# AGENT-BASED MODELING OF UP DILIMAN INTRACAMPUS PEDESTRIAN MOBILITY USING NETLOGO AND GIS

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**KEY WORDS:** ABM, Deterministic, MNL Regression, Pedestrian Density, Shortest Route Network, Student Schedule

**ABSTRACT:**

In the Philippines, campus mobility studies remain underexplored. Since small-scale models help in policy making that may also be applied in a large spatiotemporal context, intracampus mobility modeling and simulation offer support for future mobility research. In this study, we designed a NetLogo model to apply ABM and GIS in understanding intracampus student pedestrian mobility. We created a deterministic model using discrete student schedule and a probabilistic model using the multinomial logistic (MNL) regression model derived from the student demographics data to analyze student movement. To provide a realistic representation of student pedestrians and campus environment, GIS spatiotemporal data was proven crucial to the pedestrian mobility models. The generated pedestrian count heatmaps show a significant increase in student count from online learning switching to face–to–face instruction. The overall campus building occupancy served as the key factor influencing the changes in agent behaviors such as walking speed and student tardiness. Moreover, the probabilistic model showed erratic movements of students. The model evaluation depends on the heavily imbalanced datasets and its multiclass nature with relatively higher model performance (F1 score > 0.8) is observed during morning, noon, and end schedule times, whereas suboptimal performance (F1 score < 0.6) where the dataset has a higher number of classes. The simulations demonstrate that ABM is a useful tool for examining pedestrian and transport patterns and can be enhanced further to allow multimodal and multiagent systems.

## 1. INTRODUCTION

Understanding mobility within complex interconnected environments has been a sought-after research topic for several years (Gu and Blackmore, 2015) It is influenced by various conditions, including (but not limited to) climate change, poverty, poor governance, instability, and conflict (Barbosa et al., 2021). Among others, the COVID-19 outbreak is one key mobility change of the 21st century that has a substantial impact on worldwide mobility. Due to this, numerous studies were conducted to model the effectiveness of control measures in mitigating the transmission of the virus within the subject communities and social spaces (Alessandretti, 2021).

While there are human mobility studies focused on large-scale systems, smaller-scale processes within the systems are also investigated relating the implications of its consistency to bigger-scale systems with comparable characteristics. Due to their large population, university campuses are identified as one of the common areas of interest for mobility studies. Most universities are also designed with dense walking infrastructures for on-foot campus navigation. The array of mobility modes along with the dynamic behaviors of their members grants opportunities for researchers to examine human mobility and complex systems in a microcosm (Vlahogianni et al., 2019).

Since 2021, the Commission on Higher Education (CHED) has been undertaking the gradual reopening of universities and colleges for face-to-face instruction, yet we still observe the lack of studies investigating the changes in student dynamics during and after the transition. In addition to the still looming threat of outbreaks and new epidemics, we recognize the need for understanding the complexity of student mobility in the context of health, environmental sustainability, and social engagement.

A relatively recent method of modeling complex systems, agent-based modeling (ABM) is a widely known method of simulating human mobility by focusing on discrete units, called “agents”. These agents operate within an established set of rules and varying degrees of autonomy designed to mimic their real-world counterparts. They exhibit behaviors that are shaped by their interaction with other agents and their environment (MacAl and North, 2010). ABM allows the integration of a Geographic Information System (GIS) in monitoring complex systems which provides the spatial and temporal information of the agents and the model environment (Crooks, 2015).

The main objective of the study is to apply ABM and GIS in understanding the pedestrian mobility dynamics inside the UP Diliman campus. The agent-based model allows us to identify the pedestrian traffic characteristics of the campus pathway network, compare the changes in campus pedestrian mobility during the learning mode transition, and investigate the student pedestrian mobility on a deterministic and probabilistic approach.

In this study, the NetLogo model is the primary output of the research, but there are also other model derivatives such as pedestrian count heatmaps, building occupancy maps, student tardiness, and walking speed plots, as well as a list of routes traversed by tardy students. With the university-wide implementation of face-to-face classes, the models can guide students on their campus route selections and gain insights into the walkability of the location of their enlisted classes. These results can aid in establishing safety standards in addressing and mitigating possible COVID-19 outbreaks due to the increase in student enrollment and significant changes in intracampus mobility patterns. It can also be used to support university planners for possible walkway rehabilitation, street repair or replacement, and network diversification.

