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Master's degree in Computational Social Sciences
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Master Thesis

"Modeling perceived urban insecurity: an empirically grounded agent-based simulation"

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Abstract

This thesis develops a novel methodological framework to simulate perceived insecurity in urban public spaces through an empirically grounded agent-based model (ABM), using Pamplona as a case study. The model integrates spatial features (crime proxies, lighting, youth presence), daily routines, and individual characteristics (gender, nationality, victimization) to reproduce how insecurity perceptions emerge and vary across contexts.

Statistical outputs from CATPCA and multivariate regressions inform agent behavior. Individual-level variation is central: agents differ in how they react to contextual cues depending on their profile, allowing the simulation of heterogeneous responses of insecurity. Validation combines input calibration, theoretical consistency checks, and sensitivity analysis focused on key parameters like crime weight and insecurity thresholds.

Beyond theoretical contributions, the model functions as a tool for both research and applied urban analysis. It supports hypothesis testing and scenario-based simulations, offering valuable insights into the social and spatial stratification of perceived insecurity for both urban planners and academic researchers.

Keywords:

Agent-based modeling; safety perception; urban simulation; model calibration; perceive urban insecurity; validation.

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1. INTRODUCTION

Insecurity in public spaces remains a key determinant of how individuals interact with the urban environment, affecting mobility, spatial inclusion, and social participation. Yet, subjective perceptions of insecurity often diverge from objective crime data: people may feel unsafe in statistically secure areas, while some high-crime zones provoke little fear.

Far from being just a subjective impression, perceived insecurity has concrete behavioral effects. It constrains mobility, limits access to services and reinforces socio-spatial inequalities. Vulnerable populations such as women, the elderly, or racialized groups, often adjust their routines to avoid certain spaces, even in the absence of direct victimization. For this reason, perceived insecurity has increasingly been reframed as a fundamental urban need, closely linked to psychological well-being, inclusion and the equitable right to the city (As Azevedo et al., 2021).

Therefore, perceived insecurity is a complex dynamic that is shaped not only by crime, but by an interplay of spatial cues, symbolic meanings, and social interactions. Poor lighting, visible disorder, or fear of harassment give rise to so-called *fearscapes* (Pain, 1997): urban configurations that trigger avoidance behaviors and deepen social fragmentation.

1.1. Why using an ABM? From static description to dynamic simulation

Traditional approaches to urban insecurity, such as victimization surveys, police statistics, or spatial correlation analyses have been instrumental in identifying broad patterns of victimization and fear. However, they face structural limitations: perceived insecurity is inherently relational and cannot be reduced to an individual-level account (Fileborn & O'Neill, 2021; Valera & Guàrdia, 2014). Moreover, these methods cannot capture the dynamic interactions between individual and contextual factors, nor simulate future scenarios. As Fraile (2007) notes, knowing crime rates or public opinion disaggregated by area is insufficient; what matters is capturing the interaction between perception, daily practices, and urban morphology.

In this regard, agent-based models (ABM) provide an innovative methodological approach that overcomes the static and descriptive logic of conventional tools. As Crooks et al. (2021) explain, ABMs allow researchers to represent urban phenomena as complex systems. In these models, simple rules define how individual agents behave and interact with others. When these individual actions are combined, they can give rise to complex patterns at the city level. This makes ABMs especially useful for studying how local decisions and interactions can produce unexpected or emergent effects at a larger scale. Therefore, ABMs are particularly suitable for studying phenomena such as perceived insecurity.

Beyond their explanatory potential, ABMs are also powerful tools for prospective simulation. They allow researchers and policymakers to test "what-if" scenarios and explore the potential effects of interventions before they are implemented. For example: *What happens if street lighting improves? What if youth gatherings are redistributed across the city? What if people's leisure routines change?* As noted by Izquierdo et al. (2020), ABMs can make the expected impacts of safety policies easier to understand, offering spatially explicit and intuitive visualizations that support more informed decision-making.

As Crooks et al. (2021) explain, a key strength of ABMs lies in their ability to simulate interactions between autonomous agents who differ in behavior, preferences, and experiences. These interactions (with one another and with the environment) can give rise to complex patterns that are not explicitly programmed but emerge through nonlinear processes. This makes ABMs especially suitable for studying relational and dynamic issues like perceived urban insecurity.

The model developed in this thesis does not attempt to reproduce reality exactly, but rather to offer a tool for exploring possible strategies. It allows perceptions of insecurity to emerge dynamically from the interaction of physical, social, and temporal elements. At the same time, it captures individual differences in perception: people in the same context may feel more or less unsafe depending on their gender, past victimization, or sensitivity to darkness.

1.2. Objectives

This study aims to develop and validate an empirically grounded ABM to simulate perceived insecurity in urban environments. The model integrates survey data, spatial indicators, and contextual parameters, allowing insecurity to emerge dynamically from the interaction between agents and their environment. Pamplona is used as a case study due to the availability of detailed and recent survey data and spatial information. To guide this process, a set of specific objectives were defined:

a. Theoretical and conceptual goals

- To contribute to the study of urban fear as a stratified, relational, and context-sensitive phenomenon, moving beyond simplistic or crime-centric interpretations.
- To model perceived insecurity as an emergent outcome of interactions between individual-level traits, like gender, victimization history or routine activity, and contextual factors, such as lighting, crime proxies or the presence of youth groups.

b. Empirical grounding and calibration

- To calibrate agent behavior using real survey data, combining regression-derived parameters with latent constructs, like the general insecurity index, and spatial crime indicators.
- To implement and test the model in a spatially explicit environment, integrating high-resolution GIS data from Pamplona to represent neighborhood-level variation, urban infrastructures, and simulate how urban spatial context shapes insecurity through interaction with agent routines and vulnerabilities.

c. Validation and analysis

- To evaluate the model's robustness and behavioral coherence through stochastic replication and One-at-a-Time (OAT) sensitivity analyses across key parameter configurations.
- To explore stratified patterns of perceived insecurity, focusing on gendered differences exposure-related variability, enabling the empirical testing of sociological hypotheses within the simulation.

d. Applicability and future use

- To explore stratified patterns of perceived insecurity, focusing on gendered differences of exposure-related variability, enabling the empirical testing of sociological hypotheses within the simulation. .

2. LITERATURE REVIEW

Recent research consistently shows that perceived insecurity is not merely a reflection of crime rates, but a multidimensional construct shaped by environmental, social, psychological, and emotional factors. For instance, Syropoulos et al. (2024) propose and validate a multidimensional model of perceived personal safety composed of three interrelated dimensions (feeling of safety, fear of crime, and safety confidence) each of which is linked differently to psychosocial outcomes such as life satisfaction, depressive symptoms, and institutional trust.

Empirical studies reinforce this perspective by illustrating how demographic characteristics and spatial familiarity influence individual experiences of perceived insecurity. As Fraile (2007) argues, relying solely on official crime statistics or police interventions is insufficient. It is equally important to consider the perceptions and emotions of individuals, as they ultimately shape the rhythms and nature of social life. The author proposes examining the issue through four complementary lenses: public opinion about insecurity, the blurred boundaries between crime and conflict (including attitudes toward specific places and social groups), social victimization, and finally, official crime data reported by the police.

These insights are echoed by theoretical contributions from feminist and human geography, which conceptualize fear as both socially constructed and spatially situated; this is what has been termed a *geography of fear* or *fearscapes*. For instance, Pain (1997) argues that fear is mediated by identity, embodiment, and spatial relations, generating *fearscapes* where certain groups (particularly women and racialized individuals) are subtly excluded through behavioral norms and spatial dynamics. Fileborn and O'Neill (2021) further show how street harassment reshapes public space by encouraging avoidance behaviors, thereby informally excluding individuals and reinforcing spatial inequalities.

The need for more dynamic and interactional models has led researchers to increasingly adopt computational approaches to capture these complexities. One of the most relevant contributions in this area is the ABM developed by Izquierdo et al. (2020), which simulates perceived insecurity in a Mexican informal settlement by combining urban metrics (such as visibility, surveillance, accessibility, and cohesion) with survey data and participatory mapping. Their study reflects a growing consensus on the situated and layered nature of safety perception[1] and the limitations of purely quantitative or crime-centered approaches. It also validates the use of ABM to simulate heterogeneous responses to complex spatial configurations.

However, this study did not fully integrate individual heterogeneity, spatiotemporal context and symbolic environments. he present project addresses this gap by proposing an ABM in which perceived insecurity does not exist as only as a fixed attribute but also emerges through agents' interactions with their environment, accumulated exposure, and socially meaningful cues. Agents vary in key traits (such as gender, sensitivity to darkness, and leisure patterns) and interact within an urban space shaped by lighting conditions, group presence, and daily routines. In doing so, the model offers a novel tool for exploring how insecurity evolves over time and

[1] Safety perception can be understood as the inverse of perceived insecurity; as insecurity increases, perceived safety decreases.

space, not as a linear response to crime, but as a relational and embodied process. This approach aligns with the evidence discussed throughout this section, which frames perceived insecurity as a multidimensional and stratified phenomenon resulting from the interplay between physical environments, social structures, and affective experiences.

2.1. Validation strategy

The validation of ABMs in social research requires careful attention to both theoretical grounding and empirical credibility. In the context of computational social science, three main methodological frameworks offer complementary strategies to address this challenge.

First, Fagiolo et al. (2007) highlight the importance of indirect calibration, especially in contexts where individual behavior is unobservable or difficult to measure: rather than aiming to replicate specific micro-level actions, the goal is to reproduce macro-level empirical regularities by tuning agent behaviors to reflect theoretically and statistically grounded patterns.

Second, Tesfatsion (2017) provides a comprehensive taxonomy of validation types tailored for ABMs. She identifies four key dimensions to evaluate the conceptual soundness and empirical relevance of ABMs:

- Input validation, ensuring that the data and assumptions used to set up the model are rooted in empirical reality.
- Process validation, which assesses the internal consistency and plausibility of agent logic with the real world.
- Descriptive output validation, which assesses whether the model can reproduce patterns we already know from the data used to build it
- Predictive validation, which evaluates a model's ability to forecast outcomes in new or future scenarios.

Third, Collins et al. (2024) differentiate between foundational and advanced validation strategies**.** Foundational methods include empirical grounding (like parameter calibration using real-world data) and dynamic validation (such as visual inspection of time-evolving simulation behavior). Advanced techniques such as bootstrapping, sensitivity testing, and replication analysis enhance credibility by quantifying uncertainty, checking for robustness, and identifying stable parameter ranges. These tools contribute to both the internal validity of the model and its external interpretability, especially in exploratory and policy-relevant applications.

