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# Integrating Web GIS and Agent-Based Simulation for the Analysis of a University Bus Transportation System

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**Abstract**

Bus systems at higher education institutions often suffer from a mismatch between supply and peak academic demand, which affects their efficiency and reliability. This gap leads to long waiting times, overcrowding at bus stops or on vehicles, and limited operational information. Combined with urban traffic congestion, these factors negatively impact the quality of life of the academic community, class punctuality, and consequently academic performance, thereby turning transportation into a barrier to effective access to quality education. This study presents the development and integration of a Web GIS, a collaborative mobile application, and an agent-based simulation model for collecting, recording, and analyzing georeferenced information regarding a university bus system. The simulation results reveal that, although the system achieves approximately 80% demand coverage, there are structural imbalances between saturated and underutilized routes. These findings suggest that an integrated platform can support evidence-based decision-making for university transport planning and may serve as a basis for future studies aimed at evaluating optimization strategies and real-time operational adjustments.

**Keywords**

Agent-Based Modeling; Computer simulation; Geographic Information Systems; Bus system; Web applications; Mobile applications.

**Registration**

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## Integración de Web GIS y simulación basada en agentes para el análisis del sistema de autobuses universitarios

**Resumen**

Los sistemas de buses en instituciones de educación superior suelen presentar desajustes entre la oferta y los picos de demanda académica, afectando su eficiencia y confiabilidad. Esta brecha genera tiempos de espera prolongados, hacinamiento en paraderos o vehículos y una limitada información operativa. Junto con la congestión del tráfico urbano, estos factores impactan negativamente la calidad de vida de la comunidad académica, la puntualidad en las clases y, por ende, el desempeño académico, configurando el transporte como una barrera para el acceso efectivo a una educación de calidad. Este trabajo presenta el desarrollo e integración de un Web GIS, una aplicación móvil colaborativa y un modelo de simulación basado en agentes para la recolección, registro y análisis de información georreferenciada del sistema de buses universitarios. Los resultados de la simulación revelan que, si bien el sistema alcanza una cobertura aproximada del 80% de la demanda, existen desbalances estructurales entre rutas saturadas y subutilizadas. Estos hallazgos sugieren que la plataforma integrada puede respaldar la toma de decisiones basada en evidencia para la planificación del transporte universitario y servir como base para futuros estudios destinados a evaluar estrategias de optimización y ajustes operativos en tiempo real.

**Palabras clave**

Modelado basado en agentes; simulación computacional; sistemas de información geográfica; sistema de transporte de buses; aplicaciones web, aplicaciones móviles.



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## 1. Introduction

Public transportation systems, particularly bus services, are a fundamental component of urban and peri-urban life, as they enable population efficient mobility, promote social equity, reduce environmental impact, and strengthen territorial cohesion, all of which directly influence accessibility, quality of life, and the overall functioning of cities (Verano-Tacoronte, Flores-Ureba, Mesa-Mendoza and Llorente-Muñoz, 2024). Mobility within bus transportation systems at universities and higher education institutions (HEIs) has evolved from a purely logistical issue into a key factor in student well-being and educational equity. In recent decades, university campuses growth and the geographic dispersion of their communities have established institutional transportation systems as the backbone of academic access, particularly for vulnerable low-income populations (Nadimi, Zamzam and Litman, 2023). However, managing these systems faces critical challenges stemming from the stochastic nature of demand, which is intrinsically linked to peak class schedules, users' socioeconomic status and place of residence, as well as peaks in university activity that do not always align with available transport capacity and infrastructure (Zhou, 2012). Unlike conventional urban transportation systems, transportation networks at HEIs typically exhibit extremely sharp load fluctuations over very short time intervals (Harrath, AlYusuf, Ghulam and AlDoseri, 2024). These challenges often result in a recurring mismatch between bus route services supply and peaks in academic demand, affecting their efficiency and reliability.

Typically, the inefficiency of these systems stems from long waiting times at bus stops, which lead to overcrowding (Arif Khan, Patel, Pamidimukkala, Kermanshachi, Rosenberger, Hladik and Foss, 2023). As well as overcrowding on buses when they exceed capacity, which can compromise passenger safety (Ceder, 2016), and the lack of real-time recording, tracking, and monitoring systems to support data-driven decision-making. On the other hand, exogenous factors also affect these systems, such as urban traffic congestion, which introduces uncontrollable variability in travel times, undermining the system's reliability (Daganzo and Ouyang, 2019). Finally, transportation should not be viewed as an isolated service, but rather as a barrier to access. The stress resulting from uncertainty in commutes and systematic tardiness impacts the quality of life of students and faculty, limiting effective study time, participation in extracurricular activities, and academic performance (Tigre, Sampaio and Menezes, 2017; Taylor and Mitra, 2021).

Some previous studies have addressed the challenges of bus transportation systems at universities or HEIs through various technological and methodological approaches. Information systems, software applications, and geographic information technologies (GIT) have been employed to model and visualize transit networks, offering structured representations of routes and stops that facilitate planning (Eken and Sayar, 2014; Lovelace, 2021; Godfrid, Radnic, Vaisman and Zimányi, 2022; Colque, Valdivia, Navarrete and Aracena, 2021); however, these approaches often rely on static data and do not support real-time interaction or dynamic updates. Internet of Things (IoT) devices, GPS tracking, and mobile applications have enabled real-time location and user notifications, improving perceived service reliability (Ingle, 2015; Rodríguez-Ibarra and Bobrek-Fernández, 2016; Durga and Ravi, 2017; Chan, Wan Ibrahim, Lo, Suaidi and Ha, 2020; Suresh, Saranya, Punitha and Kowsalya, 2023; Chawuthai, Sumalee and Threepak, 2023). Nevertheless, their deployment typically requires significant infrastructure investment and tends to address individual routes rather than integrated multi-route systems. Agent-based simulation has been used to model complex demand patterns and evaluate operational scenarios under varying load conditions (van der Spek, van Stein, van der Holst and Bäck, 2018; Liyanage and Dia, 2020; Huang, Cui, Zhang, Tong, Shi and Liu, 2022; Sai and Challapalli, 2024), yet these models are computationally intensive and their results are not always transferable to operational decision-making tools accessible to administrators. Across these approaches, a common limitation is the absence of integrated, publicly accessible web platforms that consolidate geospatial route visualization, multi-route management, and user-oriented interaction within a single system tailored to the specific operational context of HEIs (Nadimi et al., 2023). Therefore, the present study addresses this gap through the development and integration of an open-source web-based platform based on above technologies for georeferenced recording, management, and operational analysis of a university bus transportation network in Colombia.

This article is structured to systematically build and validate an integrated platform for the analysis of a university bus transportation system. The theoretical background section establishes the conceptual foundation by critically reviewing contributions and limitations of prior work on the application of geographic information systems (GIS), Internet of Things, mobile devices, and agent-based simulation to university transit systems, thereby justifying the technological choices and integrated approach adopted in this study. Building on this foundation, the methodology section details the design and development of the three core components of the platform: the Web GIS, a collaborative mobile application, and an agent-based model in AnyLogic; explaining how each was conceived to address the data collection, geospatial management, and operational analysis challenges identified in the introduction. The results section then presents the outcomes of applying this methodology: geospatial recording of bus stops and routes, functional Web GIS and public web application, and simulation experiments conducted over multiple runs, together providing empirical evidence of the platform's feasibility and system's operational behavior. The discussion section interprets these findings considering the theoretical background, examining the structural imbalances between saturated and underutilized routes, the implications of the system's partial demand coverage for equitable academic access, and the methodological limitations that future work should address. Finally, the conclusions synthesize study's contributions and connect them to the stated objective and outline specific directions for future research.

## 2. Theoretical background

A university bus transportation system is defined as a public transit service with fixed routes designed to connect students, faculty, and administrative staff to the university campus, constituting a cornerstone of equity and well-being by ensuring academic access in the face of the community's geographic dispersion, especially for vulnerable student populations (Nadimi et al, 2023). To address the operational challenges inherent to such systems, three main technological and methodological approaches have been explored in literature: geographic information technologies, IoT and mobile devices, and agent-based simulation. As reviewed below, each approach has demonstrated specific strengths while also exhibiting limitations that the present study seeks to address through an integrated platform.

### *2.1. Geographic Information Technologies in Transportation Systems*

Geographic information technologies (GIT) integrate tools such as GIS, global navigation satellite systems (GNSS), including GPS, remote sensing, for spatial data management, and Web GIS, whose web-based client-server architecture enables the dissemination and spatial analysis of geospatial information critical for transportation decision-making (Longley, Goodchild, Maguire and Rhind, 2015; Fu and Sun, 2011). Applied to bus transportation, GIT-based systems have demonstrated their capacity to structure and visualize transit networks with varying degrees of interactivity and real-time capability.

Early implementations focused on isolated functional solutions. Eken and Sayar (2014) proposed a QR-code-based bus tracking system, via Google Maps, in Turkey, that uses the C4.5 algorithm to estimate arrival times at bus stops and notify users via SMS and email, demonstrating the value of integrating location data with user-facing interfaces, though within a single-route, proprietary architecture. In contrast, Lovelace (2021) argued for open-source tools such as MATSim and SUMO for transport simulation, and AequilibraE and QNEAT3 for network-level transportation planning in QGIS, emphasizing interoperability and spatial analysis but stopping short of operational real-time management. Moving toward integrated data architectures, Godfrid et al. (2022) combined static data using the General Transit Feed Specification (GTFS) with real-time streams with MobilityDB on PostgreSQL to evaluate punctuality and operational deviations in Buenos Aires (Argentina), while Colque et al. (2021) implemented a full Geographic Information System for Transportation (GIS-T) stack in Arica (Chile), integrating Traccar, TransiTime, OneBusAway, and PostgreSQL under the real-time GTFS standard, achieving measurable improvements in user satisfaction. Collectively, these studies confirm that GIT can effectively support route visualization and operational monitoring. However, they predominantly address conventional urban transit systems and rely on proprietary infrastructure or GTFS-compliant data pipelines that presuppose standardized data availability, limiting their direct applicability to the informal and heterogeneous operational context of university transportation systems in Latin America.

### *2.2. The Internet of Things and mobile devices*

The Internet of Things (IoT) enables physical objects to exchange data over the Internet through the integration of identification and tracking technologies, wireless sensor networks, and distributed communication protocols without human intervention (Atzori, Iera and Morabito, 2010). Mobile devices, particularly smartphones, have emerged as the most accessible IoT endpoint for transportation applications due to their widespread adoption and sensor capabilities (Gubbi, Buyya, Marusic and Palaniswami, 2013). Within this space, a clear progression can be identified from infrastructure-dependent solutions toward user-centered crowdsourcing approaches.

