Simulación del Desplazamiento Estudiantil entre Aulas en la Experiencia Académica

Claudio Álvarez[1,[0003−1969−2978]]

Matías Calderón[1,[0009−0007−3846−2840]] Camila LLamirez[1,[0009−0009−3725−8287]]

Veronica Gil-Costa[2,[0003−4637−9725]]

Mauricio Marin[1,[0003−0662−7149]]

[1]Universidad de Santiago de Chile,
{claudio.alvarezs,matias.calderon,camila.llamirez,mmarin}@usac
h.cl
[2]Universidad Nacional de San Luis, gvcosta@unsl.edu.ar

Resumen Este trabajo presenta una simulación basada en agentes para analizar el impacto del desplazamiento estudiantil entre aulas en la planificación académica y la experiencia universitaria. El modelo desarrollado incorpora dinámicas de contagio emocional, patrones de movilidad y distribución de espacios, permitiendo evaluar de manera detallada cómo estos factores afectan la asistencia a clases y la ocupación de aulas a lo largo de la jornada académica. Los resultados obtenidos muestran que el contagio emocional negativo tiende a disminuir la asistencia de los estudiantes a clases, mientras que las emociones positivas fomentan una mayor participación en las actividades académicas. Además, se identificaron patrones de congestión en pasillos y zonas de alto tránsito que afectan la movilidad de los estudiantes, generando retrasos en los desplazamientos y posibles impactos en la eficiencia del uso de los espacios.

Palabras claves: Simulación basada en agentes, contagio emocional, planifi-cación universitaria.

Simulation of Student Movement Between Classrooms in the Academic Experience

Claudio Álvarez[1,[0003−1969−2978]]

Matías Calderón[1,[0009−0007−3846−2840]] Camila LLamirez[1,[0009−0009−3725−8287]]

Veronica Gil-Costa[2,[0003−4637−9725]]

Mauricio Marin[1,[0003−0662−7149]]

[1]Universidad de Santiago de Chile,
{claudio.alvarezs,matias.calderon,camila.llamirez,mmarin}@usach.
cl
[2]Universidad Nacional de San Luis, gvcosta@unsl.edu.ar

Abstract. This paper presents an agent-based simulation to analyze the impact of student movement between classrooms on academic planning and the university experience. The developed model incorporates emotional contagion dynamics, mobility patterns, and space distribution, allowing for a detailed assessment of how these factors affect class attendance and classroom occupancy throughout the academic day. Results show that negative emotional contagion tends to decrease student attendance, while positive emotions encourage greater participation in academic activities. Furthermore, congestion patterns in hallways and high-traffic areas were identified that affect student mobility, generating travel delays and potentially impacting the efficient use of space.

Keywords: Agent-based simulation, emotional contagion, university plan-ning.

1. Introduction

This paper analyzes the impact of student movement between classrooms on academic planning and the student experience within a university campus. Specifically, it focuses on the Universidad de Santiago de Chile (USACH), where academic planning considers various logistical factors but lacks tools to dynamically assess space utilization based on students' emotional states and their influence on class attendance.

The Integrated Academic System (SAI) provides information on academic workload and classroom availability. However, it does not account for the evolving use of these resources throughout the semester or the influence of emotional factors on attendance and student mobility. In this context, this work proposes the development of an agent-based simulation model to study campus mobility, student distribution, and the utilization of available spaces, offering valuable insights for optimizing academic planning and enhancing the student experience. Our approach incorporates students' emotional states and emotional contagion, which influence their decision-making processes and overall engagement in academic activities.The computational model is grounded in a clear conceptual framework that combines two main theoretical pillars: (1) the theory of emotional contagion in group settings, and (2) the Belief-Desire-Intention (BDI) architecture for modeling agent cognition. The model assumes that students decisions regarding class attendance and movement are influenced not only by schedules or infrastructure, but also by dynamically evolving emotional states shaped through social interactions. This theoretical foundation is operationalized through agents with internal states (emotions, fatigue, teacher perception) and socially influenced behaviors (emotional contagion, movement decisions).

The remaining of this paper is organized as follows. Section 2 presents related work. Section 3 describes our proposed agent-based simulation model. Section 4 presents the experimental results and Section 5 concludes.

