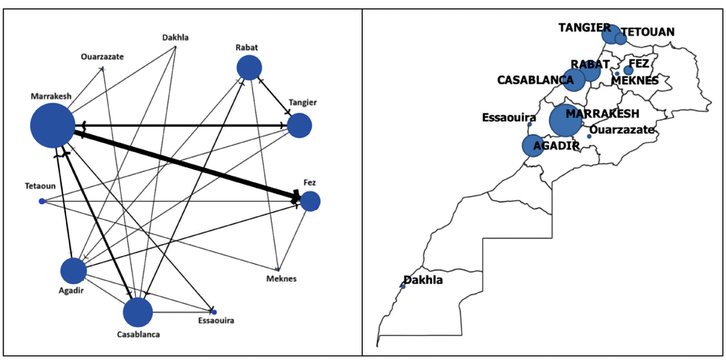

Figure 1. Moroccan touristic network considered in this paper [30].

			Attractions			
City	Port City	Percentage of Arrivals	Sea	Gastronomy	Visiting Monuments	Calm and Rest
Ouarzazate (OZZ)	No	00%	00%	10%	35%	12%
Essaouira (ESU)	No	00%	05%	12%	43%	08%
Dakhla (VIL)	No	00%	20%	10%	20%	20%
Marrakesh (RAK)	Yes	35%	00%	10%	75%	11%
Agadir (AGA)	Yes	16%	38%	14%	16%	12%
Tangier (TNG)	Yes	12%	17%	16%	38%	14%
Rabat (RBA)	Yes	14%	08%	15%	46%	17%
Casablanca (CMN)	Yes	17%	08%	11%	33%	20%
Meknes (MEK)	No	00%	00%	00%	18%	39%
Fez (FEZ)	Yes	02%	00%	21%	67%	16%
Tetouan (TTU)	Yes	04%	07%	03%	14%	20%

Table 1. Percentages of annual arrivals and attractiveness for the port and non-port Moroccan destinations [35].

Our agent-based model will be described following the overview, design concepts and details (ODD) protocol as proposed by Grimm et al. [36].

3.2 Overview

3.2.1 Purpose

The suggested model is a network agent-based model intended to explore the impact of social influence on tourists' decision-making processes and the distribution of tourists among various destinations within a tourist network. It seeks to simulate how tourists are influenced by experiences and opinions shared by others online, and how this influence shapes their destination choices by affecting how tourists are distributed across the network.

3.2.2 Entities, State Variables and Scales

The model includes two types of agents: destinations and tourists [13, 30, 33].

Destination agents. Destinations differ in attractiveness, shaped by features like access to the sea, culinary offerings, historical monuments and opportunities for relaxation. They also vary in accessibility, influenced by transportation infrastructure and the number of visitors arriving through ports. (See Tables 2 and 3.)

Agent	Property
Tourist Agent	Autonomy: tourists make decisions autonomously based on their preferences (sea, gastronomy, visiting monuments, and calm and rest), social influence and environmental stimuli.
	Heterogeneity: tourists exhibit diversity in preferences and susceptibility to social influence. Tourists are categorized into five profiles based on their country of origin (France, Spain, Germany, United Kingdom and Italy). This classification helps to better simulate the diverse preferences by considering the specific characteristics and tendencies of tourists from various countries.
	Adaptation: tourists adapt their behavior over time in response to changes in their environment and social context.
	Mobility: Tourists travel through destinations.
Destination Agent	Heterogeneity: Destinations vary in attractiveness based on the availability of the sea, gastronomy, visiting monuments and opportunities for calm and rest. They also vary based on the number of visitors arriving via the port.
	Accessibility: Destinations differ in accessibility, influenced by transportation infrastructure.

Table 2. Agent properties.

Destination Agent	
Variable name	Brief description
Attractions AttractionSea AttractionVisitingMonuments AttractionGastronomy AttractionCalmRest	Refer to the key features or activities that draw tourists to a particular destination.
Port city	Port or Non-port.
Annual percentage of arrivals	The influx of visitors arriving through the port of a particular city.
Coordinates	x and y coordinates of the destination.

Table 3. Destination variables.

