Bons-AI: An Agent-Based Model to Evaluate the Behavior of Bonsai Grower According to Different Levels of Communication and Experience

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ABSTRACT

Knowledge transfer and social learning are fundamental challenges in multi-agent systems (MAS), particularly in domains where decisions require long term knowledge and environmental factors. In this paper, we introduce Bons-AI, an agent-based model (ABM) that simulates the interaction between bonsai growers with different levels of expertise, aiming to investigate how experience and communication affect the health and style preservation of bonsais. Our model integrates Q-learning with climatic and biological conditions, to simulate plant growth and human decisions. We conducted experiments comparing scenarios with inexperienced growers, autonomous learners, and master–apprentice relationships. The results show that knowledge sharing reduces mortality by 18% and increases overall health by 9.5%, highlighting the role of social communication in the learning process. Beyond the specific domain of bonsai cultivation, this work contributes to the MAS by offering a framework for studying adaptive behavior, distinct expertise level, and communication based knowledge transfer in complex environments.

KEYWORDS

Agent-Based Modeling; Multi-Agent Systems; Social Learning; Reinforcement Learning; Bonsai.

ACM Reference Format:
Sara Satake, Guilherme Nakahata, and Claus Aranha. 2026. Bons-AI: An Agent-Based Model to Evaluate the Behavior of Bonsai Grower According to Different Levels of Communication and Experience. In *Proc. of the 25th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2026), Paphos, Cyprus, May 25 – 29, 2026*, IFAAMAS, 8 pages. https://doi.org/10.65109/UHQU6299

1 INTRODUCTION

Learning and knowledge transmission are fundamental processes in both natural and artificial multi-agent systems (MAS). Agents often differ in experience, background, and capabilities, and must adapt to dynamic environments through cycles of trial, error, and social interaction [26]. Understanding how such adaptive mechanisms emerge remains a challenge in artificial life, reinforcement learning and MAS [2, 11].

Proc. of the 25th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2026), C. Amato, L. Dennis, V. Mascardi, J. Thangarajah (eds.), May 25 – 29, 2026, Paphos, Cyprus. © 2026 International Foundation for Autonomous Agents and Multiagent Systems (www.ifaamas.org). https://doi.org/10.65109/UHQU6299

This work explores these questions through bonsai cultivation. Caring for bonsai trees requires careful timing of actions such as pruning, wiring, and repotting, while adapting to changing environmental conditions like rainfall, wind, and seasonal variation. Expertise in this practice is often transmitted through 'master-apprentice' relationships, providing a useful model for investigating knowledge transfer and social learning in heterogeneous systems.

To investigate this challenge, we introduce Bons-AI, an agent-based model (ABM) designed to capture the interaction between learning, experience, and communication. The model involves two types of agents: **bonsai agents**, representing trees with biological states, and **grower agents**, representing human caregivers with varying levels of expertise. Grower agents can act autonomously, improve through reinforcement, or acquire knowledge from more experienced growers. This allows us to examine how accumulated experience and social interaction influence collective results.

The simulation considers 30 bonsai and growers with experience ranging from 0 to 30 years. Agents perform actions inspired by real cultivation practices—Pruning, Wiring, Unwiring, Watering, Fertilizer Application, and Repotting—while aiming to sustain bonsai health and preserve traditional styles such as Formal Upright, Informal Upright, Slanting, Cascade, and Semi-Cascade [3, 18].

This work contributes by introducing a novel ABM that combines reinforcement learning and environmental dynamics to the biological and social aspects of bonsai cultivation, analyzing how heterogeneous expertise and communication influence agent performance and social learning in MAS, positioning bonsai cultivation as a complex and underexplored scenario.

Our results indicate that knowledge sharing reduces bonsai mortality and improves overall health, while individual experience tends to preserve styles. These findings highlight the role of accumulated knowledge and communication in shaping collective behavior, demonstrating the relevance of bonsai cultivation as a model and experimental domain for studying multi-agent learning.

2 BACKGROUND

This section presents the motivation and context for modeling bonsai cultivation in a MAS. Bonsai care involves sequential process, learning over time, and interaction between practitioners, making it an ideal scenario to study adaptation and knowledge transfer in heterogeneous agents. To understand these dynamics, it is important to explore the art, history, and cultural significance of bonsai, which guides the practices and interactions modeled in our simulation.

2.1 The art of Bonsai

A *bonsai* is a miniature tree grown in a shallow pot. It originated as the Japanese interpretation of the ancient Chinese art form called "penjing" or "penzai" [12].

