Modeling Social Learning: An Agent-Based Approach

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Learning is the process of acquiring or modifying knowledge, behavior, or skills. The ability to learn is inherent to humans, animals, and plants, and even machines are provided with algorithms that could mimic in a restricted way the processes of learning. Humans learn from the time they are born until they die because of a continuous process of interaction between them and their environment. Behavioral Psychology Theories and Social Learning Theories study behavior learned from the environment and social interactions through stimulus-response. Some computer approaches to modeling human behavior attempted to represent the learning and decision-making processes using agent-based models.

This dissertation develops a computer model for social learning that allows agents to exhibit behavior learned through social interactions and their environment. The use of an agent-based model allows representing a complex human system in a computer environment. Behavioral Psychology Theories and Social Learning Theories provide the explanatory theoretical framework. The learning processes are implemented using the Rescorla-Wagner Model. The learning structure is implemented using an adaptation of Agent Zero. The decision-making process is implemented using a threshold equation. A use case in youth gang homicides is developed, calibrated, validated, and used for policing and decision making through simulation of multiple case scenarios. The simulation results show the model accuracy in representing
learning and decision-making processes similar to those exhibited in the complex human system represented.
This thesis is dedicated to Marco, Diego, and Piero, for their unconditional love and support all these years.
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NOMENCLATURE

SLA  Social Learning Agent

$D_i(t)$  Definitions attribute of $i-th$ SLA in time $t$

$A_i(t)$  Association attribute of $i-th$ SLA in time $t$

$O_i(t)$  Observation attribute of $i-th$ SLA in time $t$

$R_i(t)$  Reinforcement attribute of $i-th$ SLA in time $t$

$L_i(t)$  Social Learning attribute of $i-th$ SLA in time $t$

$M_i(t)$  Motivated? attribute of $i-th$ SLA in time $t$

$P_i(t)$  Position attribute of $i-th$ SLA in time $t$

$x_i(t)$  $x$ component attribute of $i-th$ SLA in time $t$

$y_i(t)$  $y$ component attribute of $i-th$ SLA in time $t$

$S_i$  Cellular Automaton State

$LV$  Local Vision

$SN$  Social Network

$GA$  Gang Affiliation

$SZ$  Social Network Size

$p$  Grid’s Number of patches

$\tau$  SLA’s Threshold

$H$  Number of Homicides
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CHAPTER 1
INTRODUCTION

1.1 Thesis Statement

Agent-Based Modeling can be used to develop a model of social learning agents able to exhibit behavior learned from social interactions and the environment using Behavioral Psychology Theories and Social Learning Theory of Crime as an explanatory framework and an adaptation of Agent Zero for modeling human behavior. For calibration, validation, and policing and decision-making, a use case is developed for representing Youth Gang Homicides1.

1.2 Problem Statement

Learning is the process of acquiring or modifying knowledge, behavior, or skills. The ability to learn is inherent to humans, animals, and plants, and even machines are provided with algorithms that could mimic in a restricted way the processes of learning. Humans learn from the time they are born until they die because of a continuous process of interactions with their environment. The processes of learning are studied in many sciences such as pedagogy, psychology, and neurology.

Behavioral Psychology studies observable stimulus-response behavior learned from the environment. In 1913, John Watson set the assumptions and methodology for behavioral analysis [1]. Watson stated that all behavior is learned from the environment. Watson also stated that Behavioral Psychology should be seen as a science to study observable behavior that could be scientifically measured, and the theory should be supported by empirical data obtained through observation and measurement of behavior.

1 IEEE Transactions and Journals style is used in this thesis for formatting figures, tables, and references.
The learning and decision-making problem for representing human behavior had been widely studied. Some theoretical approaches to modeling human behavior are rational choice, threshold equations, planned behavior theory, and game theory, among others. Some computer approaches attempted to represent the learning and decision-making processes using agent-based models. Agent-Based Models (ABM) allow representing multiple agents interacting with each other within a computer environment, while the result of this micro behavior is the emergence of group or aggregated behavior [2-4]. Among these models, the Schelling’s Segregation Model shows that relative mild preference of neighbors from the same race could lead to high levels of segregation [5]. Axelrod’s Dissemination of Culture Model studies the process of cultural diffusion under the assumption that people are more likely to interact with others who share similar cultural attributes [6]. Miller and Page’s Standing Ovation Problem assesses an audience’s decision to stand and applaud or not after a performance [7]. Epstein’s Civil Violence Model assesses the decision to become active and join a riot or not [8]. Epstein’s Agent Zero Model represents individual behavior in groups by modeling three behavioral components emotional, rational, and social [9]. Ardiles-Cruz et al. developed an Insider Threat ABM [10] that represents the disposition of employees to commit a threat based on previous behavior.

This dissertation develops a computer agent-based model of social learning agents able to exhibit behavior learned from the environment and social interactions. The explanatory framework will be developed using Behavioral Psychology Theories and Social Learning Theories. We propose to model human behavior using an adaptation of Epstein’s Agent Zero Structure for representing individual behavior in groups in an agent-based computer environment. The model should consider the processes of stimuli-response that lead to learning, the individual’s decision-making process that determines whether or not to exhibit the learned
behavior, and the development of a use case that allows us to measure the emergence of behavior.

1.3 Motivation

This section contains a survey on Behavioral Psychology Theories, Social Learning Theories, and computer agent-based models of human behavior. These theories will be the explanatory theoretical framework for our proposed model.

1.3.1 Behavioral Psychology

Behavioral Psychology studies observable stimulus-response behavior learned from the environment. In 1913, John Watson set the assumptions and methodology for behavioral analysis [1]. Watson stated that all behavior is learned from the environment. This assumption emphasizes the role of environmental factors for exhibiting a behavior while nearly excluding inherited factors. Watson also stated that Behavioral Psychology should be seen as a science to study observable behavior that could be scientifically measured, and the theory should be supported by empirical data obtained through observation and measurement of behavior. Watson experimented with animals by measuring behavior that was the result of stimulus-response trials, under the assumption that there is little difference between learning that takes place in humans and learning that takes place in animals. While an advantage of Behavioral Psychology is its ability to define behavior clearly and measure changes in behavior by introducing stimulus-response measurable events, its main criticism is that it only provides a partial model of human behavior. Essential factors like emotions, expectations, and motivations are not considered.
In 1903, Ivan Pavlov developed the theory of Classical Conditioning. Classical conditioning assumes that animals (as well as humans) learn by the association between stimulus and responses. Classical conditioning is the process of learning that occurs when a non-conditioned stimulus elicits a response that was caused initially by a conditioned stimulus. Classical conditioning is non-conscious instinctual learning. Pavlov experimented with conditioning salivation in dogs. Garcia experimented with food aversion conditioning [11], Öhman and Mineka experimented with fear conditioning [12]. Gorn, McSweeney and Bierley, Stuart, Shimp, and Engle researched strategies to influence consumer behavior [13-15]. Also, classical conditioning was applied to heart rate conditioning [16-18] and eye-blink conditioning in animals [19, 20].

Operant conditioning is a type of learning in which consequences influence behavior. Thorndike taught cats to push a lever to get a reward. These experiments lead to his famous Law of Effect. Thorndike’s Law of Effect states that responses that produce a satisfying response become more likely to occur again. Skinner developed operant conditioning based on Thorndike’s Law of Effect. Skinner coined the term operant conditioning meaning changing of behavior using reinforcement given after the desired response. Skinner taught rats to press a lever to get food or to avoid an electrical current. Applications of operant conditioning can be found in behavior shaping and behavior modification therapies [21, 22], token economy [23-25], and educational applications [26-28], among others.

Observational learning involves changes in behavior and knowledge as a result of observing and imitating others. Many of the things we do are because we observed others. Examples include dietary choices, clothing style, holiday traditions, and music preferences, among others. Socially transmitting behavior is the primary way that adaptive behavior spreads
within a population. Bandura et al. [29] performed the Bobo Doll Experiments to show that children learn social behavior such as aggression through the process of observational learning. Observational learning [30] was used in animals for learning behavior such as ants, honeybees, chimpanzees [31-35]; for motor skills acquisition [36, 37]; to analyze the effects of media violence and aggressive models [38-40] among others. Later, Bandura [41] renamed the theory Social Learning. The theory adds to the ideas of classical conditioning and operant conditioning, two observational learning and mediational processes.

1.3.2 Social Learning

Social Learning Theory of Crime and Deviant Behavior states that individuals learn criminal behavior from their environment and through imitation. In 1947, Sutherland presented his Differential Association Theory of Crime to explain the development of criminal behavior as the result of interactions with others, mainly in primary groups. Social Learning Theory of criminal and deviant behavior is an integration of Sutherland’s sociological theory of differential association with behavioral principles from psychology. It was originally presented by Robert Burgess and Ronald Akers [42] as differential association-reinforcement, and later renamed Social Learning Theory of Criminal and Deviant Behavior [43] by Akers. The theory states that “the probability that persons engage in criminal and deviant behavior is increased and the probability of them conforming to the norm is decreased when they differentially associate with others who commit criminal behavior and expose definitions favorable to it (differential association), in-person or symbolically are relatively more exposed to salient criminal/deviant models (imitation), define it as desirable or justified in a situation discriminative for the behavior (definitions), and have received in the past and anticipate in the current or future situation
relatively greater reward than punishment for the behavior (differential reinforcement)” [43]. Although it refers to all aspects of the learning process, the theory relies mainly on four principal explanatory concepts: differential association, definitions, differential reinforcement, and imitation. Later Akers added Social Structure to the theory. It proposes that variations in one or more of the dimensions of social structure produce variations in the magnitude, direction, and patterning of the social learning variables

- **Differential Association:** Differential association was proposed by Edwin Sutherland to explain criminal behavior as the result of interactions with other people, mainly in primary groups. The theory includes a theoretical framework with nine propositions explaining criminal behavior as the result of learning from social processes of association with crime-oriented people.

- **Definitions:** The concept of definitions represents the individual’s own beliefs and attitudes to a certain behavior. Definitions could be positive or neutral towards committing crimes.

- **Differential Reinforcement:** Burges and Akers proposed differential reinforcement as Differential Association-Reinforcement. Burgess and Akers proposed that the mechanisms of learning criminal and deviant behavior are those of learning in psychological behaviorism and fused them with Sutherland’s theory. The learning processes added to the theory were operant conditioning developed by Skinner (learning by reinforcement) and observational learning developed by Bandura.

- **Imitation:** Bandura developed observational learning. Observational learning states that people learn much of their attitudes and behavior from observing and later imitating.

- **Social Structure:** Finally, Akers expanded and renamed the theory Social Learning Theory. One concept Akers added to the theory was social structure. Sutherland found that conflict
and disorganization were the cause of differences in the group or societal crime rates. Akers’ SLT proposes that variations in one or more of the dimensions of social structure produce variations in the magnitude, direction, and patterning of the SLT variables.

The theory performed well on the major criteria by which a theory could be judged, such as logical consistency, scope, parsimony, testability, empirical validity, and usefulness. Models to test the Social Learning Theory were developed with descriptive and inferential statistical analysis, linear regression models, multivariate regression models, or logistic regression models, assuming linear relationships between explanatory variables and the predictor variable while the correlation measures this fit. The theory was tested in samples across the US and South Korea on teenagers, middle-aged adults, and the elderly for crimes such as marijuana and alcohol delinquency, cigarette smoking, drug abuse, property crimes, and violence. The criticism of SLT is that it appears to be tautological, meaning that the variables and measures used to test its validity are true by definition. Another criticism of the theory is that individuals may engage in criminal activity without being taught; then they associate with individuals with attitudes and behavior like their own. Most recent studies point to the occurrence of both causal processes: criminal associations cause more crime and committing crime causes more criminal associations, but the differential association theory has accounted only for half of the process.

More recent models of social learning were developed using non-linear approaches such as system dynamics, hot spots analysis, agent-based models, multi-agent systems, social networks analysis, in an effort to account for the characteristics inherent to social complex systems.
1.3.3 Modeling Human Behavior

Learning is the process of acquiring or modifying knowledge, behavior, or skills. The ability to learn is inherent to humans, animals, and plants, and even machines are provided with algorithms that could mimic in a restricted way the processes of learning. Humans learn from the time they are born until they die because of a continuous process of interaction with the environment. The processes of learning are studied in many sciences such as pedagogy, psychology, and neurology, among others.

The learning and decision-making problem for representing human behavior has been widely studied. Some approaches to modeling human behavior are rational choice, threshold equations, Behavioral Psychology, and planned behavior, among others. Rational Choice assumes that people rationalize their decisions by maximizing rewards and minimizing risks. Behavioral Psychology assumes that all behavior is learned from the environment by the association between stimuli-response. Threshold Equations are used to model the occurrence of behavior when a threshold is reached. The theory of planned behavior states that the attitude towards behavior, subjective norms, and behavioral control together shape an individual’s intentions and behavior.

Models of human behavior developed in an agent-based computer environment allow representing behavior exhibited by agents as the result of social interactions of agents placed in a computer environment. ABMs allow representing multiple heterogeneous individuals within a computer environment. ABMs provide these individuals with a decision-making algorithm based on events that provide the stimuli-response mechanisms to learn from the environment, their local and spatial information, and their social network connections. Among these models, the Schelling’s Segregation Model [5] shows that relative mild preference of neighbors from the
same race could lead to high levels of segregation. This model represents the agent’s choice of moving to another random position if they have below a threshold number of neighboring agents of this same type. Axelrod’s Dissemination of Culture Model [6] studies the process of cultural diffusion under the assumption that people are more likely to interact with others who share similar cultural attributes. Miller and Page’s Standing Ovation Problem [7] assesses an audience’s decision to stand and applaud or not after a performance. Epstein’s Civil Violence Model [8] assesses the decision to become active and join a rebellion or not. Epstein’s Agent Zero Model [9] represents individual behavior in groups by modeling three behavior components: emotional, rational, and social. Ardiles-Cruz et al. developed an Insider Threat ABM [10] that represents the disposition of employees to commit a threat based on precursors of behavior such as initial predisposition, access to the system, skills, and level of disgruntlement.

1.3.4 Summary

Behavioral Psychology Theories provide a theoretical framework for explaining how individuals learn and exhibit behavior. They were developed mainly using animals for testing and in a few cases using humans. These models lack the time component because they were developed based on the number of trials.

The current approaches to modeling social learning from the criminology point of view are statistical. These models use regression and correlation analysis, multi regression analysis, logistic regression, t-tests, or independent samples t-tests to test the significance of the variables statistically. These approaches do not account for non-linear relationships, heterogeneous populations, and social network connections.
Human behavior was represented using optimization of risks/rewards (rational choice), threshold equations, or game theory using an agent-based environment. These approaches lack the learning processes that lead to exhibiting a behavior while they are focused on the decision-making processes.