Tourist agents. Tourists are autonomous individuals with diverse preferences, such as enjoying the sea, gastronomy, visiting monuments or seeking relaxation. They are influenced by social interactions and environmental factors, adapt their behaviors over time and travel between destinations. Tourists are categorized into five profiles based on their country of origin (France, Spain, Germany, the United Kingdom and Italy) to reflect varied tendencies and characteristics. (See Tables 2 and 4.)

Tourist Agent	
Variable name	Brief description
Profile	Profiles/nationalities: France, Spain, Germany, United Kingdom and Italy.
Preferences PreferenceSea PreferenceVisitingMonuments PreferenceGastronomy PreferenceCalmRest	Are subjective and individualistic, representing tastes, interests and priorities of each traveler.
LengthPath	Number of cities to visit. LengthPath: varies between 1 and 3 (59% for a single stage, 19% for two stages and 22% for three stages).
Location	x and y coordinates of the visited destination.
Satisfaction	Satisfaction is subjective and varies based on individual experiences, which can often be represented on a scale from 0 to 1.

Table 4. Tourist variables.

To select the most suitable destination from a set of candidate destinations located in the tourist agent's neighboring network, criteria such as the availability of the sea, gastronomy, the presence of monuments and opportunities for calm and rest are considered. To address this complexity, we chose to use the fuzzy analytical hierarchy process (FAHP) to calculate the weights of tourism preferences/criteria for each profile. FAHP was used to assign weights α_k^j to each criterion k for each profile j. To streamline the task, we designed a FAHP code in C language. This code takes the pairwise matrix as input and produces the weights for each criterion as output. Figure 2 illustrates the weights of the criteria for the country of origin of each tourist [30].

Social network. The tourists' social network is created using the BA model [10, 29], where tourists are successively added, and the probability of a new link connecting to an existing tourist is proportional to the number of links that tourist already possesses. The probability p_i that a new tourist will be connected to tourist i depends on the degree k_i of tourist i, such that:

$$p_i = \frac{k_i}{\sum k_j}, \tag{1}$$

where k_i is the degree of node i and the sum is made over all pre-existing nodes j.

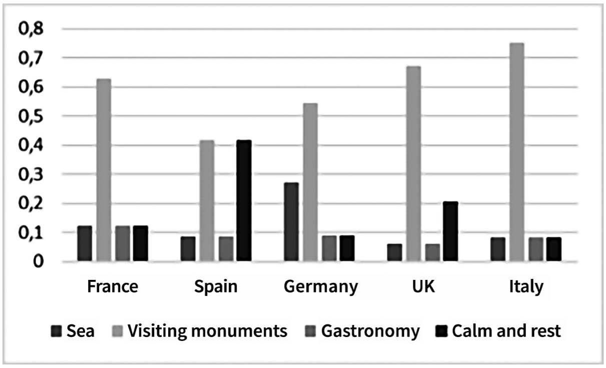

Figure 2. Criteria weights for each profile.

where k_i is the degree of node i and the sum is made over all pre-existing nodes j.

In other words, a new added tourist is preferentially attached to an existing popular tourist (influencer).

The 2016 report from the Moroccan Tourism Observatory on tourist satisfaction provides an in-depth analysis of how visitors perceive various Moroccan destinations. It outlines the overall levels of satisfaction, evaluating aspects such as transportation accommodations, catering and quality of activities. The report captures tourists' impressions and ratings for each destination, offering insights into which destinations are most favored by travelers and which areas may need improvements to enhance visitor experiences. Table 5 illustrates the overall appreciation of Moroccan destinations, based on data from the 2016 Monitoring Tourist Satisfaction report [35].

Destination	Satisfaction
Ouarzazate (OZZ)	[0,4 ; 0,6]
Essaouira (ESU)	[0,4 ; 0,6]
Dakhla (VIL)	[0,4 ; 0,6]
Marrakesh (RAK)	[0,8 ; 1,0]
Agadir (AGA)	[0,6 ; 0,8]
Tangier (TNG)	[0,4 ; 0,6]
Rabat (RBA)	[0,8 ; 1,0]
Casablanca (CMN)	[0,6 ; 0,8]
Meknes (MEK)	[0,4 ; 0,6]
Fez (FEZ)	[0,4 ; 0,6]
Tetouan (TTU)	[0,4 ; 0,6]

Table 5. The overall appreciation of Moroccan destinations.