2. Related Work

Agent-based simulation models (ABMs) allow complex systems to be represented through the interaction of autonomous entities called agents. These models are widely used for urban planning, economics, and education, as they allow the analysis of emergent phenomena based on individual rules of behavior. In the university context, ABMs are useful for simulating student mobility and evaluating the use of educational spaces, especially when agents' decisions are influenced by emotional and social factors (Hatfield et al., 1993).

Fortu et al., 2024 explore the pedestrian mobility patterns within the University of the Philippines Diliman campus. It applies Agent-Based Modeling (ABM) and Geographic Information Systems (GIS) to simulate student movements and analyze changes in pedestrian traffic before and after the transition from online learning to face-to-face instruction. The study develops a NetLogo-based ABM model that integrates deterministic (based on student schedules) and probabilistic (using multinomial logistic regression) approaches to simulate student mobility. The outputs include pedestrian count heatmaps, building occupancy maps, and insights into student tardiness and walking speeds. These results can assist in campus route planning, improving walkability. Additionally, the study highlights the challenge of capturing erratic student movements, which affects prediction accuracy.

Alvarez Castro and Ford, 2021 present a 3D agent-based model (ABM) designed to simulate COVID-19 transmission among university students living in student accommodations. The model integrates geospatial data and pedestrian movement patterns to analyze how different intervention strategies (e.g., facemasks, lockdowns, and self-isolation) impact virus spread. The study provides a detailed spatial simulation of disease transmission using agent-based modeling, which allows for testing multiple intervention scenarios in a controlled digital environment.

On the other hand, emotional contagion is a psychological phenomenon in which one person's emotions influence those around them (Barsade, 2002a). This process is particularly relevant in educational settings, where students' motivation and engagement can be affected by the group atmosphere and the prevailing emotional state (Pekrun et al., 2007). Pekrun et al., 2006 show that positive emotions, such as enjoyment and hope, can enhance participation in academic activities, while negative emotions, such as boredom and hopelessness, tend to decrease attendance and academic performance. Emotions play a crucial role in student learning and motivation (Fredrickson, 2001). Additionally, the accumulated fatigue throughout the academic day contributes to emotional deterioration, increasing the likelihood of transitions to negative states such as anger and boredom (Young et al., 2019).

Barsade, 2002b examines how emotional contagion—the transfer of moods among group members—affects group dynamics. Through a laboratory study, it was found that when group members experienced positive emotional contagion, they exhibited improved cooperation, reduced conflict, and perceived higher task performance. The authors conclude that people continuously influence the moods and then the judgments and behaviors of others.

Neumann and Strack, 2000 investigate the existence of unintentional mood contagion and its underlying mechanisms. Participants, anticipating a text comprehension test, listened to a neutral speech delivered with subtly sad or happy intonations. The results indicated that the emotional tone of the speech evoked corresponding mood states in the listeners. Also, traditional inferential explanations for emotional sharing did not align well with these observations. The findings suggest that the perception-behavior link may explain these effects, given that participants who repeated the philosophical speech spontaneously mimicked the speaker's vocal emotional expressions.

Manzoor and Treur, 2015 explore a computational model of social agents that integrates emotion regulation, emotional contagion, and decision-making in social settings. The framework emphasizes the role of emotional evaluation in shaping socially influenced decisions. By simulating interactions between two individuals, the model helps examine how regulating emotions impacts decision-making and how emotional states are influenced by both regulation and contagion. The work assumes that decisions are guided by the valuation of future outcomes and incorporates Hebbian learning to adapt behavior. Simulations reveal that emotion regulation not only influences beliefs and feelings in static environments but also remains effective in dynamic settings where behavior evolves over time.

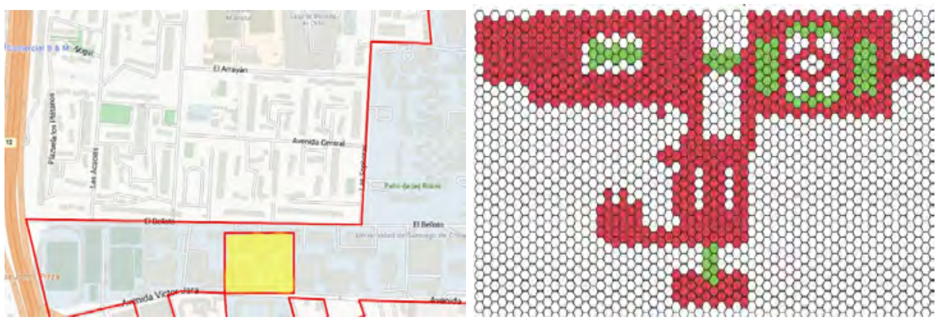
van Haeringen et al., 2023 provide a thorough examination of agent-based modeling approaches for simulating emotion contagion in crowds. It categorizes existing models based on different contagion mechanisms and evaluates their applications and findings. The study highlights significant theoretical advancements in the field while noting the challenges in empirically validating these models due to the complexity of measuring emotional responses in large groups. A key contribution is the identification of fundamental theoretical differences in contagion mechanisms, reflecting diverse perspectives on how emotions spread and their implications. However, comparative studies yield inconclusive results. The authors emphasize the need for improved validation strategies to enhance the reliability and applicability of emotion contagion models in real-world scenarios.