Infrastructure-constrained early solutions include Ingle (2015), who proposed an SMS-based system in India that operates without GPS or internet access, expanding reach to users with basic devices but sacrificing spatial precision, and Durga and Ravi (2017), who addressed GPS-GSM signal limitations and RFID cost barriers through Wi-Fi modules installed on buses, enabling position tracking via a mobile app. More capable GPS-based systems followed: Rodríguez-Ibarra and Bobrek-Fernández (2016) developed STOPBUS, an Android application with GPS georeferencing that reduced waiting times and promoted sustainable mobility, while Chan et al. (2020) demonstrated in Malaysia that real-time GPS tracking significantly increases user satisfaction and loyalty. Building on this, Suresh et al. (2023), showed that crowdsourced smartphone location data can generate reliable arrival time estimates, and Chawuthai et al., (2023) demonstrated in Bangkok that combining GPS data with spatial information enables the computation of key performance indicators for service evaluation. While these studies confirm the value of mobile and IoT-based approaches for real-time data capture and user engagement, they predominantly address individual routes or single-system implementations. None integrates crowdsourced trajectory data within a multi-route geospatial management platform designed for the institutional context of a university transportation system.

### *2.3. Agent-Based Simulation of Transportation Systems*

Agent-Based Simulation (ABS) models complex and dynamic systems through individual behavior of autonomous entities (agents) that interact within a shared environment according to locally defined rules, enabling the emergence of collective phenomena such as congestion, saturation, or distributional inequities (Wilensky and Rand 2015). In transportation, ABS has proven particularly effective for capturing the stochastic and heterogeneous nature of passenger demand.

Studies in this area reflect progression from descriptive modeling toward optimization. van der Spek et al. (2017) developed a hybrid agent-based and discrete-event simulation (DES) model in AnyLogic, using OpenStreetMap to analyze how passenger increases affect delays, occupancy, and service regularity, establishing a methodological precedent for spatially explicit ABS in transit systems in the Netherlands. Liyanage and Dia (2020) extended this approach to on-demand public transportation in Melbourne (Australia), demonstrating reductions in waiting times and improvements in vehicle utilization relative to fixed-route alternatives. Huang et al. (2022) provided a theoretical synthesis of ABS advantages, such as heterogeneity capture, environmental adaptability, and optimization integration; emphasizing its suitability for representing realistic and dynamic transportation behavior. Most recently, Sai and Challapalli (2024) applied ABS in AnyLogic to optimize the Dallas-Fort Worth bus system in Texas (USA) by adjusting frequencies and schedules according to demand patterns. Despite these advances, existing ABS studies of transit systems share a critical limitation: their models are calibrated with survey or administrative data and are not connected to live or collaboratively collected geospatial platforms, precluding their use as operational decision-support tools integrated with real-world data infrastructures.

Table 1 summarizes the contributions and limitations of studies reviewed across the three technological approaches discussed above. As shown, each line of work has advanced a specific dimension of bus transportation system analysis: geographic information technologies have enabled route visualization and spatial data management, IoT and mobile devices have supported real-time tracking and crowdsourced data collection, and agent-based simulation has provided a means to model stochastic demand and evaluate operational scenarios. However, these approaches have largely evolved in isolation from one another, each addressing a partial dimension of the problem without being combined within a single operational framework.

No studies were identified that simultaneously integrate Web GIS, collaborative mobile applications, and agent-based simulation for the analysis of university bus transportation systems. This gap is particularly relevant given specific operational challenges of HEIs, such as sharp short-term demand fluctuations and the need for georeferenced, user-generated data to calibrate realistic simulation models. The present study addresses this gap by developing and integrating these three components, as described in the following sections.

**Table 1.**
Summary of contributions and limitations of previous studies on technological approaches to bus transportation systems.

| Study | Context | Method / Technology | Main contribution | Limitations |
|---|---|---|---|---|
| Eken and Sayar (2014) | Turkey | QR codes + C4.5 algorithm | Bus tracking with arrival notifications via SMS/email | Single-route, proprietary architecture |
| Lovelace (2021) | Review study | Open-source GIS or transport system (MATSim, SUMO, AequilibraE, QNEAT3, QGIS) | Network-level transportation planning tools | No real-time operational management |
| Godfrid et al. (2022) | Buenos Aires, Argentina | MobilityDB + GTFS | Evaluated punctuality and operational deviations | Rely on GTFS-compliant infrastructure |
| Colque et al. (2021) | Arica, Chile | GIS-T (Traccar, TransiTime, OneBusAway) | Real-time location, arrival prediction, alerts | Depends on standardized data pipelines |
| Ingle (2015) | India | SMS-based (no GPS/ internet) | Expanded access for users with basic devices | Low spatial precision |
| Rodríguez-Ibarra and Bobrek-Fernández (2016) | | STOPBUS (GPS, Android) | Reduced waiting times, promoted sustainable mobility | Single platform, no crowdsourcing |
| Durga and Ravi (2017) | India | Wi-Fi modules on buses | Low-cost alternative to GPS-GSM/RFID | Limited range, infrastructure-dependent |
| Chan et al. (2020) | Malaysia | Real-time GPS tracking | Increased user satisfaction and loyalty | No integration with multi-route management |
| Suresh et al. (2023) | | Crowdsourced smartphone location | Reliable arrival time estimation | No persistent geospatial platform |
| Chawuthai et al. (2023) | Bangkok, Thailand | GPS + spatial KPIs | Generated performance indicators for service quality | Focused on evaluation, not management |
| van der Spek et al. (2017) | Netherlands | Hybrid (ABS + DES) | Evaluated delays and occupancy | No Web GIS integration |
| Liyanage and Dia (2020) | Melbourne, Australia | ABS | Reduced waiting times | Focused on on-demand transport |

Continued on the next page

| Study | Context | Method / Technology | Main contribution | Limitations |
|---|---|---|---|---|
| Huang et al. (2022) | Review study | ABS | Highlighted adaptability advantages | No empirical application |
| Sai and Challapalli (2024) | Dallas–Fort Worth, TX, USA | ABS | Optimized schedules and frequencies | No participatory data collection |

***Note:*** Own elaboration.

## 3. Methodology

For this work, our goal was to develop an information system that integrates geographic information technologies with a web and mobile application to record bus stops and route's locations, schedules, and collaborative spatiotemporal data on trips to and from university. With the consolidation of this information, along with the sampling of arrival times of students and faculty at the main bus stops, we proceeded to perform computational modeling of the university's bus transportation system for simulation and analysis.

Figure 1 presents an overview of the architecture of the web-based geographic information system (Web GIS), including client applications for information management and analysis to support monitoring and decision-making, a publicly accessible web application to view bus routes and stops (to and from university), and a collaborative mobile application (mobile crowdsourcing) for recording information on bus trips along each route.

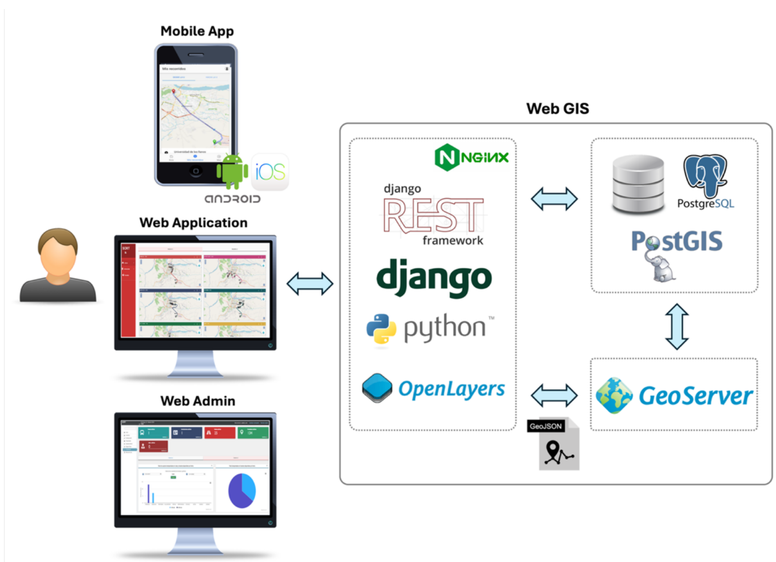


**Figure 1.** General diagram of the Web Geographic Information System (Web GIS) architecture, showing the administrative, web, and mobile client applications for recording, managing, and tracking bus routes.
***Note:*** Own elaboration.

Web GIS forms the core of the university's bus route transportation information system, supported by a PostgreSQL relational database extended with PostGIS for the storage and management of geographic data on bus stops, bus routes, and trips to and from university. Geoservices are published via the open-source code server, GeoServer, and visualized on the web interface using the OpenLayers library, which enables geospatial services consumption and interactive maps display of bus routes and stops in the browser. Integrated into this architecture is a collaborative mobile application (mobile crowdsourcing) developed for Android and iOS to record trips (spatial location and time) of bus route users anonymously, voluntarily, and collaboratively (crowdsensing). This mobile application communicates via web services and an API implemented with the Django REST Framework. Finally, the web application for public visualization of routes and stops, as well as the administrative web application for configuring, managing, and visualizing system data analysis, were developed in Django, a free and open-source platform based on Python, which manages the system logic and data access under the model-view-template (MVT) architectural pattern.

To test and validate the functionality of the integrated platform, which includes a mobile app, Web GIS, and web application, a computational modeling and simulation study was conducted at a university with a bus transportation service operating in the urban and peri-urban areas of the municipality of Villavicencio, Meta (Colombia). The study area is located between coordinates 4.06° and 4.15° north latitude and -73.56° and 73.68° west longitude, covering an approximate area of 85 km². The experimental quantitative evaluation technique used involved computational modeling and simulation. Data on routes, buses, and bus stop arrival rates, among other factors, were based on consolidated information from 2018 to 2019, prior to COVID19 pandemic when bus route service was suspended.

This research complied with the provisions of Colombia's Statutory Law 1581 of 2012 on the protection of personal data and the Higher Education Agreement 007 of 2025 of University of Los Llanos, which establishes the university's policy on personal data processing and protection. Finally, the information provided voluntarily and collaboratively (crowdsourced) by users of the mobile application was anonymized in accordance with the international standard ISO/IEC 20889.

Subsections 3.1 and 3.2 below detail the development of the information system for recording and displaying georeferenced data on bus stops and routes, as well as user trips to and from university (Web GIS and mobile app), while Subsection 3.3 details the agent-based modeling and computational simulation process of the university's bus transportation system for subsequent analysis.