Environment. A network composed of 11 destinations and a set of links that connect them. At each time step, the agent follows established rules and selects the best destination (with one time step representing a single trip). The size of each destination reflects the number of tourists visiting the corresponding city. The simulation continues until all tourists leave the network (tourists reach their length of path).

3.2.3 Process Overview and Scheduling

Tourists start their journey in the simulation by arriving at port cities. From there, they choose potential destinations (neighboring locations) and assess each option according to their personal preferences. Subsequently, tourists engage with their social networks, taking into account shared experiences and recommendations from others. Tourists select the best destinations, visit them and evaluate their experiences. This cycle of selection, visitation and evaluation is repeated several times until tourists have explored a predetermined number of destinations. (See Figure 3.)

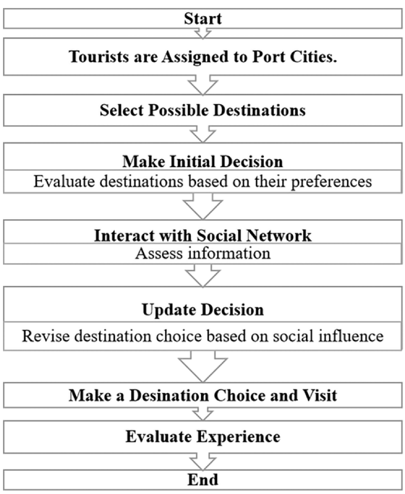

Figure 3. Tourist decision-making process.

3.3 Design Concepts

Emergence

Interactions among tourists, their environment and each other shape tourist behaviors. Certain destinations gain popularity through positive feedback loops, ultimately leading to emergent patterns of tourist concentration and distribution.

Interaction

- *Tourist-tourist interaction*. Tourists interact with each other through social networks and by influencing each other's decision-making.
- *Tourist-environment interaction*. Tourists interact with the environment by visiting destinations.

Stochasticity

- *Random initialization*. Tourists are initialized with random preferences, number of destinations to visit and social connections, introducing variability in the initial conditions of the simulation.
- *Probabilistic decision making*. Tourists make decisions probabilistically based on their preferences and social connections.

Observation

During the simulation, tourists navigate through different destinations within the network. As tourists visit destinations, the number of visitors to each destination fluctuates dynamically. This fluctuation affects the size of destinations. This dynamic reflects the evolving patterns of tourist movement and choices within the simulation. The visitation volume of a city, defined as the total number of agents visiting a node i, is calculated as $\text{Volume}_i = n_i + \sum F_{ji}$, where n_i represents the number of tourists arriving at city i via a port and F_{ji} the tourist flow from j to i [30, 37].

3.4 Details

3.4.1 Initialization and Input Data

The initial step of the simulation involves loading the Moroccan tourism network. Next, the tourist agents are randomly assigned to the port cities:

- The initial population of tourists is created with random but plausible destination preferences.
- Moroccan destinations are initialized with values for attractiveness and annual percentage of arrivals. (See Table 1.)
- Tourists have diverse profiles and a randomly determined number of destinations to visit. (See Table 6.)
- The social network is generated using the BA model: before starting the simulation, each newly added tourist is preferentially connected to an existing tourist, referred to as an influencer. The simulation models a total of 5100 tourists, each making decisions based on their social influences and personal preferences.
- Tourist satisfaction: The rating for each destination is a randomly selected value within the range of overall appreciation for Moroccan destinations, assigned after visiting the destination. (See Table 5.)

Input Data and Parameters	Brief Description
Number of tourists entering the simulation	5100 tourists
Percentage of tourists for each profile	France: 41%; Spain: 22%; United Kingdom: 20%; Germany:12%; Italy: 5%
Number of destinations to visit	Between 1 and 3 (59% for a single stage, 19% for two stages and 22% for three stages)

Table 6. List of input data and parameters [30].

3.4.2 Submodels

In this paper, we simulated the travel behavior of 5100 tourists, each defined by a distinct profile, as they navigated through a network of 11 tourist cities. These destinations were designed to feature a diverse range of attractions, including seaside experiences, gastronomy, historical monuments and opportunities for calm and relaxation.

