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*Master Thesis*

“Safety perception in public spaces: an agent-based model (ABM) approach”

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## **Introduction**

Insecurity in public spaces is one of the main factors shaping how individuals use, inhabit, and appropriate the urban environment. However, multiple studies have shown that the subjective feeling of insecurity does not always align with actual crime levels: statistically safe environments are often perceived as dangerous and avoided, while high-crime areas may not always trigger the same public concern (Zhang et al., 2021). This disconnect, often described as perception bias, has become a topic of growing interest in environmental criminology, urban psychology, and spatial justice research (Zhang et al., 2021; Azevedo et al., 2021).

Subjective insecurity has tangible behavioural consequences: it reduces pedestrian mobility (Lizárraga et al., 2022), limits access to public space for specific groups (Fileborn & O’Neill, 2021), and reinforces patterns of socio-spatial segregation (CityScope, 2021). In particular, women, older adults, and youth from certain social profiles tend to adapt their daily routes to avoid spaces they perceive as dangerous, even without ever having been victims of crime (Park & Garcia, 2019). As Azevedo et al. (2021) stress, safety is not merely an external condition, but a basic human need whose absence undermines psychological well-being and the right to the city.

**Objetivos del proyecto** :

In this context, it becomes especially important to develop tools that allow us not only to measure perceived insecurity but to understand how it is constructed, reproduced, and distributed across space and time. **[Insert your personal motivation for choosing this topic here.]**

Aquí podrías separar los **objetivos generales y específicos** como en tu otro trabajo. Por ejemplo:

* **Objetivo general:** Simular la percepción de inseguridad en el espacio público a través de un modelo basado en agentes.
* **Objetivos específicos:**
* This situated simulation logic renders ABM a particularly powerful method for analysing perceived insecurity from a **micro-social, contextual, and agent-centred perspective**.
  + Integrar factores físicos, sociales y afectivos en la simulación.
  + Representar la heterogeneidad individual en la percepción.
  + Explorar escenarios contrafactuales (mejora del alumbrado, redistribución de grupos juveniles, etc.).
* Failure to ensure convergence in stochastic agent-based models may result in misleading conclusions due to sampling variability rather than model dynamics. By establishing a stable replication count and confirming convergence visually and statistically, this study enhances the robustness and reproducibility of the simulated outcomes.

This work aims to develop an agent-based model capable of simulating the emergence of perceived insecurity as a product of situated, dynamic interactions in urban space. The remainder of this document is structured as follows: Section 2 reviews the relevant literature; Section 3 outlines the methodology and modelling decisions; Section 4 presents the results of the simulation scenarios; and Section 5 discusses implications, limitations, and avenues for future research.

## **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 accounts (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, where individual decisions and aggregate effects emerge from simple rules and local interactions. These interactions generate nonlinear collective patterns that cannot be inferred directly from individual behaviour, making ABM particularly suitable for studying phenomena that unfold across different scales, such as perceived insecurity.

Beyond their explanatory power, ABMs are valuable for prospective simulation. They enable the evaluation of counterfactual scenarios that support policy design: *What if lighting improves? What if youth gatherings are redistributed? What if leisure routines shift?* As Izquierdo et al. (2020) argue, ABMs can help decision-makers understand the impact of safety interventions in intuitive, spatially grounded terms.

As Crooks et al. (2021) further state, what distinguishes agent-based models from other simulation frameworks is their emphasis on interactions among autonomous, heterogeneous agents with differentiated behaviours. Through these interactions (with one another and with the environment) emergent patterns arise that are not directly encoded in individual rules but instead result from a nonlinear collective process. This capacity to simulate both micro-level decision-making and macro-level patterns makes ABM especially powerful for addressing complex, relational problems such as urban insecurity.

The model developed here does not aim to replicate reality exactly, but to serve as a tool for exploring strategies. It allows perceived insecurity to emerge dynamically from interactions between physical, social, and temporal dimensions, rather than being imposed by external indices. It also captures perceptual heterogeneity: individuals in the same setting may feel more or less insecure depending on their gender, victimization history, or sensitivity to darkness.