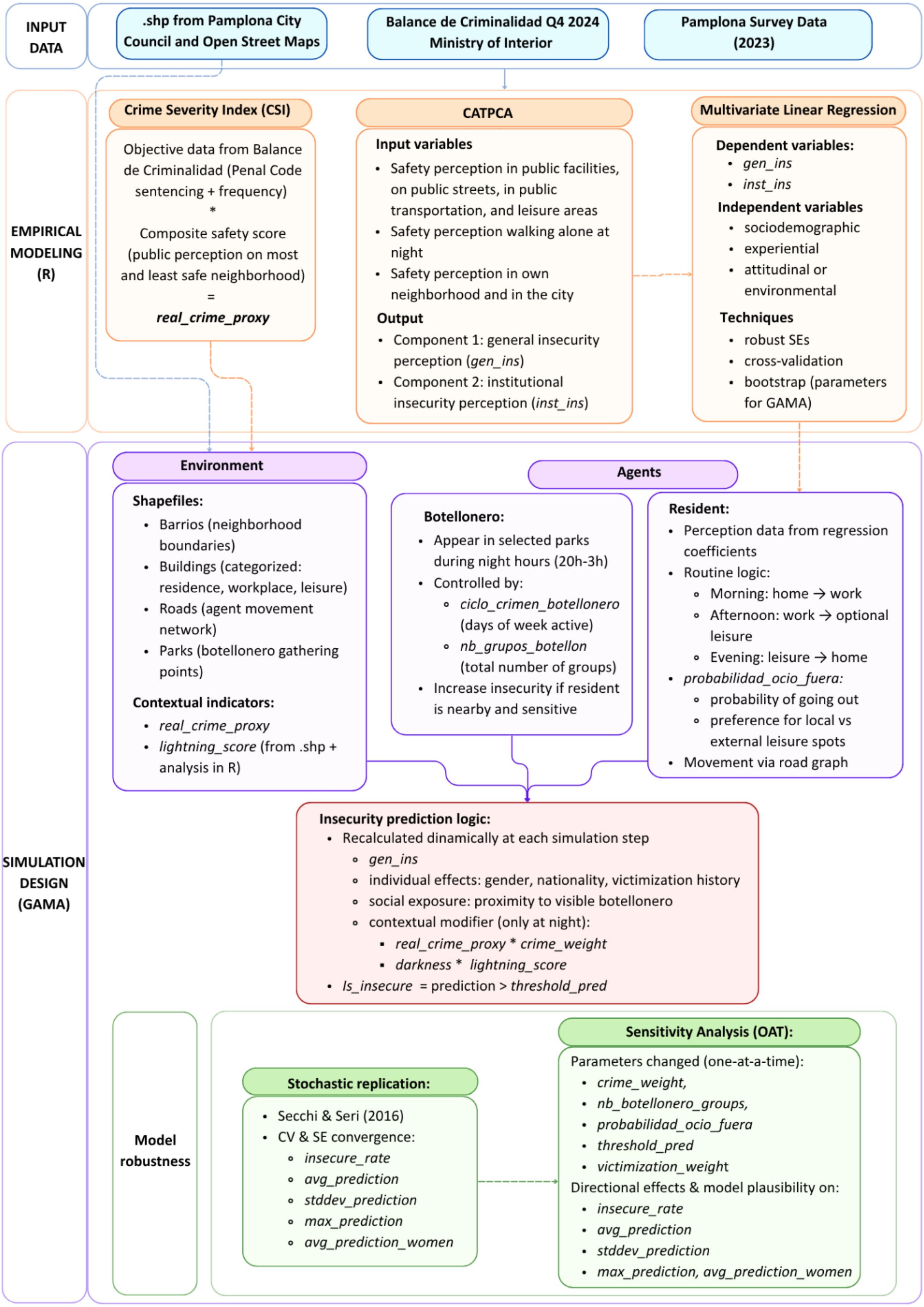
3. METHODOLOGY

This chapter presents the full methodological workflow followed to develop, calibrate, and validate an agent-based model of perceived insecurity in urban public spaces. The process is structured in two interrelated phases:

- An **empirical phase**, conducted in R, which focused on constructing latent indices of perceived safety from survey data, building a crime severity index tailored to the local context, and estimating behavioral parameters through regression modeling.
- A **simulation phase**, implemented in GAMA, which translated these empirical findings into agent behaviors, spatial dynamics, and scenario testing. The simulation robustness was validated through stochastic replication and sensitivity analysis.

Image 1 summarizes the main stages and components covered in the chapter.

Image 1. Overview of the methodological workflow



Source: own elaboration

3.2. Empirical model development and parameter calibration in R

The first phase of the methodological process involved a comprehensive empirical analysis using the statistical analysis program R, aimed at constructing theoretically meaningful variables, exploring key relationships, and extracting parameters for the simulation[2]. This analysis relied on data from the **Pamplona Citizen Security Perception Survey**, provided by Pamplona's City Council, and crime statistics from the **Balance de Criminalidad (cuarto trimestre 2024)** published by the Spanish Ministry of the Interior.

3.2.1. Construction of a spatialized Crime Severity Index (CSI)

To account for not just the frequency but the severity of different types of offences reported in Pamplona, a Crime Severity Index (CSI) was constructed. This approach draws inspiration from internationally recognized indices, such as the Canadian Crime Severity Index (Statistics Canada, 2022) and the Cambridge Crime Harm Index (Sherman et al., 2016). These models use judicial sentencing guidelines as proxies for crime seriousness, under the rationale that the more severe the punishment assigned by courts, the greater the societal harm attributed to the offence.

The foundational work of Sellin and Wolfgang (1964), who emphasized the importance of assigning ratio-scaled seriousness weights to criminal events, is also essential for the construction of this index. They proposed assigning proportional seriousness weights to offences, allowing multiple crimes within a single event to be summed, reflecting cumulative harm. Their approach assumes that an offence with twice the weight is twice as serious, enabling more precise scaling. Seriousness is treated not as a fixed legal label but as a measurable dimension of social harm, based on representative judgments or proxies like sentencing guidelines.

Given that individual conviction data is not available for the local context, the CSI was built using minimum and maximum sentencing ranges from the Spanish Penal Code. Offences were assigned weights proportional to these legal penalties, anchored to a baseline offence (minor assault = 1.0). Offences with vague or residual classification (e.g., "resto de criminalidad convencional") were conservatively weighted. The frequency of each offence type was extracted from Balance de Criminalidad (2024) published by the Spanish Ministry of the Interior. The resulting weighted scores were normalized to create a continuous index of crime severity.

Since official crime data is reported only at the municipal level, the CSI was spatially redistributed across neighborhoods using survey-based perceptions of neighborhood safety and unsafety (called *composite safety score*). Full weight tables, offence classifications, and calculation procedures can be found in Annex 1.

[2] Data preparation and preprocessing, imputation of missing values, exploratory analysis and feature engineering steps can be consulted in the .rmd or the .html file available in the GitHub repository, which is also referenced in Annex 1. It constitutes an important annex, with in detail explanations of all the steps and results obteined in R and GAMA.

3.2.2. Construction of latent indices: insecurity perception

To quantify latent dimensions of perceived insecurity, a Categorical Principal Components Analysis (CATPCA) was conducted. This method, suitable for mixed ordinal and nominal variables, enabled the reduction of a set of perception-related survey items into continuous indices capturing broader interpretable dimensions:

- Component 1 was interpreted as general insecurity (*gen_ins*), based on items such as feelings of unsafety walking alone, avoidance of public spaces, or self-reported fear.
- Component 2 was interpreted as institutional insecurity (*inst_ins*)**,** involving trust in police, satisfaction with municipal responses, and perceptions of local effectiveness.

Together, the first two components explained 47,66% and 15,81% of the total variance, respectively, with their combination covering 63,47% of the original data variation. These continuous indices were later used as dependent variables in the regression model used to empirically ground the behavioral logic of agents in the simulation[3]. The whole process can be consulted in Annex 3.

3.2.3. Regression modeling and empirical parameter extraction

A multivariate linear regression model was then fitted using *gen_ins* and *inst_ins* as dependent variables. Although different models were assessed to find the best one, the final model selection followed a stepwise approach guided by AIC and theoretical relevance. Predictor variables included sociodemographic characteristics (gender, age, income, nationality and employment status), experiential factors (prior victimization, safety perception at home, safety perception when encountering police patrols, safety perception when encountering young people drinking in public places, and thoughts on changing residence because of fear), and attitudinal or environmental variables[4] (installation of security cameras in residence, avoiding certain areas when walking through the city, opinion on the installation of public security cameras, evaluation of the most secure and insecure neighborhoods in Pamplona, and evaluation of police services).

Once the model was specified, diagnostic testing revealed violations of Ordinary Least Squares (OLS) assumptions, including non-constant variance (heteroskedasticity) and the presence of influential observations**.** To address these, robust standard errors (HC1) were computed, ensuring that coefficient estimates remained valid under heteroskedastic conditions.

Finally, sensitivity checks were conducted to validate model robustness and derive stable coefficients for use in the agent-based model (ABM). A 10-fold cross-validation assessed out-of-sample performance, mitigating risks of overfitting given the moderate sample size and categorical predictors. The forward-selected models performed well, particularly for general insecurity (*gen_ins*: $R^2 = 0.42$, RMSE = 0.76, MAE = 0.62), with more modest results for

[3] In the simulation, only the first component (*gen_ins*) was used to model perceived insecurity. While this choice is partially justified by its higher explained variance, the primary reason was time constraints, which limited the inclusion of the second dimension. Future work is encouraged to incorporate these additional components to enhance the model's explanatory scope.

[4] While they may not be directly simulated in the ABM, they are essential for capturing higher-order cognitive processing and may inform the probabilistic decision rules governing agent behavior.

institutional insecurity (*inst_ins*: R^2 = 0.07, RMSE = 0.98, MAE = 0.77) (other results can be consulted in Annex 4).

In parallel, bootstrap-based confidence intervals[5] were computed using 1,000 resamples with replacement. This procedure offered an additional robustness check under weaker distributional assumptions and allowed for more flexible inference when traditional standard errors might be biased. The resulting bootstrap distributions of regression coefficients also provided credible bounds for behavioral parameters later used in the ABM, since they provide a confidence range for how strongly each predictor affects perceived insecurity.

Together, these steps support both the statistical robustness (ensuring that coefficient estimates are interpretable, stable, and not artifacts of modeling assumptions) and the predictive generalizability (supporting confidence that the model structure will hold beyond the training data), strengthening confidence in the model's use as a calibration base for simulating individual-level behavior.

3.3. Simulation development in GAMA

To explore how contextual and individual-level factors interact to shape perceptions of urban public insecurity, an agent-based model (ABM) was implemented using the GAMA platform, a high-level modeling environment tailored for spatially explicit simulations. GAMA supports complex georeferenced behavior, allows direct integration of empirical data (e.g., shapefiles, CSVs), and provides a rich syntax for specifying heterogeneous agent attributes and adaptive logic.

This model constitutes a flexible and empirically grounded computational tool for analyzing perceptions of insecurity in urban public space, with particular attention to contextual, temporal, and demographic effects. It simulates the daily routines of a residential population (residents, n = 167), whose demographic attributes and individual perceptions are drawn from a CSV of real survey data from Pamplona. The key components of the model are:

- **Spatial context**: the model includes shapefiles[6] for neighborhoods (barrios), buildings (classified as residential, workplace, or leisure), roads, and parks, enabling agent movement and environmental interactions. Each neighborhood is associated with two contextual indices:
    - A **crime proxy score (*real_crime_proxy*)**: normalized composite safety score, integrated into the insecurity prediction formula.
    - A **lighting score**, a normalized continuous variable that computes streetlights' electric power in each neighborhood and represents perceived darkness.

[5] Drawing repeated samples with replacement from the original dataset and re-estimating the model for each sample. This technique is particularly useful when normality assumptions may be violated or when inference must account for complex sampling distributions.

[6] Shapefiles for buildings, roads and parks where drawn from Open Street Maps, while those used for neighborhood limits and lightning came from the Pamplona City Council official website.