### *3.1. Web-based Geographic Information System for recording stops and routes*

Web GIS was developed, such as the mobile app, using an adaptation of the agile software development methodology Feature-Driven Development (FDD) (Palmer and Felsing, 2002), following these sequential stages: i) develop overall model, ii) build feature list, iii) plan by feature, iv) design by feature, and v) build by feature.

#### Develop overall model

During this initial phase, the basic system information was gathered and consolidated through four working sessions with the university's transportation system administrator, aimed at identifying the operational structure of the bus transportation system. As a result, the fundamental domain entities were defined for both the base design of the database's entity-relationship (ER) model and the class structure. These defined entities were users (students, faculty, and staff), drivers, buses, routes, stops, schedules, services, and trips. Ten routes were characterized, and the service schedules were tabulated. To support this model, technologies based on open-source software and open standards were selected: PostgreSQL/PostGIS for spatial database management due to its high performance and low cost; GeoServer for geographic data interoperability via Web Feature Service (WFS) protocols; Django as a web development framework due to its robust security; and OpenLayers with QGIS for dynamic map visualization and editing, ensuring a scalable system free from the licensing restrictions of proprietary tools.

#### Build feature list

As shown in Figure 1, two main Web GIS applications were defined: (i) the publicly accessible Web application for unauthenticated users (students, faculty, and the general public), for viewing bus routes and their stops to and from university via interactive maps; and (ii) Web administrator, with restricted access requiring authenticated users to log in for comprehensive management of the information system through create, read, update, and delete (CRUD) operations on bus stops, buses, segments, routes, schedules (services), users, and application groups, as well as statistics on travel times and number of users, by route, date, and time. During this phase, the functional requirements, as well as non-functional requirements such as usability, security, and maintainability, were consolidated into a list of identified features, including the following: access to both Web application and Web GIS administration application (authentication); map interaction through display, minimization, enlargement, export, zoom control, and full-screen mode; recording and management of routes, stops, segments, buses, drivers, services (schedules), trips, and journeys (trajectories); and display of stops and routes (to and from university) on the maps.

### Plan by feature

In this phase, the identified functionalities were grouped according to their operational purpose, and priorities were established to structure the development and implementation schedule, giving priority to security and data infrastructure modules. This planning resulted in the following four groups of functionalities:

- Access to Web GIS, which includes domain configuration and security protocols for authenticating the administrator's web application.
- Information management operations (CRUD), which form the dynamic core of the system by enabling the administration of users, routes, stops, segments, buses, and drivers, as well as the scheduling of services (timetables) and tracking of routes, trips, or georeferenced trajectories.
- Interaction with maps, focused on managing the user interface for map visualization and navigation using zoom in and zoom out tools, full-screen mode, and map export.
- General interaction with the Web GIS system, which integrates the display of route directions (to and from university), control of active layers, and window management.

### Design by feature

In this phase, we began by designing prototypes (mockups) of the Web GIS user and administration interfaces using Balsamiq (Figure 2), including individual and combined views of routes and stops, as well as a full-screen view showing all routes. A standardized three-character naming convention was established for route names based on the final destination (e.g., BCN, CNT, PRF), as well as for stops (e.g., VLC-H, UNC-D) and the segments comprising them, indicating the direction—from (D) or to (H) the university (e.g., MDD-CGT-H, CTM-MTC-D). This was done to facilitate the management and identification of each component in the university's transportation system, in addition to its description in natural language.

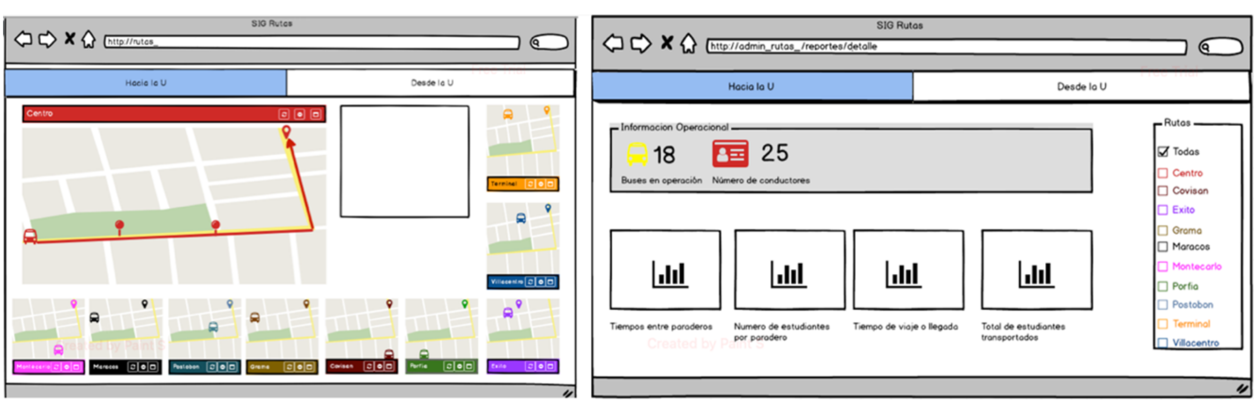


**Figure 1.** User interface examples of Balsamiq mockups for displaying routes (routes and stops) on interactive maps (left), and of the administrator interface with operational information and usage statistics over time (right).
***Note:*** Own elaboration.

The MER was supplemented and structured with a total of thirteen tables to store information on users, drivers, buses, services, routes, georeferenced trajectories, and route composition through the use of containers (bags) of data structures for stops and segments, to assemble segments from sequences of two consecutive stops and assemble routes from two or more segments, thereby avoiding data redundancy and duplication of geographic data. Finally, an API architecture was designed for bidirectional communication between the server and client applications. This design allows the web or mobile client to consume GeoServer's geographic services (routes, segments, and stops) for visualization, while the mobile application sends user location data to store and process route trajectories and service times in Web GIS, for subsequent analysis and monitoring in the administrator web system.

#### Build by feature

In this final phase, the technical implementation and programming of the Web GIS system components were carried out, beginning with the georeferenced registration of bus stops and routes using an open-source tool, QGIS. The spatial information for bus stop locations, including their geographic coordinates, and the lines for the routes was integrated into a PostgreSQL database using the PostGIS extension to ensure the persistence of spatial geometries. To enable data interoperability, GeoServer was configured under the Web Feature Service (WFS) standard, using GeoJSON as the exchange format. Additionally, filtering was implemented in the Django REST Framework API web services on the server side to minimize the processing load on the client and optimize Web GIS response times. The applications were implemented in Python using the Django framework in accordance with the consolidated list of features and the MVT design pattern for displaying maps with routes to and from university.

The information was visualized by accessing GeoServer services through OpenLayers library in JavaScript, implementing specific functions for loading vector layers that enable the rendering of routes and bus stops in the web browser. Finally, the web administrator interface was developed, a robust management dashboard that enables CRUD operations on all system entities (buses, drivers, routes, and schedules). This process allows the travel paths captured by users via mobile application to be visualized in an anonymous and collaborative manner for analysis.

### *3.2. Mobile application for collaborative bus trips tracking*

The mobile application, as well as the Web GIS, was developed using an adaptation of the FDD agile software development methodology, following the stages outlined below.

#### Develop overall model

This first phase focused on the conceptual design of a mobile application as a means of capturing data for the university's bus transportation information system through crowdsourcing. It was determined that the mobile application should act as a bridge between the device's GPS sensor and the Web GIS, establishing a hybrid architecture based on the Ionic and Angular frameworks, given their ability to support multi-platform deployment (Android and iOS) and their ease of integrating geospatial services. It was determined that the application's scope would revolve around three main entities: an institutional user (verified via email), a user's trip route (as an active session from origin to destination), and the trajectory (as a sequence of geographic points over time). To address the challenge of intermittent signal coverage along routes, a scheme was proposed to ensure routes persistence and data availability in scenarios with limited connectivity through a local database, ensuring that the logical design allows for data storage on a mobile device for subsequent synchronization with Web GIS.

#### Build feature list

In this phase, the overall model and the main requirements of the mobile application were taken into account to specify the following list of features by module: (i) Access management, which includes registration with an institutional email address, secure login, and password recovery; (ii) Data capture and reporting, which allows users to view their current location, select routes and directions (to or from university), and enable or disable the transmission of geospatial location data in real time during the journey; (iii) History module, allowing the user to view and filter previous routes; and (iv) Settings and security, covering password changes, mobile application's terms and conditions of use, and control of technical hardware parameters such as GPS activation, data usage, or time interval for data transmission, within the framework of distributed open collaboration (crowdsourcing).

### Plan by feature

In this third phase, identified functionalities were prioritized and arranged in chronological order to establish a logical deployment structure. The planning was organized into four functional groups, prioritized according to the list of functionalities in their respective order based on their criticality and dependency on the requirements:

- Access and security management: Defined as the core component, focused on authentication via institutional email to ensure data validity.
- Geographic data acquisition and recording: This is the component with the highest operational priority, in which integration was planned with the Web GIS backend API and geographic server (GeoServer), enabling the use of web services to obtain routes, stops, itineraries, and record trajectories over time (coordinates and timestamps).
- History and local storage: Focused on data persistence using a local database on a mobile device (e.g., SQLite), allowing the user to view their previous routes asynchronously as well as providing temporary backup for anonymous synchronization with Web GIS.
- Settings and information: Includes tools for adjusting time intervals of spatio-temporal recording of users' routes during active journeys, as well as managing hardware permissions for use of the device's mobile data or GPS to send data to Web GIS, and information on the terms and conditions of use.

### Design by feature

During this phase, technical specifications and detailed design of components that integrate the mobile application in accordance with established functional groups (Table 2), based on a hybrid architecture using the Ionic and Angular frameworks. A key aspect of this stage was the design of a MER model with three entities (user, trajectory, and journey) for the local SQLite database, which ensures the persistence of routes and user-provided information even without an Internet connection.

In addition, the user experience (UX) was designed with a focus on minimalist ease of use, featuring interfaces for institutional user registration and login, as well as a geospatial dashboard (map). Finally, integration with external web services was designed by mapping specific endpoints, ensuring that data exchange between the mobile device and the backend server under the REST protocol is seamless and adheres to user-configurable time intervals to optimize hardware resource consumption.