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## 2. MATERIALS AND METHODS

### 2.1 Study Area

The University of the Philippines – Diliman Campus situated in Quezon City, Metro Manila (4° 38' N, 121° 2' E) which spans an area of approximately 493 hectares was selected as the simulation subject area due to a few reasons.

First, the University is recognized for its wide range of educational programs catering to a diverse and substantial student population. Given the heterogeneous composition of the student body, each individual attends to unique schedules which results in complex and discrete interactions – two valuable characteristics in Agent-based Modeling. Second, the community dedicates a significant amount of time to pedestrian activities. The road and pathway infrastructure within the campus encourages the students to walk to their classes and as means of general navigation. Third, the implementation of the phased resumption of face-to-face (F2F) instructional activities in 2022, from remote learning due to the COVID-19 pandemic, brings forth an opportunity to investigate the changes in intracampus mobility during the transition period.

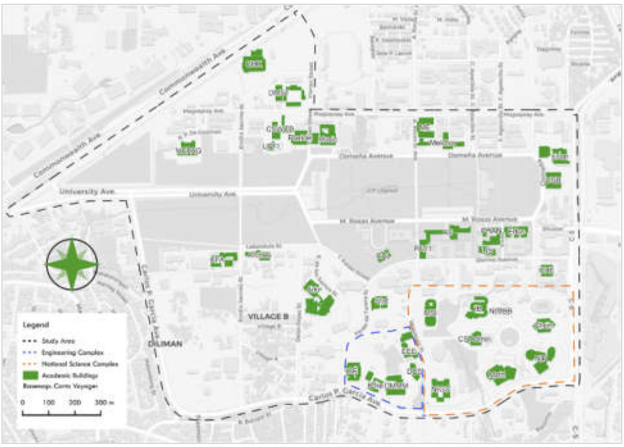


**Figure 1.** Map of the University of the Philippines (UP) Diliman Campus

### 2.2 Data Requirements

The data collected for this study is summarized in Table 1. The student information consists of the student demographics, schedule, and course data for the First and Second Semesters of Academic Year 2022-2023. These datasets were provided by the UP Diliman Office of the University Registrar (OUR). It is also important to note that these datasets are anonymized and were handled with confidentiality throughout the study in accordance with the Data Privacy Act of 2012.

Meanwhile, the UP Diliman campus information, includes the campus digital elevation (surface) model of 1-meter resolution sourced from NAMRIA. The building footprints, pedestrian pathways, and road network shapefiles were extracted from OpenStreetMap. Due to unavailability of other campus data components, digitization was necessary to enhance the overall spatial environment of the model. In addition, to accommodate the simplicity of the model, only one entry point was designated for each building location. The width of roads and pathways were also set uniformly. The former measures 5 meters, while the latter measures 2 meters in width. The University Academic Oval was designed with a road width of 16 meters while the existing crossroads were digitized with 5-meter width.

| Data | Dataset | Source |
|---|---|---|
| UP Student information | Anonymized Student Schedules (A.Y. 2022-2023) | UP Diliman Office of University Registrar (OUR) |
| | Anonymized Course Schedule (A.Y. 2022-2023) | |
| | Anonymized Student Demographics (A.Y. 2022-2023) | |
| UP Diliman Campus | DEM/DSM (1m resolution) | NAMRIA |
| | Building Footprints Shapefile | OpenStreetMap |
| | Pedestrian Pathways Shapefile | |
| | Road Network Shapefile | |

**Table 1**. Data requirements of the study

### 2.3 Model Implementation using NetLogo

To examine the pedestrian mobility behaviors of UP Diliman Campus, we created an agent-based model that simulates student agents as they navigate the campus throughout the entirety of a class day. For this study, we specifically implemented our model in NetLogo. It is a free, open-source program designed by Uri Wilensky and is used for simulating natural and social phenomena and capturing complex systems over a specific period (Wilensky, 1999). Figure 2 shows the model implementation workflow in NetLogo comprises procedures for both setup and transition phases.