In addition to the artistic perspective, bonsai management offers different benefits [6], such as: i) natural therapy, which provides routines, reducing physical and mental stress; ii) minimization of indoor pollution, especially in urban areas; iii) conservation of species, where plants at risk of extinction can be preserved.

A significant cultural increase in bonsai occurred in Edo's period (1603-1868), when the stories of bonsai were widely shared through poems and paintings [20]. International recognition started with the first exhibitions that took place in Paris (1878) and London (1909), followed by the publication of [28], which accelerated the global spread of bonsai culture, particularly in the west [20].

The Japanese formalized many of the core principles still used in bonsai cultivation today, including classification by genus, species, size, composition and style [3, 16]. These classifications are very important for how bonsai trees can be managed and directly impact pruning, wiring, watering, and repotting activities [18]. In this work, these practices are explored through an Agent-Based Modeling approach, allowing us to simulate the behavior of bonsai and bonsai growers.

2.2 Related work

In recent years, several studies have used ABM to simulate different scenarios and domains, such as ancient civilization behavior [22], zombie apocalypse [10] and cellular processes in biology [4]. These studies highlight the flexibility of ABM in modeling unconventional scenarios, which directly inspired the design of our model.

In addition to these unconventional scenarios, ABM has also been successfully applied in biologically inspired models. For example, Mußmann et al. [15] demonstrate the complexity of modeling plant systems by simulating root growth using ABM. Similarly, Liu et al. [9] presents an ABM model for forest development, which directly inspired several aspects of the present model, including growth function, nutrients simulation, and tree dynamics.

In Sert et al. [23]'s work, the authors employ Q-learning to model interactions between heterogeneous agents, resulting in emergent segregation. Ormazábal et al. [17] explores the teaching learning process through ABM, presenting various scenarios in which learners acquire knowledge from teachers. Their approach guided the modeling of the teacher as a more experienced bonsai grower in our simulation. Inspired by their use of environmental noise and attention loss, we introduced varying levels of learning effectiveness into our model.

Despite the variety of scenarios explored in the literature, to the best of our knowledge, there are no existing ABM studies specifically focused on bonsai cultivation or the behavior of bonsai growers. Our model draws on previous work on plant growth, learning processes, and agent interaction, adapting these elements to simulate the unique context of bonsai cultivation.

3 MODEL DESCRIPTION

This section details the components and actions defined within the model, which simulates the growth and care of bonsai trees through the interaction between agents. We define two main agent types in our model: the Bonsai Agent, representing the bonsai itself, and the Bonsai Grower Agent, representing human caretakers who apply real life bonsai techniques. The implementation of our model can be found in the weblink available here[1], along with the experiments described in this work.

3.1 Bonsai Agent

The Bonsai Agent represents an individual bonsai tree, characterized by a set of features that define its visual, structural and beauty identity. These include its height, angle in relation to the pot, and curvature of the trunk. These factors are used to classify bonsai into different styles [16, 21], which are not only aesthetic categories, but also determine specific care practices such as pruning frequency and wiring techniques [3, 18].

In our model, these characteristics are represented as continuous variables. The combination of angulation and curvature assigns to one of the classic bonsai styles: Formal Upright, Informal Upright, Slanting, Cascade, or Semi-Cascade [3]. These style definitions were derived from bonsai literature and expert sources, with angle ranges and curvature calibrated to common bonsai guidelines [1, 3, 8]. Figure 1 illustrates each style, emphasizing the structural patterns used for classification, while Table 1 summarizes the quantitative thresholds used in our model.

3.2 Bonsai Grower Agent

The Bonsai Grower Agent represents a human caregiver who interacts with one or more Bonsai Agent over time. These agents are modeled to simulate the decision making processes and techniques applied by real life bonsai practitioners. Each agent can perform one action per day, such as adjusting its angle, modifying its curvature, or controlling its height through pruning and wiring techniques.

The actions available to these agents are based on traditional bonsai care practices, as documented in books and manuals [7, 18]. The bonsai styling techniques and their effects on the bonsai model are as follows:

Pruning: This technique involves pruning excess growth to shape the bonsai. It helps reduce the tree's height and remove undesired branches [19]. Pruning increases the plant's health if performed during the appropriate season. In this work, pruning is restricted to spring and health more than 30. Its effects on the bonsai include decreasing the height to its original size and increasing or decreasing health by 10, depending on the pruning season and the bonsai's health.