**Table 2.**
Description of mobile application's features.

| Feature | Description |
|---|---|
| Access and security | |
| Registration | This feature allows users to register for the mobile application; to do so, users must have an institutional email address. |
| Sign in | This allows users to log in to the mobile application using their previously registered institutional email address and password, so they can report and view their data. |
| Password recovery | If the users forget their password, they can reset it by entering the institutional email address they used to register. |

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| Feature | Description |
|---|---|
| Acquisition and recording of geographic data | |
| Routes | Show the user their current location, allowing them to select a route and indicate whether they are traveling to or from university to report their location data. |
| History and local storage | |
| My journeys | Allow you to keep a record of your journeys, displaying information such as route, whether it is to or from university, as well as journey's date and time. |
| Settings and information | |
| Change password | Allow users to change their password for the mobile application. |
| Terms and conditions | Users can view the terms and conditions of use for the mobile application at any time. |
| Configuration | Users can choose whether to allow the mobile application to use GPS, access their mobile data plan, and set the time interval at which information is reported. |
| Exit | It allows users to log out if necessary. |

***Note:*** Own elaboration.

### Build by feature

This phase involved implementing the modules according to the specifications for each set of functionalities, organized within the Ionic framework project in the src folder, where the assets subfolder was used for multimedia resources and the app and pages subfolders were used to separate the logic and user interface for each module.

The technical implementation involved programming the pages component controllers to manage the GPS lifecycle and web service usage. Local storage logic was implemented using the SQLite database via the cordova-sqlite-storage plugin, and network services were integrated to enable asynchronous data transmission at user-configured intervals. The process concluded with the code compilation, dependency management via the Node Package Manager (npm) for successful installation on a mobile device, e.g., Android 4.0 or higher

Through a mobile application interface, in addition to logging in, signing up, and recovering a password, you can search for available routes (to and from university), start or stop the collection and transmission of geospatial data during a trip, view the history of trips made by the user to and from university, as well as additional options that allow users to change their password, configure permissions for GPS and mobile data use, and set the time interval for collaborative data submission (crowdsourcing), review the app's terms and conditions, or log out, as shown in Figure 3.

## *3.3. Agent-Based Modeling and Simulation of bus transportation system*

The computational modeling and simulation study of bus transportation system was conducted following the ODD protocol (Overview, Design Concepts, Details) (Grimm, et al., 2006), to describe, structure, and document the model using agent-based simulation (ABS) (Wilensky and Rand, 2015). To this end, objectives, entities, state variables, and main processes were defined (Overview); the agents' decision-making and adaptation mechanisms were established (Design Concepts); and the parameters, input data, and initialization procedures were described (Details). For implementation, a computational simulation software AnyLogic was selected because it supports hybrid simulation paradigms, allowing the integration of agent-based and discrete-event modeling within a GIS environment, which was essential to represent both stochastic passenger arrivals and the spatial behavior of buses using georeferenced data from the Web GIS platform.

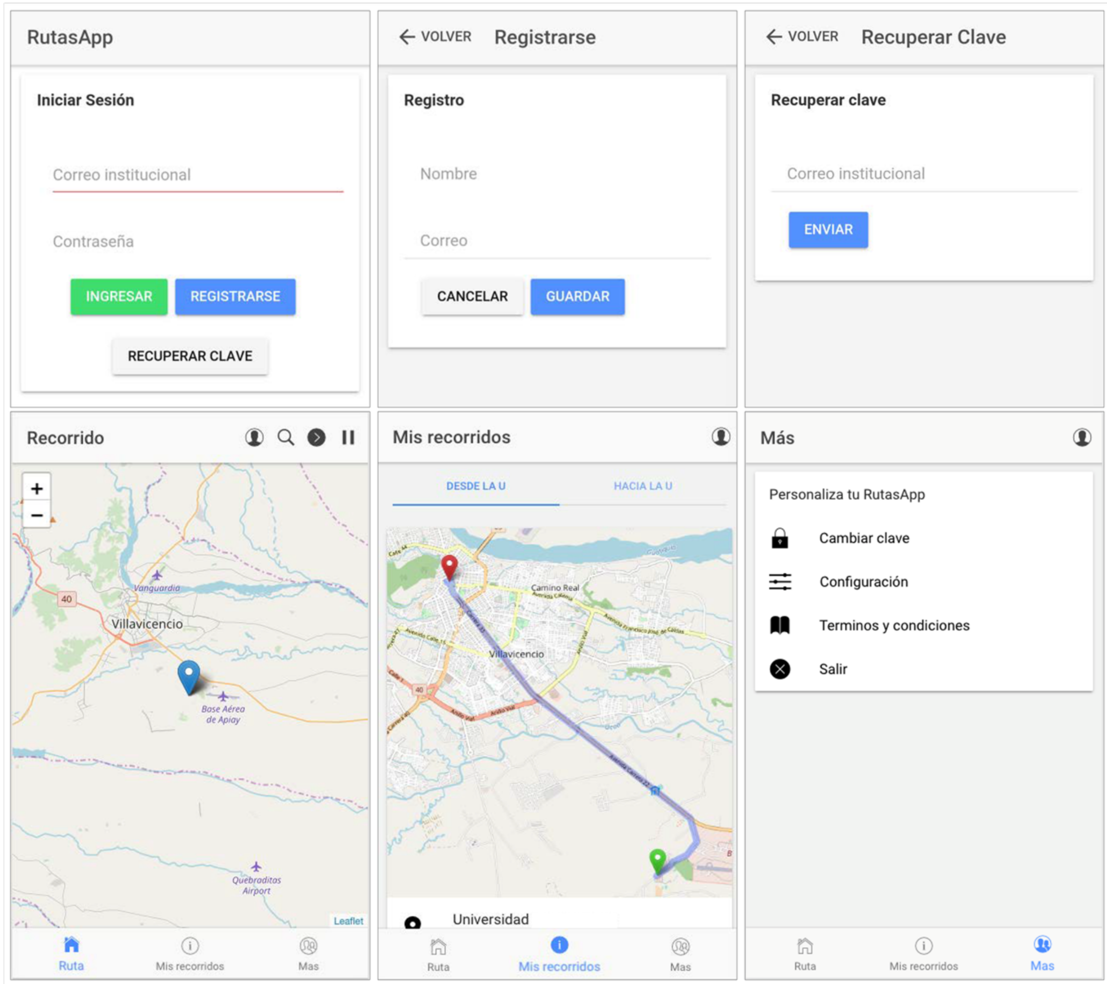


**Figure 3.** Mobile application. Interfaces for sign in, registering, and password recovery (top); route search and selection; starting or stopping the transmission of journey data to or from university; journey history; and settings or additional options (bottom).
***Note:*** Own elaboration

## Overview

The model's objective is to represent and analyze the behavior of the university's bus transportation system by simulating the stochastic demand dynamics of users (students, faculty, and staff), bus operations on multiple routes, and interactions with road segments and bus stops. The model seeks to identify imbalances between supply and demand, evaluate waiting times, travel times, and bus and stop occupancy to support decision-making. Georeferenced data from Web GIS (stop locations, route maps, schedules, and collaborative trajectories captured by a mobile application) serve as input to calibrate and validate the model.

One type of agent and two environmental entities were established. Buses in the transportation system were defined as agents. For simplicity, different types of transportation system users (students, faculty, and staff) were grouped together and were not treated as agent entities; instead, the events of users arriving at bus stops were modeled as random variables. Finally, the decision was made not to consider drivers as another type of agent; therefore, they are implicitly represented directly by buses. The bus stops and routes were established as environment entities, considering that a route is a sequence of segments and that users arrive at the bus stops to board buses bound for their destination, which is another bus stop. The state variables considered include a total number of passengers transported over time, the number of passengers transported per route, the total number of passengers waiting at bus stops, and the number of passengers on each bus, as well as the states of the passengers (at origin stop, on bus, at destination stop) and buses (start of trip, at stop, in transit, end of trip). The spatial scale of the simulation covers the urban area of Villavicencio city, based on spatial boundaries of the routes and georeferenced stops. For simplicity, a temporal scale was set such that one simulation step (tick) corresponds to one minute. The simulation horizon corresponds to route's operating hours (service schedule).

For the process overview and scheduling, the following sequence of processes was established: (i) Generation of users arrivals at bus stops based on Poisson probability distributions, with the arrival rate ($\lambda$) estimated according to collected data; (ii) Movement of buses along route segments, considering an average speed of 37 km/h for the routes based on data from the mobile application; (iii) Boarding and alighting of users at bus stops, based on the maximum bus capacity of 40 passengers; (iv) Updating of user and bus state variables; (v) Output performance metrics.

### Design concepts

The basic principles of the model are based on queueing theory and principles of stochastic transportation systems. Users demand follows Poisson probability distributions, with the arrival rate ($\lambda$) adjusted based on collected data. Urban traffic introduces uncontrollable variability in bus travel times; therefore, the model is based on an average bus speed of 37 km/h for each route, calculated using data collected from the Web GIS statistics module and the mobile application. System performance metrics emerge from the interactions between users arriving at stops and buses traveling along routes picking up and dropping off users. They are not explicitly programmed but result from collective dynamics and are therefore calculated for system analysis.

It is assumed that users follow the first-come, first-served (FIFO) policy at the bus stop based on the stop's capacity, boarding the first available bus according to the available spaces at the stop without adjusting their behavior, with the goal of minimizing their total travel time. Bus agents follow their assigned route and schedule every two hours starting at 5:15 AM without active optimization or autonomous adaptation. The model does not incorporate adaptive learning or predictions. The Poisson probability distributions associated with user arrivals at each stop are fixed, calibrated for the selection of their respective user arrival rate parameters ($\lambda$) using historical data from the Web GIS and mobile application. Interaction between agents occurs exclusively at bus stops: buses detect vehicle occupancy relative to their maximum capacity of 40 and the number of users waiting at the stop to decide whether to stop, while users detect the bus's arrival and its availability of space for boarding. Users who are unable to board due to maximum capacity accumulate waiting time while waiting for the next bus, which serves as a performance metric.

The established output variables, or performance metrics, are: total number of trips completed (to and from university), total number of passengers transported, total number of passengers who waited, historical average occupancy rate, average travel time, average waiting time, total number of trips per route, total number of passengers transported per route, occupancy rate per route, average waiting time per route, average travel time per route, total number of trips per bus, total number of passengers transported per bus, occupancy rate per bus, average waiting time per bus, and average travel time per bus.

### Details

Bus route segments and stops are initially loaded into AnyLogic using data stored in the Web GIS platform (PostgreSQL/PostGIS) and exported by the geographic server (GeoServer) in .shp format for route segments and .csv format for stop coordinates (latitude, longitude, and route code), respectively. Similarly, bus service schedules (timetables) by route are initialized starting at 5:15 AM, along with bus departure points and the parameters of the Poisson probability distributions based on the arrival rates ($\lambda$)

of passengers at the bus stops. There are no users in the system at time t=0, and their generation begins at 5:00 AM with the first activation of the model for their arrival at the bus stops, awaiting the scheduled start of bus service at 5:15 AM.