**2.3.1 GIS Environment:** The spatial component of our model is a bounded plane GIS environment, encapsulating a large portion of the UP Diliman campus, and enclosed by Magsaysay Avenue on the North, Commonwealth Avenue on the West, C.P. Garcia Avenue on the South, and Katipunan Avenue on the East.

The model environment is composed of these GIS datasets: (1) slope raster, (2) digitized road network shapefile, (3) OSM-derived academic buildings shapefile, (4) non-academic buildings shapefile, (5) building entrances shapefile.

| Attribute Name | Attribute Type | Description |
|---|---|---|
| slope | Float | Slope values in degrees |
| pathway-use | Integer | Monitors pathway use of students |
| cumulative-pathway-use | Integer | Monitors the cumulative pathway use of students |
| road? | Boolean | Identifies road patches |
| entrance? | Boolean | Identifies entrance patches |
| entrance-name? | String | Identifies entrance name |
| bldg-name | String | Identifies academic building name |

**Table 2**. Summary of Patch Attributes of the Pedestrian Mobility Model

**2.3.2 Student Agent Definition:** The main agents of this model exist at individual level, representing all undergraduate students at the University of the Philippines Diliman for the Academic Year 2022 – 2023.

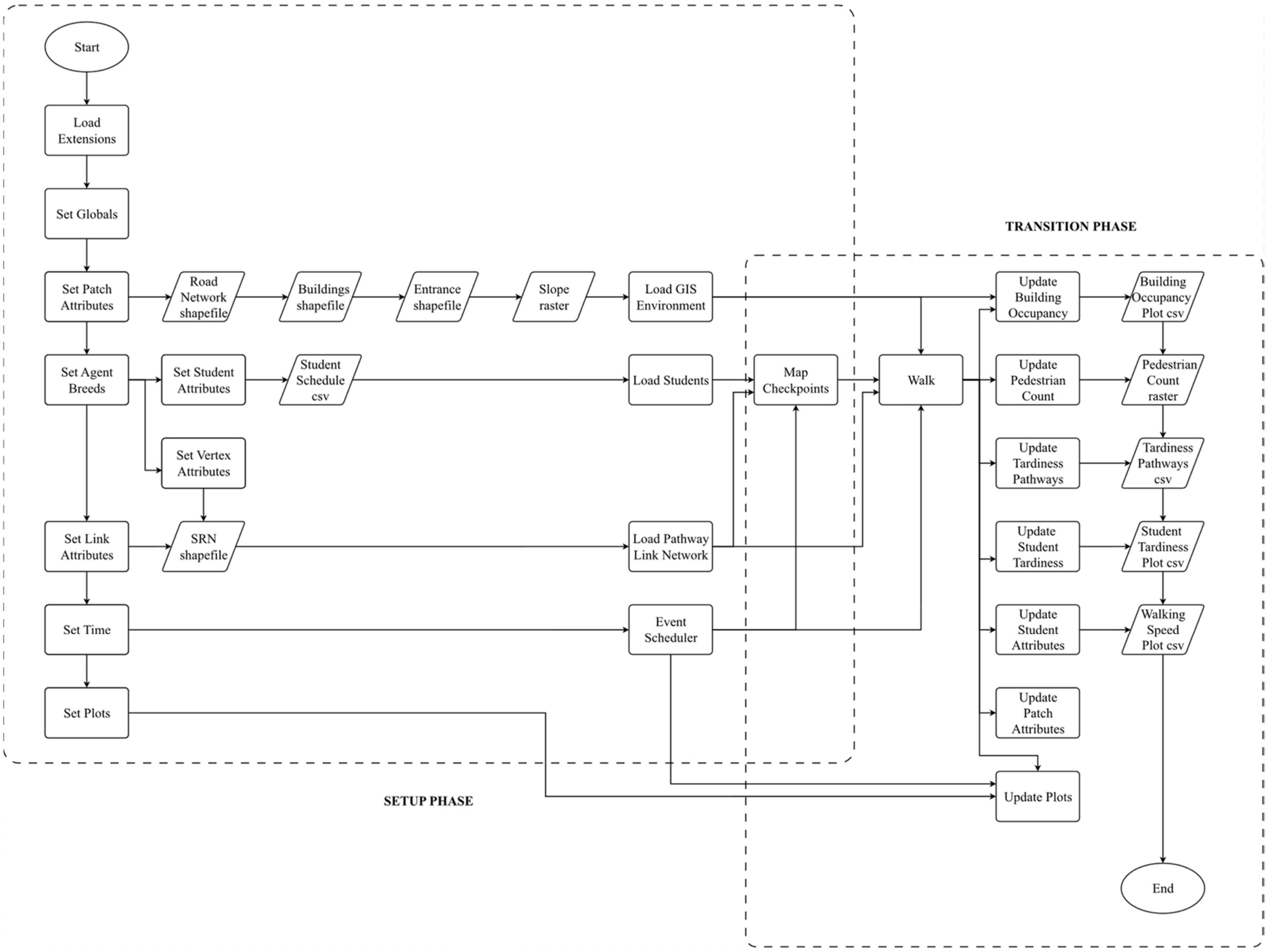


**Figure 2.** NetLogo Model Implementation Workflow of the Pedestrian Mobility Model

| Attribute Name | Attribute Type | Description |
|---|---|---|
| identifier | Integer | Unique identifier code of every student |
| college | String | College name |
| progname | String | Degree program |
| tardy? | Boolean | Tardiness condition of students |
| tardy-count | Integer | Instantaneous tardiness count |
| departure | Timestring | Departure time of students |
| start-location | String | Starting location (building) of students |
| current-location | String | Current location (building) of students |
| next-location | String | Succeeding location (building) of students |
| building-list | List | List of class locations (buildings) |
| walking-speed | Float | Instantaneous walking speed of students in m/s |
| target | Agent (Vertex) | Current target vertex of students |
| checkpoints | List | List of vertices |