The primary objective of the simulation was to model and analyze the decision-making processes of tourists as they selected their destinations. This process was influenced by three main factors:

- *Environmental factors*. Conditions such as accessibility and attractiveness.
- *Tourist preferences*. Individual inclinations toward specific types of attractions.
- *Social influence*. The impact of social networks on tourists' choices.

The tourist decision-making process was structured into four distinct steps, each designed to capture critical aspects of how choices are influenced:

1. *Selecting neighborhoods*. In the first step, tourists identified potential neighborhoods or destinations within the network based on transportation accessibility. This filtering process was crucial for narrowing down the options to a manageable and realistic set for further evaluation. Once a short list of destinations was established, each tourist t evaluated potential destinations d based on relevant factors.
2. *Preference evaluation*. Once potential neighborhoods were identified, tourists assessed each destination based on their personal preferences:

$$p_{td} = \alpha_t \times A_d^T, \tag{2}$$

where:

- P_{td} is the evaluation score of destination d by tourist t.
- α_t is a weight vector representing the tourist's preferences (sea, gastronomy, visiting monuments, calm and rest).
- A_d is the transpose of the attribute vector of the destination's attractiveness (sea, gastronomy, visiting monuments, calm and rest).

The equation calculates the total evaluation score by multiplying each tourist preference weight α_t with the corresponding attribute value A_d for each destination. The sum of these products provides a single score that represents how well a destination matches the individual tourist's preferences.

3. *Social influence evaluation*. In this step, the evaluation of a destination by tourist t is influenced by the opinions of other tourists within their social networks:
$$S_{td} = \frac{\sum_{k \in N_t} R_{kd}}{|N_t|} \tag{3}$$

where:

- S_{td} is the social influence score for destination d on tourist t.
- N_t is the set of tourists in the social network of tourist t.
- R_{kd} is the rating given by tourist k to destination d. This rating is a randomly selected value within the range of overall appreciation for Moroccan destinations.
- $|N_t|$ The size of the social network N_t.

In equation (3), social influence is calculated by taking the average evaluation scores R_{kd} given by all the tourists k in tourist t's social network N_t. The social influence score S_{td} shows how much the opinions of other tourists within the network shape tourist t's view of destination d.

This social influence factor plays a crucial role in understanding how tourists' decisions are affected by the people around them.

4. *Combined evaluation*. In this final step, tourists make their decision by combining the insights from both their personal preferences and the social influence they have experienced:
$$E_{td} = (1-\gamma) \times P_{td} + \gamma \times S_{td}, \tag{4}$$

where:

- E_{td} is the combined evaluation score for destination d by tourist t.
- γ is a parameter representing the relative importance of personal preference versus social influence.

After evaluating potential destinations based on their preferences and considering the influence of their social network, tourists make a well-rounded decision. They select the destination with the highest combined evaluation score E_{td}.

By bringing together both these elements, the model captures a more realistic and comprehensive view of how tourists choose their destinations, reflecting the dynamic interplay between personal choice and the influence of others.

3.4.3 Verification and Validation

Verification and validation are crucial stages in a simulation project. To confirm the accuracy of the simulation model, it must be evaluated and validated in comparison to the real-world target system [38].

The verification phase ensures that the agent-based model is implemented correctly and functions as intended. It involves checking that the model's code accurately represents the conceptual design and that there are no errors in the simulation's logic or execution. The model's code is thoroughly tested to ensure that all agents (tourists and destinations) behave according to the rules and algorithms defined in the design. Any issues identified during the coding process are resolved to ensure that tourists follow correct decision-making processes, social networks are formed accurately, and destinations receive tourists as expected. The model's outputs are systematically compared with expected results at different stages of the simulation to ensure consistency and accuracy in the results.

The validation phase, in turn, assesses whether the model reflects real-world behaviors and processes. This step ensures that the model can reproduce actual tourist behaviors and destination dynamics. The model's results are compared to real tourism data (distribution of visitation volume).

A calibration phase was essential to adjust the model's parameters to better align its results with observed data. A key parameter in this process is the social influence weight γ, which plays a crucial role in defining tourist behavior by determining how much an individual's destination choice is influenced by recommendations and shared experiences within their social network. Calibrating this parameter ensures that the model simulates the real impact of social influence on decision making.