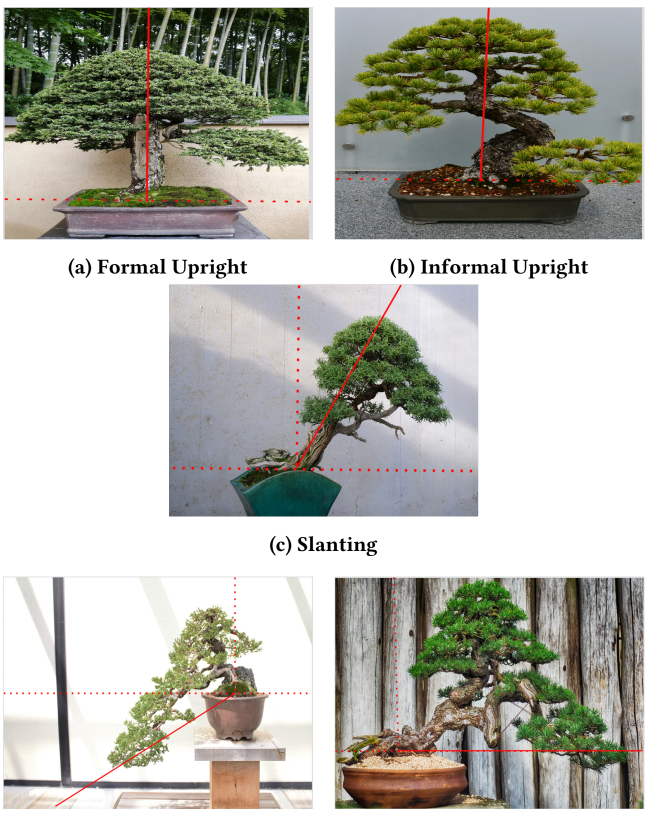
Wiring: It is is used to reshape the tree by adjusting branch inclination and curvature [27]. It requires the tree to be healthy, within the intervention period, and not wired for more than one year. The bonsai style is evaluated, and target inclination and curvature are set according to bonsai design standards. Wiring sets the tree as wired and adjusts the inclination and curvature based on style targets.

Unwiring: The duration for which the tree remains wired depends on species, age, and health [14]. Unwiring is allowed only after a minimum duration, and if the tree remains wired beyond the maximum period, its health decrease. Unwiring sets the tree as

[1] https://github.com/GuilhermeNkht/Bons-AI

Table 1: Bonsai Style Classification Criteria

Bonsai Style	Features	Angulation	Curvature
Formal Upright	The tree has straight, upright trunk.	80° to 100°	<= 2
Informal Upright	The trunk and branches has curves, but the apex is centralized above the root base.	60° to 120°	>= 3
Slanting	The apex of the bonsai is located to the side of the root base.	10° to 60° and 120° e 170°	<= 2
Cascade	The apex of the tree falls below the base of the pot.	180° to 0°	>= 3
Semi-Cascade	The apex of the tree extends just at the level of bonsai pot.	0° to 10° and 170° to 180°	<= 3 and >= 2



(a) Formal Upright **(b) Informal Upright**

(c) Slanting

(d) Cascade **(e) Semi-Cascade**

Figure 1: Bonsai styles and their patterns of angulation and curvature. Images sourced from Pixabay (https://pixabay.com) under free use license.

unwired and increases or decreases health by 10, depending on the unwiring period.

Watering: Watering is essential and must reach both the bonsai and its soil. Bonsai are highly susceptible to water deficiency, which is more dependent in summer, followed by spring, autumn, and lowest in winter [3]. Watering increases water levels and prevents the plant's death.

Fertilizer Application: Fertilizer is vital due to limited soil in bonsai pots, a typical fertilizer used is a 5:3:2 NPK ratio, it prevents health loss and promotes recovery [3]. In this paper, applying fertilizer increases health and prevents decay, however in excessive use reduces health. The maximum fertilizer capacity is 30, and excessive use decreases health.

Repotting: Fast growing species require annual repotting, while slow growing ones need it every 2–3 years [18]. In this paper repotting is allowed if the last was over 255 days ago and it is spring. If it is done correctly, it increases health by 10, whereas an incorrect one reduce it by 10. If the bonsai exceeds its ideal pot size (2/3 ratio), the tree size is adjusted and becomes the new pruning original size.

In a real life environment, bonsai growers are able to socially interact between them, allowing the exchange of knowledge and the imitation of techniques, as discussed by Mansourian [13]. This social learning introduces variation and adaptation in different scenarios, reflecting how communities contribute to the evolution of the bonsai style and care [13].