This dissertation develops a computer agent-based model of social learning Agents (SLA) able to exhibit behavior learned from the environment and social interactions. The model considers the processes of stimuli-response that lead to learning, the individual’s decision-making process to whether or not to exhibit the learned behavior, and the development of a use case that allows measuring the emergence of behavior. The research question is will agents be able to exhibit behavior learned from social interactions and the environment? We hypothesize that, over time, agents will be able to exhibit the learned behavior. To represent this model of SLAs, we propose to model human behavior using an adaptation of Epstein’s Agent Zero Structure. The explanatory framework will be developed using Behavioral Psychology Theories and Social Learning Theories. The use case will represent Youth Gang Homicides. The model will be set using demographic data from the city of Pittsburgh, PA. The occurrence of homicides will be represented using a micro definition of crime proposed by routine activity. The process of calibration, verification and validation, and policing and decision-making analysis will be performed using aggregated homicide data from the city of Pittsburgh, PA.

1.4 Approach

This dissertation uses an ABMS approach. ABM represents the individuals’ characteristics or attributes, social network, and interactions in a multi-agent computer environment, while simulation provides a way to run different case scenarios to test which
factors have the highest impact on the outcome. This modeling approach started with the concept of a self-replicating cellular automaton, game theory, discrete event simulation, and multi-agent modeling. While there is no universal definition of an agent, according to Wooldridge and Jennings [44] a weak definition of an agent is a hardware or software computer system that has the properties of: autonomy (control over their actions), social ability (allows communication with other agents), reactivity (response to changes in the environment), and pro-activeness (goal-directed behavior by taking the initiative). ABMs represent complex adaptive multi-agent social systems by modeling agents and their interactions with each other and their environment, while the evolution of the system shows the emergence of social structures and group behavior. Simulation provides a way to test the impact of different strategies on a complex system while gaining practical insight into which factors have the highest degree of influence on the outcome [2, 4, 45-47].

The use of ABMs in this dissertation is supported by the next characteristics that social complex human systems exhibit and an ABMS allow representing:

- **Agents:** Agents represent individuals. Agents have attributes and behavior rules. Behavior rules allow updating attributes based on time and the occurrence of events in the environment. Agents could have a mechanism to represent decision-making processes.

- **Heterogeneity:** ABMs could represent diversity across the population using random numbers and probability distributions.

- **Environment:** Agents are contained within a virtual environment represented by squared cells within which they could interact and from which they could collect information.

- **Agent’s Vision and Mobility:** Agents have protocols for movement and interaction with other agents within their limited neighborhood vision. These protocols allow communication,
sharing resources, movement, and contention for space, responses to the environmental inputs, ability to recognize and distinguish the traits of other agents, among others.

- **Social Network:** Agents can be connected with weighted directed links. These links represent social network connections with other agents and the weight represents the strength of the connection.

- **Proactiveness:** Agents will be able to react to stimuli from their environment.

- **Learning and Adaptation:** As a result of the agent's interactions, agents will update attributes and decisions. Agents will adapt to their environment based on the information about their own past experiences, their local neighborhood, or their social network.

- **Emergent Phenomena:** All complex systems exhibit the emergence of social structures and group behavior as the result of local interactions between agents with each other and their environments.

- **Simulation:** The use of simulation provides a way of testing different case scenarios in the environment.

The following list describes the main steps of the research method for this research:

1. **Social Learning Structure.** Development and implementation of a social learning structure able to replicate the SL processes that lead to exhibiting a behavior learned from social interactions and the environment. This social learning structure will have four components: the learning component (the agents’ attributes that represent the level of learning acquired), the local component (the limited part of the environment that agents are able to see), the social component (the social network connections to other agents), and the behavior component (the behavior rules to update attributes). The social learning structure also includes a decision-making algorithm to assess the readiness of SLAs to exhibit a behavior.
Use Case. A use case will be developed for representing Youth Gang Homicides. This step includes the definition of the agents and environment, the model calibration, the model verification and validation, and the policing and decision-making analysis. These steps are listed below.

a. **Agents and Environment.** The environment will be represented as a squared grid of cells. Each cell could host agents that move within the grid with a random walk. The occurrence of homicides will be represented using a micro definition of crime proposed by routine activity. The environment and agents’ parameters will be set using demographic data from the city of Pittsburg, PA.

b. **Calibration:** The calibration of the model will allow us to analyze the surface response for the number of homicides and tune parameters. To achieve this goal, we will use aggregated homicides rates data from the city of Pittsburgh, PA, specifically the number of homicides per year.

c. **Verification and Validation:** For the process of verification and validation, the developed model will be set using demographic data for the represented neighborhoods in the city of Pittsburgh, PA. For the conceptualization of the model, we will use grounded theories for learning and decision-making. The fitness between the model and the real system will be performed using aggregated homicide rates from the city of Pittsburgh, PA, specifically the number of homicides per year.

d. **Policing and Decision-Making:** The constructed and validated model will be used for analyzing interventions aimed at homicide reduction.
1.5 Contributions

The main contribution of this dissertation to the field of modeling and simulation is to develop a model of social learning able to replicate the learning processes that lead to behavior. The behavior will be learned from social interactions and the environment. To model this structure, we propose to join Behavioral Psychology Theories and Social Learning Theories with Agent-Based Modeling. An adaptation of Agent Zero will be used for representing the learning component and the decision-making processes. Finally, the Rescorla-Wagner Model for acquisition and extinction of response will be used to represent the processes of learning a behavior.

Another contribution of this dissertation is to develop a use case representing Youth Gang Homicides. We propose to use the social learning structure developed to represent social learning processes in our SLAs. A micro behavior rule definition of crime from the routine activity theory will be used to represent the occurrence of homicides. To set inputs and parameters, we propose to use demographic data from the city of Pittsburgh, PA. From the modeling and simulation perspective, this use case allows performing the calibration and verification and validation of the model using aggregated demographic and crime data from the city of Pittsburgh, PA and exploring the agents and environment configurations that lead to the emergence of behavior. From the criminology perspective, this use case provides a simulation tool to explore the differences in crime rates that arise from different neighborhoods and to explore the correlation between the number of gang members and the number of homicides.

1.6 Dissertation Organization

Chapter 2. Literature Review. Surveys Behavioral Psychology Theories, Social Learning Theories, and Agent-Based Modeling and Simulation. This research focuses on the development
and evolution of Behavioral Psychology Theories, Social Learning Theory and the impact that Behavioral Psychology Theories had in its development, and Agent-Based Modeling and Simulation for representing human behavior. The most relevant mathematical, computational and statistical models will be described in detail.

Chapter 3. Methodology. This section proposes a model of social learning in an agent-based environment by developing a social learning structure based on four components for representing human behavior: the learning component, the local component, the social component, and the behavior component. The behavior component allows dynamically updating SLA’s attributes (learning component) based on social interactions (social component) and the environment (local component) as time evolves and events occur.

Chapter 4. Validation and Results. This section develops a use case to represent Youth Gang Homicides for the city of Pittsburgh PA. This section includes the calibration of the model using sensitivity analysis, the validation of the model by constructing confidence intervals to test the model outputs and collected aggregated homicides data from the city of Pittsburgh, PA, and testing the patterns of learning that agents’ exhibit. The last component of this chapter is the policing and decision-making analysis for gang violence reduction.

Chapter 5. Conclusions and Recommendations. This section concludes with a summary of the research results found in chapters 3 and 4, discusses the limitations of the research and proposes possible future work to expand this dissertation.
CHAPTER 2
LITERATURE REVIEW

This section provides research on Behavioral Psychology Theories, Social Learning Theory, and agent-based models for representing complex multi-agent social systems.

2.1 Behavioral Psychology

Behavioral Psychology studies observable stimulus-response behavior learned from the environment. In 1913, John Watson set the assumptions and methodology for behavioral analysis [1]. These assumptions are:

- All behavior is learned from the environment. This assumption emphasizes the role of environmental factors for exhibiting a behavior while nearly excluding inherited factors.
- Behavioral Psychology studies observable behavior that could be scientifically measured.
- Behavioral Psychology should be considered as a science in which the theory should be supported by empirical data obtained through observation and measurement of behavior.
- There is little difference between learning that takes place in humans and learning that takes place in animals; therefore, research can be done in animals as well as in humans.
- Behavior is the result of stimulus-response.

Watson also stated that the mind is a tabula rasa or a blank slate at birth.

While an advantage of Behavioral Psychology is its ability to define behavior clearly and measure changes in behavior by introducing stimuli-response measurable events, its main criticism is that it only provides a partial model of human behavior. Important factors like emotions, expectations, and motivations are not considered.
The main theories researched in this section are classical conditioning, operant conditioning, and cognitive and observational learning.

2.1.1 Classical Conditioning

In 1903, Ivan Pavlov developed the concept classical conditioning. Classical conditioning sometimes is referred to as Pavlovian conditioning. Classical conditioning assumes that learning is the result of the association between stimuli and responses. Classical conditioning is the process of learning that occurs when a non-conditioned stimulus elicits a response that was caused originally by a conditioned stimulus. Classical conditioning is non-conscious instinctual learning.

Pavlov experimented with conditioning salivation in dogs while ringing a bell. A dog was hooked to a mechanism that measured the amount of salivation. A tone sounded just before the dog was given meat powder. By repeating the experiment several times, eventually, conditioning occurred, and the dog salivated just to the bell alone. Of course, the dog salivated instinctively in response to the food, but it also learned to salivate to the sound of the bell that preceded the food. Pavlov used this relatively simple experiment as a model for describing much of the automatic non-conscious learning that occurs in everyday life.

Pavlov identified four basic components in his classical conditioning model. The unconditioned stimulus (UCS) is the stimulus that naturally and instinctively elicits the target response, which in this case, is the meat powder. The conditioned stimulus (CS) is the stimulus that comes to elicit the target response. In Pavlov’s experiment was the ringing bell. The unconditioned response (UCR) occurs because of the unconditioned stimulus and conditioned response (CR) occurs in response to the conditioned stimulus. In Pavlov’s experiment, they were
both salivations, but the unconditioned response is salivation in response to the meat powder, and the conditioned response is salivation in response to the tone.

Watson proposed that classical conditioning was able to explain all aspects of human psychology; everything from speech to emotional responses were patterns of stimulus-response (Psychology as the behaviorists view it, 1913). Watson denied the existence of the mind or consciousness. He believed that an individual’s differences in behavior were due to different experiences of learning.

In 1920, Watson and Rainer experimented with phobias in humans with the famous though ethically dubious Little Albert Experiment. Little Albert was a 9-month infant who was tested on his reactions to various stimuli. He was shown a rat, a rabbit, a monkey, and different masks, and he showed no fear of any of these stimuli. However, what caused him to fear and burst into tears was a hammer that struck a steel bar behind his head. When Little Albert was 11-months, a rat was presented to him, and seconds later, a hammer was stuck against a steel bar. This experiment was repeated seven times over a seven-week period, and each time Little Albert burst into tears. After the stimulus-response trials, Little Albert burst into tears when he saw the rat, whether the bar was hit or not, and he tried to crawl away. Watson and Rainer found that Little Albert developed phobias of objects with shared characteristics with the rat; they called this process generalization. A few weeks after the experiment, they noticed that the fear was less marked; they called this process extinction. Watson and Rainer’s Little Albert Experiment showed that classical conditioning can be applied not only to animals but also to humans.

Classically conditioned responses may be reliable and strong if the CS and UCS have a long history of being paired together. However, CR may diminish over time if the stimuli is no longer present or it may occur with new stimuli with which the response has never been paired.
These processes are known as acquisition, extinction, spontaneous recovery, and generalization. *Acquisition* is the initial phase of learning, in which a response is established; a critical part of the acquisition is the predictability of the occurrence of CS and US. *Extinction* is the loss or weakening of a conditioned response when the CS and the US are no longer paired. *Spontaneous Recovery* is the reoccurrence of the extinguished conditioned response after the extinction phase again because of pairing CS and US. Generalization is when the response that originally occurs to a specific stimulus occurs to a similar stimulus.

In any case where the individuals have learned to respond automatically to some stimulus with fear, joy, excitement, or anticipation, they have become classically conditioned, and the learning is automatic and non-conscious. Garcia experimented with food aversion conditioning [11], Öhman and Mineka experimented with fear conditioning [12], Gorn, McSweeney and Bierley, Stuart, Shimp, and Engle researched strategies to influence consumer behavior [13-15]. Also, classical conditioning was applied to heart rate conditioning [16-18] and eye-blink conditioning in animals [19, 20].

**Rescorla-Wagner Model**

In 1972, Rescorla and Wagner [48] presented a mathematical model that intended to account for several well-known phenomena of classical conditioning, including the acquisition and extinction of the conditioned response, the spontaneous recovery process, the conditioned inhibition, and conditioning to a compound CS (overshadowing and blocking).

The mathematical equations 1 and 2 describe the learning curves for the strength of the association that is tied to external stimuli. $V_i$ represents the strength of association on stimuli $i$ and could take positive values due to conditioned excitation and conditioned inhibition.
\[ \Delta V_i = \alpha \beta (\lambda - V_{i-1}) \]  

(1)

and

\[ V_i = V_{i-1} + \Delta V \]  

(2)

where:

- \( \alpha \) Acquisition rate parameter associated with the conditioned stimuli.
- \( \beta \) Acquisition rate parameter associated with the unconditioned stimuli.
- \( \lambda \) maximum value for \( V \).

For the acquisition trial, the maximum value that \( V_i \) can reach is \( \lambda = 1 \), while for the extinction trial the minimum value that \( V_i \) can reach is \( \lambda = 0 \). Figure 1 below shows the acquisition and extinction trials for different acquisition rates (\( \alpha = 0.75, \alpha = 0.50, \alpha = 0.25 \)) calculated using equations 1 and 2.

![Rescorla-Wagner Model](image)

Fig. 1. Rescorla-Wagner Model for acquisition and extinction of response.
The Rescorla-Wagner model has been successful in modeling the acquisition and extinction of response processes through stimuli-response trials. However, the model has failed many tests in research conducted over the years. Consequently, other models and adaptations have offered alternative proposals for modeling classical conditioning [49-51]. These newer alternatives have had successes and difficulties; however, at the moment, there is no entirely satisfactory theory that can handle all the data and experiments on classical conditioning. The Rescorla-Wagner model served to stimulate a considerable amount of research on classical conditioning designed to evaluate the model and test its implications. In this sense, the model has been successful, even if eventually it began to show its weaknesses.

It is important to notice that the Rescorla-Wagner model was not designed to account for some features of classical conditioning, and it was considered as a starting point toward a more inclusive theory. A significant parameter left out of the model is time. All changes take place as a function of trials. Although trials follow themselves in time, parameters such as the length of CS presentation, the time between UCS presentations, or the duration of a trace interval are not explicitly included in the Rescorla-Wagner model. As these factors have substantial effects on the course of conditioning, their absence from the model was always a limitation.

2.1.2 Operant Conditioning

Operant Conditioning is a type of learning in which consequences influence behavior. The term operant is used because the individual operates on the environment before consequences occur. In contrast with classical conditioning that affects reflexive or automatic responses, operant conditioning involves voluntary actions that depend on the individual’s unique history with consequences.
In 1095, Thorndike’s work lead to the development of operant conditioning. Thorndike experimented with cats using a puzzle box. A cat was put into a box, encouraged to escape by pressing a lever to open the box, and reaching a scrap of fish placed outside. In successive trials, cats would learn that pressing the lever had favorable consequences and adopted this behavior, becoming increasingly quick at pressing the lever. Based on these experiments, Thorndike proposed his Law of Effect, which states that any behavior followed by pleasant consequences is likely to be repeated, and any behavior followed by unpleasant consequences is likely to be stopped.