The reviewed literature reveals an ongoing tension between technically oriented approaches and those that seek to incorporate psycho-emotional dimensions into the modeling of human behavior. While studies such as Fortu et al., 2024 and Alvarez Castro and Ford, 2021 emphasize spatial accuracy and behavioral patterns to optimize infrastructure or manage health crises, other works—such as those by Manzoor and Treur, 2015 or van Haeringen et al., 2023—challenge the sufficiency of such models by highlighting the complexity of emotions in dynamic social settings. This divergence raises a fundamental debate: can human behavior truly be modeled without accounting for the affective mechanisms that shape it? From a critical standpoint, this work aligns with perspectives that advocate for a deeper integration of cognitive, emotional, and social processes within agent-based models, recognizing that behavioral realism depends not only on spatial and statistical fidelity but also on the nuanced dynamics of emotional influence.

3. Agent-Based Simulation Model for Student Movement Between Classrooms

In this work we simulate student movement and attendance within the campus of the Universidad de Santiago de Chile (USACH), by using an agent-based model (ABM) that integrates factors such as emotional contagion, fatigue, and the affinity with the teacher. We model two types of agents: students with predefined schedules, who must move between classrooms according to their academic plan, and random agents that represents floating population that moves around the campus without a fixed destination. That is, the student agent represents people who have a class schedule (associated with teaching planning) and move around the university campus (defined area) to their classrooms in corresponding time-slot (modules). This attendance is affected by their emotional state, attraction to the teacher, and contagion from a close group. The floating population agent represents the rest of the population that transits through the university campus and is not necessarily associated with the sector's teaching planning (they do not use the sector's classrooms) but must transit for other reasons. Therefore, it corresponds to the normal flow of additional population that transits to go to other places on campus or consume spaces intended for other purposes (food, recreation, study, etc.).

The model represents a geospatial environment where agents make decisions based on their emotional state, interactions with others, and environmental conditions. We implement our model with GEOMESA [1], which follows topological rules (agents cannot overlap). Figure 1.(a) shows the map of the Universidad de Santiago de Chile. The red line marks the boundaries of the university campus. The yellow box represents the simulated area which corresponds to the area used by the computer engineering department (DIINF). Figure 1.(b) shows the simulated environment. The red dots are spaces where people can move. The green dots are areas where people cannot walk or do not belong on campus. Assistance and mobility evolve dynamically throughout the day, allowing for the analysis of behavioral patterns and their impact on space occupancy.



(a) (b)

Fig. 1. (a) Map of the University of Santiago de Chile; (b) Geospatial model of the simulated area.

Table 1 describes the main variables used in the simulation, including their role within the model and the factors that affect their evolution over time.

We use input data obtained from official USACH sources, including teaching plans (schedules, room assignments, and student numbers), the georeferenced location of classrooms, and an OpenStreetMap campus map with boundaries and access points.

Each student agent is initialized with a predefined schedule, an emotional state based on a probabilistic distribution, and a probability of attendance that varies according to their emotional state, emotional contagion, and attraction to the teacher, allowing for dynamic and realistic behavior modeling.

The simulation time advance in 75-minute blocks (the length of a class), plus 15 minutes for movement in common spaces. We simulate a full academic day with the following events:

- Campus Entry: Agents appear at access points and begin heading to their classrooms.
- Class Attendance: The likelihood of attendance is assessed based on emotional state and contagion.