Through repeated interactions with bonsai trees, each agent develops a distinct behavior. This characteristics allows us to explore emergent patterns in style adoption and care practices in a socially-informed agent-based framework.

3.3 Bonsai Growth Simulation Model

Given that bonsai growth does not follow a linear pattern, this work uses the Generalized Logistic Growth Function, as proposed by [25], to model its development dynamics, as shown in Equation 1.

$$\frac{dN}{dt} = r \cdot N^{\alpha} \cdot \left(1 - \left(\frac{N}{K}\right)^{\beta}\right)^{\sigma} \tag{1}$$

This model was chosen for its ability to incorporate sigmoidal growth behavior, capturing the maximum size limit of the bonsai (K), which reflects constraints imposed by resources such as pot space, water, and nutrients. The parameters used in the model are presented in Table 2.

Bonsai growth is also influenced by water availability, which can come from agents or natural rainfall. The rainfall simulation in our model is based on average seasonal precipitation data for the Kanto region in Japan, spanning the years 1901 to 2012 [5]. The annual average ranged from 1400 mm to 1700 mm, distributed as

Table 2: Growth Model Parameters

Parameter	Value	Definition
r	0.0005	Growth rate coefficient
α	1.2	Growth exponent
K	200	Carrying capacity (maximum size)
β	1.2	Competition exponent
σ	1.5	Density dependence factor

follows: Spring – 350 mm, Summer – 650 mm, Autumn – 650 mm, and Winter – 81 mm.

Based on an average of 22 consecutive dry days in the selected area, we adopted a daily rainfall probability of 0.043 in our model. On rainy days, between 20% and 30% of the seasonal rainfall falls, directly affecting the amount of water received by the plant. Table 3 presents the rainfall thresholds for each type of rain and the corresponding increase in water applied in the model.

Table 3: Rain Intensity and Water Increase for Bonsai

Rain Type	Rainfall Amount (mm)	Water Increase
Weak	< 75 mm	0.5×
Moderate	75–150 mm	0.8×
Strong	> 150 mm	1.0×

In addition to rainfall, we also considered wind and light, as they directly influence the health and characteristics of bonsai [3]. In our model, strong winds can alter the inclination by a range of -0.05 to 0.05, while light affects the curvature within a range of -0.005 to 0.005, these two factors are applied daily. Wind parameters were defined based on wind patterns in Japan [24] and can be seen in Table 4.

Table 4: Wind Patterns and Inclination Ranges

Month	Wind Direction	Wind Pattern	Inclination Range
January	NW1	Strong C, local AC	[0,-0.05]
February	NW1	Strong C, local AC	[0,-0.05]
March	W1	Strong C	[0,-0.05]
April	S-SE	C, local AC	[0,0.05]
May	S-SE	C, local AC	[0,0.05]
June	S-SE	C, local AC	[0,0.05]
July	S-SE	C, local AC	[0,0.05]
August	S-SE	C, local AC	[0,0.05]
September	NE	C, AC	[0,-0.05]
October	NW2	Mostly C/AC	[0,0.05]
November	NW1	Strong C/AC	[0,-0.05]
December	N	Strong C/AC	[0,-0.05]

At the start of each simulation day, new environmental conditions are generated, and the bonsai's internal state is updated, including fertilizer, water, and health. A health decline occurs if any of the following conditions are met: absence of fertilizer, insufficient water supply, delayed repotting, or exceed the allowed wiring duration.

Fertilizer decreases at a constant rate of one unit per day. Water levels also decrease daily according to seasonal demand, using reduction factors 1.5 in summer, 0.5 in winter, 0.8 in autumn, and 1.0 in spring. These values are based in bonsai growers' experience and literature, which mention increased water requirements during hot seasons [3, 18]. Daily water consumption is calculated using Equation 2, which w is the base water consumption (10), c the seasonal constant and h the height.

$$C = w \times c + h \times 0.1 \tag{2}$$

4 EXPERIMENT SETUP

We define different scenarios to analyze agent behaviors under varying circumstances as follows:

4.1 Inexperienced Bonsai grower:

In the first set of experiments, we aimed to analyze the behavior of bonsai and bonsai growers, with a particular focus on how experience influences plant development. Bonsai grower agents were assumed to have no prior knowledge and randomly selected actions. This scenario represents a bonsai grower who acquires a bonsai without prior experience and does not gain any knowledge over time.

We run each scenario 10 times with 30 bonsai trees and a single bonsai grower per simulation. The collected data included mortality, health, and style. These variables were stored and analyzed using measures of central tendency and dispersion.