The model uses three sources of input data: geospatial data from Web GIS regarding the locations of bus stops; georeferenced route segments and routes exported from Web GIS; operational data on schedules (services), bus capacity per route, and number of available buses; and data collected on the distribution of passenger arrivals at bus stops, by route and direction at different times based on data collection and statistical records from the Web GIS and the mobile application via crowdsourcing. The submodels used include one for generating the demand of users arriving at each bus stop as a Poisson process with a probability distribution and associated parameters based on collected data.

#### Model calibration and validation

Model calibration was carried out by adjusting input parameters to reproduce the operational conditions of the university's bus transportation system as observed on data collected during 2018–2019, prior to the suspension of service during the pandemic of COVID-19. Three main sources of empirical data were used for this purpose. First, bus stop locations and route geometries were extracted directly from the Web GIS platform (PostgreSQL/PostGIS and GeoServer), ensuring that spatial representation of the model corresponds to current system infrastructure. Second, average bus travel speeds were calibrated at 37 km/h based on the average speed of the statistical module of Web GIS, which aggregates georeferenced travel data collaboratively collected through a mobile application by route users. Third, passenger arrival rates ($\lambda$) at bus stops were estimated by fitting probability distributions to field data collected at 12 representative bus stops across three routes, with a minimum of 50 observations per bus stop consolidated in Web GIS. The resulting distributions were used to parameterize the passenger arrival process at each stop in the simulation model.

Model validation was approached through two complementary strategies. First, internal statistical validation was performed by executing 30 independent simulation replications and computing 95% confidence intervals for the main performance metrics. Low dispersion could confirm the numerical stability and replicability of the model, consistent with the convergence criteria recommended for stochastic simulation models. Second, face validity was assessed by contrasting the model's aggregate outputs with the known operational parameters of the system: the simulated demand coverage rate and periodicity of load peaks was found to be coherent with service schedules and structural demand patterns reported by the transportation system administrator and documented in the theoretical background. The qualitative consistency of these outputs with the empirical evidence available constitutes a reasonable basis for accepting the model as a valid representation of the system's operational behavior under the simplifications adopted, which are discussed in section 5.

## 4. Results

### *4.1. Geospatial recording and structuring of bus routes and stops*

According to information provided by the administrator of university's bus transportation system, there are 10 routes in each direction (to and from university), for a total of 20 when accounting for the full round trip. It was also noted that some routes vary in their paths depending on schedule; therefore, for some of these routes, there is more than one path in a given direction, resulting in a total of 25 routes. Service operates from 6:00 AM every two hours, covering class periods through the final block from 4:00 PM to 6:00 PM. Subsequently, Google Earth was used to precisely locate each bus stop on a map and obtain its geospatial coordinates (latitude and longitude), as illustrated in the example in Figure 4 for the BCN-CNT1 route. This process was repeated for each route and bus stop, resulting in a total of 134 bus stops.

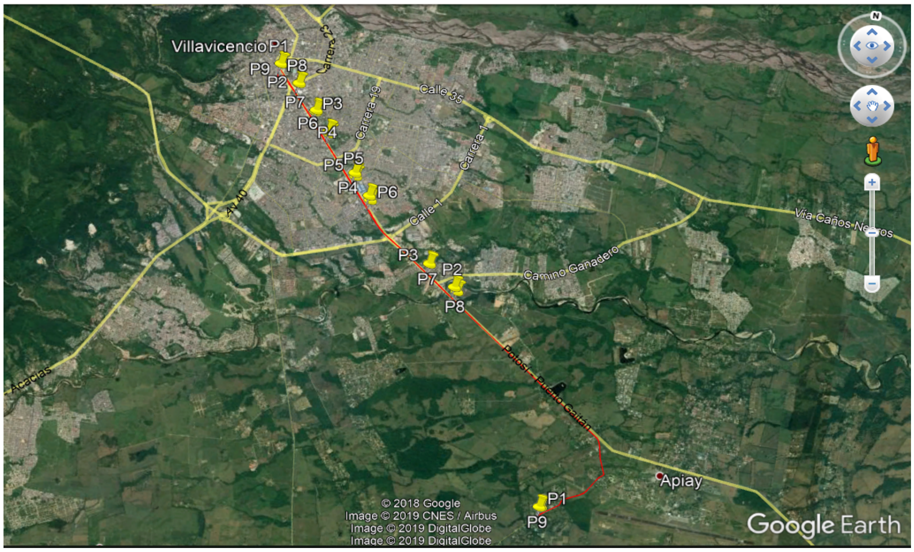


**Figure 4.** Example of bus stop locations along the BCN-CNT1 route on Google Earth.
***Note:*** Own elaboration

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Using QGIS, bus stops and route segments were created in geospatial format, with each segment representing the path connecting two adjacent bus stops in one direction Figure 5. This information was stored in geospatial format in the database using the PostGIS extension for PostgreSQL in Web GIS.

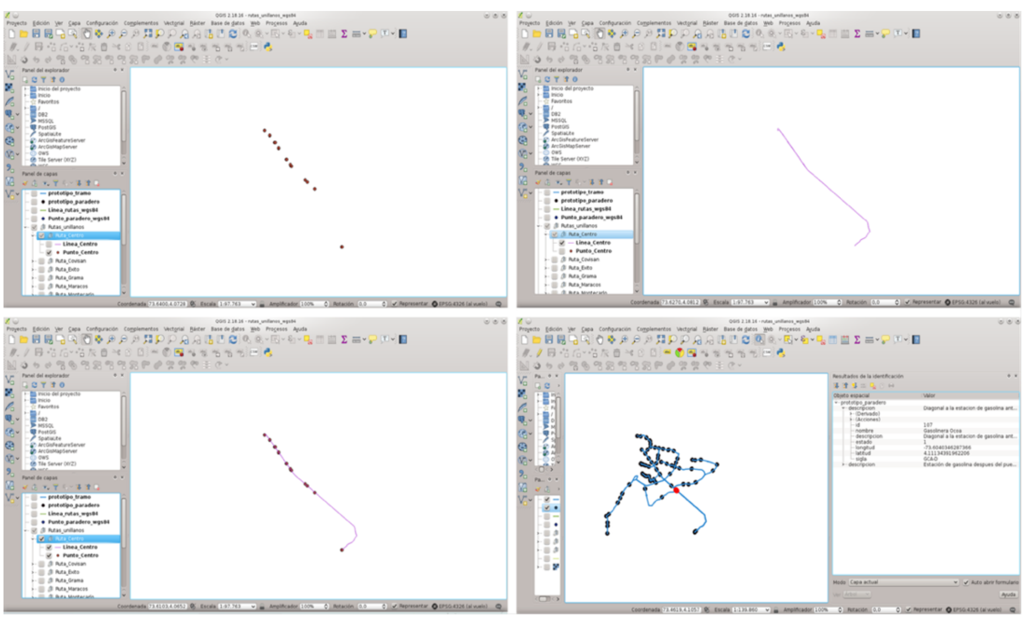

**Figure 5.** Layers showing bus stops (top left), route segments (top right), and a combined layer of bus stops and route segments (bottom left) for the BCN-CNT1 route, and of all stops and route segments in QGIS with their attributes (bottom-right).
***Note:*** Own elaboration

### *4.2. Web GIS platform deployment: geospatial services, map visualization and system administration*

Once GeoServer was deployed, a workspace and a geographic data store were configured, along with a connection to a PostGIS-type database for storing data organized into layers for publication and access, such as bus stops and route segments previously created in QGIS (Figure 6).

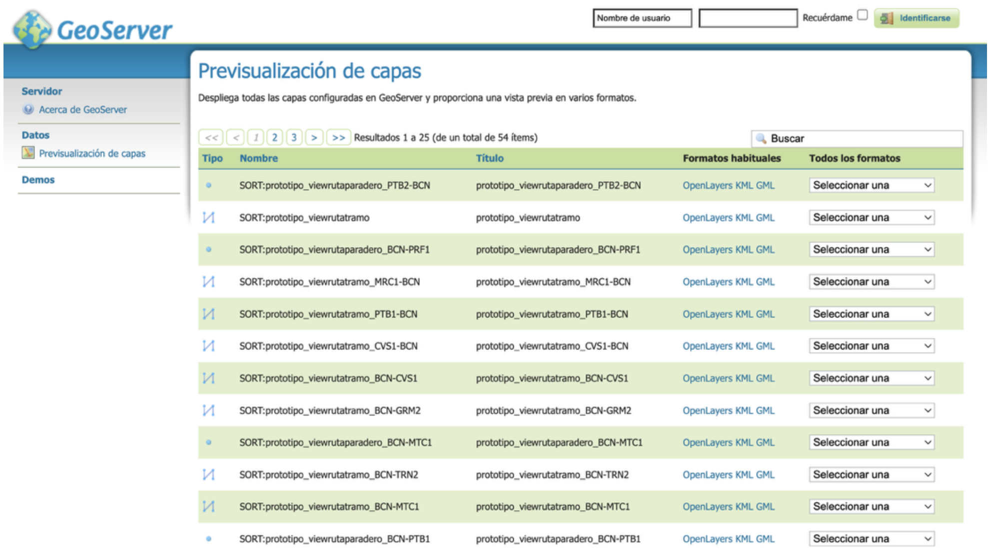


**Figure 6.** Interface of layers previously configurated in GeoServer, displayed via Web GIS and available in various file formats for download and viewing.
***Note:*** Own elaboration.

Figure 7 shows a layer preview of the bus stops and route segments in OpenLayers format. In this interface, you can select one or more bus stops. Additionally, the bottom section displays information associated with the selected bus stop. GeoServer web services are accessed via JavaScript, using the OpenLayers library to load and manage geospatial data. Additionally, specific functions were developed to facilitate the integration of components needed to build route maps, including the loading of route segments, stops, and sets of these elements per route, using the GeoJSON format. This approach enabled the implementation of features for generating route maps, assigning the corresponding layers of stops and segments to base maps such as OpenStreetMap (OSM) or Bing Maps for rendering and display. Furthermore, the LayerSwitcher component was integrated, allowing users to control the display of different layers and routes, as illustrated in Figure 8. Once the map-building functionality described above was implemented, it was integrated to allow users to load individual routes or all routes independently within the main interface for viewing, interacting with, and using them in the public web application at https://sort.unillanos.edu.co/, as shown in Figure 9.