- ***Botellonero*[7] agents**, used as a proxy for public disorder, are created in selected parks and become visible only during nighttime hours and specific days of the week. Their presence raises the perceived insecurity of nearby residents. This effect is modulated by *real_crime_proxy* and individual sensitivity scores (depending on whether they reported feeling unsafe in the presence of such groups). It can be set how many times a week people can encounter *botellonero* (*ciclo_crimen_botellonero*).
- ***Resident* agents**. These follow a daily routine: commuting to work, optionally engaging in leisure after work, either in the own neighborhood or in a different one (*probabilidad_ocio_fuera*) and returning home. Their **prediction of insecurity** is continuously updated based on personal vulnerability factors (gender, nationality, past victimization), neighborhood context, time of the day (nighttime increases insecurity for those with fear of darkness), exposure to *botellonero* groups and the weight they give to crime (*crime_weight*: a proxy, not based on real data, used to develop the model).
- **Initialization** includes loading spatial data, creating agents, distributing them across neighborhoods, assigning routines, and tracking global indicators that are displayed in the dynamic visualizations. Several parameters can be configured at runtime to shape both agent behavior and contextual conditions:
    - number of residents (*nb_residents*),
    - movement speed bounds (*min_speed*, *max_speed*),
    - temporal routines, such as earliest and latest work start and end hours (*min_work_start*, *max_work_start, min_work_end, max_work_end*),
    - the probability of engaging in leisure activities (*probabilidad_ocio_fuera*),
    - the number of *botellonero* (*nb_grupos_botellon*) and their weekly visibility (*ciclo_crimen_botellonero*),
    - the weight of crime in shaping perceived insecurity (*crime_weight*),
    - the threshold at which an agent is considered insecure (*threshold_pred*).

Insecurity prediction (*prediction*) is modeled as a linear combination of several factors. The formula used is:

$$prediction = base + individual\ effects + social\ exposure + contextual\ modifiers$$

Where:

- Base = *gen_ins*: base insecurity. It is the first component from the CATPCA and one of the dependent variables in the multivariate regression model from regression. Prior to its inclusion in GAMA, this variable was normalized to facilitate its interpretation in the model.

[7] These agents were created directly in GAMA as they are not a population of interest, but contextual agents whose visible presence triggers changes in residents' perceived insecurity.

- Individual effects, derived from regression analysis. These include *gender_effect*, *nationality_effect*, and the product of *victimized_effect* by *victimization_weight*[8].
- Social exposure, which includes *botellonero_cerca* (within 5m), *botellonero_boost* (temporary effect from recent encounters) and p7_8_effect (survey-based sensitivity to *botellonero*).
- Contextual modifiers, such as *crime_weight* by *real_crime_proxy*, and *lightning_barrio* by modifiers, either *darksens_b* (if in home barrio) and *darksens_c* (generic sensitivy if elsewhere).

This dynamic formulation allows perceived insecurity to emerge from the interaction of personal vulnerability, spatial context, and routine exposure. *Prediction* is recalculated at each cycle and used to determine whether an agent is considered insecure, based on a configurable threshold (*threshold_pred*).

In addition, the model collects **detailed outputs during runtime** through dynamic visualizations and monitors, which provide real-time feedback on key variables, supporting both interpretability and validation. These include:

- Monitors for the number of insecure and secure residents, updated at every simulation step (see Image 2).

Image 2. Monitor display example in visual outcome

Source: simulation outputs generated in GAMA Platform

[8] These variables correspond to the coefficients obtained from the multivariate regression. For instance, *gender_effect* reflects the estimated effect of gender on perceived insecurity, and so on for each predictor. *victimization_weight*, in particular, was created as a proxy to modify *victimization_effect* and tets it in the OAT analysis.

- 3D spatial renderings of agents, their behavioral states, and urban layout (see Image 3).

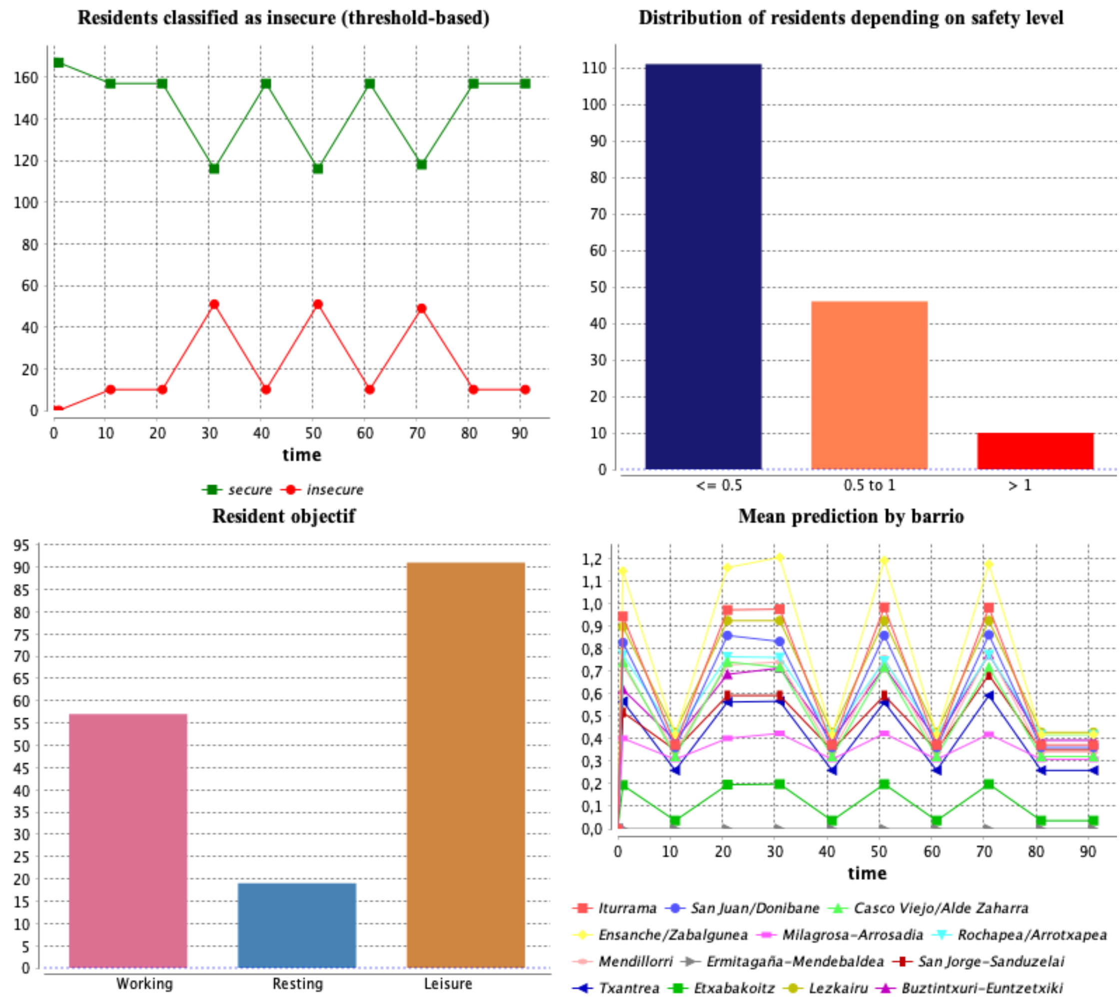
Image 3. 3D spatial rendering of agents, behavioral states and urban layout

Source: simulation outputs generated in GAMA Platform (own elaboration)

1. *Not initialized model.*
2. *Initialised model in the morning (12 am).*
3. *Initialised model in the evening (9pm), with visible botellonero groups.*
4. *Initialised model at night (2 am), no visible botellonero groups*.

- Dynamic charts capturing:
    - Residents classified as insecure, based on the threshold set,
    - Distribution of residents depending on safety level,
    - Resident objectives (working, resting, leisure),
    - Average prediction of insecurity per neighborhood,

Image 4. Visual summary of simulated insecurity dynamics



Source: simulation outputs generated in GAMA Platform (own elaboration)

3.4. Stochastic replication analysis

ABMs are by nature **stochastic systems**: different runs of the same configuration can produce different outcomes. Therefore, ensuring that simulation outputs are statistically stable and robust requires determining the minimum number of replications needed per configuration before interpreting results or comparing scenarios.

As emphasized by Secchi and Seri (2016), many ABMs in the social sciences employ an arbitrary number of repetitions without formally justifying it, which can undermine the credibility of their findings. For example, insufficient repetitions may yield unstable or misleading outputs, making it impossible to distinguish between systematic effects and stochastic noise. These authors propose a method to solve this gap by offering a computationally grounded rationale for ensuring convergence in stochastic outputs and determining replication counts based on expected effect size and model complexity. The replication estimation formula developed by them, which calculates the number of required simulations runs (n) as a function of the number of configurations (J, model dimensionality) and the expected effect size (ES, statistical sensitivity), was applied here:

$$n(J, ES) \approx 14.091 \cdot J^{-640} \cdot ES^{-1.986}$$ [9]

In this case, where a single parameter configuration was evaluated (J = 1) and a moderate expected effect size was assumed (ES = 0.3), the formula yielded an estimated of **153 simulation runs**. Each run generated values for five core indicators:

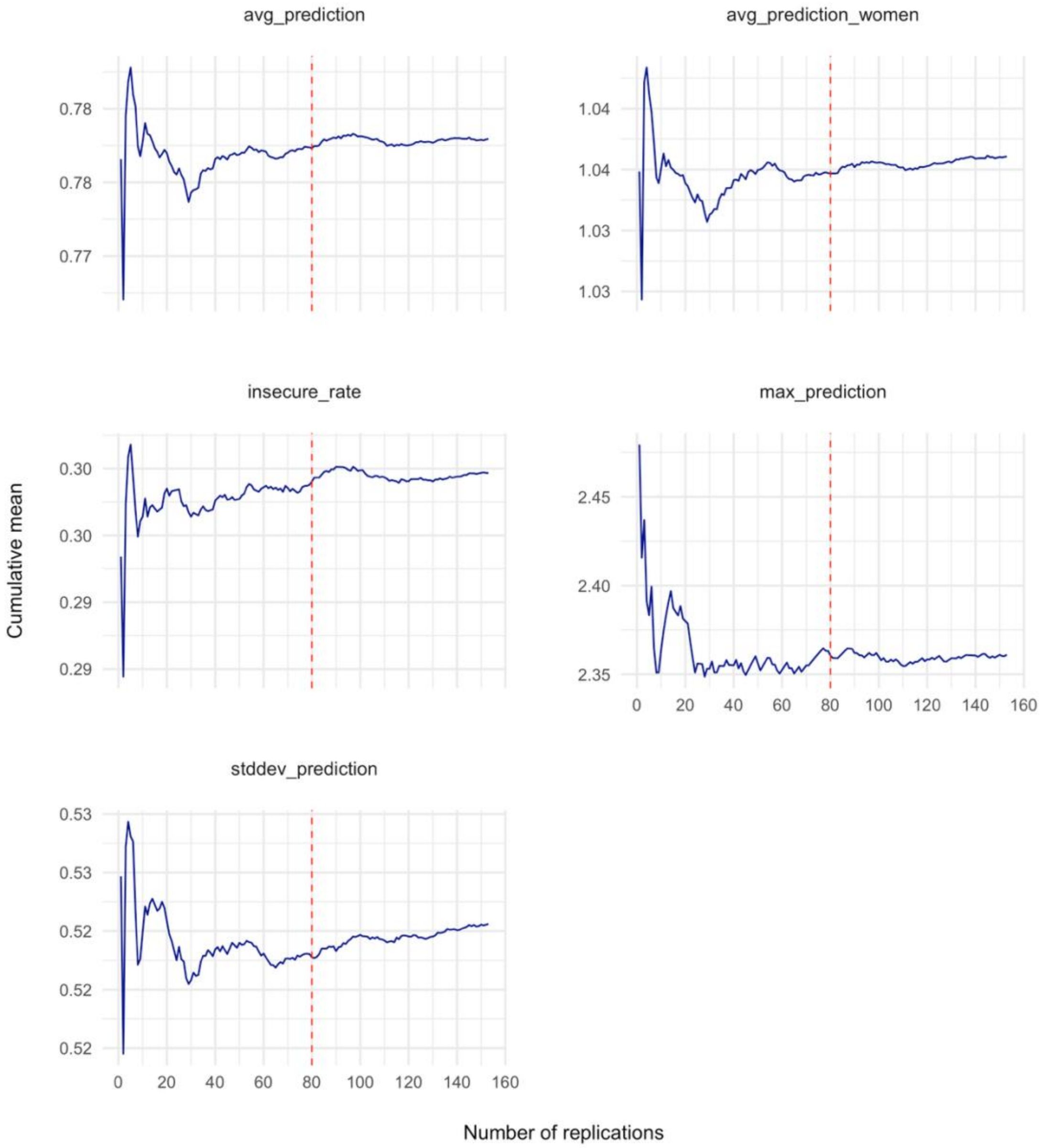
- *insecure_rate*: proportion of residents classified as insecure.
- *avg_prediction*: mean predicted insecurity across the population.
- *stddev_prediction*: standard deviation of individual predictions.
- *max_prediction*: highest insecurity score observed.
- *avg_prediction_women*: average prediction for female agents.