4.2 Aspiring Bonsai grower:

The second experiment explored the same initial setup. However, in this case, the bonsai grower was allowed to acquire knowledge over time. Our focus is on modeling this learning process and analyzing the grower's behavior in relation to bonsai care and maintenance.

The Q-learning parameters were selected following standard practice and adapted to the characteristics of our domain, as summarized in Table 5. We set the learning rate $\alpha = 0.1$ to ensure stable Q-table updates without overwriting prior knowledge, which is important in environments with long decision cycles. The discount factor $\gamma = 0.99$ underscores long-term rewards, which is appropriate since correct actions influence outcomes throughout multiple seasons. Finally, the exploration rate ϵ was designed to encourage broad exploration in the early stages, gradually achieving a balance between exploration and exploitation, reflecting how bonsai masters refine their techniques through practice.

To limit the size of the state space, bonsai values were discretized into three levels, as shown in Table 6. In this table, the variable x denotes the current value of the corresponding parameter being evaluated. In addition, counters were used to track the number of days since the last wiring, repotting, or pruning event, based on real bonsai care intervals [3].

The agent's reward is based on performing care and interventions during the appropriate seasons. Table 7 presents the reward values associated with each action.

Table 5: Hyperparameters for Q-Learning Algorithm

Parameter	Value
α (Learning rate)	0.1
γ (Discount factor)	0.99
ϵ (Initial exploration)	1.0
ϵ (decay)	0.999
ϵ_{min} (Minimum exploration)	0.01

Table 6: Discrete Categorization of Bonsai Variables

Parameter	Value Ranges or Categories
Health	$0 \le x \le 50$, $51 \le x \le 80$, $x > 80$
Water	$0 \le x \le 30$, $31 \le x \le 70$, $x > 70$
Fertilizer Counter	$0 \le x \le 10$, $11 \le x \le 30$, $x > 30$
Actual Season	*Spring*, *Summer*, *Autumn*, *Winter*
Wired	Yes or No
Repotting Counter	$x < 255$, $255 \le x < 365$, $x \ge 365$
Wire Counter	$x < 182$, $182 \le x < 365$, $x \ge 365$
Pruning Counter	$x < 255$, $255 \le x < 365$, $x \ge 365$

After calculating the reward r, the table is updated using the parameters of Table 5 and the rewards of Table 7, as shown in Equation 3.

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \tag{3}$$

4.3 Expert Bonsai grower:

For the third experiment, we aimed to simulate a 'master–apprentice' scenario and analyze how communication between them affects the bonsai. We also applied Q-learning using the same parameters from Table 5, but with a greater number of years of experience: 5, 15, and 30 years. In this case, we assumed that the bonsai grower had more time to learn how to care for bonsai trees and refine their techniques.

Furthermore, in this set of experiments, the experience of a beginner was combined with an expert with 30 years of experience. Communication occurs when the beginner asks for help, which occurs when the bonsai's health drops to 50 or below.

Communication occurs via the Q-table; based on the action taken by the more experienced grower, the beginner updates its own table. Equation 4 shows the learning update process, where $Q(s,a)$ represents the value of the action for the beginner, $Q(s,a)\_master$ corresponds to the action taken by the expert, and α denotes the learning rate.

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha Q_{\text{master}}(s,a) \tag{4}$$

In addition to the above experiments, we also investigated the influence of the grower's experience on bonsai styling. In this scenario, growers were categorized into three levels of experience: experienced, no experience, and some knowledge. Experienced growers adjusted the bonsai curvature and angle according to the target values presented in Table 8. Growers with no experience performed random adjustments, without any prior knowledge, varying the bonsai's angle between 0 and 7 degrees and the curvature between 0 and 0.5. Finally, growers with some knowledge adjusted parameters based on a five element array, where each value between 0 and 1 indicated their degree of familiarity with a specific bonsai style.

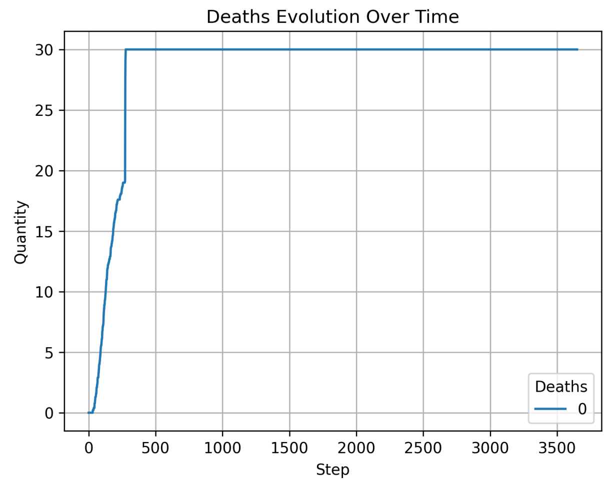


Figure 2: Mortality rate in the scenario with no prior knowledge or learning.