[1] https://www.geomesa.org/

Table 1. Variables used in the simulation

Variable	Description
Emotional state	Each student is assigned an initial emotional state based on a probabilistic distribution. Changes throughout the day depend on emotional contagion and accumulated fatigue.
Emotional contagion	The probability that an agent adopts the emotional state of nearby peers based on a contagion matrix.
Faculty attraction	Probability of attending classes based on the perceived quality of the faculty member.
Attendance probability	A function that considers emotional state, faculty attraction, and resistance to emotional contagion.
Travel time	Modeled based on the distance between classrooms and the available routes within the campus.
Hallway and classroom congestion	The density of agents in different areas of the campus is evaluated to identify critical saturation points.

- Movement Between Classrooms: Agents move between rooms following optimal routes, avoiding congested areas.
- Social Interactions: Emotional contagion is simulated based on the proximity between agents.
- Cumulative Fatigue: Agent' fatigue increases over time, affecting their emotional state and attendance.
- End of Day: Agents finish their activities and leave the campus.

3.1. Probability of Class Attendance

The probability of a student attending class is calculated as:

$$PA = Ei + Cem - Ft + Ad \tag{1}$$

where PA represents the probability of attendance, Ei is the student's initial emotional state, Cem corresponds to the emotional contagion received from other agents, Ft is the fatigue accumulated throughout the day, and Ad represents the affinity toward the teacher. All the values are a weighted sum and that ensures that it remains between 0 and 1. If the probability of attendance $PA < 0.3$, the agent decides not to attend class. This equation represents the influence of emotional and motivational factors on students' decisions to whether to attend to their academic activities. On the other hand, emotional contagion is computed by:

$$Et = Et - 1 + \alpha \sum (Evecinos - Et - 1) \tag{2}$$

where Et represents the agent's new emotional state, $Et - 1$ is the previous emotional state, $Evecinos$ is the average emotional state of nearby agents, and α is the contagion susceptibility coefficient. This coefficient determines the agent's sensitivity to the emotional influence of its environment. Students with high emotional resilience have low α values, reducing their vulnerability to contagion. This equation allows to simulate how individual emotions can spread within a campus, affecting students' attendance and academic experience.

3.2. Campus Movement Model

We model the agents' movement using a spatial graph of the campus, where each node represents a location (classroom, hallway, courtyard) and edges represent connections between these points. The A^* algorithm is used to find the optimal route between two points, minimizing distance and avoiding congested areas.

4. Experimental Evaluation

We implement our proposed simulation model using Python 3.x with GeoMesa. We also use GeoPandas for the geospatial analysis and NetworkX to model the mobility rutes. Additionally, Shapely facilitates geometry manipulation, while Matplotlib and Seaborn are used for data visualization and graphical analysis of results. In the following experiments, 10 simulations were run for each case with a total of 1.100 agents: 660 student agents and 440 random agents (floating population).

The baseline scenario models a typical academic day at the School of Arts and Crafts (EAO) of the University of Santiago de Chile (USACH), from 8:15 a.m. to 8:05 p.m. Emotional contagion is not considered, so attendance depends only on the students' initial status. In mobility, students follow the shortest route between classrooms, while the floating population moves randomly without affecting agents with schedules. Metrics such as room distribution, hallway flow, and space occupancy are analyzed using heat maps.

A second scenario introduces dynamic variables such as emotional contagion, teacher perception, and fatigue, allowing for a more realistic analysis. Here, emotions spread among students, affecting their attendance. Perceptions of teacher quality influence motivation, while accumulated fatigue increases the likelihood of absences. Therefore, hallway congestion and its impact on mobility are assessed, and attendance becomes more dynamic, varying according to emotional state, fatigue, and teacher perception. Table 2 summarizes the key differences between the two scenarios.

4.1. Assessment of Emotional States

Figure 2 shows the relationship between the fatigue and the distribution of emotions (hope, anger, rage, boredom, anxiety, enjoyment, hopelessness). Negative emotions such as boredom, anger, and hopelessness are more persistent

Table 2. Comparison between the two proposed scenarios.