For each variable, the coefficient of variation (CV) and the standard error (SE) were computed as replications increased. Table 5 in Annex 7 summarizes the minimum number of replications required for each metric to stabilize under different convergence thresholds. Following GAMA's internal logic, three convergence thresholds were tested (0.05, 0.01, and 0.001) representing increasing levels of precision.

The 0.01 threshold was adopted as the default criterion for all further experiments, balancing precision with computational feasibility, and based on the results observed, a default replication of 80 was established for subsequent batch and sensitivity experiments, ensuring that all reported outputs remain within acceptable error margins. This threshold was confirmed by inspecting the convergence curves for each output variable, which show stabilization of the cumulative mean well before the 80th replication in all cases (see Image 5).

[9] More information about the formula can be found in Annex 6.

Image 5. Convergence diagnostics for stochastic replication analysis (153 replications)



Source: output data from GAMA (own elaboration)

3.5. One-at-a-time sensitivity analysis

To assess the internal behavioral validity of the model, a One-at-a-Time (OAT) sensitivity analysis was conducted. This method varies individual parameters independently, allowing for the evaluation of whether the model responds in a directionally consistent and plausible way to changes in input. While OAT does not account for interaction effects between parameters, OAT is particularly suited for early-stage analysis in agent-based models, as it isolates parameter effects without the computational cost of global methods (Ligmann-Zielinska et al., 2014).

The OAT sensitivity analysis consisted of four independent experiments, each varying a single input parameter while keeping all others constant. For each parameter, the model was run for

80 replications per configuration, holding other values constant. The results can be found in Annex 8. Key outputs recorded include:

- **Crime weight**: varied from 0.0 to 1.0 (step = 0.2). Theoretically, higher values increase the nighttime penalization applied to residents living in high-crime areas, leading to higher perceived insecurity. This parameter produced the most robust and monotonic effect. As *crime_weight* increases from 0 to 1, all indicators rise markedly. *insecure_rate* more than doubles (from 0.18 to 0.47), while *avg_prediction* doubles (from 0.52 to 1.02), confirming the role of contextual crime in shaping perceived insecurity
- **Number of *botellonero* groups**: varied from 3 to 15 (step = 3). An increase is expected to elevate perceived insecurity through more frequent agent exposure to informal gatherings, especially among those who declared fear in the survey. While *avg_prediction* and *insecure_rate* remain largely stable across levels, there is a clear peak in *max_prediction* in 6 and 12 groups. This suggests localized or stratified effects, for example, only specific individuals (such as women) experience heightened insecurity.
- **Probability of leisure outside**: varied from 0.1 to 1.0 (step = 0.2). Higher values simulate more residents moving through public space at night, potentially increasing their exposure to contextual risks and raising perceived insecurity. However, in the OAT, perceived insecurity metrics remained relatively flat across configurations. This suggests that this parameter may only exert meaningful effects in interaction with others (e.g., lighting conditions, *botellonero* encounters, or gender), rather than independently.
- **Insecurity threshold**: varied from 0.0 to 1.0 (step = 0.2). This parameter controls the cutoff used to classify agents as insecure. Lower thresholds should result in a higher *insecure_rate*, even with unchanged prediction levels. In the OAT, as the threshold increases from 0.0 to 1.0, the insecure rate drops sharply, as expected, from 0.95 to 0.28. Importantly, other metrics such as *avg_prediction* remain stable, demonstrating output independence.
- **Victimization weight**: varied from 1.0 to 4.0 (step = 1.0). This multiplier amplifies the effect of past victimization experiences. Increasing it should raise perceived insecurity among previously victimized individuals, impacting aggregate metrics. As expected, the incremental increases in the weight assigned to past victimization experience resulted in moderately rising trends across all outputs, with a higher scalation on *max_pred*, indicating that this parameter might affect more to those with high victimization rates.

Across all scenarios, *avg_prediction_women* consistently exceeds *avg_prediction*, aligning with empirical literature on gendered safety perceptions, and supporting the model's capacity to reproduce stratified subjective outcomes.

4. RESEARCH POSSIBILITIES ENABLED BY THE MODEL

After assessing the methodology employed for developing the model, it is relevant to mention its functions as both an **exploratory and confirmatory research tool**. It allows scholars and analysts to:

- Simulate the micro-mechanisms underpinning the subjective experience of urban insecurity, including dynamic interactions between residents, environmental cues (e.g., lighting, crime scores), and social stimuli (e.g., informal youth gatherings/*botellonero*).
- Analyze spatiotemporal variability in perceived risk across distinct urban neighborhoods, operationalized through high-resolution GIS data.
- Conduct controlled experiments that manipulate specific parameters (e.g., *crime_weight*, *nb_grupos_botellon*, *probabilidad_ocio_fuera*) to observe their isolated and interactive effects on emergent insecurity patterns.
- Validate model behavior by testing whether it aligns with theoretical and empirical expectations. This includes checking for monotonic trends in response to parameter changes, replicating known gender differences in perceived insecurity, and confirming output stability through convergence diagnostics across multiple stochastic runs.

In addition to its academic value, the model serves as a **practical tool for public policy and urban intervention design**. It can support:

- Pre-intervention assessments, by simulating how different resident profiles might respond to changes in neighborhood conditions (for example, reduced or increased lighting), helping anticipate the unequal impact of environmental changes.
- Post-intervention analysis, by comparing model outputs before and after adjusting specific contextual variables, such as increasing lighting intensity or altering the spatial distribution of high-crime proxies.
- Identification of priority areas by mapping neighborhoods with the greatest discrepancies between objective crime indicators and perceived insecurity, helping guide targeted interventions such as safety audits, community engagement, or participatory planning processes.
- Participatory scenario exploration, where urban planners or local communities co-explore possible futures, by adjusting parameters and visualizing the resulting insecurity maps to inform consensus-based decisions.
- Policy experimentation through virtual testing of interventions (such as increasing the *crime_weight*) to assess differential impacts across population groups and anticipate potential risks like spatial stigmatization or unintended exclusion.

This tool also allows for **empirical testing of different criminological and sociological hypotheses**, such as:

- **H1** *(disorder hypothesis)*: an increase in visible disorder (*nb_grupos_botellon*) is associated with elevated mean levels of perceived insecurity (*avg_prediction*) and a greater proportion of residents classified as insecure (*insecure_rate*).

- **H2** *(gendered safety perception)*: female agents exhibit systematically higher predicted insecurity scores (*avg_prediction_women*) than their male counterparts under equivalent contextual conditions, reflecting survey-based findings on gendered fear of crime.
- **H3** *(night-time vulnerability amplification)*: the impact of contextual crime scores on predicted insecurity is more pronounced during nocturnal hours, consistent with theories of situational fear intensification.
- **H4** *(spatial exposure and routine activity)*: increasing the probability of leisure activity in other neighborhoods (*probabilidad_ocio_fuera*) increases agents' unsafe feelings, amplifying variability in insecurity estimates across agents.
- **H5** (*mismatch hypothesis*)**:** some neighborhoods with low objective crime proxies still display high simulated insecurity, suggesting that symbolic, affective, or historical factors may mediate fear perceptions independently of actual risk.

5. CONCLUSIONS AND LIMITATIONS

This study presents an empirically grounded agent-based model (ABM) to explore the dynamics of perceived insecurity in urban space, emphasizing the interplay between individual effect, social exposure and contextual modifiers. Drawing on sociological theory, statistical modeling, and spatial simulation, the model demonstrates internal coherence, empirical plausibility, and theoretical consistency.

The empirical analysis identified stable predictors of perceived insecurity, which were translated into behavioral rules. The model was validated using a combination of input realism, statistical analysis, and output testing through stochastic replication and one-at-a-time (OAT) sensitivity analysis. Overall, the results show coherent responses to parameter changes, especially *crime_weight*, and successfully reproduce known patterns, such as higher insecurity among women.

The validation strategy adopted throughout this study followed a multi-layered approach. In line with Fagiolo et al. (2007), the model was indirectly calibrated using aggregate empirical regularities derived from survey data: individual responses were synthesized into latent variables (via CATPCA) and contextual indices (such as the composite crime score), which were then used to inform agent behaviors. Due to the absence of longitudinal or geolocated micro-level data, this approach is particularly appropriate as it prioritizes the replication of collective patterns over individual trajectories.

In terms of the typology proposed by Tesfatsion (2017), the model achieved input validation through the empirical derivation of parameters from regression models, and process validation by ensuring internal coherence between behavioral rules and theoretical expectations. Although descriptive output validation was limited by the reuse of input data for benchmarking, the model's ability to reproduce stratified outcome, such as higher insecurity among women, supports its empirical plausibility. Following Collins et al. (2024), both foundational methods (regression-based calibration and dynamic visual inspection) and one advanced method (bootstrap-enhanced sensitivity testing) were integrated into the workflow, strengthening the model's overall methodological credibility.

Beyond methodological rigor, this model also makes a conceptual contribution to the study of urban insecurity. Building on previous work, such as the ABM by Izquierdo et al. (2020), this project expands the field by integrating individual heterogeneity, contextual, and social-temporal dynamic routines into the simulation. Perceived insecurity is modeled not as a fixed attribute but as an emergent, dynamic outcome, offering a nuanced lens to explore how insecurity is produced. Because of this, it offers a step forward in modeling perception as a relational and stratified phenomenon, contributing to a growing body of research that challenges purely criminological approaches to safety.

Despite its contributions, this model also presents several limitations that can be addressed in future research. First, the lack of individual-level longitudinal data or precise geolocation prevented direct predictive validation. Although descriptive output validation and internal coherence were ensured, future versions should incorporate independent datasets to assess the model's forecasting capabilities more rigorously. Second, while the use of One-at-a-time (OAT) sensitivity analysis provided valuable insights into the directionality of parameter effects, it cannot capture interaction effects or nonlinear dynamics. As stated by Saltelli et al. (2008) and

Ligmann-Zielinska et al. (2014), more robust global sensitivity analysis methods, such as Sobol indices or Latin Hypercube Sampling, should be incorporated in future iterations.