**Table 3**. Summary of Agent Attributes of the Pedestrian Mobility Model

Primarily, these agents possess goal-based cognition which signifies that they operate to fulfill their goal– in this case, to navigate across the campus while following their assigned class schedules. Additionally, these student agents are reflexive, indicating that they function based on a set of rules that we assigned. They are also adaptive in nature due to their inherent spatial awareness which allows them to change their movement based on the existing pedestrian traffic conditions along the pathways. Table 3 summarizes the attributes of agent behavior within the model. These attributes are extracted mainly from the anonymized student information dataset provided by the Office of University Registrar.

**2.3.3 Model Time Definition:** Inspired by the NetLogo Distribution Center Discrete Event Simulator model (Railsback and Wilensky, 2022), we created this model to utilize two of three main functions of the NetLogo Time extension. First, it relates the simulation time into actual real date and time. For this model, we followed a 24-hour format and fixed the *start-time* to 07:00 and the *end-time* to 22:00 to cover all the undergraduate courses throughout a class day.

Second, it activates the Discrete Event Scheduler which anchors all discrete events to tick values, NetLogo's native time tracking mechanism. With this, our model gained the functionality to organize subsequent model actions that were classified into either repeating or non-repeating tasks, as summarized in Table 4.

| Action Name | Start Time | Repeat Interval |
|---|---|---|
| update-plots | start-time | 15 minutes |
| go-walk | start-time + 0.001 minutes | 15 minutes |
| stop-walk | start-time + 15 minutes | 15 minutes |
| export-patch-to-raster | start-time + 15 minutes | 15 minutes |
| update-student-attributes | start-time + 15 minutes | 15 minutes |
| export-tardy | end-time | |
| export-plots | end-time | |

**Table 4.** Summary of Discrete Events of the Pedestrian Mobility Model

**2.3.4 Pedestrian Mobility Behavior:** During the model initialization, the student agents appear or at the appropriate building location (*start-location*) of their first class where they remain throughout the class duration. In preparation for the next destination, NetLogo's path-finding algorithm was implemented to determine the shortest path that the students must take from their current location to their next class.