## **Approaches to studying urban safety perception**

Recent academic literature has consistently emphasized that perceived insecurity is not merely a derivative of crime rates, but a multidimensional construct shaped by the interaction of environmental, social, psychological, and affective factors. In one of the most comprehensive contributions to this debate, Syropoulos et al. (2024) propose and validate a multidimensional model of perceived personal safety comprising three interrelated dimensions:feeling of safety*,* fear of crime*, and* safety confidence. Drawing on theories such as Social Safety Theory (Slavich, 2020), Attachment Theory (Bowlby, 1951), and personality psychology, the authors demonstrate that each of these dimensions is differentially associated with psychosocial outcomes, including life satisfaction, depressive symptoms, trust in institutions, and locus of control. Their findings decisively show that perceived safety cannot be adequately captured through a single indicator and must be understood as a complex, multidimensional experience.

This perspective aligns with empirical studies highlighting how factors such as gender, age, and familiarity with the urban environment mediate the perception of safety. In a large-scale study of urban parks, Ianniello et al. (2022) conceptualize perceived safety as a composite of fear of crime, perceived risk, experience of victimization, and neighborhood opinion, and explore its variation across demographic groups and spatial configurations. Their methodology combines objective environmental audits, spatial crime data, and usage patterns, revealing that physical conditions—such as maintenance, lighting, and accessibility—interact with social variables to shape how safe spaces are perceived and used. Notably, women and elderly respondents reported significantly higher levels of avoidance, regardless of actual crime statistics.

Other spatial studies reinforce this argument. In a spatially disaggregated analysis of perceived insecurity across urban neighborhoods, Roman et al. (2022) find that **objective crime rates only partially explain spatial variations in fear**. Instead, perceived disorder, signs of neglect, and symbolic cues, such as graffiti or broken windows, exert a stronger influence. Moreover, the effect of **spatial familiarity** emerges as a protective factor: those who live or transit regularly through a neighborhood tend to feel safer, even in statistically unsafe contexts. These findings underscore the need to incorporate **contextual and symbolic dimensions** into models of perceived safety, rather than relying solely on crime metrics.

Parallel to these empirical developments, a rich theoretical corpus has emerged around the **geography of fear**. Originating in feminist and human geography, this perspective conceptualizes fear not as an individual emotion but as a **spatially distributed and socially mediated phenomenon** (Pain, 1997). The experience of fear is shaped by the intersection of identity, embodiment, and spatial relations, leading to the production of “fearscapes” where certain bodies (particularly women and racialised individuals) are systematically marginalized. Fileborn and O’Neill (2021) document how street harassment functions as a mechanism that reorders public space, creating informal exclusions through behavioural adaptation and spatial avoidance. This literature strongly supports the need for modelling frameworks that account for heterogeneity, symbolic space, and temporal routines.

The need for more dynamic and interactional models of perceived insecurity has led some researchers to turn to computational methods. Recent studies have begun to apply this approach to urban safety. For example, Collins et al. (in Izquierdo et al., 2020) developed an ABM to simulate gang behaviour, using simple rules to model attraction and group affiliation. Similarly, Malleson (2010) applied ABMs to study burglary patterns. Most relevant to this work, however, is the model by Izquierdo et al. (2020), developed an ABM to simulate safety perception in a Mexican informal settlement, integrating nine urban metrics including visibility, formal surveillance, accessibility, and social cohesion. This study not only reflects a growing consensus around the **situated and layered nature** of safety perception and the inadequacy of purely quantitative or crime-focused measures but also validates the use of ABM to simulate heterogeneous reactions to complex spatial configurations, notably integrating surveys, participatory observation, and local mobility data.

Despite the richness of these approaches, they lack the capacity to simulate the **emergent, intersubjective, and situated character** of insecurity as it unfolds in real-time space. No reviewed study to date has fully integrated **individual heterogeneity, spatio-temporal context, symbolic environments, and dynamic decision-making** in a unified simulation framework. It is precisely this methodological gap that the present project seeks to address.