Additionally, the spatial redistribution of crime exposure based on survey data introduces a degree of circularity, as perceived insecurity helps define crime proxies that then influence simulated insecurity. This methodological issue could be mitigated by using georeferenced crime incidents data[10].

From a behavioral perspective, the model currently assumes agents follow fixed routines and respond to context without the capacity for adaptation or learning. Future developments could include feedback mechanisms, allowing agents to modify their behavior based on prior experiences, or interact with one another. Likewise, incorporating symbolic and communicative layers, such as media narratives or affective meaning of place, would enrich the model.

Finally, the simulation developed here can be used as a practical tool to support participatory decision-making. It allows urban planners, public institutions, and communities to explore how different environmental and behavioral factors influence the feeling of insecurity in the city. By virtually testing interventions and visualizing their impact on different groups and areas, the model helps anticipate potential effects and inequalities. It also makes it possible to detect discrepancies between objective crime indicators and perceived insecurity, pointing to the role of symbolic or social elements. In this way, it serves not only as an academic contribution but as a practical resource for collaborative diagnosis and policy experimentation in complex urban settings.

Therefore, despite its limitations and its exploratory nature, the model provides a solid foundation for understanding how insecurity is shaped and stratified in urban settings, and lays a robust foundation for more complex, interactive simulations for both research and policy use, paving the way for applied use in urban planning, safety interventions, and participatory design.

[10] I attempted to obtain disaggregated crime data at the neighborhood level by submitting a formal request to the Spanish Ministry of the Interior. However, the request was denied on the grounds that fulfilling it would require recalculating all Pamplona crime indicators. The documentation of this request is publicly available in the project's GitHub repository.

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7. ANNEX

7.1 Github repository

The complete code developed for this project is available on my GitHub repository, which includes both the R scripts used for statistical analysis and the GAMA code for simulation. All the datasets used in both environments are also accessible through the repository.Here is the link: https://github.com/sarisham/thesis.git

7.2. Crime Severity Index

Developing midpoint approach

For each offence, the Spanish Penal Code was consulted to identify the minimum and maximum **prison sentences**, or the **financial penalty range** (*multas*) where applicable. To estimate the expected sentence, the **midpoint approach** was applied calculating the average between the minimum and maximum legal penalties:

$$Expected\ \ Sentence = \frac{Minimum\ Sentence}{Maximum\ Sentence}$$

One methodological challenge is the treatment of offences grouped under the label *resto de criminalidad convencional*. This category is not disaggregated into specific offence types, and may include a heterogeneous mix of criminal acts—from low-level infractions to moderate or even serious offences. The lack of specificity makes it impossible to assign a precise sentencing-based weight to each offence. To address this, the category was assigned a baseline weight equivalent to the reference crime, namely, the minimum prison sentence legally defined in the dataset (0.25 years or 3 months). This way, the category is not excluded from the index and it is not overrepresented.

To compare fines with prison terms, **relative harm equivalence is asumed**, inspired by the Cambridge model (Sherman et al., 2016): a **1-month prison sentence** is treated as more severe than a **1-month fine**. However, to maintain scale comparability, fines are assigned **lower weights** across the board.

Determining the reference sentence

Once expected sentences were computed, to calculate weights a **baseline** crime for comparison was needed: the minimun possible prison term from the dataset (**0.25 years (3 months)** for minor assault or *riña tumultuaria*) This was set **as the reference = 1.0**, so that all other crimes are scaled relative to this, normalizing all offences so that the least severe offence has a weight of 1.0, and more serious offences are assigned proportionally higher values

Computing weights

Now, each **expected sentence length** is divided by **0.25** (reference crime):

$$wi = \frac{Expected\ Sentence\ Length\ for\ Offence\ \ i}{0.25\ years}$$

These **weights** can be used to compute the **Crime Severity Index (CSI)** by using the standard formula and applying the weights to the relative values of the crimes:

Table 1. Crime offence, sentence range, expected years and weight.

Offence	Sentence Range	Expected sentence (Years)	Weight (relative to 0.25 y)
Homicide	10 – 15 years	12.5	50
Aggravated Homicide	15 – 25 years	20	80
Minor Assault / Riña Tumultuaria	0.25 – 1 year 6 - 24 months (fine)	0.625	2.5
Sexual Offence (Minor Grade)	1 – 4 years	2.5	10
Rape	4 – 12 years	8	32
Robbery with Force (minor)	1 – 3 years	2	8
Robbery with Force (aggravated)	2 – 6 years	4	16
Robbery with Violence	2 – 5 years	3.5	14
Theft (>400€)	0.5 – 1.5 years	1	4
Theft (<400€, fine)	1 – 3 months (fine)	0.165 (approx.)	0.66

Source: own elaboration.

Disaggregated crime data at the neighborhood level was formally requested from the Spanish Ministry of the Interior del. However, the request was denied. A copy of the official request and response is available in the GitHub repository. Consequently, a **composite safety score** for each neighborhood was computed, based on survey responses was to two questions: which neighborhood is perceived as the safest (p13a) and which as the most unsafe (p13b). Since each respondent picked **only one barrio**, the **number of times each barrio was chosen** was used as a proxy for positive perception (p13a) or a proxy for negative perception (p13b). Then, these counts were normalized into proportions or scores, creating the composite score:

$$Safety\ Score = \frac{Votes_{safe}}{Total\ votes} - \frac{Votes_{unsafe}}{Total\ votes}$$

The resulting score reflects overall public perception, with higher values indicating neighborhoods perceived as safer. This safety score was then multiplied by the total Crime Severity Index to generate a crime_proxy value for each neighborhood.

7.3. Building the safety perception index using CATPCA

The dependent variable in this study aims to capture individuals' subjective **perception of insecurity in public space**. This construct is multidimensional, encompassing not only how safe people feel in various contexts but also their emotional responses, behavioral adaptations, and evaluations of their local environment. The following items from the questionnaire were selected based on their conceptual relevance to the concept:

- **P7 (situational safety perceptions):** these items ask respondents how safe they feel in specific environments (e.g., at home, in parks, in public transport). Items such as **P7_2 to P7_6** were retained as they directly reflect situational insecurity. **P7_7** and **P7_8** measure perception when seeing a police patrol and when seeing people drinking on the street; both were excluded from the main construct as it relates to institutional presence and social stimuli rather than the respondent's environment per se.

  P7_1 refers specifically to the private domain of the respondent's home. Since this study focuses on public space and collective urban environments, this item was excluded from the perception index to ensure conceptual coherence, as including it could introduce interpretive inconsistencies in the latent construct.

- **P10 (statements of security and avoidance behaviors):**
  - **P10_1 and P10_2** are retained, as they capture generalized perceptions of safety in the city and neighborhood.
  - **P10_3 and P10_7**, which involve behavioral self-restraint (e.g., avoiding going out or visiting areas), are interpreted as **self-defense strategies** (behaviors likely resulting from prior insecurity). These were excluded to avoid endogeneity and maintain conceptual clarity, since they are also behaviors that agents in the ABM may enact based on model parameters. However, these variables are still included in regression models as **predictors**, in order to assess their statistical association with perceived insecurity and to inform rule development in the ABM.
  - **P10_4 to P10_6**, which capture attitudes towards surveillance technologies, were excluded, as they reflect political or normative beliefs rather than actual insecurity perceptions.

- **P11 (global evaluations of safety):** both P11_1 and P11_2 provide scalar ratings of perceived safety in the respondent's **neighborhood** and **city**, respectively. These are highly relevant and were included in the composite index.

- **P12 (perceived neighborhood degradation and crime)** reflects the respondent's perception of environmental disorder and local criminality. While not a direct emotional perception, it represents contextual perception of insecurity and is excluded.

- **P8** (installing a security system) and **P9** (considering relocation) represent self-protective responses to perceived risk. As behavioral outcomes, they were excluded from the CATPCA to avoid conceptual circularity, but are included in regression models to assess their relationship with perceived and contextual insecurity.

The first two components account for approximately **63.4% of the total variance**, while the inclusion of a third component raises that figure to **72.9%**. Only the first two where retain for the analysis, as this decision provides a more parsimonious model and facilitates interpretation and integration in the ABM, and the total variance they account for is statistically enough.

Table 2. Results from the CATPCA for the first three components

	Comp1	Comp2	Comp3
Eigenvalues	5.2422	1.7397	1.0398
VAF	47.6561	15.8158	9.4526
Cumulative VAF	47.6600	63.4700	72.9200

Source: output data from CATPCA analysis in R.

The numerical **loadings** associated with each component indicate the **strength and direction of the association** between that variable and a given component. Loadings above **±0.70** are considered strong contributors to the component, loadings between ±0.40 and ±0.69 are considered moderate, and loadings between ±0.25 and ±0.39 may still be interpretable if theoretically meaningful.

Component 1 reflects general urban insecurity, particularly in public and semi-public spaces such as commercial areas, solitary streets, and nightlife zones. It also includes general evaluations of security in one's neighborhood and city. This component represents the core emotional and experiential dimension of perceived insecurity, meaning, how unsafe people feel in the places where they live and move. The inverse loadings from p10_1, p10_2, p11_1r, and p11_2r (which are inverse because the item is framed in terms of feeling safe) indicate that higher scores on this component correspond to stronger feelings of insecurity in both local and city-level settings.

Component 2 captures a sense of institutional or service-related insecurity. It includes feelings of insecurity in public facilities, like community centers, and in public transportation. This dimension likely reflects a breakdown in the implicit trust citizens place in infrastructure and public institutions as protectors of safety, possibly due to past incidents, social cues, or poor maintenance. The weak-moderate cross-loading variables, such as the ones referred to the safety feeling in the city and the neighborhood, add context but is less distinctive.

Table 3. Variable loadings for each component (CATPCA)

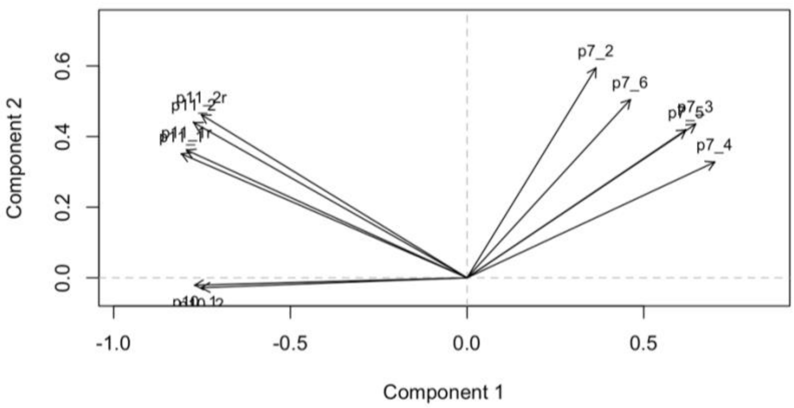
	D1	D2	D3
p7_2	0,364421	0,593743	0,428212
p7_3	0,646658	0,434973	0,148392
p7_4	0,700596	0,327424	-0,29654
p7_5	0,619258	0,418721	-0,1632
p7_6	0,461712	0,50419	0,360107
p10_1	-0,77011	-0,02085	0,459012
p10_2	-0,75162	-0,02823	0,479431
p11_1	-0,80781	0,35105	-0,18494
p11_2	-0,77337	0,439481	-0,19691
p11_1r	-0,79403	0,361541	-0,19316
p11_2r	-0,75137	0,461453	-0,19825

Source: output data from CATPCA analysis in R.