Skinner developed operant conditioning based on Thorndike’s Law of Effect. In 1938, Skinner coined the term operant conditioning meaning changing of behavior using reinforcement given after the desired response. He identified three types of responses or operants that can follow behavior. Neutral Operants, that are responses from the environment that neither increase nor decrease the probability of behavior been repeated. Reinforcers that are responses from the environment that increase the probability of a behavior being repeated. Punishers that are responses from the environment that decrease the probability of behavior been repeated.

Skinner showed positive reinforcement (strengthening a behavior by providing positive consequences) by placing a hungry rat into a box. The box contained a lever. If, as the rat moved along the box, it accidentally pressed the lever, a food pellet immediately would drop into a container next to the lever. The rats quickly learned to press the lever to get the food. The consequence of receiving the food ensured that the rats would repeat the action.

Skinner showed negative reinforcement (strengthening a behavior by removal of a negative consequence) by placing a rat in a box and subjecting it to electric current. As the rat moved along the box, it would accidentally press the lever, and the electric current immediately
was switched off. The rats quickly learned to press the lever to escape the electric current. The consequence of escaping the electric current ensured that the rats would repeat the action.

*Punishment* is an aversive event designed to weaken or eliminate a response. There are many problems while using punishments such as the behavior is not forgotten, it is suppressed and will return when the punishment is no longer present, causes increased aggression, creates fear that could lead to undesirable behaviors, among others. *Positive Punishment* is a process in which a behavior decreases because it adds or increases a stimulus. *Negative Punishment* is a process in which a behavior decreases because it removes or diminishes a stimulus.

Applications of operant conditioning can be found in behavior shaping and behavior modification therapies [21, 22], token economy [23-25], educational applications [26-28], among others.

*Schedules of Reinforcement*

Schedules of Reinforcement are patterns of reinforcement. Behaviorists discovered that different schedules of reinforcement have different effects on the speed of learning and extinction. *Continuous Reinforcement* means that reinforcement is given every time that the behavior is exhibited. *Fixed Ratio Reinforcement* means that reinforcement is given after the behavior occurs a given number of times. *Fixed Interval Reinforcement* means that reinforcement is given after a fixed time interval, assuming that the behavior is exhibited at least once. *Variable Ratio Reinforcement* means that the reinforcement is given after an unpredictable number of times. *Variable Interval Reinforcement* means that the reinforcement is given after an unpredictable amount of time given that the behavior was exhibited at least once. Skinner found
that the slowest rate of extinction is obtained with variable ratio reinforcement and the quickest rate of extinction is obtained with continuous reinforcement.

2.1.3 Observational Learning

Observational Learning involves changes in behavior and knowledge as a result of observation and imitation of others. Many of the things we do are because we observed others, for example, dietary choices, clothing style, holiday traditions, music preferences. Socially transmitting behavior is the primary way that adaptive behavior spreads within a population [52].

Bandura, Ross, and Ross [29] performed the *Bobo Doll Experiment* to show that children learn social behavior such as aggression through the process of *observational learning*. They tested 36 boys and 36 girls from the Stanford University Nursery School between 3 to 6 years old. Twenty-four of the children (12 boys and 12 girls) were exposed to an aggressive model (the adult model behaved aggressively towards the Bobo Doll). Twenty-four children (12 boys and 12 girls) were exposed to a non-aggressive model (the adult model ignored the Bobo Doll). Finally, 24 children (12 boys and 12 girls) were not exposed to a model (control group). The test for delayed imitation was done in a separate playing room in which each child separately was placed with aggressive and non-aggressive toys. Each child was 20 minutes in the playing room while the behavior was recorded. The results showed that children who observed the aggressive model imitated more aggressive responses than the children who observed the non-aggressive model. Boys were more likely to imitate same-sex models than girls, and boys imitated more physically aggressive acts than girls.

*Observational Learning* involves changes in behavior as a result of watching others. Children observe people around them or *models* such as parents, TV characters, and friends,
teachers, and they may imitate the behavior they have observed. Several processes make it more likely that a child imitates behavior. First, the child is more likely to attend and imitate those people perceived like himself or herself. It is more likely that children imitate behavior exhibited by models of the same gender. Second, if a child imitates a behavior and the consequences are rewarding, the child is likely to continue performing the behavior. Third, the child will also observe what happens to other people imitating behavior when deciding whether to copy someone’s actions. This process is called vicarious reinforcement.

Mediational Processes are a bridge between traditional learning theory and the cognitive approach. According to Bandura [30, 53] observational learning occurs because of cognitive processes. Individuals do not automatically observe the behavior and imitate it. There is some thought prior to imitation. These processes are called Mediational Processes. The mediational processes are attention, retention, reproduction, and motivation. Attention is the extent to which an individual is exposed to or notices the behavior. Retention is how well the behavior is remembered. Reproduction is the individual’s ability to perform the behavior. Motivation is the will to perform the behavior. If perceived rewards outweigh perceived punishments, then the behavior is more likely to be repeated. Cognitive and observational learning provide a more comprehensive explanation of human learning by including the role of mediational processes. However, it cannot explain how humans develop thoughts and feelings. Later, Bandura renamed the theory Social Cognitive Theory [54], but the theory continues having the criticism that behavior is the result of an interaction between biology and the environment.

Observational learning was used in animals such as ants, honeybees, and chimpanzees [31-35], for learning behavior for motor skills acquisition [36, 37] and to analyze the effects of media violence and aggressive models [38-40].
2.2 Social Learning Theory

SLT is an integration of Sutherland’s sociological theory of differential association with behavioral principles from psychology. Robert Burgess and Ronald Akers originally presented the theory as differential association-reinforcement [42], and later it was presented as SLT by Akers [43, 55]. Although it refers to all aspects of the learning process, the theory relies mainly on four principal explanatory concepts: differential association, definitions, differential reinforcement, and imitation.

The central proposition of the SLT of criminal and deviant behavior provided by Akers states that “the probability that persons engage in criminal and deviant behavior is increased and the probability of them conforming to the norm is decreased when they differentially associate with others who commit criminal behavior and expose definitions favorable to it (differential association), in-person or symbolically are relatively more exposed to salient criminal/deviant models (imitation), define it as desirable or justified in a situation discriminative for the behavior (definitions), and have received in the past and anticipate in the current or future situation relatively greater reward than punishment for the behavior (differential reinforcement)” [43, 55].

The theory performs well in the major criteria by which a theory is judged, such as logical consistency, scope, parsimony, testability, empirical validity, and usefulness. Abundant research was developed using SLT as a theoretical framework for explaining criminal and deviant behavior using descriptive and inferential statistical analysis, linear regression models, multivariate regression models, and logistic regression models supporting the main assumption of SLT: individuals learn criminal behavior through interactions with other people. The theory was tested in samples across the US and South Korea on teenagers, middle-aged adults, and the
elderly, supporting the model assumptions in crimes such as marijuana and alcohol delinquency, cigarette smoking, drug abuse, property crimes, and violence among others. Akers tested the theory finding that deviant behavior was the result of the combination of differential association, differential reinforcement, and imitation, and these variables combined accounted for 68% of the variance in marijuana use and 55% of the variance in alcohol use by adolescents [43]. Akers tested Social Learning Theory, social bonding, and anomie theory with survey data on adolescent drug use [56]. Akers and Lee found age-related variations in social learning in marijuana use and a weaker relationship for the similar hypothesis using social bonding variables [57]. Lee, Akers, and Borg found a substantial relationship between age and substance abuse (alcohol and marijuana) by adolescents using the SLT variable’s differential peer association, differential reinforcement, definitions favorable and unfavorable to substance use, and imitation [58]. Krohn et al. [59] found that the theory was more effective in accounting for maintenance or cessation of cigarette smoking than in explaining initiation. Chappell and Piquero found that factors of SLT, such as peer association, attitudes, reinforcement, and modeling, were predictors of police misconduct [60]. Jang tested age varying effects of attachment to parents, commitment to school, and association with delinquent peers on delinquency [61]. Rogers found that criminal computer behavior was predicted by differential association and moral disengagement, and differential reinforcement had a lower effect on the explanatory variable [62]. Skinner and Fream found that differential association, differential reinforcement and punishments, definitions, and sources of imitation are significantly related to computer crime using a multiple regression model and data from 581 university students [63]. Jennings et al. found that there is a strong degree of overlap between dating violence perpetration and victimization, and Social Learning Theory and self-control theory cannot explain away the overlap [64].
The main explanatory concepts the theory relies on are differential association, definitions, differential reinforcement, and imitation. These explanatory concepts are explained below.

2.2.1 Differential Association

Between 1939 and 1947, Edwin Sutherland developed and proposed differential association to explain the development of criminal behavior as the result of interactions with others mainly in primary groups [65]. Sutherland proposed his theory with nine statements each one accompanied by a comment. These nine statements are as follows:

1. Criminal behavior is learned.
2. Criminal behavior is learned in interaction with other persons in a process of communication.
3. The principal part of the learning of criminal behavior occurs within intimate personal groups.
4. When criminal behavior is learned, the learning includes (a) techniques of committing the crime, which are sometimes very complicated, sometimes simple; (b) the specific direction of motives, drives, rationalizations, and attitudes.
5. The specific direction of motives and drives is learned from definitions of the legal codes as favorable or unfavorable.
6. A person becomes delinquent because of an excess of definitions favorable to violation of the law over definitions unfavorable to violation of the law.
7. Differential associations may vary in frequency, duration, priority, and intensity.
8. The process of learning criminal behavior by association with criminal and anti-criminal patterns involves all of the mechanisms that are involved in any other learning.
9. While criminal behavior is an expression of general needs and values, it is not explained by those needs and values, since non-criminal behavior is an expression of the same needs and values.

The first principle states that criminal behavior is learned, while the second and third refer to learning in primary groups. The fourth principle refers to the content of learning. The fifth and sixth refer to the definitions favorable or unfavorable to the law. The sixth principle was identified by Sutherland as the main principle of differential association. It proposes that people commit crimes because they have learned definitions favorable to violating the law in excess of the definitions unfavorable to violating it. The seventh principle refers to frequency, duration, priority, and intensity.

Sutherland used the dominant theory of learning in his era: classical conditioning primarily developed by Ivan Pavlov. Classical conditioning assumes that people learn through associations between stimuli and response, and over time they learn to associate stimuli with responses.

In the cultural context of the development of Sutherland’s theory, most academics and others in the early 20th century believed that something was wrong with individuals who committed crimes (low IQ, body type, biology). Sutherland’s theory suggested something completely different for the time: that a normal person when exposed to attitudes favorable to crime, will learn criminal behavior, and the mechanisms of learning criminal behavior are the same as the ones for most everyday behaviors -- social interactions in primary groups such as family, friends, teachers, peers, and coworkers.

Research on Sutherland’s differential association theory is wide and supports criminal behavior as a result of socialization processes. Matsueda and Heimer showed that the effect of
broken homes and attachment to parents and peers are mediated by the learning of definitions of delinquency [66]. Tittle, Burke, and Jackson developed a theoretical model for Sutherland’s theory and tested it with six different crimes finding that differential association plays a substantial role in criminal behavior [67]. Thornberry stated that whenever the links to attachment to parents, commitment to school, and belief in conventional values are attenuated, there is substantially increased potential for delinquent behavior. His research also represented relations with delinquent peers, delinquent values, and delinquent behavior to form a causal loop that leads to increasing delinquency [68]. Ploeger found that association between employment and some forms of delinquency, especially alcohol and drug use was correlated to differential association with delinquent peers [69].

In 1960, Cressey conducted an exhaustive review of the criticisms on the differential association theory. He argued that much of the criticism was due to misunderstandings from the critics. About the argument that not everyone that had contact with criminals becomes a criminal, he argued that the theory refers to the ratio between favorable and unfavorable contacts by individuals that lead to a lower or higher likelihood to learn criminal or deviant behavior. About the critiques on associations with criminals as a category of persons, he argues that the theory hypothesizes that the effect on an individual’s behavior comes from contacts with patterns of definitions regardless of the person presenting them, and more significant than exposure is the frequency, duration, priority, and intensity. Cressey found two weaknesses in the theory: the lack of clarification and operationalization of the concept of definitions, and how to measure the ratio between definitions favorable and unfavorable to the law and the lack of specification of the learning processes involved. These two points became the focus of his efforts to revise or reformulate the theory.
In 1956, Glaser proposed differential identification as a reconceptualization of Sutherland’s theory. He proposed that individuals could identify with real or imaginary persons from whom criminal behavior seems acceptable. These individuals may be close friends, distant reference groups, or people or characters presented in the mass media.

2.2.2 Definitions

SLT identified or incorporated four dimensions of definitions: beliefs, attitudes, justifications or rationalizations and orientations. Donald Cressey was the first to made clarifications, modifications, and extensions to the concept of definitions. Cressey recognized that the statements in Sutherland’s theory were ambiguous about the relationship between definitions and the concepts of rationalizations and attitudes. Cressey studied violations of financial trust, categorizing rationalizations and attitudes as subtypes of definitions favorable to crime. He found that none of the convicted embezzlers in his study committed the crime until they had reached the point of rationalizing it as justified or excusable [70]. Cressey also studied compulsive crimes, finding that rationalizations can be learned as definitions justifying or excusing the offense. Although Cressey did not propose a new theory nor a modification on the differential association theory, he found rationalizations to be forms of the operationalization of definitions favorable to crime [71].

Sykes and Matza found several techniques of neutralization learned by adolescents as justification for delinquent behavior. They found that criminals are still committed to the dominant social order and hold conventional beliefs and values. However, they vacillate or drift between complete conformity and complete nonconformity to justify and rationalize a behavior they know is wrong to alleviate their guilt. The techniques of neutralization they found were the
denial of responsibility, the denial of injury, the denial of the victim, the condemnation of the
condemners, and the appeal to higher loyalties [72].

Hartung proposed that definitions justifying crime could be learned in contact with
specifically deviant subcultures or from the acceptable excuses or justifications already present
in the general culture.

2.2.3 Differential Reinforcement

Differential Association-Reinforcement was developed by Burgess and Akers [42] in an
effort to specify the learning processes and enhance the conceptualization and testability of
Sutherland’s theory. They stated that the basic mechanisms of learning criminal and deviant
behavior are identified by the principles of learning in psychological behaviorism and fused them
with Sutherland’s theory. The learning mechanisms added to the theory were operant
conditioning (influence of reinforcements and punishments on behavior) developed by Skinner
and observational learning developed by Bandura. The theory was formulated as seven
statements listed as follows:

1. Criminal behavior is learned according to the principles of operant conditioning.

2. Criminal behavior is learned both in nonsocial situations that are reinforcing or
discriminative and through that social interaction in which the behavior of other persons is
reinforcing or discriminative for criminal behavior.

3. The principal part of the learning of criminal behavior occurs in those groups that comprise
the individual’s major source of reinforcements.
4. The learning of criminal behavior, including specific techniques, attitudes, and avoidance procedures, is a function of effective and available reinforcers, and the existing reinforcement contingencies.