During the calibration, various values of γ were tested, and it was observed that $\gamma = 0.2$ provided the best alignment with real-world data, with social influence accounting for 20% of the tourist's decision. This indicates that while social influence significantly impacts tourists' choices, personal preferences still play a crucial role.

By performing both verification and validation, the model's reliability and credibility are strengthened, allowing it to provide useful insights into the dynamics of inbound Moroccan tourism.

4. Results

In the context of ABM or Moroccan inbound tourism, scenarios serve as essential tools for examining and understanding the complex relationships between tourists and destinations. By simulating various conditions, these scenarios provide valuable insights into how tourists make decisions. Each scenario represents a distinct set of assumptions and variables, allowing the model to test how changes in these factors can impact overall tourism dynamics. These scenarios are also beneficial for policymakers, tourism boards and destination managers, as they help anticipate challenges and identify opportunities to promote balanced tourism [13].

Various scenarios will be outlined, explaining the assumptions behind each and presenting the results of the simulations. These scenarios examine factors such as the role of social influence, the impact of promoting lesser-known destinations and the consequences of negative reviews. Together, they offer a comprehensive view of how different conditions can affect the patterns and dynamics of Moroccan inbound tourism.

Under the proposed scenarios, we assess the overall impact on tourist distribution by calculating the change in visitation volume for each destination. This is expressed as $\Delta\text{volume} = \text{volume}' - \text{volume}$, where volume′ denotes the visitation volume under the scenario, and volume represents the visitation volume from the real-world simulation.

We simulated 5100 tourists with different tourist profiles traveling through 11 tourist cities with various attractions. Since ABM is a stochastic tool, it yields different results in each simulation. Twenty simulations were conducted to determine the average values of both visitation volume and tourist flow within each of the previously mentioned scenarios.

4.1 Scenario 1: High Social Influence

This scenario explores the dynamics of high social influence on tourist destination choices, focusing on how recommendations shape travel behavior. Social influence plays a critical role in modern tourism, as individuals increasingly rely on advice, reviews and recommendations from their social networks when selecting travel destinations. This scenario examines the effects of heightened social influence on tourist behavior, destination popularity and overall tourism patterns.

In the context of high social influence, tourists are significantly affected by the opinions and recommendations shared within their social networks. This scenario simulates a situation where social influence is amplified, leading to a greater reliance on peer recommendations and online reviews when making travel decisions. The aim is to understand how such a high level of social influence alters tourism dynamics, including destination popularity, tourist behavior and the distribution of visitor flows.

To check the generality of the results, a sensitivity analysis is necessary. To assess the impact, we adjust the social influence weight γ

incrementally. In the first simulation, the social influence weight is set equal to personal preference $\gamma = 0.5$, meaning tourists balance their own preferences and social recommendations equally. In the second simulation, the social influence weight is increased above personal preference (e.g., $\gamma = 0.8$), suggesting that tourists place greater emphasis on recommendations and feedback from their social networks when selecting destinations. This will illustrate how social recommendations significantly impact tourist behaviors and the distribution of visitation volume (destination popularity).

Tourists rely strongly on social feedback, which has a major impact on their choice of destinations. As depicted in Figure 4, the majority of tourists were attracted to highly recommended locations, leading to a significant rise in visits to Marrakech and Tangier, while other destinations maintained relatively stable visitor numbers.

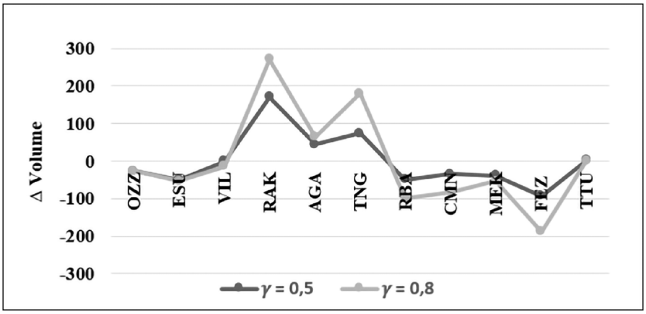

Figure 4. Effect of higher social influence weight on tourism dynamics. The weight of social influence is analyzed at two fixed levels: $\gamma = 0.5$ and $\gamma = 0.8$. Δvolume indicates the visitation volume variation.