In sum, existing literature confirms the multidimensional and stratified nature of perceived insecurity, validates the role of space and time, and signals the limitations of both survey-based and index-based approaches. Building upon this foundation, the present work proposes a methodological innovation capable of simulating how insecurity emerges and evolves in public space, not as a linear response to crime, but as a relational and behavioural process distributed across urban landscapes. The agent-based model proposed here introduces agents with differentiated traits (e.g., gender, sensitivity to darkness, leisure behaviour), situated in a dynamic urban environment characterized by lighting variation, group visibility, and temporal cycles. Perception does not pre-exist as a fixed score but arises from the agent’s **interaction with context, memory of exposure, and social cues**. This model conceives that perceived insecurity exemplifies such a phenomenon, shaped simultaneously by physical factors (e.g., lighting, accessibility, visibility), social factors (e.g., group presence, density, gender), and affective dimensions (e.g., past experiences, emotional memory).

**3. Methodology**

**3.1. Foundations and validation strategy**

The methodological design of this study integrates statistical modeling and agent-based simulation. To ensure conceptual coherence, technical robustness, and empirical relevance, the approach adopted here aligns with recent and classical methodological frameworks in the field of computational social science.

A fundamental concern in simulation-based research is the **empirical validation of models**. In this regard, **Fagiolo, Moneta, and Windrum (2007)** argue that, especially in social systems where micro-level behavior is often unobservable, a model’s credibility should rest not on reproducing individual decisions but on its ability to reflect **stylized macro-level patterns**. This leads to what they define as **indirect calibration**: tuning model parameters so that simulated aggregate outcomes resemble known empirical regularities, rather than raw individual data. This principle underpins the modeling strategy of this thesis: survey data on perceived insecurity and institutional trust were reduced into latent dimensions using categorical principal components (CATPCA), while a crime proxy index was constructed by combining official crime statistics with residents’ district-level perceptions. These data-driven constructs formed the basis for calibrating agents’ behavioral parameters, such as risk sensitivity, visibility response, and movement routines.

Complementing this approach, the framework proposed by **Moss and Edmonds (2007)** offers an operational taxonomy of validation processes that is particularly suitable for ABMs. According to their typology, four types of validation are relevant: **input validation** (ensuring the realism of parameters), **process validation** (testing internal logic and mechanisms), **descriptive output validation** (comparing simulated and observed outcomes), and **predictive validation** (forecasting unseen data). In this project, input validation was achieved by deriving agent attributes from empirical regression results. Process validation was addressed through the internal consistency of behavioral rules and their grounding in theory and qualitative accounts. Descriptive output validation was carried out by comparing aggregate simulation outputs with observed patterns in the survey data. Predictive validation, while desirable, falls beyond the scope of this exploratory implementation.

To reinforce the methodological credibility of the model, this thesis also draws on the recent classification by **Collins, Koehler, and Lynch (2024)**, who outline nine methods to support ABM validation, distinguishing between foundational and advanced strategies. Two of the foundational methods—**empirical validation** and **visualization**—are directly applied here: the model is empirically validated by tuning agent parameters according to regression results obtained from real survey data and by reproducing distributions of perceived insecurity comparable to those observed; the model also integrates real-time visualization techniques to support dynamic validation: spatial and temporal displays track how agents’ perceived insecurity evolves, both globally and per district, providing immediate visual feedback to detect inconsistencies or unexpected dynamics. In addition, an advanced method identified by these authors, **bootstrapping**, is employed in the statistical analysis phase to assess the robustness of model estimates through confidence intervals and sensitivity checks (both in the statistical phase, using robust estimators, and in the simulation, through One-At-a-Time (OAT) experiments varying key parameters like crime weight, leisure probability, and insecurity threshold to observe their impact on predicted perceptions).

Finally, this validation strategy is situated within the broader process-oriented model verification framework described by **Sargent (2013)**. Sargent distinguishes between **data validity**, **conceptual model validation**, **computerized model verification**, and **operational validation**. The current model meets data validity standards by relying on well-documented, structured sources: a representative urban safety survey and official crime reports. Conceptual validation was achieved by basing agent behavior and simulation logic on existing sociological and criminological literature. Computerized model verification was conducted through iterative testing in the GAMA platform to ensure consistency between the conceptual and implemented models. Operational validation is addressed by comparing simulated outputs with empirical data and by examining their behavior under varying conditions of crime exposure and neighborhood characteristics.