5. The specific class of behaviors which are learned, and their frequency of occurrence are a function of the reinforcers which are effective and available and the rules and norms by which these reinforcers are applied.

6. Criminal behavior is a function of norms which are discriminative for criminal behavior, the learning of which takes place when such behavior is more highly reinforced than noncriminal behavior.

7. The strength of criminal behavior is a direct function of the amount, frequency, and probability of its reinforcement.

2.2.4 Imitation

Bandura developed observational learning. Observational learning states that people learn much of their attitudes and behavior from observing, modeling, and imitation. Bandura experimented with the Bobo doll in a controlled environment. He demonstrated that children could learn through observation of adults’ violent behavior and then mimic this behavior. Bandura also proposed that observational learning occurs because of cognitive processes. Individuals do not automatically observe the behavior and imitate it. There is some thought before imitation. These processes are called Mediational Processes. The mediational processes are attention, retention, reproduction, and motivation. Attention is the extent to which an individual is exposed to or notices the behavior. Retention is how well the behavior is remembered. Reproduction is the ability of the individual to perform the behavior. Motivation is
the will to perform the behavior. If perceived rewards outweigh perceived punishments, then the behavior is more likely to be imitated [30, 53, 54].

2.2.5 Social Structure

Sutherland’s original theory had a structural dimension called differential social organization. The original differential association theory included statements referred to as concepts of conflict and disorganization. However, the final version of the theory included the nine statements referred to in differential association theory, while the statements referred to the differential social organization were retained separately in comments. Sutherland found that the concepts of conflict and disorganization were the cause of differences in the group or societal crime rates.

Akers’ SLT, in addition to all social learning variables, includes four dimensions of social structure [55]. Differential social organization is identified as integral and aggregated measures of demographic, social, and cultural characteristics of societies. Differential location in the social structure is identified as the relative position of collective groups, social roles, and individuals, indicated by age, gender, race, class, and other sociodemographic and socioeconomic attributes, indicators, and characteristics. Theoretically defined structural variables is identified as abstract conceptual categories of criminogenic social structural factors or variables such as anomie, social disorganization, conflict, inequality, or patriarchy. Differential social location occurs in primary, secondary, and reference groups. The model proposes that variations in one or more of the dimensions of social structure produce variations in the magnitude, direction, and patterning of the social learning variables.
2.2.6 Criticism to the Theory

Differential Association was developed in the early 20th century when the common assumption was that there was something wrong with individuals who committed crimes (low IQ, body type). Between 1939 and 1947, Sutherland proposed differential association theory of crime, stating that people learn criminal behavior through social interactions with other people, mainly in primary groups. His theory proposes that individuals make associations between stimuli and responses, and over time they learn to associate certain stimuli with a developed response. Sutherland used the most dominant theory of learning of his era as a basis for his theory, classical conditioning of learning developed by Ivan Pavlov. More current versions of his framework had incorporated other learning models developed after classical conditioning and differential association such as operant conditioning and observational learning [29, 30, 53, 54]; these models provided a novel framework and were easier to test. Glazer’s theory incorporated identification with characters in media, movies, TV as processes of observational learning.

Since its publication, many of the principles of Differential Association have been tested and replicated. However, researchers usually found it nearly impossible to conceptualize and measure a ratio between associations favorable to conforming to the law and associations favorable to violation of the law. SLT researchers identified or incorporated four dimensions for the concept of definitions: beliefs, attitudes, justifications and rationalizations, and orientations.

Another criticism of the theory is that individuals may engage in criminal activity without being taught; then they associate with individuals with attitudes and behavior like their own. Most recent studies point to the occurrence of both causal processes: criminal associations cause more crime and committing crime causes more criminal associations, but the differential association theory has accounted only for half of the process.
Finally, Akers unified the above theories to propose Social Learning Theory, including four main explanatory concepts for the processes that lead to learning and exhibiting criminal behavior: differential association, definitions, differential reinforcement, and imitations. The criticism of SLT is that it appears to be tautological, meaning that the variables and measures used to test its validity are true by definition.

2.3 Agent-Based Modeling and Simulation

The modeling approach selected for developing a social learning agent able to exhibit behavior learned from social interactions and the environment is Agent-Based Modeling. ABMs allow modeling complex human systems in a multi-agent environment, representing a group of agents interacting with each other, with their environment, and with their social network.

The use of simulation allows exploring social structures and group behavior emerging from the interactions of individuals with each other and with their environment according to simple behavioral rules [2, 4, 45-47].

This section reviews the most relevant concepts that lead to the development of ABM: cellular automaton, multi-agent systems, autonomous agents, and ABMS.

2.3.1 Cellular Automaton

A cellular automaton is a collection of colored cells on a grid that evolves with a discrete finite number of steps according to a set of rules based on the state of the neighboring cells. The type of grid is important for computation. The simpler grid is a one-dimension grid with n cells. Two-dimension grids could be square, triangular, or hexagonal. Figure 2 below shows the different grids’ configuration.
The number of colors represents the number of states the cellular automaton can reach. The simplest choice is two states. For a binary automaton, state 0 is called white, and state 1 is called black. Cellular automatons with a color scale may be considered. A state function is a mathematical or computational equation that allows the cells to transition between states until they reach the final state. This equation can be modeled based on time increments, probabilities, or events, among another factor.

In addition to the grid in which the cellular automaton lives and the states each cell may reach, the neighborhood of cells that affect one another must be specified. The simplest choice is the nearest neighbors, in which only adjacent cells may be affected per step time. For two-dimensional cellular automatons on a square grid, the Moore (square shape) neighborhood and the Von Neumann (diamond shape) neighborhood are the most used. Figure 3 below shows these neighborhood configurations.
In the late 50s, John Von Newman and Stanislaw Ulam invented a method for calculating liquid motion; they considered the liquid as a group of discrete units and calculated the motion as the result of its neighbors’ behavior. This is considered the first cellular automaton. Conway’s Game of Life made popular cellular automata [73]. The Game of Life is a zero-player game in which the evolution is determined only by the initial state. The set of rules are applied in a Moore neighborhood configuration in which: (1) A live cell with fewer than two live neighbors dies (under-population). (2) A live cell with two or three live neighbors lives. (3) A live cell with more than three live neighbors dies (over-population). (4) A dead cell with three neighbors becomes a live cell (reproduction). Conway and other researchers studied the evolution of patterns.

In 1983, Wolfram studied elementary cellular automata composed of cells in a line with a binary state finding that despite the simplicity of the construction, these systems exhibited very complicated behavior [74]. Burstedde et al. studied pedestrian behavior of lane formation and evacuation by modeling a stochastic cellular automaton. Cellular automata represented particle’s attraction and repulsion to model lane formation, and long-range interactions between
pedestrians are modeled as chemotaxis where pedestrians follow a virtual trace that diffuses and decays [75].

2.3.2 Autonomous Agents

Agents are autonomous, intelligent, goal-oriented entities that interact with their environment. The main areas of research that contributed to the development of agents are artificial intelligence, object-oriented programming, concurrent programming, and human-computer interface design, among others. While there is no universal agreement in the definition of the term agent, Wooldridge and Jennings listed properties that define a weak notion of agent [44] such as autonomy (agents operate without intervention of humans or other agents), social ability (agents interact with other agents), reactivity (agents perceive their environment and respond to changes), pro-activeness (agents exhibit goal-directed behavior by taking the initiative), with a strong notion agents may have mobility (ability to move in a grid or network). According to North and Macal, agents may also have other useful characteristics such as adaptiveness (ability to learn and adapt its behaviors based on its accumulated experiences, this requires some form of memory) and heterogeneity (considering a full range of agent diversity across a population) [3, 47].

Behavior rules provide agents the ability to interact with other agents. Agents interact with a limited number of agents within a limited local spatial location or a network configuration called the local neighborhood. Also, agents interact with the environment. The environment is set with a given topology. Topologies for interaction could be a grid or lattice of cellular automatons (the agent’s location is given by the grid cell index), a Euclidian space in the 2D or 3D dimension (the agent’s location is the geospatial coordinates), geographic information system
(GIS) patches of geospatial landscapes (the agent’s location is given by the geospatial location – ZIP code, geospatial coordinates), networks of directed or indirect unweighted or weighted links between agents (the agent’s location is the node location in the network).

As North and Macal stated [3], agents are autonomous, with the capability to adapt and modify their behaviors. Decision-making algorithms provide agents the capability of learning and adaptation. Such algorithms could be implemented as threshold equations, optimization algorithms, neural networks, fuzzy logic.

2.3.3 Multi-Agent Systems

Multiagent Systems (MAS) are computer systems of multiple autonomous, intelligent, interacting agents that are goal oriented. According to Jennings et al. [76], a MAS can be considered as a group of entities that work together to solve a problem that is beyond the individual capability or knowledge of each entity, being these entities autonomous, intelligent, goal-oriented, and heterogeneous. The characteristics of MAS are limited viewpoint (each agent has incomplete information or capabilities to solve the problem), lack of a global system control, decentralized data, and asynchronous computation.

MAS have been used for distributed problem-solving in optimization, competition or coordination, process control, telecommunications, air traffic control, transportation systems, non-cooperative game theory, learning, communication, social choice, auctions, electronic commerce, patient monitoring, among others. Some approaches for representing intelligence in MAS include methodic, functional and procedural approaches, algorithmic search, or reinforcement learning (the agents maximize a reward) [77-79], consensus protocol [80-82].
There is an overlap between MAS and ABM. While MAS is concerned with solving engineering problems (usually MAS research is related to software agent’s development), ABM is concerned with searching the explanation for the collective behavior of agents obeying simple rules typically in natural systems.

2.3.4 Agent-Based Modeling and Simulation

ABM represent multiple agents interacting with each other and their environment in a computer environment, while simulation provides multiple scenarios for analyzing the effects of changing variables in the system. ABM could capture the emergence of group and social behavior that results from the individual agent’s rules of interaction [2, 4, 45-47].

ABM could be used when the interactions between agents are non-linear, discontinuous, or discrete, when an agent’s position is not fixed, when the population is heterogeneous, when the topology of interaction is heterogeneous and complex, when the agents exhibit memory, learning, and adaptation to the environment, among others.

In Growing Artificial Societies from Bottom Up, Epstein and Axtell applied agent-based computer modeling techniques to the study of human social phenomena such as trading, migration, group formation, combat, the transmission of culture, disease propagation, and population dynamics. These models exhibit the emergence of social structures and group behavior from the interactions of individuals contained in this computer environment under rules that place bounded demands on an individual’s information and computational capacity. These computer environments involve three components: agents, environment, and rules. Agents are the people of artificial societies; they are provided with internal states and behavior rules. The
environment is the landscape that contains agents. Rules drive an agent’s behavior and interactions with the environment [2].

ABM of social complex phenomena have been widely studied. The objective was to analyze the emergence of social and group behavior that emerges from the micro-behavior rules implemented. Schelling’s Segregation Model represents the dynamics of racially mixed neighborhoods; by modeling local interactions for agents looking for similar race neighbors, the model exhibits high levels of segregation [5]. Reynolds’s Boids Model simulates the flocking behavior of birds by implementing individual behavior rules for separation, alignment, and cohesion [83]. Epstein and Axtell’s Sugarscape Model represents an artificial society of agents competing for resources by modeling an artificial society of sugar-consuming agents. The model exhibits patterns of food gathering, mating with suitable partners, bearing offspring, bartering goods with other citizens, migrating, dying and leaving an inheritance for their survivors [2]. Miller and Page’s Standing Ovation Model represents the audiences’ applause at the end of a performance; by modeling the decision making to whether to stand and applaud or not, the model explores the influence of other agents in the agent’s own decision making [7].

ABM of crime and deviant behavior were used to represent the dynamics that lead to the emergence of crime. Bernasco, Block, and Ruiter [84] demonstrated that street robbers attack near their own homes, on easily accessible blocks, and where cash economies are present, using a discrete choice framework. Groff [85] studied space and temporal constraints in the context of Routine Activity in an agent-based environment to test whether time away from home increases rates of street robbery. Malleson, Heppenstall, and See [86] developed a framework for analyzing human and environmental factors in the occurrence of residential burglary. Birks, Townsley, and Stewart [87] applied Agent-Based Modeling to represent regularities of crime
such as spatial clustering, repeated victimization, and journeys to crime, finding significant increases when virtual offenders operate according to the mechanisms proposed by routine activity, rational choice and geometry/pattern theories of crime. Liu et al. [88] used an agent-based model to represent crime patterns where tension represents the psychological impact of crime to human beings. The model was calibrated using data from Cincinnati and was able to generate crime patterns similar to real patterns.

Models of human behavior developed in an agent-based computer environment allow representing behavior exhibited by agents as the result of social interactions of agents placed in a computer environment. Agent-based models can represent multiple heterogeneous individuals within a computer environment to provide these individuals with a decision-making algorithm based on events occurring in the environment, or to learn from the environment, their local and spatial information, and their social network connections. Among these models, the Schelling’s Segregation Model [5] shows that relative mild preference of neighbors from the same race could lead to high levels of segregation. This model represents the agent’s choice of moving to another random position if they have below a threshold number of neighboring agents of the same type. Axelrod’s Dissemination of Culture Model [6] studies the process of cultural diffusion under the assumption that people are more likely to interact with others who share similar cultural attributes. Miller and Page’s Standing Ovation Problem [7] assesses the audience’s decision to stand or not after a performance. Epstein’s Civil Violence Model [8] assesses the decision to become active and join a rebellion or not. The model represents dynamics between two ethnic groups while analyzing the tolerance level. Epstein’s Agent Zero Model [9] represents individual behavior in groups by modeling three behavior components: emotional, rational, and social. Ardiles-Cruz et al. developed an Insider Threat ABM [10] that represents the disposition of
employees to commit a threat or not based on precursors of behavior such as initial predisposition, access to the system, skills, and level of disgruntlement.

Epstein’s Agent Zero Model represents individual behavior in groups. Agent Zero has defined an emotional (affective), cognitive (deliberative), and social modules that interact to generate individual behavior in groups [9]. This neuro-cognitive grounded agent can generate a wide range of phenomena such as collective violence, financial panic, and endogenous dynamic networks, among others. Epstein’s Agent Zero structure was used to model human behavior. Sokolowski, Banks, and Dover developed an agent-based model of insider threat using Epstein’s agent zero structure that considers disgruntlement, rational behavior, and social contagion as the drivers of insider’s behavior while organizational culture influences disgruntlement of employees [89]. Sokolowski and Banks developed an ABM of population displacement in Aleppo, Syria using the Agent Zero structure to represent government troops patrolling the zone. The environment represents the city of Aleppo. Each square in the grid represents a portion of the population living within the city. The model accurately represents population displacement, as occurred in 2013 [90].

Agent Zero was used as a base for our social learning structure for representing SLAs able to learn and exhibit behavior. The section below provides a description of the Agent Zero structure and the decision-making algorithm.