4.2 Scenario 2: Negative Reviews

In this scenario, we explore the impact of negative social influence on tourist destination choices, focusing on how bad reviews or poor experiences shared within social networks can alter tourism dynamics. The goal is to understand how negative feedback can shift tourist flows, change destination popularity and ultimately affect the overall tourism landscape.

In the real world, tourists often rely on the experiences and recommendations shared by others, especially through online platforms and social networks. Negative reviews about a destination, whether related to poor service, overcrowding, safety concerns or unfulfilled expectations, can have a significant impact on how future tourists perceive and select their travel destinations. This scenario simulates the effect of a wave of negative reviews spreading through tourists' social networks and the resulting behavioral changes in destination choice.

Figure 5 illustrates the impact of declining tourist satisfaction in specific locations, such as Marrakesh and Casablanca, on the overall distribution of visitation volume. The Δvolume term indicates changes in tourist numbers. As satisfaction levels decrease in these areas, the number of tourists declines, resulting in a shift in visitation patterns. Negative social influence contributes to this decline, prompting tourists to seek alternative destinations. As a result, over time, previously less popular destinations begin to attract more visitors, altering the overall dynamics of tourism. However, this decline remains gradual, as social influence can take time to build.

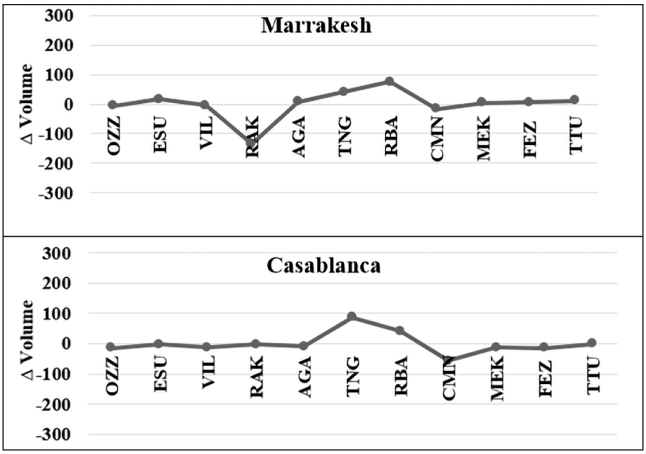

Figure 5. Effect of declining tourist satisfaction on visitation volume. This effect is modeled by reducing the overall appreciation interval of the most attractive destinations, such as Marrakesh and Casablanca.

4.3 Scenario 3: Promotion of Lesser-Known Destinations

The promotion of lesser-known destinations is an essential strategy for sustainable tourism development. It involves enhancing the visibility of under-visited locations to spread tourism demand more evenly, reduce the pressure on popular hotspots and provide economic benefits to local communities. This strategy is particularly important in countries like Morocco, where iconic cities dominate the tourism landscape, leaving many beautiful but less recognized destinations with untapped potential.

However, the strategies for promoting these hidden locations can vary widely, particularly when deciding whether to leverage the power of social media influencers or to pursue a more traditional, noninfluencer strategy.

This scenario examines the impact of promoting less-known destinations, enhancing their visibility and reputation, thereby significantly improving the tourist experience by increasing the ratings R_{kd} given by tourists k to destination d.

Figure 6 highlights a significant contrast in tourist flow to lesser-known destinations based on the involvement of influencers in the promotional efforts. The findings indicate that promoting these locations without influencers yields only a slight or insignificant rise in visitor numbers, whereas the involvement of influencers significantly boosts tourist interest and engagement.