The ideal values used as references for the "experienced" and "with some knowledge" categories for each bonsai style were derived from the average values of angle and curvature, as presented in Table 8. If the bonsai does not have a defined style, the bonsai grower determines the closest style by calculating the Euclidean distance, as shown in Equation 5, where θ represents the difference in angle to the closest style, and κ represents the curvature. In cases with two target angles, such as in the Slanting and Semi-Cascade styles, the nearest target angle to the current one is selected.

$$d_{\text{target}} = \sqrt{(|\theta - \theta_{\text{target}}|)^2 + (|\kappa - \kappa_{\text{target}}|)^2} \tag{5}$$

During the experiment with bonsai grower agents with some experience, the acquisition of knowledge by the agent was also incorporated. We used a value of 0.05 for this process, which occurs when the agent is able to maintain the same bonsai style and maintain or improve the bonsai's health compared to the previous year. If the bonsai's health is lower than the previous year, the learning rate is reduced by half.

4.4 Simulation Results

We adopted a 10-year period for all experiments, with no replacement of bonsai trees once they died. In the first scenario, agents had no prior experience or learning sources, performing random actions throughout the simulation. As a result, a high mortality rate was observed, with bonsai trees often failing to reach two years of age, as shown in Figure 2. Caring for a bonsai becomes complex over time due to the progressive decline in health, which can create a cascading effect on the tree's survival and well-being.

This effect is expected, as the bonsai requires very specific care, and making interventions at the wrong times can lead to death or

Table 7: Reward Actions for Bonsai Care Activities

Action	Condition	Reward
Watering	Water <70% of Max and <Water Need	20
	Water <70% of Max and ≥ Water Need	10
	Water ≥ 70% of Max	0
Fertilization	Fertilizer == 0	-10
	Fertilizer <5	15
	Fertilizer <15	5
	Fertilizer ≥ 15	-10
Pruning	In Pruning Season and Health >Threshold	10 (if Pruning Counter is low) or 15 (if high)
	Otherwise	-10
Wiring	Wired	-20
	Not Wired and in Pruning Season	20
	Not Wired and not in Pruning Season	-10
Unwiring	Not Wired	-20
	Wire Counter ≥ Max and ≥ 1 Year	-10
	Wire Counter within Range	20
	Otherwise	-10
Repotting	Repotting Counter ≥ Required and in Pruning Season	20 (if within year) or 10 (if exceeding)
	Repotting Counter <Required	-20

Table 8: Target Parameters for Bonsai Styling

Style	Target Inclination	Target Curvature
Formal Upright	90	0.5
Informal Upright	90	4.5
Slanting	35, 145	1.5
Cascade	270	3.5
Semi-Cascade	5, 175	2.5

a loss of health. Based on this result, it became evident that prior knowledge is necessary for the agents. Therefore, we conducted experiments with agents having 5, 15, and 30 years of experience. As shown in Figure 3, the results represent the health evaluation across the steps of one run of a 5 year experiment, illustrating how health changes over time and how it increases or decreases depending on correct or incorrect actions taken at each timestep.

Table 9 presents the mortality statistics over time. We observed that as the agents' experience increases, the mortality rate significantly decreases. In the first 5 years, the average mortality rate is high, however, over 15 and 30 years, the agents demonstrate more efficient learning, drastically reducing death occurrences. This indicates that, over time, the agents are able to develop more effective caring strategies.

Table 9: Death Occurrences Across 5, 15, and 30 Year Simulations

Statistic	5 years	15 years	30 years
Mean	14.74	0.19	0.07
Median	16.0	0.0	0.0
Std. Dev.	5.82	0.99	0.25
Minimum	0	0	0
Maximum	22	7	1

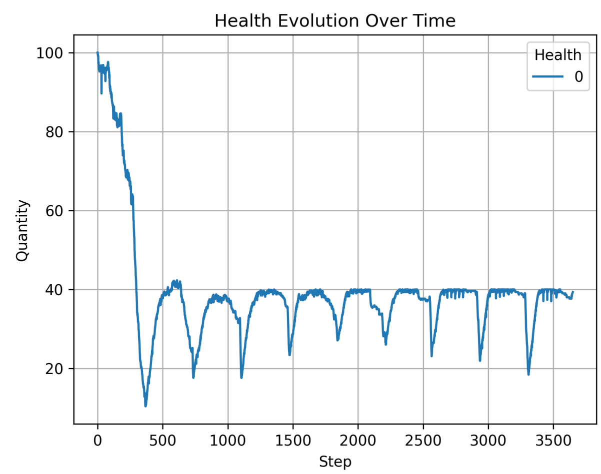


Figure 3: Health rate in a scenario with 5 Year experience.