2.3.5 Agent Zero

Epstein’s Agent Zero [9] is a structure for representing human behavior and decision making. Agent Zero is a neuro-cognitively grounded agent capable of generating social phenomena such as collective violence, financial panic, and endogenous dynamic networks,
among others. Agent Zero has emotions, bounded deliberative capacity, and social connections, grounded in neuroscience. These three internal modules interact to produce individual and often far from rational behavior.

The model represents agents occupying a landscape of indigenous sites. Some sites are inactive (benign) and some are active (fear-inducing). There is a binary action an agent could take: destroy or not destroy some sites. This action is triggered when the Agent Zero’s disposition exceeds a given threshold $\tau_i$. Agent Zero disposition is the summation of three components: emotional (affective), cognitive (deliberative), and social. When multiple agents of this type move and interact, they generate dynamics of social conflict, psychology, public health, law, social networks, and economics, among others. Each Agent Zero is provided with affective $V_i(t)$ and deliberative $P_i(t)$ functions defined in a stochastic stimulus space, and their solo disposition is calculated with equation 3 below.

$$D_i^{\text{solo}}(t) = V_i(t) + P_i(t)$$  

(3)

However, agents carry weights $\omega_j(t)$ to represent the influence of other agents in their disposition.

$$D_i^{\text{tot}}(t) = D_i^{\text{solo}}(t) + \sum_{j \neq i} \omega_j D_j^{\text{solo}}(t)$$  

(4)

Replacing Agent Zero’s solo disposition from equation 3 in equation 4:

$$D_i^{\text{tot}}(t) = V_i(t) + P_i(t) + \sum_{j \neq i} \omega_j [V_j(t) + P_j(t)].$$  

(5)

Equation 5 above represents Agent Zero’s disposition and equation 6 below represents Agent Zero’s decision to act or not. This decision is binary and triggered when Agent Zero’s disposition exceeds a given threshold $\tau_i$. This means that, at any time, if Agent Zero’s
disposition exceeds its threshold $\tau_i$ then $A = 1$ (the decision to act is taken); otherwise, $A = 0$ (no decision is taken).

$$A = \text{if } (D_i^{\text{net}}(t) > 0, 1, 0)$$

(6)

where $D_i^{\text{net}}(t) = D_i^{\text{tot}}(t) - \tau_i$.

The emotional (affective) component $V_i(t)$ is represented with the Rescorla Wagner Model of associative learning [48] inducing emotional contagion through weights. Equation 7 represents the Agent Zero emotional (affective) component that solves $V_i(t)$.

$$\frac{dV_i}{dt} = \alpha_i \beta_i (V^s_i - V_i)$$

(7)

The cognitive (deliberative) component $P_i(t)$ is represented as a local sample probability. In each time step, agents calculate a probability based on local sampling represented in equation 8 below.

$$P_i(t, x, m) = \frac{1}{m} \sum_{i=m}^{i} FR(x)$$

(8)

The social component represents the influence of the social network in Agent Zero’s disposition. It is represented using a network transmission model that depends on Agent Zero’s disposition. The strength scaled affective homophily between agents is represented as $\omega_{ij}(t) = |V_i(t) - V_j(t)| [1 - |V_i(t) - V_j(t)|].$

2.4 Summary of the State-of-the-Art

Behavioral Psychology Theories provide a theoretical framework for explaining the processes of learning. Behavioral Psychology Theories account for learning by the association
between stimulus and responses (classical conditioning), learning by consequences (operant conditioning), and learning by observation and imitation of others (cognitive and observational learning). These theories were developed by experimentation with animals and in a few cases, with humans. A mathematical approach to modeling the acquisition and extinction of behavior is the Rescorla Wagner Model. Operational conditioning is represented with different schedules for reinforcement. These theoretical or mathematical models lack the time component because they were developed based on the number of trials.

Social Learning Theory of Crime and Deviant Behavior provides a theoretical framework for explaining human behavior that accounts for peers’ influence, definitions of crime, reinforcement of behavior, and imitation of behavior from role models. The social structure component explains the difference in crime rates in different locations. The current approaches to modeling social learning from the criminology point of view are statistical approaches. These models use regression and correlation analysis, multi regression analysis, and logistic regression, among others. These approaches lack accounting for non-linear relationships, heterogeneous populations, and social network connections, among other factors.

An ABM represents multiple agents interacting with each other and their environment in a computer environment, while simulation provides multiple scenarios for analyzing the effects of changing variables in the system. ABM could capture the emergence of group and social behavior that results from an individual agent’s rules of interaction [2, 4, 45-47]. Models of human behavior developed in an agent-based computer environment allow representing behavior exhibited by agents as the result of social interactions and the computer environment. Agent-based models allow representing multiple heterogeneous individuals and providing these individuals with a decision-making algorithm based on events providing stimuli-response from
the environment, their local and spatial information, and their social network connections. The surveyed models lack the learning component to exhibit behavior, while they are focused on the decision-making process.

We propose joining Behavioral Psychology Theories and Social Learning Theories as an explanatory framework to develop an agent-based computer model of human behavior that accounts for learning from the environment and social interactions.

Our model differs from current approaches in that it provides a novel approach for modeling how individuals learn and exhibit a behavior. First, the conceptualization of the model uses the explanatory theoretical framework provided by Behavioral Psychology Theories and Social Learning Theories, the learning structure and decision-making processes that lead to exhibiting (or not) a behavior will be modeled using an adaptation of the Agent Zero Structure, and the modeling of the learning processes will be represented using the Rescorla-Wagner model. Second, the measure of observable behavior in this computer environment will be performed by developing a use case for representing Youth Gang Homicides using demographic data from the city of Pittsburgh, PA to represent the environment. Third, the local geographic configuration of the cities is a square grid of $n \times n$ cells of cellular automatons in which agents can interact with each other and the environment so that the geographic differences in the cities cannot affect the resultant dynamics, either the emergence of social nor group behavior. Forth, a micro definition of crime will be implemented to represent the convergence in space and time of a motivated offender, a suitable target, and the lack of guardianship proposed by routine activity. Fifth, the aggregated and collective behavior to measure is the emergence of homicides, which will be compared with aggregated homicide rates for three target neighborhoods from the city of
Pittsburgh, PA. Sixth and finally, perform the model calibration, verification and validation, and policing and decision-making analysis.
CHAPTER 3

METHODOLOGY

This dissertation proposes to develop a model of social learning agents able to exhibit behavior learned from social interactions and the environment while the emergent phenomena we expect to emerge is behavior. We used the axioms and postulates of Behavioral Psychology [1] and Social Learning Theory of Crime [55] as an explanatory framework. For representing the processes of learning, we used the Rescorla-Wagner model [48]. For representing the decision-making processes we used an adaptation of Epstein’s Agent Zero structure [9].

The main components modeled in this section are SLA’s attributes and behavior. The attributes contain information about the SLA’s learning processes (learning component), the local spatial information from the environment (local component), and the social connections with other SLAs (social component). Behavior rules (behavior component) allow the dynamic update on time of these attributes. Figure 4 below summarizes the social learning structure developed.
3.1 Learning Component

Behavioral Psychology Theories study observable stimulus-response behavior learned from the environment. Behavioral Psychology Theories provide a theoretical framework for explaining the processes of learning. Classical conditioning assumes that learning is the result of the association between stimulus and responses. Operant conditioning considers changing of behavior using reinforcement given after the desired response. Observational Learning involves changes in behavior and knowledge as a result of observing and imitating others. These theories emphasize the role of association (between stimuli and response), reinforcement (after the desired response), and observation (that leads to imitation).
Social Learning Theory is an integration of Sutherland’s sociological theory of differential association with behavioral principles from psychology. Robert Burgess and Ronald Akers originally presented the theory as differential association-reinforcement, and later it was renamed Social Learning Theory by Akers. Although it refers to all aspects of the learning process, the theory relies mainly on four principal explanatory concepts: differential association, definitions, differential reinforcement, and imitation.

This dissertation uses an adaptation of Epstein’s Agent Zero structure to model the SLA’s learning and motivation to exhibit behavior [9]. Agent Zero represents individual behavior in groups. Agent Zero has three components of behavior: emotional, rational, and social. Their summation represents the Agent Zero disposition to act. The decision to act or not is triggered by a threshold equation when the disposition exceeds a given threshold.

Our approach considers Behavioral Psychology Theories [1] and Social Learning Theories [55] as an explanatory framework. It adapts the Epstein’s Agent Zero Structure [9] by considering four components that lead to learning a behavior: definitions, association, observation, and reinforcement. These four components are dynamic and updated on time using behavior rules. The selection of these four components was made based on the postulates and axioms of Social Learning Theory [55] and the Behavioral Psychology Theories [1] previously mentioned.

We calculated the SLA’s learning attribute with a similar modeling approach that Agent Zero calculates its disposition, as the summation of its three behavior components: emotional, rational, and social. The attribute learning represents the level of social learning that an SLA has acquired over time. Learning is represented as the summation of the four components of
learning: definitions $D_i(t)$, association $A_i(t)$, observation $O_i(t)$, and reinforcement $R_i(t)$ [9, 55], as equation 9 shows.

\[ L_i(t) = D_i(t) + A_i(t) + O_i(t) + R_i(t) \] (9)

We represented the SLA’s motivated attribute with a similar modeling approach; Agent Zero represents its disposition using a threshold equation. The motivation or the readiness to exhibit the behavior is binary and set to zero when the SLA had not learned the behavior and set to one when the SLA has learned the behavior. The threshold equation 10 is used to represent this process, where threshold $\tau$ represents the minimum level of social learning an SLA must acquire to be motivated to exhibit a behavior.

\[ M_i(t) = IF(L_i(t) > \tau, 1, 0) \] (10)

It is important to point out that another difference of our approach compared to Agent Zero approach is that once agent zero has set its disposition to one he is ready to act, while our SLA not. Once our SLA is motivated, he is going to inspect his local vision for conditions that allow him to act.

According to Bandura [30, 53] observational learning occurs because of cognitive processes; individuals do not automatically observe the behavior and imitate it. There is some thought before imitation; these processes are called Mediational Processes. The mediational processes are attention, retention, reproduction, and motivation. Attention is the extent to which an individual is exposed to or notices the behavior. Retention is how well the behavior is remembered. Reproduction is the individual’s ability to perform the behavior. Motivation is the will to perform the behavior. If perceived rewards outweigh perceived punishments, then the behavior is more likely to be repeated. Later, Bandura renamed this theory Social Cognitive Theory [54]. The remainder of this section defines and represents the SLA’s learning component.
3.1.1 Definitions

Sutherland stated that “a person becomes delinquent because of an excess of definitions favorable to violation of law over definitions unfavorable to violation of the law” [65]. Burgess and Akers stated that “criminal behavior is a function of norms which are discriminative for criminal behavior, the learning of which takes place when such behavior is more highly reinforced than noncriminal behavior” [42]. Cressey, Sykes and Matza, and Hartung operationalized this concept as rationalizations, neutralization, or justifications [70-72]. We used all this previous research to represent the attribute definitions.

*DEFINITION:* The attribute Definitions $D_{t}(t)$ represents the weight of norms and definitions that are discriminative for learning behavior.

The attribute Definitions $D_{t}(t)$ is represented as a real number between zero and one and is heterogeneous among the SLAs. The attribute Definitions $D_{t}(t)$ is set with a uniform probability distribution between zero and one with the equation $D_{t}(0) = U(0,1)$, where values near to zero represent individuals with negative definitions towards exhibiting the behavior and values near to one represent individuals with an excess of definitions favorable to exhibiting the behavior. The attribute definitions are static, meaning that it is not updated on time nor by events.

3.1.2 Association

The attribute association $A_{t}(t)$ was developed based on differential association [65], differential association-reinforcement [42], and classical conditioning. This component accounts for the processes of learning in primary groups by the association of stimuli-response.
Sutherland’s differential association theory suggests that a normal person when exposed to attitudes favorable to crime will learn criminal behavior and that the mechanisms of learning criminal behavior are the same as the ones for most everyday behaviors: social interactions in primary groups (family, friends, teachers, peers, coworkers).

**DEFINITION:** The attribute *Association* $A_i(t)$ represents the learning that takes place in primary groups by exposition to stimuli-response events.

The attribute association represents the social connections in primary groups that provide association between stimuli-response that influence the learning of behavior. The attribute association $A_i(t)$ is represented in binary with zero or one, where zero represents a person not associated with a social network and one represents a person associated with a social network. Association is set initially to zero with the equation $A_i(0) = 0$ and updated with the Create_SN method that updates the association component of SLAs linked to the social network with the equation $A_i(0) = 1$.

3.1.3 Observation

The attribute observation $O_i(t)$ was developed based on cognitive and observational learning. This type of learning involves changes in behavior as a result of observation of others. We used Bandura’s observational learning theory. Bandura proposed Observational Learning based on the Bobo Doll Experiments, where children, when exposed to aggressive models, were more likely to imitate aggressive responses from same-sex models and with more physically aggressive acts [29, 30].

**DEFINITION:** The attribute *Observation* $O_i(t)$ represents direct observation that could lead to the imitation of behavior.
The attribute Observation $O_i(t)$ is represented as a real number between zero and one, where values near to zero mean low or none observation of the behavior and values near to one represent an individual that observed the behavior many times. The attribute observation is set heterogeneous among all the SLAs with a uniform probability distribution between zero and one with the equation $O_i(0) = U(0,1)$.

The attribute observation is updated dynamically on time when the event exhibit behavior occurs in the environment using the Rescorla-Wagner Model for the acquisition of response [48] for SLAs within local vision. The mathematical equation used to increase observation is shown below.

$$O_i(t) = O_i(t-1) + \alpha \beta [\lambda - O_i(t-1)]$$

where the maximum value that observation can reach is set to 1 ($\lambda = 1$).

Equation 12 below calculates the SLA $i$’s observation in time $t$.

$$O_i(t) = O_i(t-1) + \alpha \beta [1 - O_i(t-1)]$$

3.1.4 Reinforcement

The attribute reinforcement $R_i(t)$ was developed based on operant conditioning learning. This type of learning accounts for behavior that is influenced by consequences. The reinforcement could be positive when the individual is exposed to stimuli that increases the likelihood of exhibiting behavior and negative when the individual is exposed to stimuli that decreases the likelihood of exhibiting the behavior. We used Skinner’s operant conditioning theory to account for behavior learned through positive or negative consequences and extinction of behavior when the stimuli-response is no longer present.
**DEFINITION:** The attribute *Reinforcement* $R_i(t)$ represents the strengthen or diminishment of the likelihood of exhibiting the behavior based on the stimuli from the environment.

The attribute Reinforcement $R_i(t)$ is represented as a real number between zero and one, where values near to zero represent low reinforcement towards exhibiting the behavior, and values near to one represent high reinforcement towards exhibiting the behavior. The component reinforcement is set heterogeneous among all the SLAs with a uniform probability distribution between zero and one with the equation $R_i(0) = U(0, 1)$.

The attribute reinforcement is updated dynamically on time with the occurrence of events in the environment. When an SLA exhibits behavior, we increase reinforcement according to the Rescorla Wagner Model for acquisition of response [48] for the SLAs associated to the social network. The mathematical equation for representing positive reinforcement is shown in the equation below.

$$ R_i(t) = R_i(t-1) + \alpha \beta [\lambda - R_i(t-1)] $$

where the maximum value reinforcement can reach is set to 1 ($\lambda = 1$).