**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. 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[[1]](#footnote-1).

#### **3.2.2. Construction of latent indices: insecurity perception**

To quantify latent dimensions of perceived insecurity, a **Categorical Principal Components Analysis (CATPCA)** was conducted using the Gifi package. 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** (exact values to be inserted), 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.

#### **3.2.3. 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 and 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 average perceived insecurity scores from the survey. ~~This hybrid integration of objective criminal exposure and subjective spatial perception aligns with the logic of~~ **~~indirect calibration~~** ~~(Fagiolo et al., 2007), allowing the model to reflect heterogeneous risk environments even in the absence of disaggregated crime records~~. Full weight tables, offence classifications, and calculation procedures are included in the Appendix.

#### **3.2.4. Regression modeling and empirical parameter extraction**

A multivariate linear regression model was then fitted using *gen\_ins* and *inst\_ins* as dependent variables. Predictor variables included **sociodemographic characteristics** (e.g., gender, age, education level, nationality), **contextual attributes** (e.g., neighborhood of residence), **experiential factors** (e.g., prior victimization, self-protection behaviors), and **attitudinal or environmental variables**[[2]](#footnote-2) (e.g., institutional trust, perceived environmental degradation). Model selection followed a stepwise approach guided by AIC and theoretical relevance.

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: R² = 0.42, RMSE = 0.76, MAE = 0.62), with more modest results for institutional insecurity (inst\_ins: R² = 0.07, RMSE = 0.98, MAE = 0.77).

In parallel, **bootstrap-based confidence intervals[[3]](#footnote-3)** 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 s**tatistical robustness** (ensuring that coefficient estimates are interpretable, stable, and not artifacts of modeling assumptions) and thep**redictive 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. In the terms of Moss and Edmonds (2007), this process contributes to both **input validation** (ensuring realistic parameter values) and **process validation** (ensuring plausible agent logic). Furthermore, the structure of the regression outputs supports initial **descriptive output validation** once compared with simulated distributions.

These procedures also reflect the principles of **indirect calibration** (Fagiolo et al., 2007): rather than matching individual behaviors, the model is tuned to reproduce empirically observed aggregate regularities, thereby enhancing credibility while acknowledging data constraints.

### **3.2. Simulation development in GAMA**

To explore how contextual and individual-level factors interact to shape perceptions of 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 (n=167), whose demographic attributes and individual perceptions are drawn from a CSV of real survey data. The **key components of the model are:**

* **Spatial context**: The model includes shapefiles for neighborhoods (barrios), buildings (classified as residential, workplace, or leisure), roads, and parks. Each neighborhood is associated with two contextual indices:
  + A **crime proxy score**, constructed from the calibrated CSI.
  + A **lighting score**, representing perceived darkness in public spaces.
* **Resident agents** follow a daily routine: commuting to work, optionally engaging in leisure after work (based on a probability), and returning home. Their state (working, resting, leisure) evolves throughout the simulation, and their **prediction of insecurity** is continuously updated based on personal vulnerability factors, neighborhood context, lighting conditions, time of day, and exposure to **botellonero groups** (youth gatherings in parks).
* **Botellonero agents** 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, weighted by contextual crime and personal sensitivity scores.
* **Insecurity prediction** is modeled as a linear combination of individual-level effects (from regression), contextual modifiers (e.g., crime\_weight, lightning\_score), and dynamic factors such as proximity to botelloneros. A resident is classified as **insecure** when their prediction exceeds a set threshold (threshold\_pred), which can be adjusted experimentally.
* **Initialization** includes loading spatial data, creating agents, distributing them across neighborhoods, assigning routines, and tracking global indicators such as the proportion of insecure agents and the average prediction per barrio.