Analyzed Factor	**Base Scenario**	**Modified Scenario**
Emotional Contagion	Not applied	Yes, based on proximity and group dynamics
Faculty Attraction	Not considered	Yes, influences attendance probability
Accumulated Fatigue	Not applied	Yes, affects emotional stability and attendance
Attendance Probability	Static	Dynamic, adjusted by emotional factors
Hallway Congestion	Not evaluated	Yes, identifying critical transit points
Emotional Variability	Not considered	Yes, with analysis of changes in each time-slot
Impact on Distribution	Based only on predefined schedule	Modified by emotions and movement patterns

in states of high fatigue. Fatigue becomes a determining factor in the prevalence of negative emotions, progressively displacing the positive emotions that dominated in the first time-slot of the day. Figure 3 shows the distribution of emotions by time-slot. As expected, the boredom and anger tend to increase as time goes by. The accumulation of fatigue amplifies states such as boredom and anger, especially in the final time-slot. Furthermore, emotional contagion is more frequent in each group due to the closeness and repetitiveness of the interactions. The enjoyment emotion, has low impact and does not usually spread among the agents. It is more frequent to record this emotion during the first time-slot of the day and tends to decrease rapidly as fatigue increases.

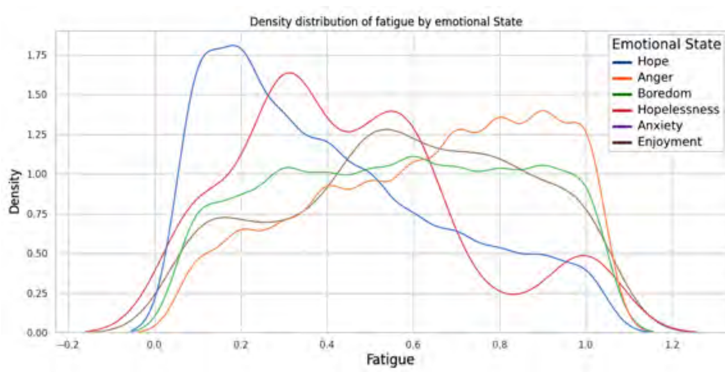


Fig. 2. Density of fatigue distribution by emotion.

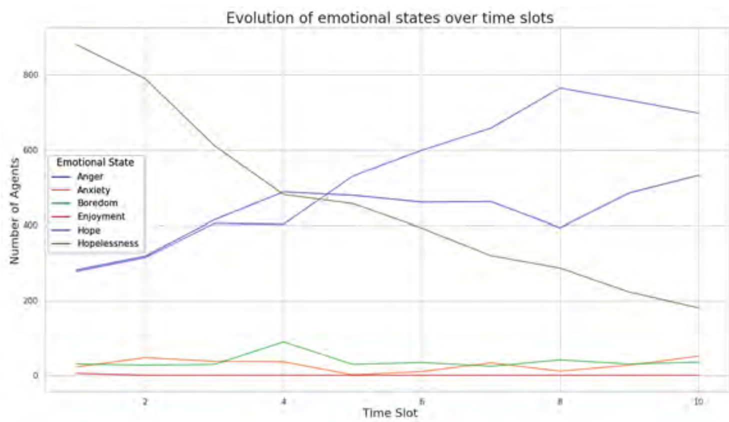


Fig. 3. Emotions evolution in different to time-slot.

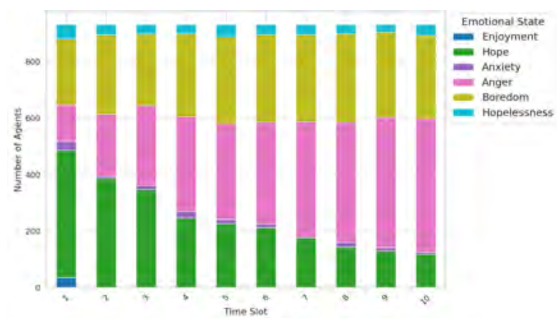


Fig. 4. Emotional state by time-slot for the simulation of 1.100 agents on Monday. The blue color is enjoyment, green=hope, pink=anger, yellow=boredom, light blue=hopelessness, purple=anxiety.

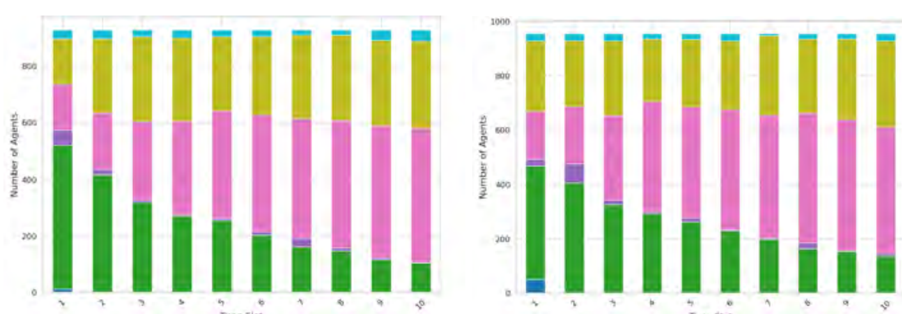


Fig. 5. Emotions reported by time-slot for the simulation of 1.100 agents on (a) Wednesdays and (b) Fridays. The blue color is enjoyment, green=hope, pink=anger, yellow=boredom, light blue=hopelessness, purple=anxiety.