Equation 12 below calculates the SLA $i$’s positive reinforcement in time $t$.

$$ R_i(t) = R_i(t-1) + \alpha \beta [1 - R_i(t-1)] \tag{12} $$

We assume that the lack of occurrence of behavior decreases reinforcement according to the Rescorla Wagner Model for extinction of response [48] for the SLAs associated to the social network. The mathematical equation for representing lack of reinforcement is stated in the equation below.

$$ R_i(t) = R_i(t-1) + \alpha \beta [\lambda - R_i(t-1)]$$
where the minimum value reinforcement can reach is set to 0 ($\lambda = 0$).

Equation 13 below calculates the SLA $i$’s negative reinforcement in time $t$.

$$ R_i(t) = R_i(t-1) - \alpha \beta R_i(t-1) $$  \hspace{1cm} (13)

3.1.5 Learning

**DEFINITION:** The attribute **Social Learning** is represented as the summation of the four above attributes: Definitions $D_i(t)$, Association $A_i(t)$, Observation $O_i(t)$, and Reinforcement $R_i(t)$.

Social Learning is updated dynamically on time with equation 9, where lower values of learning mean that the SLA is not likely to exhibit behavior and higher values of learning mean that the SLA is more likely to exhibit the behavior.

$$ L_i(t) = D_i(t) + A_i(t) + O_i(t) + R_i(t) $$

3.1.6 Motivated?

**DEFINITION:** The attribute **Motivated?** represents the SLA’s readiness to exhibit the behavior.

The attribute Motivated? represents a binary choice: the SLA’s readiness to exhibit the behavior, where zero represents that the SLA is not ready to exhibit the behavior and one represents that the SLA is ready to exhibit the behavior. Each time the SLA’s level of learning exceeds a given threshold $\tau$ the motivation is set to one. The attribute Motivated? is updated dynamically on time with equation 10.

$$ M_i(t) = IF(L_i(t) > \tau, 1, 0) $$
3.2 Local Component

SLAs have local vision and mobility. The information about an SLA’s neighboring cells is the SLA’s local vision. SLAs store information about their position and local vision; both attributes define the position in the grid and which cells to inspect to collect information. SLAs collect and use this information to move within the grid, update network connections, etc.

SLAs interact with each other within an environment. An ABM represents the environment as a squared grid of \( n \times n \) cells. These cells store information about position and state (cell color), among others. Each cell has a cellular automaton configuration, meaning that cells could transition to different states (colors) as time evolves with a transition function to represent the influence of events in the environment.

The local component allows SLAs to get information from their local neighboring environment. While in the Agent Zero approach, the local sampling allows adding the rational component to human behavior; in our approach this component allows collecting information about the SLAs’ local limited vision. Below are defined the attributes that define the local component: Position \( (P_i) \), Local Vision \( (LV_i) \), and Cell Color \( (S_i) \).

3.2.1 Position

**DEFINITION:** The attribute Position \( P_i(t) \) represents the SLA’s current location in the grid with \( x_i(t) \) and \( y_i(t) \) coordinates.

Position is represented as \( (x_i(t), y_i(t)) \) coordinates in a two-dimensional grid for agent \( i \) in time \( t \). The coordinate \( x \) is set with the equation \( x_i(0) = \text{random()} \) and the coordinate \( y \) is set with the equation \( y_i(0) = \text{random()} \).
The attribute position usually is set random or with any given \((x, y)\) coordinates within the grid. If the SLAs have mobility this attribute must be updated dynamically on time using a behavior rule. Figure 5 below shows different positions in the grid.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{grid.png}
\caption{Position \(P = (x, y)\) in the grid.}
\end{figure}

3.2.2 Local Vision

**DEFINITION:** The attribute *Local Vision* (LV) represents the neighboring cells that the SLA is able to see.

The attribute local vision (LV) represents the neighboring cells that the SLA can inspect and collect information [2, 5, 8, 9, 74]. The LV is used to implement behavior rules and decision-making. The local vision is set with a Von Neumann neighborhood with radius 1.

The simplest choice for local vision is the nearest neighbors, in which only adjacent cells may be affected per step time. For one dimensional cellular automaton, the left, current, and right neighbors is the most common local vision configuration as figure 6 below shows.
For two-dimensional cellular automatons on a square grid, the Moore (square shape) neighborhood and the Von Neumann (diamond shape) neighborhood are the most used. Figure 7 below shows these neighborhood configurations. The circle neighborhood is also used by setting the radius.

For three-dimensional cellular automatons, the sphere or cube neighborhoods could be used.

3.2.3 Cellular Automaton States

SLAs interact with each other within an environment. An ABM represents the environment as a squared grid of $n \times n$ cells. Cells store information about position and color,
among attributes. Each cell has a cellular automaton configuration, meaning that cells could transition to different states from $S_0$ and $S_n$ (colors) as time evolves with a transition function. The transition function allows representing changes in the environment due to different events.

**DEFINITION:** The attribute *Cell State* ($S_i$) represents the state of each cell within the grid with $n$ states between $S_0$ and $S_n$, using a white-red color scale.

We used a white-red color scale to transition states for each cellular automaton, where white represents zones where the behavior has not been exhibited and red represents zones with a high count of behavior exhibited. The change of states in each cellular automaton will allow collecting statistics about the number of times the behavior has been exhibited in the environment. Figure 8 below shows the possible states for each cellular automaton.

![Fig. 8. Cellular Automaton States.](image)

The initial state is $S_0$ (white). The transition function transitions the cell to the next state if the SLA exhibits the behavior. The final state the cell can reach is $S_n$ (red). The finite state machine diagram in figure 9 below shows all the possible transitioning states from the initial state through the final state.

![Fig. 9 Finite State Machine.](image)
3.3 Social Component

SLAs are linked through a *Social Network (SN)*. The social network represents all the links that SLAs have with each other. The social network represents the influence of primary groups in behavior such as peers, parents, and teachers. A directed link from one to another SLA defines the direction of the influence. The weight defines the strength of the influence.

The social component allows SLAs to get information from their social network or the people that influence them. While in the Agent Zero approach the social component allows adding the social component to human behavior as the summation of the influence of all agents, in our approach, this component allows the update on time of the SLA’s attributes that define learning from the influence of others.

3.4 Behavior Component

Time advancement and the occurrence of events in the environment could change some SLAs’ attributes. Changes in attributes are implemented as behavior rules. Behavior rules can be time-driven or event-driven.

The behavior component allows agents to update attributes based on time or events occurring within the environment. The behavior rules will be implemented in the use case section since they will depend on the use case developed.

3.4.1 Setup

A constructor method called Setup is used to set the initial values for the SLA’s attributes. This method is run only once at the beginning of the simulation. Because the setup
method set values based on initial values for SLA’s attributes, it is developed in the following chapter in the use case section.

3.4.2 Create SN

Create SN is a method that runs once at the beginning of the simulation to create weighted directed links between SLAs. Because the method Create_SN creates the social network configuration for linking SLAs it will depend on the use case. This method is implemented in the following chapter in the use case section.

3.4.3 Move

Mobility allows agents to change conditions and input for behavior rules by updating their position and local vision. If SLAs have movement, in each time step, the agent’s position should be updated using some movement rule such as random walk, walking to the nearest resources, etc. Because this method depends on the use case specification, this method is implemented in the following chapter in the use case section.

Some ABMs have non-mobile agents such as Miller and Page’s Standing Ovation ABM [7] or Sokolowski et al.’s [89] Insider Threat ABM. If SLAs have mobility, the most commonly used pattern is a random walk. In this case, the SLA randomly selects a position within his local vision or within the grid and moves to this position. Examples of this pattern of mobility include Agent Zero [9], the Predator-Prey ABM, Segregation ABM [5]. Some ABMs use a goal-oriented pattern of movement looking for resources such as Epstein and Axtell’s Sugarscape ABM [2] in which agents move to the cell with the highest amount of sugar within their local vision.
3.4.4 Exhibit Behavior

We assume that the occurrence of the events within the environment is conditioned to certain criteria. The modeling approach for these conditions will depend on the context of the behavior to be represented and depend on the use case. The conditions for exhibiting a behavior will be implemented in the next chapter in the use case section. We assume that the occurrence of the behavior is going to increase SLA’s observation and reinforcement according to the Rescorla-Wagner Model for the acquisition of response and is going to allow the transition of the current cell to the next state. In the case that the behavior is not exhibited, we assume that the SLA’s reinforcement is going to be decreased according to the Rescorla-Wagner Model for the extinction of response. Figure 10 below provides the steps for implementing the behavior rule exhibit behavior.

Fig. 10. Behavior Rule Exhibit Behavior.
The algorithm below provides the steps used for implementing the behavior rule exhibit behavior.

```c
void Exhibit_Behavior () {
    // verify if conditions hold
    IF (condition = true)
    THEN
        // transition cellular automaton to next state
        pColor_i(t) = pColor_i(t) - 1
        // increase observation
        Ask SLAs in LV [ set O_i(t) = O_i(t - 1) + \alpha \beta [1 - O_i(t - 1)] ]
        // increase reinforcement
        Ask SLAs in SN [ set R_i(t) = R_i(t - 1) + \alpha \beta [1 - R_i(t - 1)] ]
    ELSE
        // decrease reinforcement
        Ask SLAs in SN [ set R_i(t) = R_i(t - 1) - \alpha \beta R_i(t - 1) ]
}
```
CHAPTER 4
VALIDATION AND RESULTS

This section contains the use case specification, calibration, verification and validation, and the policing and decision-making analysis. The use case represents a computer model of Youth Gang Homicides. The use case is implemented based on the model developed in the methodology section using the number of homicides for the city of Pittsburgh, PA as the variable to measure. The occurrence of homicides is represented using a micro definition of crime proposed by routine activity. The model’s inputs and parameters were set using data from the One Vision One Life Program [91] for three target neighborhoods: Northside, Hill District, and Southside in Pittsburgh, PA.

The calibration of the model was performed using Latin Hypercube Sampling (LHS) and a Bi-Factorial Experimental Design (BFED). The verification, validation, and testing were performed using confidence intervals and patterns of learning analysis. The policing and decision-making analysis tested the correlation between gang affiliation and the number of homicides. Below we describe each of these steps.

4.1 Use Case

The UCR – FBI provides statistics about the number of offenses known to law enforcement. Among these offenses, we can find criminal homicide defined as the willful killing of one human being by another and killing another person through gross negligence; this category of crime does not include attempts to kill someone, deaths by accident, negligence, or suicides [92]. The use case proposes to develop a model for representing youth gang homicides.
This section will review the literature about youth gangs and the intervention policies implemented for violence reduction in the US.

According to the FBI, 33,000 violent street gangs, motorcycle gangs, and prison gangs are active in the US. Gangs use violence to control neighborhoods and for illegal activities such as robbery, drug and gun trafficking, prostitution and human trafficking, and fraud. The FBI has implemented programs dedicated to investigating, disrupting, and dismantling the most significant gangs. Some of these programs and partnerships are the Safe Streets Task Forces, the National Gang Intelligence Center (NGIC), and Transnational Anti-Gang Task Forces (TAG). The NGIC was created in 2005 at the direction of Congress. The NGIC integrates gang intelligence from federal, state, and local law enforcement and supports law enforcement by sharing information and intelligence analysis. The NGIC identifies and targets the gangs that pose the most danger to US communities. The TAGs are located in El Salvador, Guatemala, and Honduras. TAGs collaborate with host nation agencies to investigate gangs. The FBI administers 160 Safe Streets Task Forces nationwide. The Safe Streets Task Forces prosecute entire gangs, provide incentives for witnesses to cooperate, or imprison gang leaders [93].

Also, government and community efforts were implemented to address gang-related activities across US communities such as the Project Safe Neighborhoods (PSN) and the Pulling Levers Intervention. Project Safe Neighborhoods (PSN) was developed by the US Department of Justice to combat gun crimes during the 1980s and 1990s. The PSN proposes strategies to turn gang members away from gangs. PSN was implemented in various districts of Chicago with the name of Boston Gun Project’s Operation Cease Fire and later in California, Massachusetts, the District of Columbia, Nebraska, Illinois, Missouri, and New York [94].
The Pulling Levers deterrence strategy was sponsored by the US Department of Justice and is focused on a small group of recurring gang members responsible for many of the urban gun violence problems. The intervention aims to take risky individuals off the street by incarceration or rehabilitation. This intervention was implemented in Rockford IL [95], Minneapolis MN [96], Indianapolis IN [97], Nashville TN [98], Stockton CA [99, 100], Baltimore MD [101], among others.

The Safe Streets Baltimore program [101] was implemented between 2007 and 2010. The program tried to prevent shootings among youths by changing behaviors, attitudes, and social norms related to gun violence. The program targeted neighborhoods with high gun crime rates. The program hired ex-offenders as street outreach workers who identified clients among youth between 14 to 25 years by providing positive role models and offering opportunities for jobs and education.

The One Vision One Life Program intervention in Pittsburgh, PA [91] was implemented between 2004 and 2006. Most of the staff members were raised in the inner city and knew the life and code of the street. Community coordinators worked with clients, mainly male, black, between 15 to 24 years old, and in need of assistance and services. The intervention was focused on violence reduction by intervening in disputes and placing youths in social programs.

CeaseFire Chicago started in 1999 and expanded to other cities in Illinois during the 2000s [102]. At its peak, it was active in about 25 program sites. Operation CeaseFire focused on changing the behavior of a small number of carefully selected members of the community, those with a high chance of either being shot or being a shooter in the immediate future. Violence interrupters worked on the street mediating conflicts between gangs and intervening to stem retaliation following a shooting. Outreach workers counseled young clients and connected them
to a range of services. To be classified as high risk for recruitment, individuals were supposed to meet at least four criteria: be between the ages of 16 and 25, have a prior history of offending and arrests, be a member of a gang, have been in prison, have been the recent victim of a shooting, and involvement in street drug markets.

The PSN was sponsored in Stockton, CA [103]. Stockton, CA was selected for the program intervention because of its higher than average homicide rate compared with other major urban areas. The analysis of gang activity in Stockton found an estimate of 38 gangs and more than 1500 gang members, with 4% of the population between 15 to 24 years of age believed to be gang members. The analysis also found that in the period from January 2000 to June 2003, nearly 60% of gun homicides were related to gangs, while gang members were involved in incidents being the shooters or the victim.

4.1.1 Environment

In 2003, a record 125 homicides in Allegheny County, Pennsylvania, including 70 in the city of Pittsburgh, PA, was the focus of initiatives aimed at reducing the increasing levels of violence in the city. The Allegheny County Violence Prevention Initiative, later called One Vision One Life was the result of these initiatives [91]. One Vision One Life was similar to other violence prevention programs in Boston, Chicago, and Baltimore, among other cities in the US. The program used problem-solving approaches, street-level work, and intelligence to become aware of and intervene in potentially violent disputes. Programs such as One Vision One Life seek to address the violent “code of the street” prevalent among inner-city youths, a code developed in response to a lack of legitimate, successful role models. One Vision’s focus was a six-point plan to stop local shootings, including mediation and intervention in conflicts,
provision of alternatives for persons most at risk for violence, strong community coalitions, a unified message of no shooting, rapid response to all shootings, and programs for youths at risk for violence. One Vision work was conducted by an executive director, a program director, five area managers, and more than 40 community coordinators, and supported by a data manager. Most staff members were raised in the inner city and therefore were intimate with inner-city street life and the “code of the street.”