The **biplot** is a two-dimensional representation of the relationships between the original variables and the first two principal components extracted by CATPCA. It offers a geometric visualization of the multivariate data structure, enabling the assessment of variables relationship to the underlying dimensions, to one another, and to the total explained variance:

- p7_3, p7_4, and p7_5, core indicators of spatial insecurity in public places, form a tight cluster pointing almost purely along Component 1.
- p7_2 and p7_6 are projected at approximately 45° upward to the right, combining moderate contributions to both components. These vectors define Component 2, associated with insecurity in institutional or service environments.
- p10_1 and p10_2 (statements of feeling safe in city/neighborhood) point in the opposite direction to p7_3–p7_5, consistent with their strong inverse loadings: high agreement with these items indicates low insecurity.

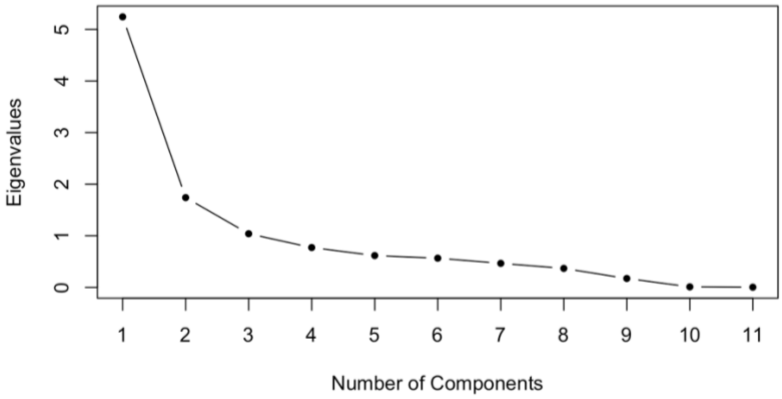
Image 6. Biplot from CATPCA



Source: output plot from CATPCA analysis in R.

The **scree plot** displays the eigenvalues (amount of variance in the data accounted for by that component) associated with each component. Before the elbow, each additional component adds substantial new explanatory power. After the elbow, each additional component adds minimal variance and may be driven by noise or overfitting. The curve flattens considerably after Component 2, suggesting that retaining two components is both empirically justified and methodologically parsimonious.

Image 7. Scree plot from CATPCA



Source: output plot from CATPCA analysis in R.

7.4. Table results from the multivariate linear regression

The cross-validation is carried out to compare a full model (with all theoretically relevant variables) and a forward-selected model chosen earlier, each applied separately to *gen_ins* and *inst_ins*. A linear regression (lm) is applied. Even though CV is implemented separately for each dependent variable in this stage (due to the lack of native multivariate CV procedures en the `caret` package), this is statistically justified: the goal is not to predict a multivariate outcome per se, but to ensure that both individual outcome models perform reliably and are grounded in a consistent and interpretable predictor structure.

Table 4. Cross validation results for each model and dependent variable

Model	RMSE	Rsquared	MAE
gen_full	0.7468163	0.4290789	0.5744655
gen_forward	**0.7058910**	**0.4884637**	**0.5642372**
inst_full	0.9725676	0.1576672	0.7794214
inst_forward	**0.9505879**	**0.1722070**	**0.7677676**

Source: output data from cross-validation analysis in R

After choosing the forward-selected model, the multivariate linear regression was carried out. For gen_ins, adjusted R-squared is 0.5047, while for inst_ins adjusted R-squared is 0.1733.

Response gen_ins

```
Call:
lm(formula = gen_ins ~ agez + gender + income + nationality +
    employment + victimized + p7_1 + p7_8 + p10_3 + p10_4 + p10_6 +
    p12 + p15 + p16 + p13a + p13b + p14z + p7_7 + p8 + p9, data = pampre)

Residual standard error: 0.7042 on 766 degrees of freedom
Multiple R-squared:  0.5412,	Adjusted R-squared:  0.5047
F-statistic: 14.82 on 61 and 766 DF,  p-value: < 2.2e-16
```

Response inst_ins

```
Call:
lm(formula = inst_ins ~ agez + gender + income + nationality +
    employment + victimized + p7_1 + p7_8 + p10_3 + p10_4 + p10_6 +
    p12 + p15 + p16 + p13a + p13b + p14z + p7_7 + p8 + p9, data = pampre)

Residual standard error: 0.9098 on 766 degrees of freedom
Multiple R-squared:  0.2343,	Adjusted R-squared:  0.1733
F-statistic: 3.843 on 61 and 766 DF,  p-value: < 2.2e-16
```

Coefficients for each variable are not included in this annex due to the magnitude of the table. However, it can be consulted in the .html file available in the public Github repository.

7.5. Understanding the visual display of the ABM in GAMA

Each agent species in the model has a visual aspect that allows users to quickly interpret simulation results in the spatial interface. These graphical elements help differentiate agent types, display environmental features, and visually encode insecurity levels.

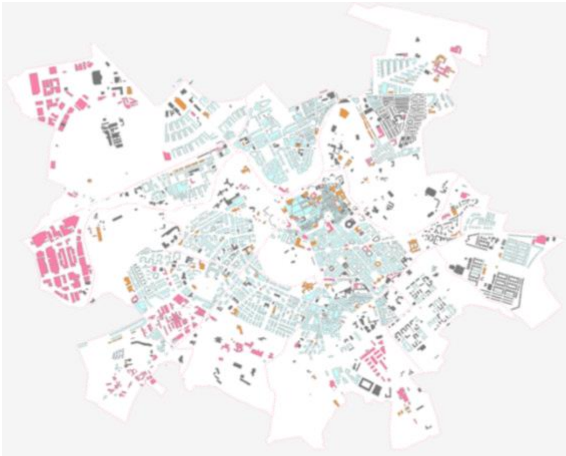
barrio (neighborhoods) are drawn with whitesmoke fill and pink borders. Each barrio contains two key attributes: a *crime proxy score* and a *lighting score*. These are used internally by residents to compute perceived insecurity.

roads appear as maroon lines with a width of 1.3, outlining the street network used for agent movement.

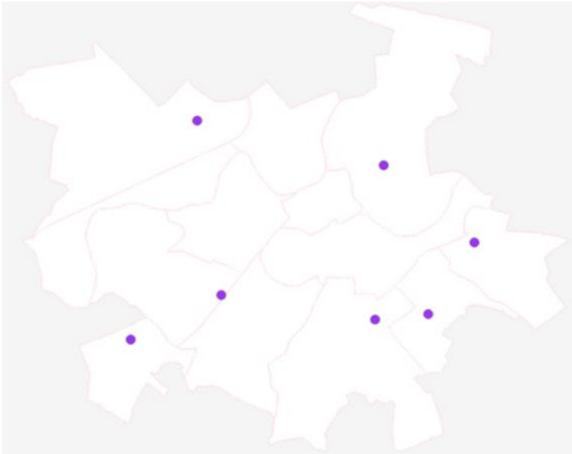
parques (parks and plazas) are informal or recreational public spaces. They serve as potential gathering spots for *botellonero* agents, are colored darkseagreen.

building are color-coded by function:

- **Residences**: powderblue
- **Workplaces**: palevioletred
- **Leisure** venues: peru
- **Others**: dimgray

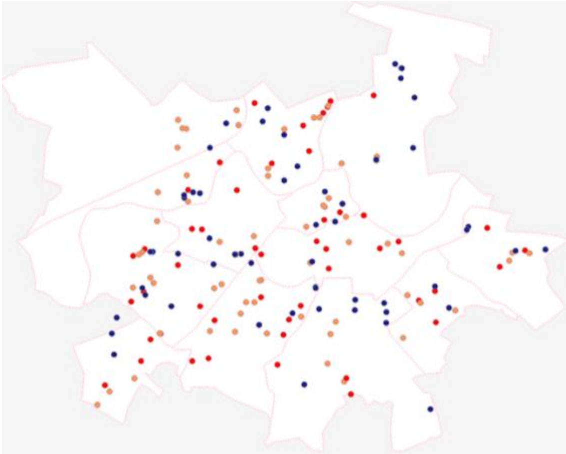


botellonero (youth groups) are visible only at night and on specific days (based on the *ciclo_crimen_botellonero* parameter). When active, they appear as blueviolet circles, signaling localized social disorder.



resident (citizens) are dynamically visualized based on their *prediction score* of perceived insecurity:

- **≤ 0.3**: midnightblue → Very safe
- **0.4 - 1**: royalblue → Neutral
- **> 1**: red → Very unsafe



7.6. The replication estimation formula from Secchi and Seri (2016)

The replication estimation formula proposed by Secchi and Seri (2016) was applied to determine the number of simulation runs needed to achieve statistically robust results. This formula calculates the required number of repetitions (*n*) as a function of the number of configurations (*J*, representing model dimensionality) and the expected effect size (*ES*, measuring statistical sensitivity):

$$n(J, ES) \approx 14.091 \cdot J^{-640} \cdot ES^{-1.986}$$

Unlike expressions derived from theoretical statistical distributions, this equation was empirically estimated through over 40,000 simulation experiments across various types of stochastic models. The constants were obtained via nonlinear regression and have the following interpretation:

- 14.091 acts as a general scaling factor, representing the baseline number of repetitions required under standard conditions.
- The exponent −0.640 reflects the diminishing marginal need for replications when testing multiple parameter configurations (J), due to cross-scenario comparisons mitigating the need for repetition.
- The exponent −1.986 indicates a nearly quadratic inverse relationship between the expected effect size (ES) and the number of required runs: smaller effects require exponentially more replications to detect reliably amid stochastic variation

7.7. Results from the stochastic analysis

In the stochastic analysis, carried out with 153 simulation runs, the coefficient of variation (CV) and the standard error (SE) were computed as replications increased for five core indicators:

- *insecure_rate*: proportion of residents classified as insecure.
- *avg_prediction*: mean predicted insecurity across the population.
- *stddev_prediction*: standard deviation of individual predictions.
- *max_prediction*: highest insecurity score observed.
- *avg_prediction_women*: average prediction for female agents.

The following Table 1 summarizes the minimum number of replications required for each metric to stabilize under different convergence thresholds. Following GAMA's internal logic, three convergence thresholds were tested (0.05, 0.01, and 0.001) representing increasing levels of precision.

Table 5. Results from the stochastic analysis

Output : insecure_rate
Coefficient of variation
0.05 : min = 8 | max = 8 | avr = 8
0.01 : min = 54 | max = 54 | avr = 54
0.001 : min = 95 | max = 95 | avr = 95
Standard error
0.05 : min = 28 | max = 28 | avr = 28
0.01 : min = 39 | max = 39 | avr = 39
0.001 : min = 72 | max = 72 | avr = 72

Output : avg_prediction
Coefficient of variation
0.05 : min = 73 | max = 73 | avr = 73
0.01 : min = 73 | max = 73 | avr = 73
0.001 : min = 152 | max = 152 | avr = 152
Standard error
0.05 : min = 19 | max = 19 | avr = 19
0.01 : min = 41 | max = 41 | avr = 41
0.001 : min = 99 | max = 99 | avr = 99

Output : stddev_prediction
Coefficient of variation
0.05 : min = 4 | max = 4 | avr = 4
0.01 : min = 24 | max = 24 | avr = 24
0.001 : min = 71 | max = 71 | avr = 71
Standard error
0.05 : min = 7 | max = 7 | avr = 7
0.01 : min = 11 | max = 11 | avr = 11
0.001 : min = 11 | max = 11 | avr = 11

Output : max_prediction
Coefficient of variation
0.05 : min = 152 | max = 152 | avr = 152
0.01 : min = 152 | max = 152 | avr = 152
0.001 : min = 152 | max = 152 | avr = 152
Standard error
0.05 : min = 10 | max = 10 | avr = 10
0.01 : min = 15 | max = 15 | avr = 15
0.001 : min = 152 | max = 152 | avr = 152

Output : avg_prediction_women
Coefficient of variation
0.05 : min = 10 | max = 10 | avr = 10
0.01 : min = 27 | max = 27 | avr = 27
0.001 : min = 134 | max = 134 | avr = 134
Standard error
0.05 : min = 22 | max = 22 | avr = 22
0.01 : min = 86 | max = 86 | avr = 86
0.001 : min = 152 | max = 152 | avr = 152

Source: simulation outputs generated in GAMA Platform (own elaboration).