### **3.3. Stochastic replication analysis**

Agent-based models are by nature **stochastic systems**, implying that 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 agent-based models 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 simulation runs (n) as a function of the number of configurations (J, model dimensionality) and the expected effect size (ES, statistical sensitivity), was applied:

This approach balances computational cost with analytical reliability.

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 (X) 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.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Coefficient of variation (CV)** | | | **Standard error (SE)** | | |
|  | **0.05** | **0.01** | **0.001** | **0.05** | **0.01** | **0.001** |
| **insecure\_rate** | 15 | 31 | 44 | 2 | 2 | 2 |
| **avg\_prediction** | 7 | 18 | 38 | 10 | 44 | 63 |
| **stddev\_prediction** | 8 | 43 | 43 | 27 | 49 | 64 |
| **max\_prediction** | 3 | 19 | 19 | 27 | 85 | 152 |
| **avg\_prediction\_women** | 6 | 27 | 50 | 19 | 49 | 50 |

The **0.01 threshold** was adopted as the default criterion for all further experiments, balancing precision with computational feasibility. The following convergence patterns were observed, all of them at the 0.01 threshold:

* **insecure\_rate** reached stability with **31 repetitions**, confirming its suitability as a global and normalized output measure.
* **avg\_prediction** stabilized at **44 repetitions**, and is retained as the key indicator of average perceived insecurity across agents.
* **stddev\_prediction** required **49 repetitions**, and captures the **dispersion or heterogeneity** in population-level perceptions.
* **max\_prediction**, reflecting the most extreme perceived insecurity values, was more volatile, stabilizing only after **85 repetitions**—a reminder of the impact of outliers.
* **avg\_prediction\_women** converged at **49 repetitions**, enabling robust gender-sensitive analysis.

Based on these results, a **default replication count 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 Figure X).

Gráfico, Gráfico de cajas y bigotes

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### **3.4. Sensitivity analysis**

To evaluate the behavioral plausibility and internal consistency of the model, a one-factor-at-a-time (OAT) sensitivity analysis was conducted by varying different parameters in the simulation.

These agents represent informal youth gatherings, often associated with nighttime disorder. Their presence is hypothesized to influence residents' perceived insecurity.

The parameter nb\_grupos\_botellon was varied from 3 to 15 in steps of 3, while holding all other parameters constant. For each value, 70 replications were run, and summary statistics were computed for key output variables: insecure\_rate (proportion of insecure residents), avg\_prediction (mean perceived insecurity), stddev\_prediction (insecurity dispersion), max\_prediction (maximum perceived insecurity), and avg\_prediction\_women (mean prediction for female agents).

Despite the behavioral expectation that more visible youth gatherings would raise perceived insecurity, most output metrics remain strikingly stable across the tested range (3–15 groups). Metrics such as avg\_prediction and insecure\_rate vary only slightly, suggesting that the model reacts proportionally and does not overstate the effect of moderate environmental disorder. Only max\_prediction shows a visibly increasing trend, which aligns with its role in capturing outlier or worst-case perceptions. This stability strengthens the model’s behavioral plausibility and highlights that increased group presence may impact specific subpopulations rather than the general average.

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### 4. Research possibilities enabled by the model

After assessing the methodology employed for developing the model, it is relevant to mention its functions as 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).
* **Analyze spatiotemporal variability** in perceived risk across distinct urban neighborhoods, operationalized through high-resolution GIS data.
* **Conduct controlled in silico experiments** that manipulate specific parameters (e.g., crime\_weight, nb\_grupos\_botellon, threshold\_pred) to observe their isolated and interactive effects on emergent insecurity patterns.
* **Validate model behavior** against empirical expectations via monotonicity checks, gender stratification, and convergence diagnostics under stochastic replication.

Such a tool allows for the formalization and empirical testing of a range of criminological and sociological hypotheses, including:

* **H1** (disorder hypothesis): an increase in visible disorder (operationalized as the number of botellonero groups) 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** (threshold sensitivity): Varying the insecurity threshold (threshold\_pred) systematically alters the population-level classification into "secure" and "insecure" residents, enabling the evaluation of classification robustness under different normative definitions of insecurity.