Community coordinators worked with clients, typically male, black, and between 15 to 24 years old. Clients were usually in need of assistance and services. Fifty percent of the clients did not have a job, twenty-five percent had substance-abuse problems, but most of them were not violent, enrolled in a gang, or in the criminal justice system. The program used street violence intelligence to become aware and intervene in potentially violent disputes. The coordinators were selected because of their familiarity and connections with the target neighborhoods and knowledge of rival groups. They were trained in dispute resolution, conflict mediation, and culturally sensitive outreach. To accomplish its mission, the program had a six-point violence intervention plan (1) mediate and intervene in conflicts, (2) conduct outreach to provide alternatives for most-at-risk persons, (3) build strong community coalitions, (4) communicate a unified message: no shootings, (5) provide a rapid response to all shootings, and (6) provide programs for at-risk youths.

The program was implemented in three target area neighborhoods: Northside, Hill District, and Southside because of their high crime rates compared with the national rates. Northside was the largest community, with 18 neighborhoods, 48,102 residents, 36% black population, and an average per capita income of $15,901.00. The Northside homicide rate was 31 per 100,000 habitants in 2003. Northside was known for drug trafficking, gang disputes, and
drive-by shootings. The violence stemmed mostly from feuds between neighborhoods, and on occasions from outsiders entering the community. Hill District was smaller and more economically disadvantaged than Northside. Hill District includes 6 neighborhoods and 18,276 residents with a 71% black population, and an average per capita income of $11,072.00. Public housing projects and urban renewal projects had displaced businesses from the community. Since the 1950s, the population has decreased from 50,000 to 15,000. Hill District’s homicide rate was 44 per 100,000 habitants in 2003. Hill District had issues with guns, drugs, disputes, and violence stemming from clashes within the community. Southside had a population of 27,054 habitants with a 12% black population and an average per capita income of $12,771.00. Southside’s homicide rate was 4 per 100,000 habitants in 2003. Southside suffered illegal activities and community disputes.

Using a comparison of neighborhood attributes, seasonal effects, and trends over time, the program showed no effect on the homicide rates and was associated with some increases in violence.

**The Computer Model**

We developed an ABM for representing youth gang homicides in Pittsburgh, PA using NetLogo 6.0.4 [104]. The environment represents each one of the three target neighborhoods of the One Vision One Life Intervention program: Northside, Hill District, and Southside. Each cell represents a street intersection that hosts three types of agents: police officers, clients (at-risk youths, affiliated or not to a gang), and people. Agents move within the grid using a random walk within their local vision and decide whether to commit homicides, assessing the conditions stated by routine activity.
Some examples of alternative environments are listed below. For modeling insider threat, the population could be the total number of employees of a given organization. The offenders could be employees with financial difficulties, rule violation history, and minor law violations. The guardians could be supervisors. The targets could be unattended terminals or workstations.

For modeling aggravated assault, the population could be the number of people living in a given city. The offenders could be young males with the absence of a role model, financial difficulties, low GPAs at school, among other attributes. The guardians could be police officers patrolling the area and the people that walk within the city limits. The targets with a high likelihood of victimization could be people that go out alone at night.

In our use case, the number of agents will be the population per each neighborhood, and agents could be police officers, clients, and citizens. The police officers are a subset of the population that represents guardianship, in this case the number of police officers per neighborhood. The clients represent the population that is more likely to be a shooter or to be shot. In this case, that is assumed to be young black males from families with low incomes, affiliated or not to a gang. This assumption was made based on population demographics for youths at risk from the intervention programs Safe Streets Baltimore [101], One Vision One Life [91], CeaseFire Chicago [102], Project Safe Neighborhoods Stockton [103]. All clients have a social learning structure. A percentage (gang affiliation percentage) of clients are linked by nodes to represent their gang affiliation. As the One Vision One Life Program reports, not all their clients were affiliated with a gang, the gang affiliation represents the percentage of clients that are gang members. Finally, the rest of the agents in the model are people.
**Inputs**

The number of police officers was set using the rate of 2.4 police officers per 1000 habitants in the US in 2004, as reported by the UCR – FBI [105]. The equation 14 below was used to calculate the number of police officers in each neighborhood.

\[
\text{PoliceOfficers} = \frac{2.4}{1000} \cdot \text{Population}
\]  

(14)

The clients were assumed to be black males between 15 to 24 years old from families with less than $25,000 per capita income year based on the One Vision Life report [91] and other intervention programs with similar client demographics such as the Safe Streets Baltimore [101], the Ceasefire Chicago [102], and the Project Safe Neighborhoods Stockton [103] clients reports. Equation 15 was used to set this value based on the statistics for each neighborhood provided in the One Vision One Life target neighborhoods report. The percent of males and population between 15 to 24 years old population was set based on the 2010 US Census. The percent of the black population was set based on the One Vision One Life target neighborhood report. The percent of population with per capita income lower than $25,000.00 per year was estimated. The One Vision One Life target neighborhood program provides the average per capita income for the three target neighborhoods as $15,901.00 for Northside District, $11,072.00 for Hill District, and $12,771.00 for Southside District. We estimated the percent of population that could have an income lower than $25,000.00 using a Normal(\(\mu,\sigma\)) distribution using these means and assuming that the standard deviation was $25,000.00.

\[
\text{Clients} = \text{Population}.\%\text{Male}.\%\text{Black}.\%\text{Youth}.\%\text{LowIncome}
\]  

(15)

The gang affiliation percentage was set using the percent of gang affiliation among One Vision One Life clients reported in [91] and used to calculate the number of clients affiliated with the gang (\(\text{SNSize}\)) using equation 16 below.
\[ SNSize = Clients.GangAffiliation \] (16)

The number of people was set as the remaining population using equation 17 below.

\[ People = Population - PoliceOfficers - Clients \] (17)

For the parameters Police Officers, Clients, People, and SNSize, we rounded the calculated values to create an integer number of agents. Table 1 below summarizes these settings.

Table 1. Environment Settings.

<table>
<thead>
<tr>
<th>Environment Settings</th>
<th>Northside</th>
<th>Hill District</th>
<th>Southside</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Population</td>
<td>48,102</td>
<td>18,276</td>
<td>27,054</td>
</tr>
<tr>
<td>Police Officers</td>
<td>115</td>
<td>44</td>
<td>65</td>
</tr>
<tr>
<td>Clients</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black %</td>
<td>0.36</td>
<td>0.71</td>
<td>0.12</td>
</tr>
<tr>
<td>Male %</td>
<td>0.48</td>
<td>0.48</td>
<td>0.48</td>
</tr>
<tr>
<td>Low Income % (&lt;$25,000)</td>
<td>0.65</td>
<td>0.71</td>
<td>0.69</td>
</tr>
<tr>
<td>Youths % (15-24 years old)</td>
<td>0.15</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>Clients (SLAs)</td>
<td>809</td>
<td>662</td>
<td>161</td>
</tr>
<tr>
<td>Gang Affiliation %</td>
<td>0.438</td>
<td>0.188</td>
<td>0.385</td>
</tr>
<tr>
<td>People</td>
<td>47,178</td>
<td>17,570</td>
<td>26,828</td>
</tr>
</tbody>
</table>

**Parameters**

The parameters to set for each computer environment are the SLAs’ threshold (\( \tau \)) and the grid’s number of patches (\( p \)).

The threshold (\( \tau \)) represents the minimum value of learning that the SLA must acquire to be able to exhibit the behavior. The threshold is the same for all SLAs.

The number of patches (\( p \)) represents the NetLogo grid’s dimension. This variable is related to the number of cells that the 2-D squared grid contains.
 Outputs

Finally, the output variable that measures the emergence of group and collective behavior is the number of homicides (H) in each computer environment. This variable is calculated by counting the number of red cells in the environment, where red cells represent the places in the environment where a homicide has occurred.

4.1.2 SLA Settings

This section details the initial configuration for the SLA and defines components and attributes to represent youth gang homicides as the use case.

 Local Vision

For our use case, we defined a Von Neumann neighborhood with a radius equal to one for the SLA’s local vision, and this configuration remains the same through time. This means that the SLAs can inspect the four neighboring cells around them, as figure 11 below shows. The equation used to set the SLA’s local vision is $LV = VonNeumann(1)$.

![Fig. 11. Von Neumann Neighborhood Local Vision.](image-url)
Some examples of additional local vision configurations that could be used in other environment configurations are listed below. Wolfram’s Elementary Cellular automata have three neighboring cells defined for local vision. Wolfram implemented rules for changing the state of the cellular automata from white to black according to different transition functions and analyzed the evolution over time of this cellular automata. Figure 12 below shows this local vision configuration.

![Fig. 12. Wolfram’s Elementary Cellular Automata Local Vision.](image)

Epstein’s Agent Zero Structure represents a neuro-cognitive agent capable of generating collective violence, financial panic, endogenous dynamic networks, among other behaviors. Agent Zero uses a Von Neumann neighborhood configuration for Agent Zero’s local vision. Agents could inspect and collect information from their four adjacent neighboring cells as figure 11 above shows. Agent Zero’s rational component is updated based on the local vision, while agents could have or not have mobility.

Conway’s Game of Life [73] uses a Moore neighborhood (8 neighboring cells shown in figure 3) to analyze the evolution of the system. The set of rules are applied in a Moore neighborhood configuration in which: (1) A live cell with fewer than two live neighbors dies (under-population); (2) A live cell with two or three live neighbors’ lives; (3) A live cell with more than three live neighbors dies (over-population); (4) A dead cell with three neighbors becomes a live cell (reproduction).
Sokolowski et al.’s [89] Agent Zero ABM of Insider Threat does not define a local vision. Agents do not have mobility, and the rational component is updated based on the assessment of risks and rewards.

**Cellular Automaton States**

The environment is a square grid of \( n \times n \) cells. Each cell is represented with a cellular automaton configuration [2, 8, 20, 73, 74, 106]. For our use case, the cellular automaton was defined with two possible states represented with white and red colors, where white represents a cell in which no homicide has occurred and red represents a cell in which at least one homicide has occurred. This assumption seemed reasonable because homicides are an infrequent event occurring 15 times per year in the Northside neighborhood, 8 times per year in the Hill District neighborhood, and 1 time per year in the Southside Neighborhood according to the One Vision One Life Report [91]. The transition from state \( S_0 \) to \( S_1 \) is implemented below with the exhibit-behavior rule to represent the occurrence of homicides in the context of routine activity using a micro definition of crime. Only the occurrence of homicides leads to the cell’s state transition to red. This cellular automaton configuration will allow us to collect statistics about the number of homicides that occurred within the environment by counting the red cells. Figure 13 below represents the transition diagram for the cellular automaton.

Fig. 13. Transition Diagram for the Cellular Automaton.
Alternative cellular automaton configurations could be implemented, such as using a red-white color scale. For ease of programing in NetLogo, a six states configuration could be useful for representing the emergence and displacement of hot spots with integer numbers between 15 and 20. If more than six states are required, states could be defined by using real numbers for representing the color scale.

**Setup**

A constructor method called Setup is created to initialize SLA attributes. Setup allows us to set all the initial values for clients using the social learning structure developed in section 3. This method runs only once at the beginning of the simulation. The following steps provide the algorithm used to implement the setup method.

```java
void Setup() {
    LV = VonNeumann(1)
    P_i(0, 0) = (random(), random())
    S_i(0) = "white"
    D_i(0) = U(0, 1)
    A_i(0) = 0
    O_i(0) = U(0, 1)
    R_i(0) = U(0, 1)
    L_i(0) = D_i(0) + A_i(0) + O_i(0) + R_i(0)
    M_i(0) = 0
    Create_SN();
}
```

For defining other use cases, here we can change the initial setting configurations assumed in the methodology section. We can set another local vision, cellular automaton configuration, or different states for the cellular automatons.
Create SN

The social network data structure is used in the social sciences to study relationships between individuals, groups, organizations, societies, and others. For this dissertation, we use a social network to represent the gang affiliation or the association with a gang. We assume that gang association between individuals could lead to learning from stimuli-response and to exhibiting behavior according to the postulates of Behavioral Psychology Theories and Social Learning Theories.

Create social network (Create_SN) is used to link clients with each other. To create the social network, we define the leader as the SLA with the highest learning among the clients and update its association component to one. Then, we link the leader with other clients randomly while updating their attribute association to one with the equation $A_i(0) = 1$. The number of SLAs linked to the social network is set with the parameter gang affiliation based on data from the three target neighborhoods: Northside, Hill District, and Southside in Pittsburgh, PA provided in the One Vision One Life report [91].

The strength of the association is represented using the Rescorla Wagner Model for Acquisition and Extinction of Behavior. This model allows SLAs to acquire the behavior on the presence of stimuli while SLAs with higher levels of reinforcement or observation will learn slower compared with SLAs with lower levels of reinforcement or observation. For the extinction case, SLAs with higher levels of reinforcement or observation will forget the behavior with faster rates than SLAs with lower levels of reinforcement or observation. This is the reason why the social network does not carry the weight in either direction of the association.
Other possible social network configurations can be defined. Epstein’s Agent Zero used weighted directed links to represent the strength and direction of the social influence [9], where the weights and directions were set randomly for each one of the three Agent Zeros defined in the application. Sokolowski et al.’s Insider Threat ABM represents the social network with random directed weights to represent how much the employee is influenced by his fellows [89], where the Agent Zero directed links and weights are set randomly between -1 and 1.

**Move**

We use a random walk algorithm within local vision for all agents in the environment. In each time, agents will randomly select a new position within their local vision and update their position as figure 14 below shows.

![Fig. 14. Behavior Rule Move.](image)

The algorithm below provides the steps used to implement the behavior rule move.

```c
void Move() {
    Select a random position within local vision
    Displace agent to selected position
}
```
Some examples of different patterns of movement are listed below. Some ABMs have non-mobile agents such as Miller and Page’s Standing Ovation ABM [7] and Sokolowski et al.’s [89] Insider Threat ABM. The Standing Ovation ABM does not provide mobility to the agents given that they are sat in an auditorium. The agent’s assessment to applaud and stand in ovation to the performance is based on its perception of the presentation and the behavior of its neighbors. In the Insider Threat ABM, Sokolowski et al. [89] do not provide mobility to the Agent Zero insider threat agents because they update their local sampling component based on the assessment of risks and rewards.

If agents have mobility, the most common used pattern is a random walk. In this case, the agent randomly selects a position within his local vision or within the grid and moves to this position. Examples of this pattern of mobility are Epstein’s Agent Zero [9], in which Epstein defines a no-movement case scenario and a movement with a random walk within the local vision scenario. The Schelling’s Segregation ABM [5] represents agents moving randomly within the grid when they are surrounded by non-similar agents.