Note: these results are available in the GAMA folder in the public Github repository: ABM in GAMA/models/Results/stochanalysis.txt

The 0.01 threshold was adopted as the default criterion for all further experiments, balancing precision with computational feasibility. This value was applied differently depending on the nature of the output: for insecure_rate, a normalized proportion, convergence was assessed using the coefficient of variation (CV); for continuous indicators such as avg_prediction, stddev_prediction, and avg_prediction_women, standard error (SE) was used to ensure robust estimation of the mean. The following convergence patterns were observed:

- *insecure_rate* CV reached stability with 54 repetitions.
- *avg_prediction* SE stabilized at 41 repetitions.
- *stddev_prediction* required 11 repetitions to stabilize. It captures the dispersion or heterogeneity in population-level perceptions.
- *max_prediction*, reflecting the most extreme perceived insecurity values, was more volatile, with its SE stabilizing only after 15 repetitions**,** probably due to the impact of outliers.
- *avg_prediction_women* converged at 86 repetitions, enabling robust gender-sensitive analysis.

Complementary analysis

The summary statistics available in the table below corroborates the visual analysis, and confirms that the model meets robustness requirements under the adopted convergence threshold (0.01):

- **Standard errors (SE)** are low for all metrics except *max_prediction*, which is expected due to its outlier sensitivity.
- **Confidence intervals (CI)** are tight, even for the more volatile indicators, indicating convergence. For example, insecure_rate has a CI width of just 0.01, affirming it as a reliable global indicator.

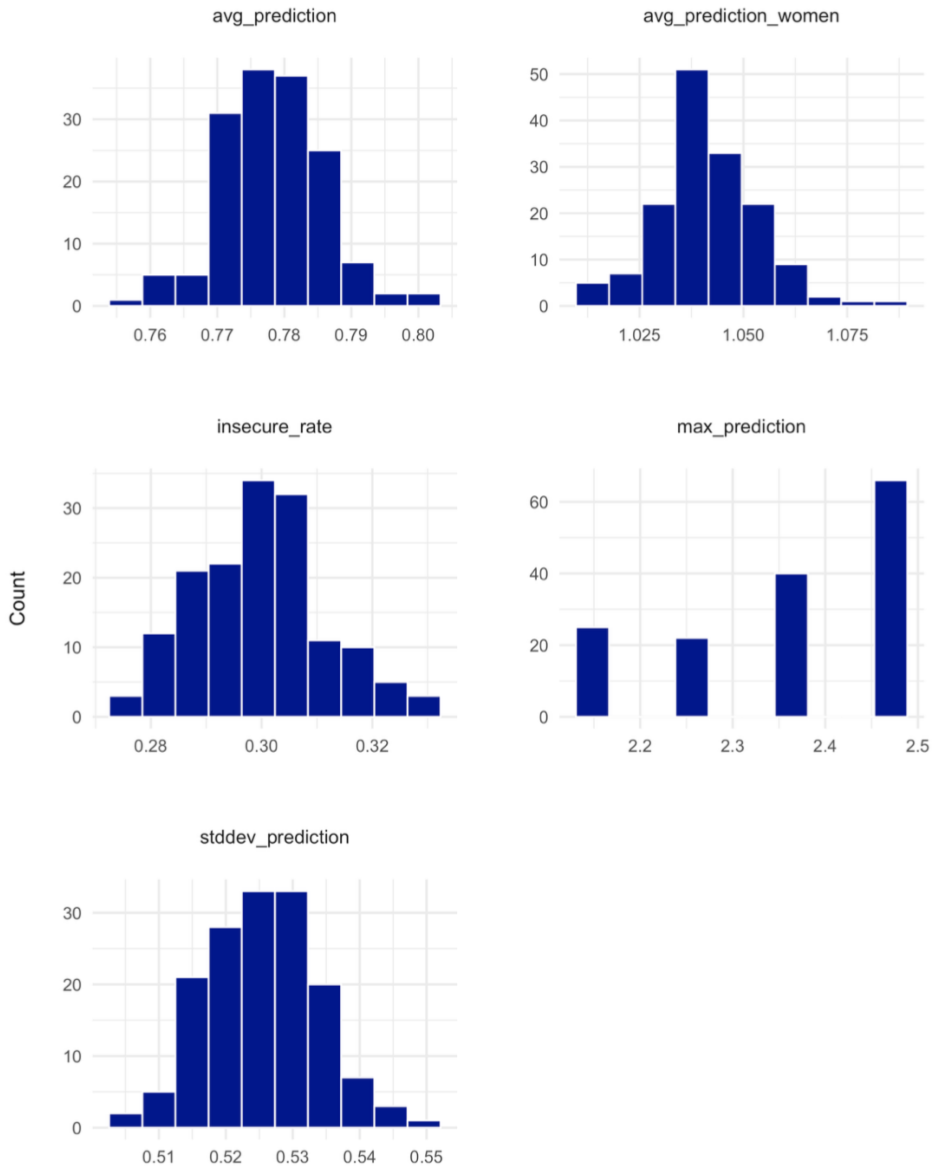
Table 6. Summary statistics of distribution output metrics from the stochanalysis

variable	mean	sd	n	se	CI_lower	CI_upper
avg_prediction	0.7783596	0.007560774	153	0.0006112524	0.7771616	0.7795577
avg_prediction_women	1.0410609	0.012189300	153	0.0009854465	1.0391294	1.0429924
insecure_rate	0.2996752	0.011724024	153	0.0009478312	0.2978174	0.3015329
max_prediction	2.3609972	0.120870510	153	0.0097718016	2.3418445	2.3801499
stddev_prediction	0.5253065	0.008419355	153	0.0006806645	0.5239724	0.5266406

Source: outputs generated in GAMA Platform (own elaboration in R).

The following histogram plots further support the model's reliability. Each histogram represents the distribution of one of the model's core outputs across 153 replications. The distributions for *avg_prediction*, *avg_prediction_women*, and *stddev_prediction* are approximately normal and tightly clustered, suggesting high internal consistency. *insecure_rate* shows discrete (since it is a binary classification bases on a threshold) but stable distribution. *max_prediction* is more dispersed and slightly right-skewed, which makes sense: as an extreme value metric, it is more sensitive to stochastic conditions, like outlier contexts.

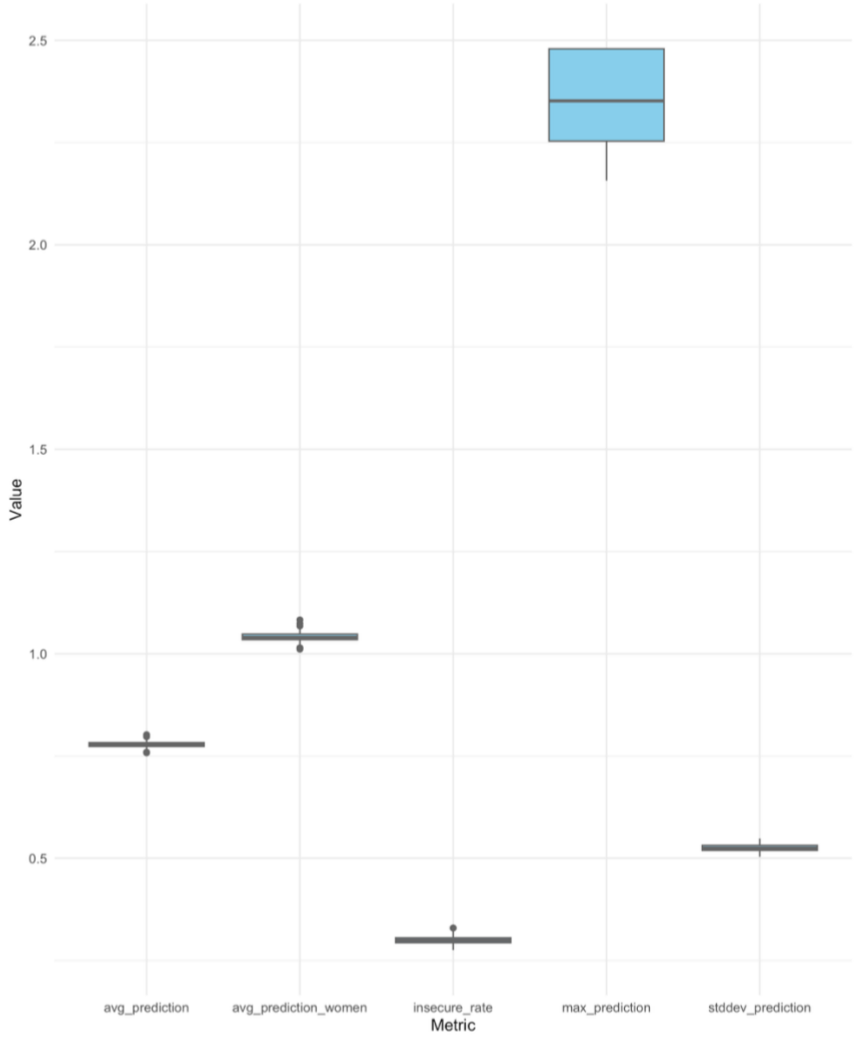
Image 8. Histogram of distribution output metrics from the stochanalysis



Source: simulation outputs generated in GAMA Platform (own elaboration in R).

The boxplot visualizes the spread and central tendency of each output metric, visually confirming that, aside from max_prediction, the model's outputs are tightly bounded and statistically reliable, as they display minimal variance and tight interquartile ranges.