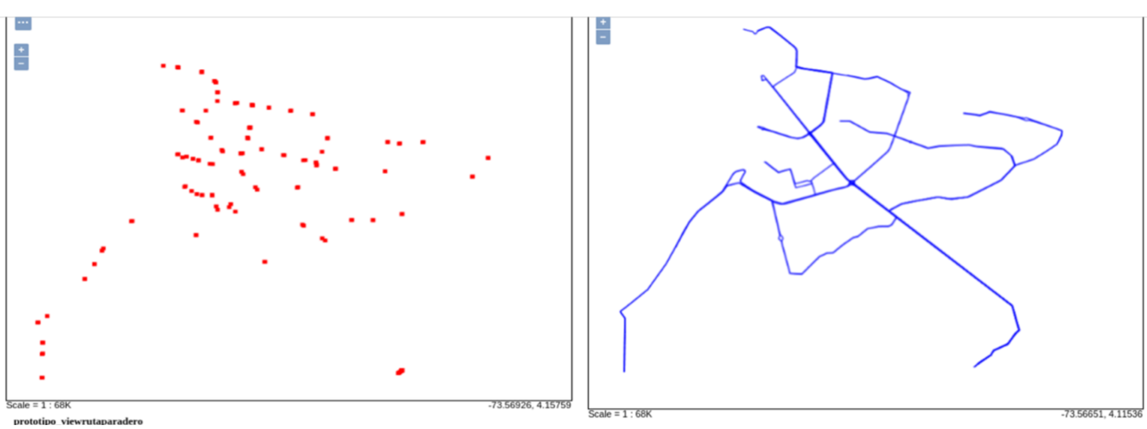


**Figure 7.** Layer preview of the bus stop layer (left) and route segments (right) in OpenLayers format.
***Note:*** Own elaboration

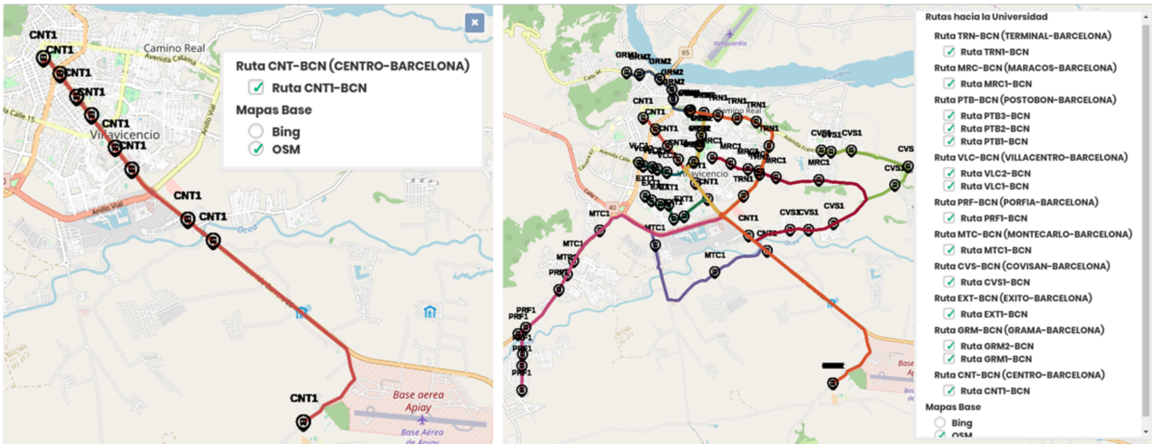


**Figure 8.** Results of the use of map-building services for the university, both for the CNT1-BCN route (left) and for all routes with their respective stops (right).
***Note:*** Own elaboration

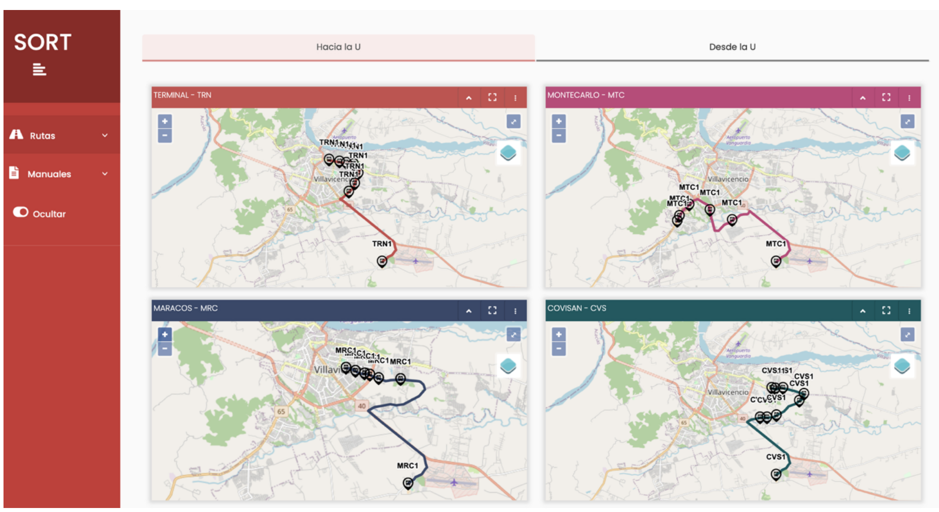


**Figure 9.** Web application of public access for the university's bus transportation system.
***Note:*** Own elaboration

Figure 10 shows the interfaces of the web application for administration of the university's bus transportation system, which requires authentication. The frontend was developed to interact with the API endpoints implemented using the Django REST Framework, enabling comprehensive management of multiple system entities. These functionalities include the creation of users and user groups, as well as the registration and editing of buses, trips, stops, segments, trajectories, routes, schedules, and the relationships between route–segment and route–stop. Additionally, the system displays key performance indicators (KPIs), such as number of buses, drivers, routes, stops, and active students. These indicators are fed, in part, by data collected through a mobile application based on crowdsourcing, as well as by information recorded directly in the system, which enables analysis and generation of operational statistics.

### *4.3. Agent-based model implementation and experimental setup in AnyLogic*

Finally, the agent-based computational simulation model was implemented in AnyLogic, integrating geospatial information on bus stops and routes stored in GeoServer, bus travel times obtained from Web GIS statistics module for speed estimation, and data collected in the environment for estimating user arrival rates at representative bus stops.

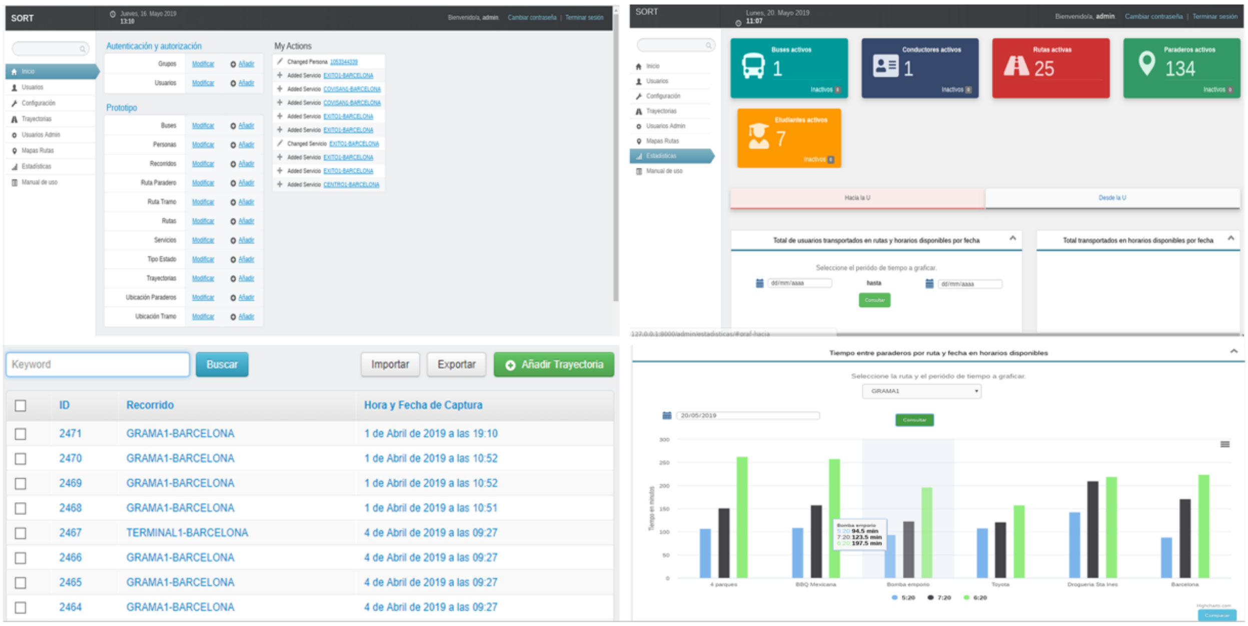


**Figure 10.** Web application for the administrator of the university's bus transportation system. For registering and editing system elements and actors (top left), KPIs for key elements (top right), routes anonymously stored by mobile app users via crowdsourcing (bottom left), and visualization of the statistics module (bottom right).

***Note:*** Own elaboration

Since the transportation system comprises 10 routes originating at different points in the city and heading to university, and 10 routes in the opposite direction, for a total of 20 routes, simplification criteria were applied to reduce the model's complexity without compromising its representativeness. First, five time-based variants of existing routes were discarded (four heading towards university and one in the opposite direction), since their paths and distances did not differ significantly from the base routes. Second, only the stops corresponding to one direction of travel were retained, considering that the spatial separation between stops in the opposite direction was minimal and did not significantly affect the simulation results. As a result, the model includes 71 stops. Similarly, the number of 10 buses corresponds to the same number of routes, with one bus assigned per route for services during the simulation period, starting from the origin of each route and heading towards university at an average speed of 37 km/h. This speed was determined by considering the estimated average speed and range of buses on the different routes, based on data from Web GIS statistics module collaboratively provided by the mobile application.

To set up the simulation environment in AnyLogic, only the consolidated route segment layers, representing the complete path of each route, were loaded. These were exported from GeoServer in shapefile (.shp) format, along with bus stop layers and their associated attributes in Excel format, which were generated from .csv files exported from the same platform. To model user's generation at bus stops, a Poisson distribution was assumed as the arrival process, with an arrival rate (l) estimated from data collected at representative bus stops and starting points of each route. The values of l ranged from 0.196 to 1.291 users per minute, with a mean of 0.457, a standard deviation of 0.214, and a median of 0.400. The GIS map in AnyLogic was centered at coordinates 4.115° north latitude and −73.620° west longitude, at a scale of 1:65,000. The simulation time unit was set so that each simulation step (tick) corresponds to one minute. Regarding the time dynamics, the simulation begins at 4:50 a.m., with a 15-minute passenger generation period prior to the bus departure, occurring between 5:00 a.m. and 5:15 a.m., at which time the routes depart from their origin stop towards university. This user generation cycle repeats every two hours, corresponding to the service frequency interval and the two-hour academic block structure, between 6:00 AM and 4:00 PM. The last bus to university departs at 4:15 PM, with service to the university ending at 4:20 PM, leaving only the return trips of the buses on their respective routes to be completed.