To set off the movement of the students to their next location, the *checkpoints* attribute is accessed. Then, the agent walking speed is calculated by using the slope value of each patch. The Tobler's hiking function establishes a threshold range of 0 to 1.4, considering the minimum to maximum slope value of the UP Diliman slope raster. By doing this, the walking speed on relatively flat terrain corresponds to Naismith's original rule of 1.39 m/s (5 km/h) for walking speed (Naismith, 1892, as cited in Irmischer & Clarke, 2018). The computation of the walking speed of agents adheres to Tobler's hiking function. This equation was derived by Waldo Tobler, utilizing empirical data furnished by Eduard Imhof in 1950, to estimate pedestrian velocity as a function of terrain gradient (Irmischer and Clarke, 2018). Equation 1 and 2 provides an estimation of the walking velocity, denoted as

$$W = 1.67^{-3.5|S+0.5|}, \text{ where } S = \frac{\Delta elevation}{\Delta distance} \quad (1)$$

$$W = tan\ tan\ \theta \text{ , where } \theta \text{ is degrees slope} \quad (2)$$

Furthermore, if a student is positioned directly ahead of another, the latter would adjust their speed to match that of the former, resulting in a slowing down. This ensures that they walk at a slower pace than the agent preceding them, and to maintain a safe following distance. Conversely, in the absence of pedestrian traffic, the student is designed to speed-up. The acceleration value specified for this study serves as a placeholder for the intended amount of speed change when the student needs to slow down or speed up. In real life, acceleration is the rate at which an object changes its velocity, and it is typically measured in meters per second squared ($m/s^2$). For this model, we assigned a fixed global acceleration value of 0.0099. Although this is not physically accurate, we assume it is a reasonable simplification for a simulation that focuses on adjusting the walking pace of students based on their proximity to other students.

While in motion, the pedestrian behaviors of the students are recorded in the *pathway-use* and *cumulative-pathway-use* attributes of the model environment. These monitor every pathway that the agents had traversed. Student agents were designed to continue moving until it meets either of these conditions: (a) the student reaches its destination or (b) the student has reached the maximum steps possible within the 15-minute interval. This is calculated using Equation 3, where WS pertains to walking speed, and SR to spatial resolution.

$$Max\ steps = 15\ min \times \frac{60\ s}{1\ min} \times\ WS \times \frac{1\ patch}{SR} \quad (3)$$

Upon arrival at their destination, the students' tardiness attributes (*tardy?* and *tardy-count*) are updated accordingly. If a student arrives within the first 15 minutes of the class he is considered on time.

## 3. RESULTS AND DISCUSSION


**Figure 3.** NetLogo pedestrian mobility model interface

The interface of our pedestrian model consists of multiple components. The choosers, and switches modify the model parameters which includes the model type, semester, day of the week, as well as plot, and export parameters. The setup button updates these parameters while the go button initializes the transition phase of the model.

The model world displays the GIS environment, the student agents and most importantly, their motion during the transition phase. The interface includes the plots for building occupancy, walking speed, and student tardiness which monitor the pedestrian mobility behaviors of the agents as they navigate throughout the model world.

### 3.1 Deterministic Model

After the completion of the pedestrian mobility NetLogo model, we executed 12 deterministic models, covering two semesters of Academic Year 2022 – 2023, and six school days per week. The main purpose of the deterministic models is to simulate campus pedestrian mobility with actual, discrete data along with the assumptions and simplifications embedded in the model.

As shown in Figure 4, the student count during Monday (M) and Saturday (S) for both Semesters was consistently low compared to the plots from Tuesday (T), until Friday (F). This corresponds to the regular class schedule of the University where the majority of undergraduate courses are held during weekdays and only a few classes, typically PE and NSTP, conducted during the weekends. Both plots gradually increased around 08:30 and18:30 which also corresponds to the typical time schedule of most classes. Notably, the daily student count throughout the week has drastically increased by about 50% during the Second Semester - A.Y. 2022-2023, as a result of the University-mandated enforcement of at least 50% face-to-face component to all undergraduate courses (Diliman Information Office, 2022).