Image 9. Boxplot of distribution output metrics from the stochanalysis

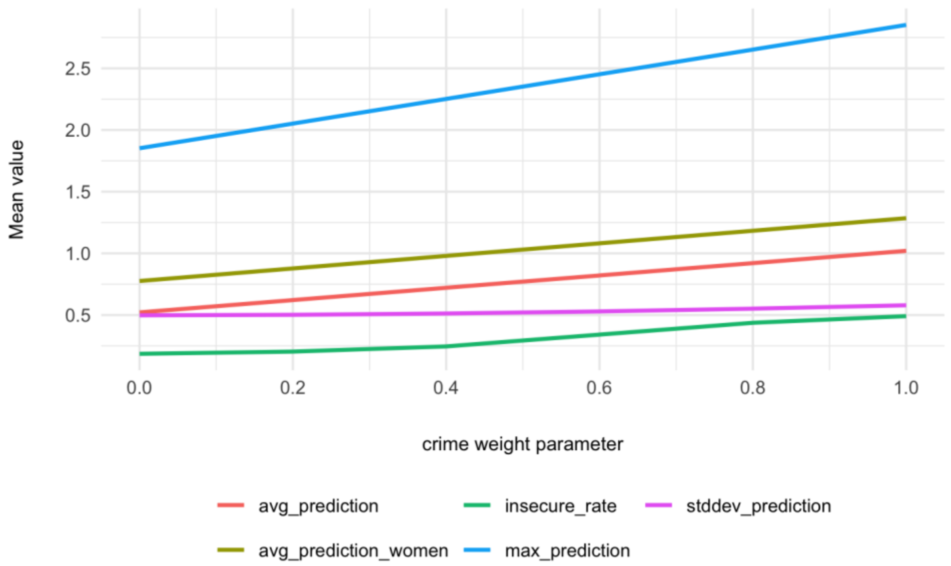


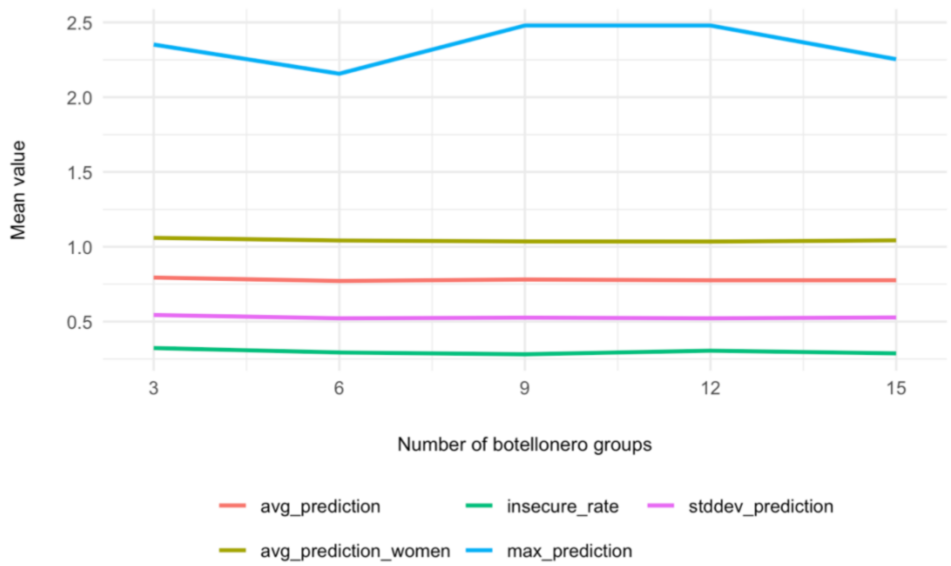
Source: simulation outputs generated in GAMA Platform (own elaboration in R).

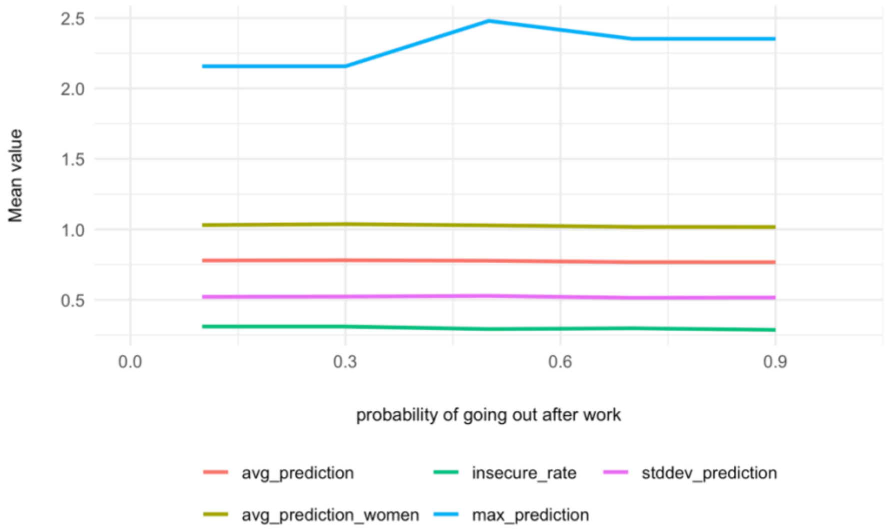
Altogether, these results confirm the statistical convergence and behavioral plausibility of the ABM under the given parameter configuration.

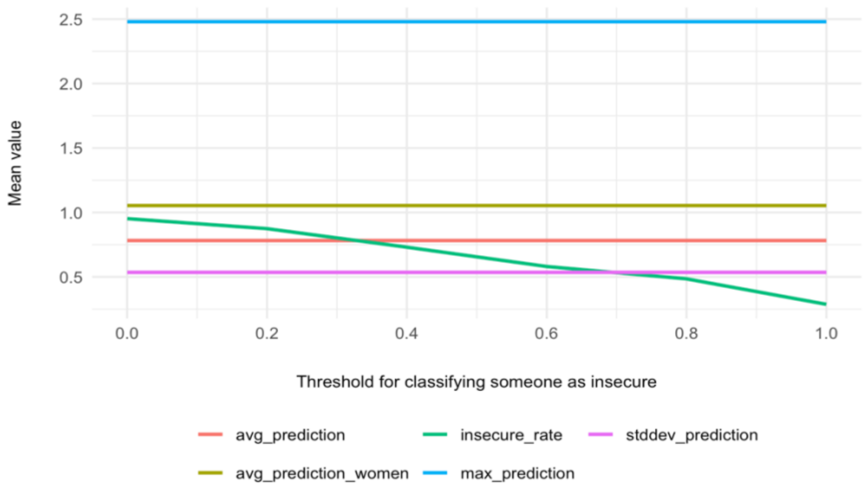
7.8. Results from the One-at-a-time sensitivity analysis

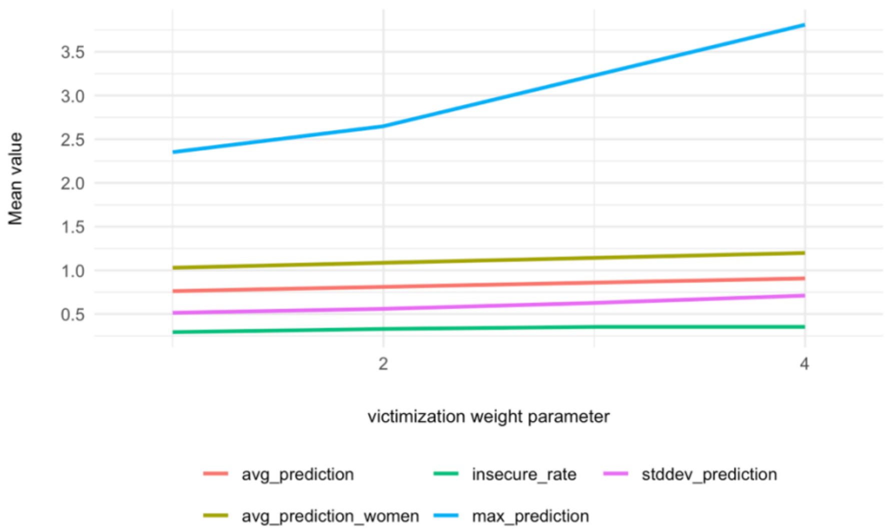
Image 10. Results from the One-at-a-time sensitivity analysis











Source: simulation outputs generated in GAMA Platform (own elaboration in R) uc3m | Universidad Carlos III de Madrid

7.7. DECLARATION OF USE OF GENERATIVE IA IN THE MASTER FINAL PROJECT

I have used Generative AI in this work

Check all that apply:

YES	**NO**

If you have ticked YES, please complete the following 3 parts of this document:

Part 1: Reflection on ethical and responsible behaviour

Please be aware that the use of Generative AI carries some risks and may generate a series of consequences that affect the moral integrity of your performance with it. Therefore, we ask you to answer the following questions honestly (*please tick all that apply*):

Question		
In my interaction with Generative AI tools, I have submitted **sensitive data** with the consent of the data subjects.		
YES, I have used this data with permission	NO, I have used this data without authorisation	NO, I have not used sensitive data
In my interaction with Generative AI tools, I have submitted **copyrighted materials** with the permission of those concerned.		
YES, I have used these materials with permission	NO, I have used these materials without permission	NO, I have not used protected materials
In my interaction with Generative AI tools, I have submitted **personal data** with the consent of the data subjects.		

YES, I have used this data with permission	NO, I have used this data without authorisation	NO, I have not used personal data

My use of the Generative AI tool has **respected its terms of use**, as well as the essential ethical principles, not being maliciously oriented to obtain an inappropriate result for the work presented, that is to say, one that produces an impression or knowledge contrary to the reality of the results obtained, that supplants my own work or that could harm people.	
YES	NO

If you **did NOT** have the permission of those concerned in any of questions 1, 2 or 3, briefly explain why *(e.g. "the materials were protected but permitted use for this purpose" or "the terms of use, which can be found at this address (...), prevent the use I have made, but it was essential given the nature of the work".*

Part 2: Declaration of technical use

Use the following model statement as many times as necessary, in order to reflect all types of iteration you have had with Generative AI tools. Include one example for each type of use where indicated: *[Add an example]*.

I declare that I have made use of the Generative AI system ChatGPT for:

Documentation and drafting:

- *Revision or rewriting of previously drafted paragraphs*

I have asked ChatGPT for a review of some of the paragraphs I have written, specially when in doubt of the correct grammar or vocabulary I was using.

- *Search for information or answers to specific questions*

When creating the first drafts for my final project, I asked ChatGPT to help me understand some of the more advanced concepts in agent-based modeling and simulation. Although I read literature on the topic, most of it was too complex for me to understand in the early stages of the project. It also helped me find examples to this complex concepts I was unfamiliar with.

Develop specific content

Generative AI has been used as a support tool for the development of the specific content of the dissertation (MFP), including:

- *Assistance in the development of lines of code (programming)*

I was already familiar with coding in R, so I did not face many difficulties while working on my thesis. However, occasional errors did arise, and ChatGPT was very helpful in resolving them. On the other hand, GAMA was completely new for me. I followed the tutorials available on its official website, but still encountered several issues with code errors that ChatGPT also helped me fix. I also asked for help to create some of the annotations (#) in R.

- *Optimisation processes*

Sometimes, I asked ChatGPT for ideas on how to optimize my code. For example, creating personalized functions that could be applied to different data.

ChatGPT was very helpful in developing my ABM model. It's an approach that requires precision and attention to detail, and it helped me model things I didn't know how to implement properly. For example, it supported me in calculating the lighting index for each neighborhood and in creating the botellonero agents.

ChatGPT also helped a lot with creating the real_crime_proxy, especially in building the weights for the Crime Severity Index (CSI). Based on the literature review I had done, it helped me adapt the method in an empirical way.

- *Data processing: collection, analysis, cross-checking of data...*

I have asked for guidance in different ways to normalize my data, in order to find the most appropriate depending on the final purpose.

- *Inspiration of ideas in the creative process*

Part 3: Reflection on utility

Please provide a personal assessment (free format) of the strengths and weaknesses you have identified in the use of Generative AI tools in the development of your work. Mention if it has helped you in the learning process, or in the development or drawing conclusions from your work.

Generative AI, particularly ChatGPT, was very useful throughout the entire process of my master's thesis. From drafting initial ideas to helping solve more complex issues (such as the practical application of the Crime Severity Index), it provided significant support. I also found it helpful for correcting grammar, as English is not my first language and some of my writing needed polishing.

Another area where it was incredibly helpful was coding in R and GAMA. Although it sometimes made mistakes or wasn't able to fix certain errors, it still saved me a lot of time by helping generate code that would have taken much longer to write on my own.
Despite all these advantages, I've also realized that overusing it,(as I have, not just in this project but in my personal life too) can be counterproductive. It makes it easier to forget things, become overly reliant, and you end up making simple mistakes by trusting it too much. Still, I've learned a lot about ABM and validation techniques thanks to its clear examples and ability to explain complex topics in simple terms.