For monitoring the simulation, graphs and tracking variables were incorporated to observe the system's behavior in real time through the following performance metrics: number of waiting passengers and passengers transported over time; overall bus occupancy rate over time; user distribution by route; individual occupancy rate for each bus; cumulative total of users transported and users who had to wait; cumulative waiting and travel times; total number of trips made and total number of trips to and from university. Similarly, the following data were stored in a .txt file: total number of trips per route, total number of users transported per route, occupancy rate per route, average waiting time per route, average travel time per route, total number of trips per bus, total number of users transported per bus, occupancy rate per bus, average waiting time per bus, and average travel time per bus. Figure 11 shows the implementation of the simulation model in AnyLogic, displaying the map with routes, bus stops marked as red dots, blue buses, and the corresponding graphs and monitoring variables used to track the behavior of the university's bus transportation system.

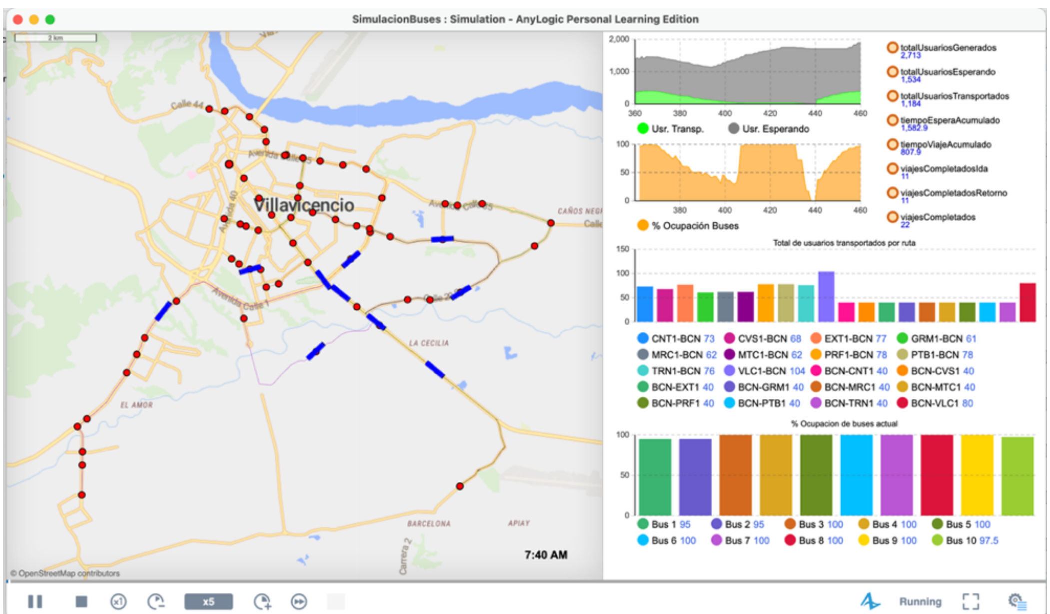


**Figure 11.** Implementation in AnyLogic of the university's bus transportation system for simulation and analysis.
***Note:*** Own elaboration

## *4.4. Experimental results of the agent-based simulation: system performance and operational imbalances*

For experimentation purposes, 30 independent simulation replications were executed covering the full daily service period from 5:00 AM to 6:00 PM. To ensure statistical independence across runs, each replication was initialized with a distinct random seed, so that the stochastic passenger arrival processes, modeled as independent Poisson processes at each stop, produced uncorrelated demand sequences. No warm-up period was required, as the simulation begins from a state of empty system at 5:00 AM, consistent with the actual operational start of the transportation service.

While simulations were running, monitoring graphs showed a recurring pattern every two hours of increased passenger arrivals at bus stops, as well as the total bus occupancy rate reaching its peak before arriving at university, while the minimum occurred shortly before starting a new route from the origin of each route towards university. While some routes arrive some minutes before the exact start time of classes, others arrive a few minutes later. Similarly, the tracking variables showed that approximately 80% of users arriving at their bus stops can board a bus to reach their destination. Table 3 presents the results of calculating the 95% confidence interval (CI) for the main performance measures, showing low dispersion of the sample standard deviation with an average waiting time of 11.32 minutes and an average travel time of 46.5 minutes, and an average total bus occupancy rate of 66.66%. This suggests the stability of the model. However, a more detailed analysis of the dispersion of performance measures by bus and route allows for the identification of certain peculiarities in the system's behavior.

**Table 3.**
Sample mean ($\overline{X}$), sample standard deviation ($S$), confidence intervals (CI) at the 95% significance level for main performance metrics after 30 simulation runs.

| Performance metrics | | S | IC |
|---|---|---|---|
| Total number of users transported | 4,427.06 | 35.51 | (4,413.80; 4,440.32) |
| Total number of users waiting | 1,075.2 | 32.44 | (1,063.08; 1,087.31) |
| Average waiting time (min) | 11.32 | 1.45 | (10.77; 11.86) |
| Average travel time (min) | 46.50 | 0.13 | (46.45; 46.55) |
| Average occupancy (%) | 66.66 | 0.52 | (66.46; 66.85) |

***Note:*** Own elaboration.

Figure 12 presents box plots of the performance metrics for each of the 10 buses: number transported users, percentage of occupancy, average waiting time for users boarding the bus, and average travel time. The plots highlight the variability in the system's operational dynamics depending on the bus and its associated route. In addition, Figure 12 presents box plots for the same performance metrics disaggregated by each of the 20 routes (10 to university and 10 back) whose behavior is consistent with that observed for the buses, given that each bus operates the same round-trip routes.

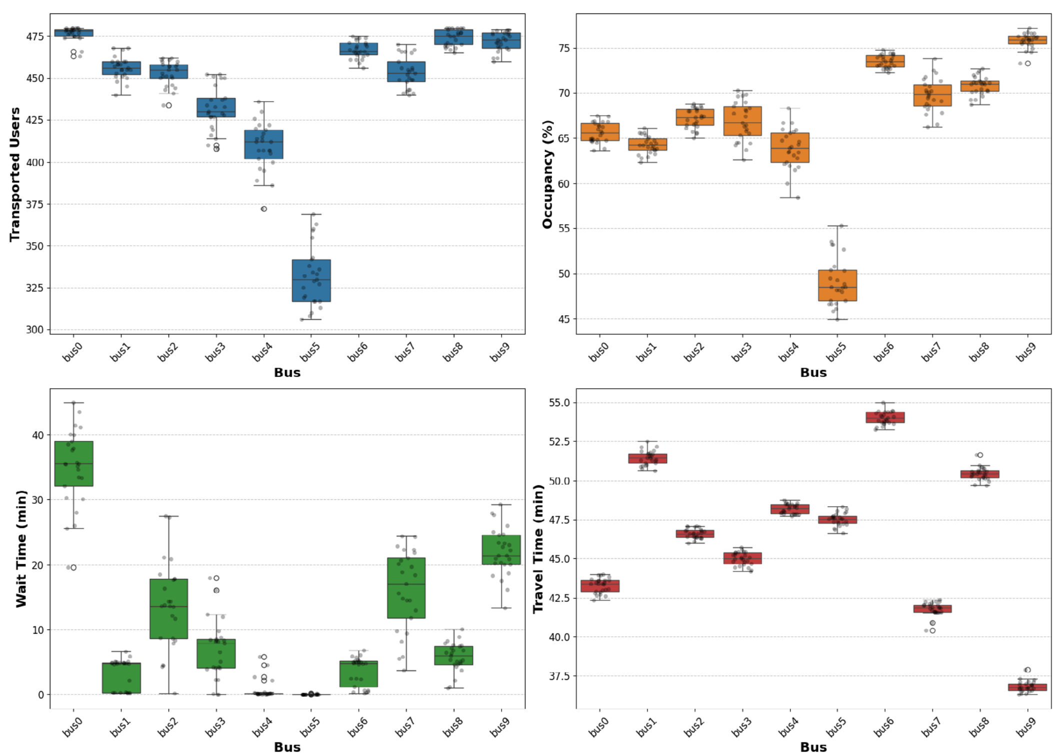


**Figure 12**. Box plots showing the variation in performance metrics for users transported, occupancy percentage, average waiting time, and average travel time for each of the 10 buses.
***Note:*** Own elaboration

A detailed analysis of Figures 12 and 13 reveals that buses 1, 7, 8, 9, and 10 (bus0, bus6, bus7, bus8, and bus9), associated with routes CNT1-BCN, PRF1-BCN, PTB1-BCN, TRN1-BCN, and VLC1-BCN, respectively, record the highest volume of users transported with relatively low variation between simulation runs. Conversely, bus 6 (bus5), corresponding to the MTC1-BCN route, has the lowest volume of users transported along with high variation. A similar pattern is observed in the occupancy percentage, with the distinction that bus 10 (bus9) achieves the highest value, exceeding 75%, with very low dispersion, while unit 6 (bus5) records the lowest value, around 50%, with considerably higher dispersion.