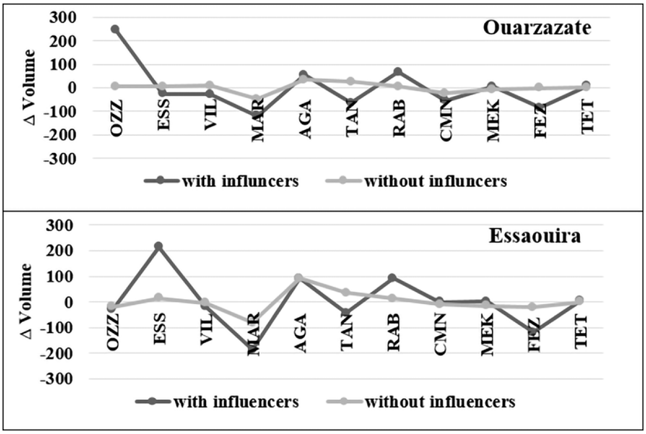

Figure 6. Impact of promoting lesser-known destinations on visitation volume. The effect is modeled by increasing the overall appreciation interval of less popular destinations, using two strategies: with and without influencers.

Thus, a tourism promotion strategy without influencers generally results in a slower growth in visitor numbers. In contrast, promotions involving influencers are highly effective for rapidly increasing visibility and generating excitement around a destination.

Moreover, this approach can contribute to a more balanced distribution of tourists, emphasizing the potential of strategic promotional efforts to attract visitors to diverse locations and ensure sustainable and inclusive tourism development.

5. Limits and Perspectives

This model serves as a flexible experimental tool, rather than a final product, and is subject to several key limitations:

- *Data limitations*. The model relies on broad assumptions and aggregated data, which limits its accuracy. Incorporating more detailed, real-time data, such as survey results or social media analytics, would significantly enhance its predictive power.

- *Limited real-time social media data*. The model does not utilize real-time social media data, which could provide timely insights into current tourist sentiments and trends. This could significantly improve the model's ability to track and predict tourism patterns based on live feedback and discussions.
- *Simplified social influence*. The model assumes uniformity in how social networks affect tourists, neglecting the impact of personal factors such as age, socioeconomic status and travel experience. A more nuanced approach could provide a deeper understanding of how different tourist profiles respond to social influence.
- *Static environmental factors*. Destination characteristics like attractiveness and connectivity are modeled as static, although these factors evolve due to urban development, natural events and shifting consumer trends. Incorporating these changes would better reflect real-world dynamics.

These limitations highlight several promising avenues for future research and practical applications:

- *Expand the ABM framework*. Future models could integrate a broader range of variables, including economic conditions, seasonal trends and local infrastructure developments, to offer more comprehensive insights into tourist behavior and its drivers.
- *Leveraging real-time social media data*. The integration of real-time data from social media platforms presents a major opportunity for improvement.
- *Analyzing social networks*. Investigating different types of social networks can provide deeper insights into how their unique structures and patterns influence the spread of information and the shaping of tourist behaviors.

These improvements would lead to more accurate simulations of tourist behavior, ultimately helping to develop more effective and data-driven tourism management strategies.

6. Conclusion

In this paper we develop agent-based modeling (ABM) methods to investigate the role of social influence in shaping tourist decision-making and distribution within a tourist network. By examining the underlying assumptions of each scenario and presenting the corresponding simulation results, we gain valuable insights into the multifaceted nature of tourist behavior and destination choice.

One key factor explored is the role of social influence, which significantly impacts tourists' decisions. The simulations reveal that positive social feedback can enhance the attractiveness of certain destinations, while negative feedback can deter potential visitors, leading to shifts in tourist flows. This underscores the importance of managing online reviews and social media perceptions, as they can have lasting effects on a destination's reputation.

Additionally, we investigated the impact of promoting lesser-known destinations. The simulations demonstrate that effective marketing strategies can not only bolster the appeal of these destinations but also help distribute tourist traffic more evenly across the country, ultimately contributing to a more sustainable tourism model.

Furthermore, declining satisfaction levels in specific tourist destinations can alter visitation patterns and overall tourism dynamics. This shift highlights the importance of managing visitor satisfaction and reputation. However, it is crucial to note that such changes occur gradually, reflecting the time it takes for social influence to manifest fully.

Together, these scenarios paint a comprehensive picture of how various conditions interact to shape the patterns of inbound tourism in Morocco. By understanding these dynamics, stakeholders can make informed decisions to enhance tourist experiences, promote sustainable practices and foster a resilient tourism industry. Ultimately, this research highlights the necessity for continuous monitoring and adaptation in response to changing tourist preferences and external influences.

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