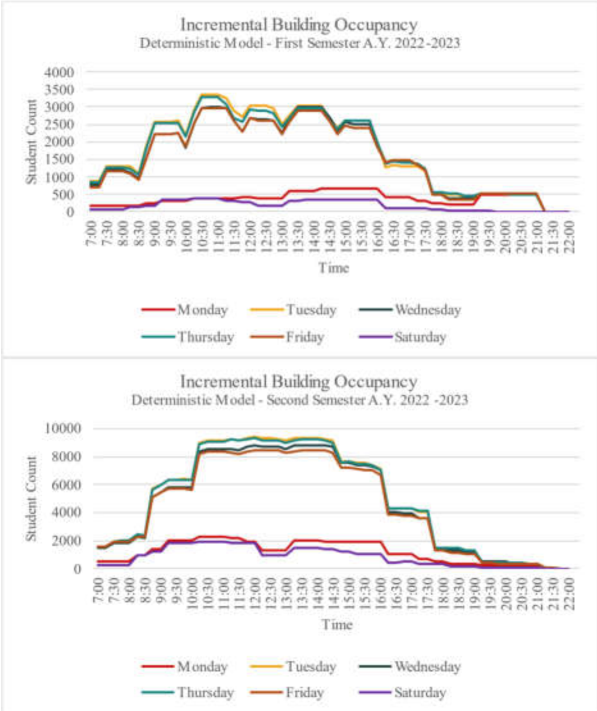


**Figure 4.** Incremental Building Occupancy: (top) First Semester, and (bottom) Second Semester

Increase in pedestrian activity during the learning mode transition was also detected in pedestrian count heatmaps (Figure 5). During the Second Semester, areas with recorded high activity include a portion of Roxas Avenue which runs from CAL to the East Wing of AS, as well as A. Roces Street which extends to Velasquez Street. Similarly, activity was also recorded along the pathways of the National Science Complex and DMST Complex, particularly along Ylanan Street which leads to CHK.

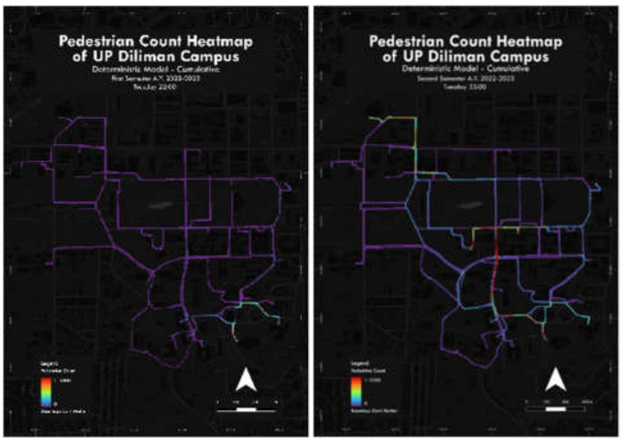


**Figure 5.** Pedestrian Count Heatmaps – Tuesday: (left) First Semester, and (right) Second Semester

The walking speed plot for both Semesters, reveal a significant increase in pedestrian traffic from Tuesday to Friday, indicated by low mean walking speed values. It was observed that plots tend to fluctuate throughout the day particularly during the peak hours when student mobility is high and dynamic. The plots eventually increase as the day ends when there are fewer classes held and low student count. However, these fluctuations are visibly less dramatic during the Second Semester with their troughs remaining above 0.908 m/s.