An analysis of the bonsai health statistics reveals that the more the agent learns, the healthier the bonsai becomes, as shown in Table 10. However, the difference between 15 and 30 years of experience is minimal, as reflected in the health rates. In contrast, the agent with only 5 years of experience makes a significantly higher number of inadequate decisions, impacting the plant's health.

Table 10: Evolution of Bonsai Health During Simulation

Statistic	5 years	15 years	30 years
Mean	43.35	97.99	98.04
Median	39.80	99.27	99.17
Std. Dev.	17.30	3.87	2.69
Minimum	5.67	67.77	75.83

As shown in Table 11, the number of deaths decreased significantly when agents trained for 10 years, regardless of the information sharing rate. In other hand, for 5 years agents, mortality remained high and the difference between 50 % and 70 % information sharing was minimal. This indicates that learning time had a greater influence on performance than the amount of information shared per action.

Table 11: Death Statistics with 50% and 70% Information Sharing for 5 and 10 Years

Statistic	5_50%	5_70%	10_50%	10_70%
Mean	12.74	12.08	0.55	0.34
Median	13.00	13.00	0.00	0.00
Std. Dev.	6.10	4.66	0.61	0.47
Minimum	0	0	0	0
Maximum	27	22	2	1

The results indicate that a longer learning period is essential for the bonsai grower agent to develop more effective strategies. Depending on the circumstances, the agent may encounter scenarios for which it is not yet prepared. This type of situation also occurs in the real world, when beginners seek guidance from experienced bonsai practitioners to save their trees, often turning to bonsai hospitals managed by bonsai growers experts.

Regarding bonsai health in these scenarios, we observed that the average health remains below 50% in the 5-year learning scenarios. This indicates that the agent frequently had to depend on the more experienced one, suggesting that the learning process was still heavily dependent on the master in most situations. However, even in these scenarios improvements were evident, there was 18.04% reduction in mortality and 9.5% increase in bonsai lifespan in the 5-year experience experiments with communication. This scenario changes significantly when a 10-year learning period is considered, as shown in Table 12.

Table 12: Health Statistics with 50% and 70% Information Sharing for 5 and 10 Years

Statistic	5_50%	5_70%	10_50%	10_70%
Mean	47.47	49.70	89.32	90.62
Median	47.60	49.50	95.10	95.97
Std. Dev.	16.43	12.32	11.34	10.63
Minimum	3.37	12.50	60.83	60.07

Comparing the mortality rates and health levels of agents with 15 years of experience without knowledge sharing, it is observed that the agent with 10 years of learning and 70% information sharing achieved similar performance. This suggests that the exchange of information allowed the agent to reach the same level of knowledge in less time. This advantage becomes even more evident when directly comparing agents with 5 years of experience, with and without sharing: the agent who received external information showed an average reduction of 2.65 in the bonsai mortality rate and an average increase of 6.35 in plant health.

The second set of experiments focused on the agent's ability to maintain the bonsai's style. In experiments with experienced agents, style variation was minimal, as they already had knowledge on how to wire the bonsai to preserve its shape.

We observed that the less experience the agent had, the more difficult it was to maintain a predefined style for the bonsai. Even with learning applied, the agent still faced challenges in preserving the consistency of the style. Figure 4 shows this variation, highlighting the large number of bonsai without a defined style in cases where the agent had no prior knowledge. Showing that when the agent has no knowledge of how to wire the bonsai, it ends up losing its style. In contrast, when the agent has the necessary knowledge, it is able to adjust the bonsai without compromising their style.

5 CONCLUSION

In this work, we used the computational technique of Agent-Based Modeling (ABM) to analyze the behavior of bonsai growers with different levels of experience, as well as the impact of their decision making on bonsai. Additionally, we also modeled knowledge transmission through communication between bonsai growers.