Figure 5 and 4 show the evolution of emotions throughout different days: Monday, Wednesday and Friday. On each day, hope begins as the dominant emotion, but rapidly declines due to the progress of the day and the impact of fatigue. The most notable difference between days is in the predominant emotions at the end of the day. On Monday, anger increases steadily toward the end of the day. On Wednesday, although anger also predominates, its increase is less pronounced than on Monday. Finally, on Friday, boredom is the most common final emotion, which could be related to a decrease in academic activity or the social context of the weekend. Furthermore, negative emotions such as hopelessness and anxiety remain in similar proportions throughout the three days, although to a lesser extent than anger and boredom.

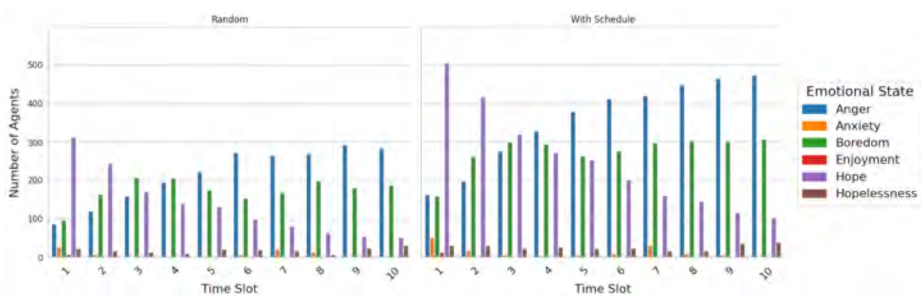


Fig. 6. Comparative evaluation of emotion reported by agents with defined schedules (right) and floating population (random agents at left).

Figure 6 shows the variation of emotions as the academic day progresses. At left we show results of random agents and at right for agents with defined schedules. In both cases, agents present high hope at the beginning of the day, but latter the anger emotion tends to predominate.

4.2. Student Movement Assessment

We analyze the student movement to identify mobility patterns based on time slots and academic load. Figure 7 represents the movement of a particular agent. Red points correspond to the classrooms in their schedule; the number indicates which time-slot the agent should have moved in. The blue line indicates the route followed by the agent.

We compare the results when simulating agents with defined schedules (Figure 8.(a)) and random agents defined as a floating or transient population within the sector (Figure 8.(b)). The thickness of the line indicates greater flow. Scheduled agents tend to concentrate in main hallways, generating congestion during class changes, especially near busy classrooms. Faced with congestion, some adjust their routes to avoid congested areas. In contrast, random agents use more diverse routes, moving primarily in courtyards and recreation areas, reducing their impact on congestion.

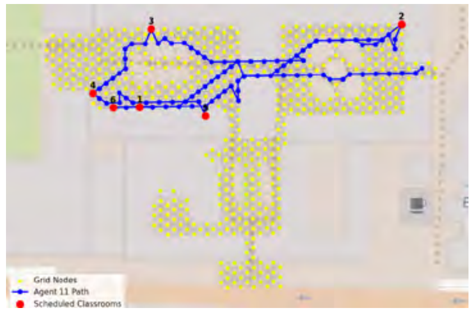
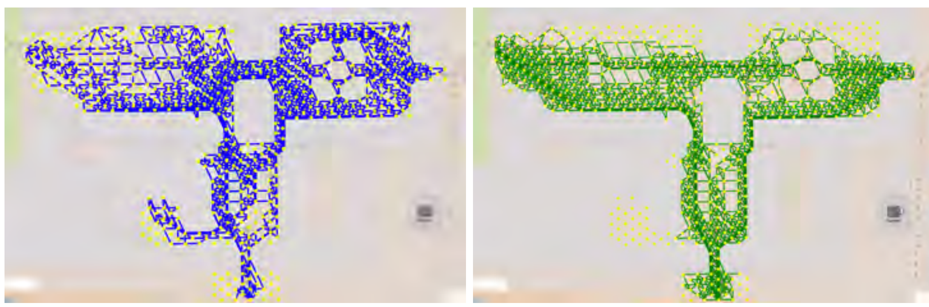


Fig. 7. Graphical representation of the movement of a single agent.