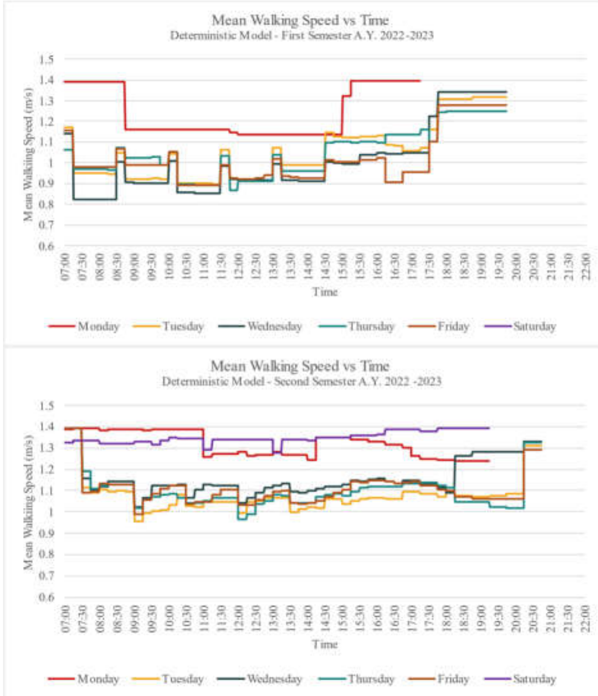


**Figure 6**. Mean walking speed: (top) First Semester, and (bottom) Second Semester

The buildings with the most appearance in the list of routes with highest tardiness instances include CHK (6 times), and Math (4 times). Notably, despite its relatively central location on the campus, CAL appeared thrice on the list. The probable reason behind this is the location of its routes' endpoints which are Math, CHK, and NIP – three buildings that are situated at the outer edges of the campus; this suggests that the likelihood of students arriving late is higher when they are either coming from or heading to buildings that are located far. However, the high occurrence of CAL on the list could also be due to the very high pedestrian traffic on the pathways nearby the building throughout the day.

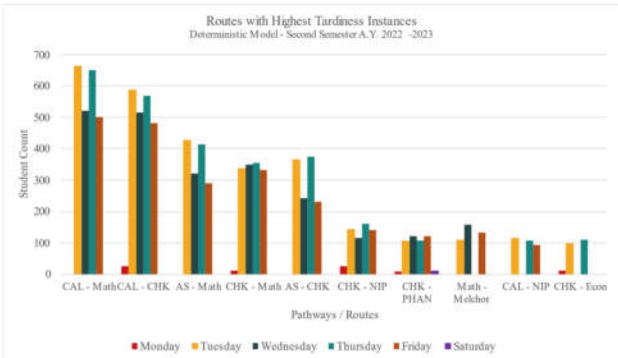


**Figure 7**. Routes with Highest Tardiness Instances: Second Semester

### 3.2 Probabilistic Model

Similar to the deterministic model, a total of twelve (12) probabilistic models were developed, comprising six models from Monday to Saturday datasets each for the First and Second Semesters. The focus of the probabilistic model is to evaluate its generalizability to alternative datasets, particularly in scenarios where class schedules are unavailable and demographic data is accessible. This is particularly relevant in forecasting scenarios, such as when a university seeks to assess the mobility patterns of incoming students.

The probabilistic model was derived from the application of MNL regression analysis on the deterministic model dataset as input. Initially, the dataset displays a notable inclination towards students who possess a "None" classification in their class schedule, denoting the absence of classes for the specified time. The generated model exhibited several limitations. Specifically, the algorithm which includes the MNL regression analysis generated a prediction model for each interval, thereby failing to consider the minimum class duration of one hour as specified in actual class schedules. This led to the implementation of a data structure wherein classes are assigned to different locations every 15-minute interval.

After the data was entered into NetLogo for simulation, the sample resulting map depicted in Figure 8 (left) represents the actual probabilistic model output from the MNL regression. The students exhibited a disordered pattern of movement as they transitioned from one building to another, without adherence to the prescribed regulation outlined in the NetLogo model algorithm such as strictly walking on the roads and walkways.

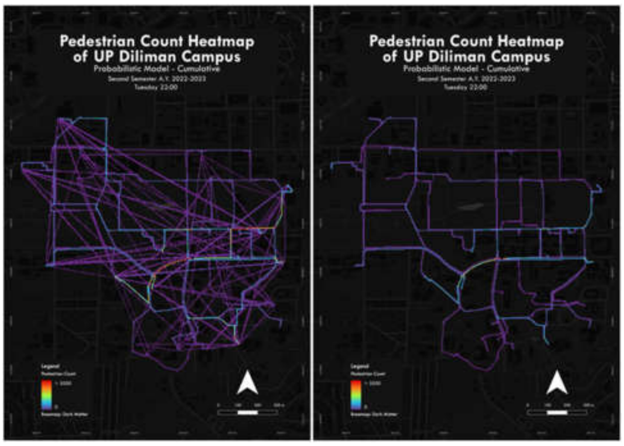


**Figure 8.** Pedestrian Count Heatmap (Probabilistic Model): (left) actual probabilistic model output, and (right) after the data cleanup.