### 3. Data architecture and model inputs

The model is parameterized using a combination of empirical survey data, contextual indicators, and spatial information. Key inputs include:

1. Agent level attributes (CSV file)

* Sociodemographic characteristics: gender, age, nationality.
* Survey-derived psychological and behavioral indicators: generalized insecurity (gen\_ins), sensitivity to darkness (darksens), prior victimization status, routine activity patterns (work, leisure, rest), insecurity to botelloneros.
* Empirically estimated regression coefficients (e.g., gender\_effect, p7\_8\_effect) used to personalize insecurity prediction at the individual level.

#### B. Contextual and Environmental Variables

* **Crime scores by neighborhood (real\_crime\_proxy)**: derived from survey-based perceptions of neighborhood safety and unsafety and real crime data for all Pamplona, normalized and integrated into the insecurity prediction formula. Since it is a proxy, it can be substituted with real objective data.
* **Lighting intensity index (lightning\_score)**: operationalized as a normalized continuous variable per neighborhood by taking into account streetlights’ electric power in each neighborhood.
* **Spatial data layers**: including shapefiles for neighborhoods, roads, buildings (residential, work, leisure), and parks, enabling agent movement and environmental interactions.

#### C. Configurable Parameters (via GUI or batch experiments)

* nb\_grupos\_botellon: number of visible botellonero groups.
* ciclo\_crimen\_botellonero: weekly cycle of botellonero visibility, how many times a week people can encounter botelloneros.
* crime\_weight: weight of contextual crime scores in nighttime insecurity calculation. This is also a proxy since the survey did not cover this topic, but its robustness was tested with the OAT.
* threshold\_pred: decision threshold above which agents are classified as "insecure", and takes into account prediction values (which Will be later explained).
* probabilidad\_ocio\_fuera: probability of leisure activity after work, either in the own neighborhood or in a differnt one.

### 4. Outputs and analytical deliverables

The model produces both aggregated summary statistics and rich spatiotemporal visualizations:

#### A. Quantitative Outputs (per simulation run)

* avg\_prediction: mean predicted insecurity across the population.
* stddev\_prediction: dispersion of insecurity scores, useful for heterogeneity analysis.
* max\_prediction: maximum predicted insecurity, capturing extreme cases.
* avg\_prediction\_women: subgroup average for female agents.
* insecure\_rate: proportion of agents exceeding the defined insecurity threshold.

These outputs are computed automatically every simulation cycle and exported during batch experiments.

#### B. Stochastic Robustness and Sensitivity Diagnostics

* **Convergence plots** (e.g., average values by replication).
* **Coefficient of variation (CV)** and standard error calculations.
* **Confidence intervals** (normal approximation) for mean estimates.
* **OAT plots** with error bars visualizing the isolated impact of each parameter.

#### C. Visual Outputs

* **3D spatial renderings** of agents, their behavioral states, and urban layout.
* **Dynamic charts** capturing activity states, insecurity evolution, and barrio-level trends.
* **Distribution histograms** of insecurity scores, mapped to safety classifications.

**Gráfico

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**References**

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ANEXO

After the initial preprocessing steps, and given the presence of item nonresponse in several variables of interest and that the dataset included **variables of different types** (nominal, ordinal, continuous) with scattered missing values, **multiple imputation by chained equations (MICE)** was employed to address incompleteness. The method selected (**predictive mean matching (PMM)**) was chosen for its ability to preserve the distribution of original values and avoid imputation artifacts. Given the complexity of the data structure, a **10-fold cross-validation** was performed to optimize the imputation model, ensuring stable predictions across imputed datasets. This process allowed for consistent handling of missing data without reducing the sample size, following best practices (van Buuren, 2018).

1. Data preparation and preprocessing, imputation of missing values, exploratory análisis and feature engeneering steps can be consulted in the .rmd available at the github repository. It constitutes an important annex, with in detail explanations of all the steps followed in R. [↑](#footnote-ref-1)
2. **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.** [↑](#footnote-ref-2)
3. This involves 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. [↑](#footnote-ref-3)