During the experiments, we observed that experience is a crucial factor for bonsai maintenance. Furthermore, as in real life, it was possible to simulate knowledge acquisition, validating that both experience and communication between agents have a significant impact on bonsai. Behaviors and characteristics described in the literature were also identified, such as the negative impact of interventions made at the wrong time, which significantly affect the quality of the bonsai.

The use of the Q-learning table proved to be efficient, especially when employing a mentor for knowledge sharing. This mechanism reduces the need for communication with each action, allowing the agent to operate with greater autonomy and independently develop new knowledge without being limited to the mentor's suggestions. Moreover, it was observed that in environments with a large number of variables, the initial learning phase is particularly challenging.

As the complexity of the environment increases, the table grows significantly, slowing down the learning process. This effect is even more evident in bonsai cultivation, where annual cycles for actions such as pruning and repotting extend the time required for knowledge acquisition. Thus, for applications with long cycles, Q-learning may not be immediately efficient, requiring adaptations to improve its applicability.

For future works, we plan to expand the diversity of bonsai styles and introduce different species with distinct biological characteristics, focusing on exploring more complex and realistic scenarios. We also plan to investigate alternative learning methods in multi-agent environments, where multiple agents can learn and share knowledge simultaneously. This may allow us to simulate a society of bonsai growers capable of exchanging not only technical expertise but also personal preferences. In this vein, we expect to increase the communication and learning mechanism, not only to improve the modeling capabilities of Agent-Based Models but also to better understand learning dynamics in real environment.

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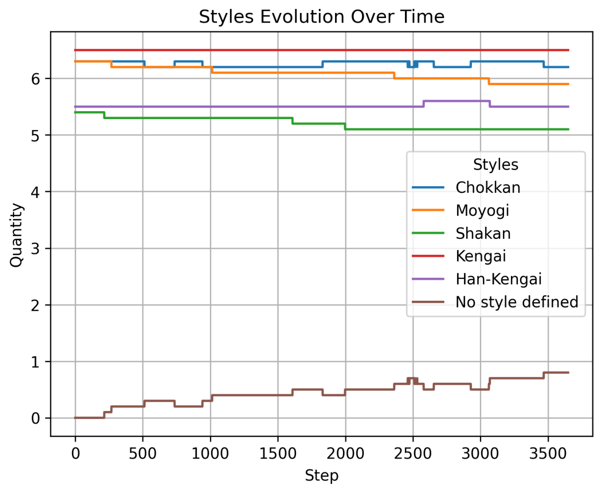
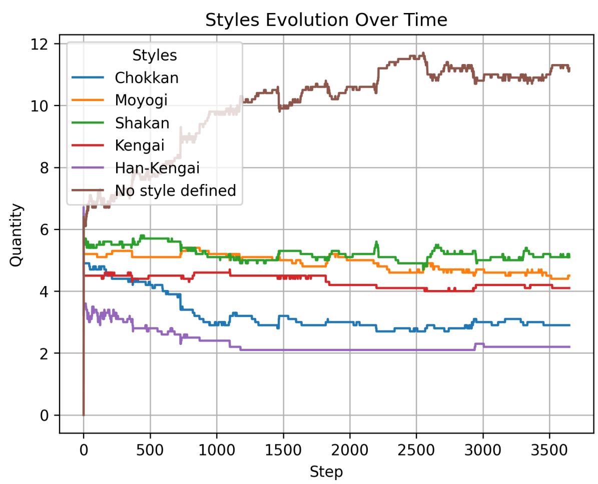
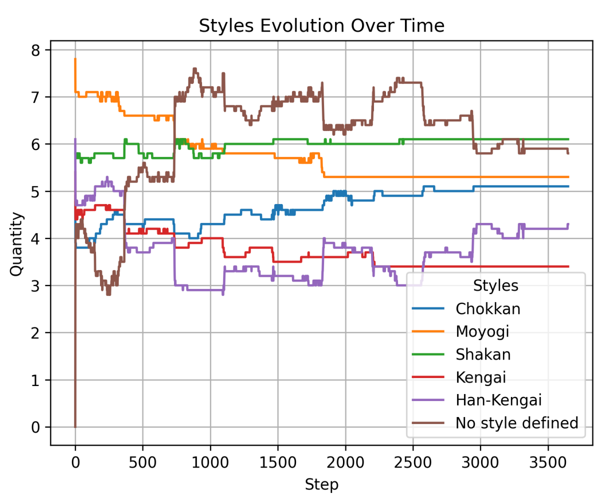


(a) With experience (5 years)



(b) No experience (5 years)



(c) Some experience (5 years)

Figure 4: Variation in bonsai style preservation according to agent experience

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