Upon inspecting the probabilistic model, it seems that the underlying cause of this issue is the structure of the input dataset. Specifically, as mentioned, certain classes do not satisfy the minimum duration requirement, leading to our findings that the NetLogo model is only effective for data that exhibit a maximum of two location changes within three intervals. This outcome aligns with the desired functionality of our NetLogo algorithm, which is tailored to accommodate class schedule formats.

Furthermore, we also observed that the map outputs for Mondays and Saturdays did not exhibit a disordered student movement in comparison to the other days. Upon examination of its data structure, we noticed that it possesses a systematic arrangement of class location placements. The disparity in the student population between the two aforementioned days and other day datasets is considered to be a contributing factor to the observed outcome, which may also be attributed to the limited availability of class locations.

We consider the significant differences in the result since we were only given data access for AY 2022–2023. In order to get better findings, we made use of these student records, and our best attempt was to clean up the data Figure 8 (right). Even though the results are not yet refined and will likely undergo further revisions, we still consider it as a starting point for campus mobility forecasting scenarios in hopes that it could have more meaningful outcomes in the future.

The performance of the probabilistic model was also evaluated using the average weighted, micro, and macro F1 scores. The F1 score considers the imbalance and multiclass nature of the model as compared to other performance metrics. We observed the high model performance (F1 score > 0.8) during morning, noon, and end interval schedule times, whereas suboptimal performance (F1 score < 0.6) in cases with a higher number of classes. These high values are expected since the majority of the students do not have schedules making it more biased to that classification. Overall, the performance values support the per-interval evaluation; however, for a more comprehensive explanation to analyze its efficacy, we recommend improving the model to consider the entire student timetable for modeling and evaluating model performance.

## 5. CONCLUSION

In the Philippines, campus mobility studies remain underexplored. With this, we investigated the UP Diliman pedestrian mobility using ABM as a starting point for analyzing future mobility dynamics. We presented the use of NetLogo, one of the widely used, open-source ABM programs as the primary simulation tool, and the integration of GIS as the source of geographic context to the model (Wilensky and Rand, 2015). Using NetLogo and GIS, we designed a pedestrian mobility model, to serve as a base model for future mobility studies, that captured the pedestrian dynamics of UP Diliman Campus. With this, we have confirmed that the return of face-to-face learning is the main driving force of the increase in pedestrian activity during the current semester. The deterministic and probabilistic model derivatives also revealed several intricacies of intracampus pedestrian mobility dynamics.

The implication of model outputs extends beyond the key agents, the students, to the entire campus community. To support policy development on class schedule and student distribution across academic buildings, and provide insights into campus navigation, we make use of simulation models and their derivatives. The models can be enhanced further to allow multimodal and multiagent systems. The simulations demonstrate that ABM is a useful tool for examining pedestrian and transport patterns.

## 6. RECOMMENDATIONS

The vast field of agent-based modeling and simulation allows the model authors and developers to explore the level of complexity or simplicity of their models depending on their end goal. As a result, there are limitless model modifications in terms of its agent cognition, granularity, environment type, resolution, scale, etc. (Wilensky & Rand, 2015). Capturing more elements of the real-world system, we see that our NetLogo algorithm can be enhanced based on upcoming research fields. By adding new agent behaviors involving extracurricular activities in various spatial ranges to the main model, it may provide more context on campus pedestrian behavior and student dynamics. In terms of model scale, future studies can focus on more specific locations to examine the mobility in greater detail or broader regions to incorporate other transportation modes as well as environmental factors. The ability to capture a range of wider-ranging behaviors is made possible by using ABM to understand more multiagent and multimodal systems. Finally, we recommend the integration of the validation procedures to ensure that the model actualizes intracampus pedestrian mobility (Wilensky & Rand, 2015). Some mobility studies used environmental sensors to count the pedestrians at a specific location (Obie et al., 2017), while others utilized optical systems in monitoring the pedestrian conditions in their target direction (Huang et al., 2018; Sandaruwan et al., 2021; Shirazi & Morris, 2016).

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