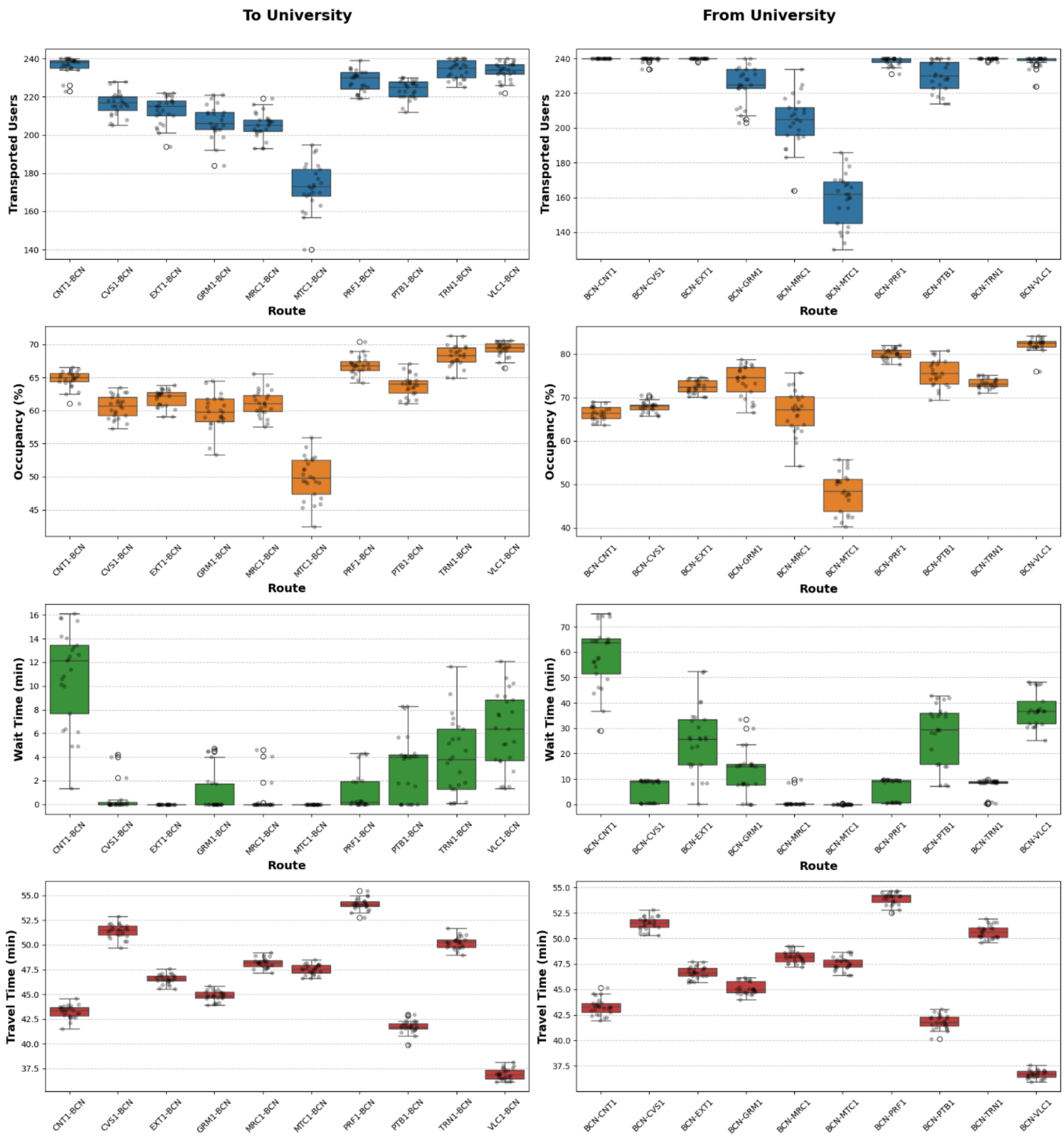


**Figure 13.** Box plots showing the variation in performance metrics for the number of users transported, occupancy percentage, average waiting time, and average travel time for each of the 10 routes to (left) and from university (right).

***Note:*** Own elaboration

## 5. Discussion

Results obtained from the integration of Web GIS, mobile application, and agent-based simulation model provide a detailed characterization of the operational behavior of the university's bus transportation system, offering quantitative evidence of its structural imbalances between supply and demand.

First, the overall stability of the model, as evidenced by the 95% confidence intervals showing low dispersion in average waiting times (11.32 min) and travel times (46.50 min), as well as in the average bus occupancy percentage (66.66%), is consistent with the findings of van der Spek et al. (2017), who report that ABS models of bus transportation systems converge toward stable distributions under conditions of periodic and stable demand. However, the variability observed in the total number of users transported and waiting time reflects the intrinsic stochastic nature of the arrival process, modeled for simplicity using Poisson distributions, a behavior widely documented in the literature on queueing theory applied to public transportation, as well as its problems of prolonged waiting times (Arif Khan et al., 2023), and overcrowding (Ceder, 2016).

Second, a breakdown of the analysis by bus and route reveals operational variations that are aggregated and obscured by the overall view of the performance metrics. The CNT1-BCN, PRF1-BCN, PTB1-BCN, TRN1-BCN, and VLC1-BCN routes, and their respective return travel, exhibit high user volumes, high occupancy percentages, and significant waiting times, indicating that these routes operate under conditions of partial saturation without being able to absorb the entire demand. This pattern is consistent with the findings of Arif Khan et al. (2023), who identify bus stop saturation as a direct consequence of the mismatch between service frequency and peaks in academic demand. Conversely, the MRC1-BCN and MTC1-BCN routes exhibit underutilization of capacity, evidenced by low occupancy percentages (~50%), minimal waiting times, and lower user volumes, suggesting that the current allocation of one bus per route is not efficient for this system as a whole. Rigidity in the fixed allocation of resources in university transportation systems can lead to redistributive inefficiencies that penalize routes with higher demand, unlike conventional transportation systems (Harrath et al. 2024).

It is worth noting that the operational patterns identified in this study such as partial demand saturation, route-level imbalances, and periodic load fluctuations aligned with academic schedules, have been reported in university transportation systems in high-income countries with well-established data infrastructures (van der Spek et al., 2017; Sai and Challapalli, 2024). However, the present study demonstrates that these patterns can be identified and quantified in a mid-sized Latin American city context using exclusively open-source tools, collaboratively collected geospatial data, and a simulation model calibrated without access to standardized transit data formats such as GTFS. This represents a methodologically accessible replication pathway for institutions in similar contexts, where proprietary infrastructure or standardized data pipelines are unavailable, contributing to the transferability of evidence-based transportation planning approaches to resource-constrained settings.

Third, the two-hour periodicity in user arrival rates, aligned with academic blocks, and the variation in travel times across routes, due to differences in distance and the number of stops, confirm that the system operates under a logic of periodic and non-uniform demand. This characteristic, also identified by (Harrath et al. 2024) in higher education transportation systems, suggests that variable-frequency strategies or dynamic reassignment of vehicles between routes could significantly improve equity of access to the service. From a methodological standpoint, the integration of Web GIS, crowdsourced mobile data and agent-based simulation in AnyLogic offers three distinctive advantages over approaches that rely on a single technological component. First, the use of collaboratively collected geospatial data as direct input for model calibration eliminates the dependence on dedicated sensing infrastructure, reducing implementation costs and making the approach replicable in institutions with limited technical resources, aligned with recent approaches that promote user participation as a data source for public transportation management (Chawuthai et al., 2023; Suresh et al., 2023). Second, the spatial explicitness of the model, enabled by the georeferenced stop and route data from Web GIS, allows performance metrics to be disaggregated at the route and bus stop level, revealing operational asymmetries that aggregate indicators would obscure. Third, the public web application provides an immediate operational output of the platform beyond simulation, offering a visualization tool directly usable by the university community.

However, several limitations constrain the representativeness of the model. The assumption of a constant average bus speed of 37 km/h across all routes and time periods does not capture the stochastic variability introduced by urban traffic congestion, which has been identified as a key source of unreliability in university transportation systems (Daganzo and Ouyang, 2019). Similarly, the consolidation of passenger arrivals into a single Poisson process per stop, without distinguishing between user types (students, faculty, and staff) or incorporating time-of-day variations within each two-hour block, simplifies the heterogeneity of demand in ways that may underestimate saturation at specific stops during peak minutes. Additionally, absence of a formal sensitivity analysis on the arrival rate parameters ($\lambda$) and the lack of an independent observational dataset for quantitative validation constitute methodological boundaries that future work should prioritize addressing. As a final limitation, the study does not include a comparative evaluation against alternative simulation paradigms such as discrete-event simulation or system dynamics, which is identified as a direction for future research to assess whether the route-level imbalances identified here would be equally detectable under less computationally demanding approaches.

Finally, the fact that approximately 80% of users arriving at bus stops can board a bus to reach their destination indicates that the system, despite its distributional inefficiencies, generally fulfills the function of providing access to education for most of its community. However, from the perspective of equitable access proposed by Tigre et al. (2017), Taylor and Mitra (2021), the remaining 20% represents a significant fraction of users who face effective barriers to access, with potential implications for punctuality and academic performance.

## 6. Conclusions

This paper presented the development and integration of a Web GIS, a collaborative mobile application, and a computational simulation model for analyzing a university's bus transportation system, thereby creating a comprehensive platform for the storage, management, and analysis of georeferenced information designed to support decision-making.

The main findings and contributions of this study were, first, the integrated architecture developed using open-source technologies such as PostgreSQL/PostGIS, GeoServer, Django, and OpenLayers, which proved to be technically feasible and functionally suitable for the recording, publication, and analysis of geospatial information on routes and bus stops, as well as for the collaborative and anonymous recording of travel routes via mobile devices in a real-world university setting. Second, the agent-based simulation model implemented in AnyLogic, calibrated with real data obtained from the platform, was able to statistically consistently represent the behavior of the transportation system, as evidenced by the low dispersion of the 95% confidence intervals in the global performance metrics after 30 simulation runs.

Third, the analysis broke down by bus and route revealed that the system has structural imbalances. The routes with the highest demand operate at near capacity, while routes such as MRC1-BCN and MTC1-BCN are underutilized, suggesting a need to review the fixed allocation of buses per route. Fourth, it was found that approximately 80% of users arriving at bus stops can board a bus to reach their destination. While this reflects broad service coverage, it indicates that 20% of users face access restrictions with potential consequences for their punctuality and academic performance.

Based on the findings of this study, three specific recommendations are directed at decision-makers responsible for university bus transportation systems. First, the reallocation of bus capacity between routes should be considered as a priority intervention: the structural imbalance identified between saturated routes, such as CNT1-BCN, PRF1-BCN, PTB1-BCN, TRN1-BCN, and VLC1-BCN, and underutilized routes, such as MRC1-BCN and MTC1-BCN, suggests that redistributing available buses or adjusting the one-bus-per-route assignment could improve overall system equity and efficiency without requiring additional fleet investment. Second, service frequency adjustments during peak academic demand periods, particularly during the first and last class blocks of the day, could reduce the average waiting time of 11.32 minutes and address the unmet demand affecting approximately 20% of users, for whom transportation currently constitutes an effective barrier to academic access. Third, the integrated solution developed in this study, comprising the Web GIS, a collaborative mobile application, and the agent-based simulation model, is recommended as an operational evidence-based planning tool, enabling transportation administrators to evaluate the impact of scheduling decisions, route modifications, or fleet reassignments prior to their implementation, thereby reducing the risk and cost associated with uninformed operational changes.

As future work, we propose, first, extending the simulation model to explicitly incorporate the variability of urban traffic using historical speed data by route segment and time slot, moving beyond the constant average speed approximation used in this study. Second, we propose exploring strategies for optimizing bus frequency and scheduling using search algorithms integrated into the simulation environment, with the goal of reducing wait times on congested routes without increasing the number of available buses or changing bus stops. Finally, the possibility of incorporating real-time data from GPS devices installed on buses, which would allow for a transition from a retrospective analysis system to one of real-time monitoring and decision-making integrated with the mobile application as a channel for communicating with the university community.

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### *Data Availability*

The authors declare that the article contains all the data necessary and sufficient for understanding the research.

### *Disclosure statement*

The authors declare that there is no potential conflict of interest related to the article.

### *Disclaimer*

The authors declare that the views, opinions, or interpretations expressed in the article are personal and do not represent an official position of their institutions.

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The manuscript was prepared and reviewed with the participation of all authors, who declare that they have no conflict of interest.

### *Co-authorship*

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