(a) (b)

Fig. 8. (a) Movement of agents with defined schedules (b) Movement of random agents.

In the baseline scenario, attendance remained stable, strictly following the predefined schedule. In contrast, in the modified scenario, accumulated fatigue and negative emotional contagion reduced participation in the final blocks of the day. It was observed that classrooms with better-rated professors maintained more stable attendance. In addition, underutilized areas within the university were identified.

Figure 9 illustrates how the number of simulated agents affects space usage. The simulation with 1.100 agents, classroom occupancy is more uniform and widely distributed, reflecting better use of available space. On the other hand, with 10 and 50 agents, usage appears to be uneven, with certain areas concentrated while others remain underutilized, highlighting the importance of a larger number of agents to simulate realistic patterns.

5. Conclusion

In this work, we presented an agent-based model to analyze student attendance and movement across the university campus. Our model considers emotional contagion, fatigue, and teacher attraction. The model includes students with academics scheduled and random or floating population which are people

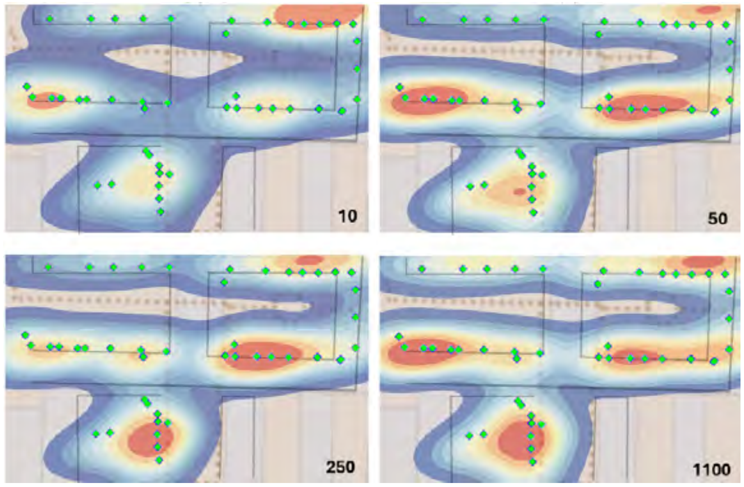


Fig. 9. Heatmap depicting classroom occupancy with different numbers of agents.

waking by the different areas. The results showed that attendance is not solely dependent on academic planning but also on emotional and group dynamics, highlighting the importance of integrating these factors into educational management.

Changes in emotional states throughout the day revealed recurring emotional dynamics, suggesting that the structure of academic activities and environmental conditions can create negative emotional cycles that impact student performance and motivation. One key finding was the effect of negative emotional contagion on attendance and student distribution. Emotions such as boredom and hopelessness increased over the course of the day, reducing participation in later class blocks. To mitigate this effect, it is recommended to reschedule demanding activities to times when students exhibit more positive emotional states and to incorporate active breaks to enhance well-being.

In terms of mobility, high-congestion areas were identified in hallways and common spaces, causing delays in student movement. These findings suggest that optimizing schedule planning, redistributing classrooms, designing alternative routes, and improving infrastructure could enhance student mobility, reducing overcrowding and facilitating smoother campus transit.

From a theoretical perspective, the proposed model is grounded at the intersection of agent-based simulation and educational psychology, integrating concepts such as emotional contagion, fatigue, and teacher perception to explain collective dynamics within the university environment. However, its relevance extends beyond the technical domain: in contexts where educational continuity and student retention are threatened by factors like demotivation, exhaustion, and emotional disengagement, this type of modeling becomes strategically valuable. Empirically, the model enables the simulation of scenarios in which affective variables influence concrete decisions—such as attending or skipping class—making it a useful tool for anticipating phenomena such as presenteeism, absenteeism, and dropout. In this way, the study takes a critical stance toward approaches that reduce academic planning to logistical factors, advocating instead for a more holistic perspective that recognizes emotions as structural variables of learning and the educational experience.

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