Some ABMs use goal-oriented patterns of movement looking for resources such as Epstein and Axtell’s Sugarscape ABM [2] in which agents move to the cell with the highest amount of sugar within their local vision. Mallerson et al. [86] represent an environment that contains the commercial district, roads, and residential houses. Burglars select a house based on its attractiveness, and then they move to the selected house using the shortest path.
**Exhibit Behavior**

The behavior rule exhibit behavior was implemented using a micro definition of crime in the context of routine activity [107] to represent the convergence in space and time of a motivated offender, a suitable target, and the lack of guardianship.

The One Vision One Life program identified clients as black, males, between 15-24 years old, from families with incomes lower than $25,000 [91]. All clients in our model are represented with a social learning structure. The motivated offender condition is represented by a client whose decision is set to one. The lack of guardianship condition is represented as the lack of police officers and people in the motivated offender’s local vision. The suitable target condition is represented as the presence of a client alone in the motivated offender’s local vision. When these three conditions converge in time and space, a homicide happens.

We assume that the occurrence of a homicide increases observation and reinforcement of SLAs and allows the transition of the current cell to the next state. In the other case (there is no occurrence of a homicide) reinforcement will be decreased. Figure 15 below provides the steps for implementing the behavior rule exhibit-behavior.
The next sequence of steps shows the implementation of the Exhibit-Behavior rule.

```c
void Exhibit_Behavior() {   
   // verify IF conditions hold
   IF (motivated offender=true) and (lack of guardianship=true) and (suitable target = true)  
   THEN  
      // transition cellular automaton to next state  
      $S_i(0) = \text{"red"}$  
      // increase observation  
      Ask SLAs in LV [ set $O_i(t)=O_{i,1}(t-1)+\alpha\beta[1-O_{i,1}(t-1)]$ ]  
      // increase reinforcement  
      Ask SLAs in SN [ set $R_i(t)=R_{i,1}(t-1)+\alpha\beta[1-R_{i,1}(t-1)]$ ]  
   ELSE  
      // decrease reinforcement  
      Ask SLAs in SN [ set $R_i(t)=R_{i,1}(t-1)-\alpha\beta R_{i,1}(t-1)$ ]  
   }
```
4.1.3 The Model Logic

Finally, the remainder of this section describes the method “go” used to run the simulation in a continuous time configuration.

Go

The method go runs the model for 365 days or one year. It calls behavior rules, methods, and procedures for all agents in the model concurrently. Starting time $t = 0$ is reserved for initial configuration; then, each run starts in time $t = 1$, increasing each time step by one until $t = 365$ days is reached. The model is run allowing continuous time increments and the occurrence of events for updating attributes. The time was set on 365 days to compare the model outputs with data from the One Vision One Life Program report [91] that provides annual data from the number of homicides in the three target neighborhoods: Northside, Hill District, and Southside before starting the program intervention.

The environment is composed of cells or patches, agents, and links. The agents can be police officers, clients, and people. All agents in the model have implemented the behavior rule move. Also, clients have implemented exhibit-behavior behavior rule and methods to update learning and decisions on each time step.

Figure 16 below shows the sequence of behavior rules each agent follows per time step from time 1 to 365 days.
4.2 Calibration

Before starting the process of verification and validation, we calibrated the model. To be able to observe the emergent phenomenon or the number of homicides in our computer environments, we had to calibrate the model to get a good fit between the SLA’s threshold and the Grid’s Number of Patches. To achieve this objective, we performed a Sensitivity Analysis by designing a Latin Hyper Cube Sampling and a Bi-Factorial Experimental Design for the variables SLA’s Threshold and Grid’s Number of Patches while recording the output or the number of homicides for each computer environment. Then we used MATLAB to generate a surface response with the 3D points generated. First, using a scatter 3D plot and then using the Interpolation Tool to interpolate the SLA’s Threshold and the Grid’s Number of Patches that gave the number of homicides reported by the One Vision One Life Report.
First, using the Latin Hypercube Sampling (LHS) we set the input parameter’s threshold (τ) and number of patches (p) to calculate the number of homicides (H). The parameter threshold (τ) was divided in four sub-intervals between one and four, with the sub-intervals being [0,1>, [1, 2>, [2, 3>, and [3, 4>. The number of patches in NetLogo defines the grid’s dimension. If the number of patches is p then the number of cells in the squared grid is \( n \times n \) or \( (2 \times p + 1) \times (2 \times p + 1) \). The parameter number of patches (p) was divided into eight sub-intervals between 40 and 200 (we assumed that we would need more patches than the NetLogo standard grid configuration because we had a bigger number of agents, so we started in 40, and finished in 200 because this appears to be the limit of patches in NetLogo). The resultant sub-intervals were [40, 60>, [60, 80>, [80, 100>, [100, 120>, [120, 140>, [140, 160>, [160, 180> and [180, 200>. This process gave us thirty-two sub-squares. Then we generated 32 random points \((τ, p)\) one per sub-square with which to run the model to calculate the number of homicides (H) in each computer environment.

Because of the randomness in the model, we got different values for the number of homicides each time the model was run, so we ran the model multiple times and calculated the mean. We started by running the model 30 times, then increased the number of replications to 50, 100, and 120, getting lower variations for the mean of the number of homicides with 120 replications. Then the number of replications was set to 120. The running times were approximately 15 mins for Northside, 6 mins for Hill District, and 8 mins for Southside. Finally, we generated a surface response with all the 3D points \((τ, p, H)\), where τ is the SLA’s Threshold, p is the Grid’s Number of Patches, and H is the number of homicides.

Second, designing a Bifactorial Experimental Design (BFED), we generated 30 random points for the number of patches interval and the threshold interval that gave the nearest results
to the number of homicides reported by the One Life One Vision intervention program. Similar to the LHC, in each case, we performed 120 runs per each random point and recorded the mean. Then we plotted the 3D points to generate the surface response.

Finally, the two sets of 3D points were used to interpolate the values of SLA’s Threshold and Grid’s Number of patches that gave the number of homicides reported by the One Vision One Life report using the MATLAB Interpolation tool. Below we describe this process for each computer environment.

**Northside Computer Environment**

Figure 17 below shows the 32 3D points generated by the LHS in blue and the surface response to which they were adjusted as a colored grid.

![Fig 17. Surface Response for the LHS - Northside Computer Environment.](image)
The number of homicides reported by the One Vision One Life Intervention Program was 15. We used the sub-square with the nearest number of homicides to 15; it was [1.42, 2.09> for the SLA’s threshold and [146, 155> for the number of patches. Then we run a Bi-Factorial Experimental Design (BFED) generating 30 random points. We run 120 replications per each point to calculate the number of homicides. Figure 18 below shows these 30 points in blue and the surface to which they were adjusted as a colored grid.

![Figure 18. Surface Response for the BFED - Northside Computer Environment.](image)

Figure 19 below shows both sets of points generated by the LHS and the BFED in blue and the surface to which they were adjusted as a colored grid.
Finally, the MATLAB Interpolation Tool allowed us to get the best 3D point with the restrictions that our calibration needed (1) Patches Restriction: \( p \) must be an integer, the MATLAB Interpolation Tool provided real numbers (2) Number of Homicides Restriction: \( H = 15 \); this number of homicides was provided by the One Vision One Life Report. We set the threshold on 1.94 and the number of Patches on 150, expecting to get the nearest to 15 for the number of homicides. Figure 20 below shows the process of interpolation.
Fig. 20. Interpolation - Northside Computer Environment.

Hill District Computer Environment

Figure 21 below shows the 32 3D points generated by the LHS in red and the surface response to which they were adjusted as a colored grid.
The number of homicides reported by the One Vision One Life Intervention Program was 8. We used the sub-square with the nearest number of homicides to 8, it was [2.52, 2.85] for the threshold and [67, 85] for the number of patches. Then we run a Bi-Factorial Experimental Design (BFED) generating 30 random points. We run 120 replications per each point to calculate the number of homicides. Figure 22 below shows these 30 points in blue and the surface to which they were adjusted as a colored grid.
Fig. 22. Surface Response for the BFED - Hill District Computer Environment.

Figure 23 below shows both sets of points generated by the LHS and the BFED in blue and the surface to which they were adjusted as a colored grid.

Fig. 23. Surface Response for the LHC and BFED - Hill District Computer Environment.
Finally, the MATLAB Interpolation Tool allowed us to get the best 3D point with the restrictions that our calibration needed (1) Patches Restriction: \( p \) must be an integer, the MATLAB Interpolation Tool provided real numbers (2) Number of Homicides Restriction: \( H = 8 \), this number of homicides was provided by the One Vision One Life Report. We set the threshold on 2.67 and the number of Patches on 75, expecting to get the nearest to 8 for the number of homicides. Figure 24 below shows the process of interpolation.

![Fig. 24. Interpolation - Hill District Computer Environment.](image)

**Southside Computer Environment**

Figure 25 below shows the 32 3D points generated by the LHS in blue and the surface response to which they were adjusted as a colored grid.
The number of homicides reported by the One Vision One Life Intervention Program was 1. We used the sub-square with the nearest number of homicides to 1, it was [0.90, 2.21> for the threshold and [131, 158> for the number of patches. Then we run a Bi-Factorial Experimental Design generating 30 random points. We run 120 replications per each point to calculate the number of homicides. Figure 26 below shows these 30 points in blue and the surface to which they were adjusted as a colored grid.
Fig. 26. Surface Response for the BFED - Southside Computer Environment.

Figure 27 below shows both set of points generated by the LHS and the BFED in blue and the surface to which they were adjusted as a colored grid.

Fig. 27. Surface Response for the LHC and BFED - Southside Computer Environment.
Finally, the MATLAB Interpolation Tool allowed us to get the best 3D point with the restrictions that our calibration needed (1) Patches Restriction: p must be an integer, the MATLAB Interpolation Tool provided real numbers (2) Number of Homicides Restriction: H = 1; this number of homicides was provided by the One Vision One Life Report. We set the threshold on 1.51 and the number of Patches on 132, expecting to get the nearest to 1 for the number of homicides. It is important to notice that the surface response shows values around 0.5 as the maximum number of homicides for this computer environment. Figure 28 below shows the process of interpolation.

![Fig. 28. Interpolation - Southside Computer Environment.](image)

**Comparison between Computer Environments**

We found that lower values for the SLA’s threshold within [0, 1> gave us the highest number of homicides and higher values for the SLA’s threshold within [3, 4> gave us the lowest
number of homicides including zeros. These results suggest an inverse relationship between the SLA’s threshold and the number of homicides in which lower values of threshold lead to the emergence of behavior.

The number of patches represents the dimension of the grid. Because we defined a two-dimensional grid in NetLogo, if the number of patches was set as an integer number $p$, then the total number of cells or the grid dimension is going to be $(n \times n)$ or $((2 \times p + 1) \times (2 \times p + 1))$. For the number of patches, from the lowest values to the highest values, the number of homicides starts to increase from zero or near to zero until it reaches a maximum and then it starts to decrease to zero or near to zero. This behavior shows that a high concentration of agents in the grid or a low concentration of agents in the grid will not produce any emergent phenomena or homicides because the routine activity condition will not hold. Only when the grid is not underpopulated or overpopulated can we observe the emergent phenomena.

We did not observe out of range values. The number of homicides was always positive and went smoothly from lower to higher values for the SLA’s Threshold and went smoothly from low-high-low for the Grid’s Number of Patches. We did not observe unexpected peaks or depressions on the surface response.

The population at the Northside neighborhood was 48,102; at the Hill District neighborhood it was 18,276; and at the Southside neighborhood it was 27,054. The number of patches set for each environment was 150 for the Northside computer environment, 75 for the Hill District computer environment, and 132 for the Southside computer environment. We can observe that the higher the population, the bigger the grid would be in NetLogo.

The number of homicides recorded was between 0 and 74 for the Hill District computer environment, between 0 and 21 for the Northside computer environment, and less than 1 for the
Southside computer environment. From these results, we could see the Hill District as the computer environment with the highest potential for disputes and confrontation to emerge and escalate to violent events such as shootings compared to the Northside and Southside computer environments. The lower number of homicides in the Southside computer environment suggest an environment with low opportunities for the occurrence of homicides and a low stimuli environment for learning behavior. These results also suggest that differences in demographic data in the computer environments could lead to differences in the number of homicides.

### 4.3 Validation

According to Balci [108], model validation is substantiating that the model within its domain of application behaves with satisfactory accuracy consistent with the study objectives, while verification deals with substantiating that the model is transformed from a real-world problem to a conceptual model to a computer model as intended with enough accuracy. In other words, model validation deals with constructing the right model, while verification deals with building the model correctly. Model testing is conducted to perform validation and verification. Some tests evaluate the behavioral accuracy (validity) and others the accuracy of model transformation (verification). This process is referred to as model verification, validation, and testing. How much to test and when to stop testing depends on the study objectives. Testing should continue until we achieve enough confidence in the credibility and acceptability of simulation results.

According to Robinson [109], the purpose of verification and validation is not trying to demonstrate that the model is correct but trying to prove that the model is incorrect. The more tests performed that cannot prove that the model is incorrect, the more the confidence in the
model grows. There are many methods for verification and validation, such as conceptual model validation to ensure that the model accurately represents the real-world system and the problem to solve. Data Validation avoids inaccurate data that could be a substantial source of inaccuracy. Verification and White-Box Validation ensures that the computer model is true to the conceptual model (verification) and that the content of the model is true to the real world (White-Box Validation). Black Box Validation ensures that the model behaves as the real-world system under the same conditions (inputs).

For verification, validation, and testing of our model, we considered Robinson’s verification and validation approach. We considered data validation, conceptual model validation, verification and white-box validation, and black box validation.

Data validation was considered in the verification, validation, and testing process to ensure that the model captured the parameters, variables, and constants that the real-world system has. We selected the One Vision One Life Intervention Program Reports as a source of data for defining our use case: three target neighborhoods in the city of Pittsburgh, PA. The city of Pittsburgh, PA has one of the biggest crime rates in the US and was the focus of many programs aimed to reduce crime rates. The main reason to use Pittsburgh, PA as our real-world system was the richness in the One Vision One Life Report detailed in the section environment. The report included tables with population and client statistics that captured the demographic, geographic, economic, and delinquent conditions in the three sample neighborhoods with deep detail for the year 2004 before the program intervention. Among the available population data, the report included total population, population density, black population, income per capita, households in public assistance, female head of house with children under 18, vacant housing, homicide rates, guns assaults, and aggravated assaults among other details for the Northside, Hill
District, and Southside neighborhoods. At the client’s level, the report included percentages of race, gender, age, income, adult in care, school status, gang status, criminal status, drug use, among others for the Northside, Hill District, and Southside neighborhoods. At the crime rates level, the program included data for homicides, aggravated assaults, and assaults. This data was used to set the variables, parameters, and constants for our computer environments and to compare the model outputs with the number of homicides.

For conceptual model validation, we studied the processes of learning based on grounded theories, such as Behavioral Psychology Theories and Social Learning Theory and tried to build a model that resembles these processes as accurately as possible. We put special effort into modeling the learning patterns based on Behavioral Psychology Theories using the Rescorla-Wagner model to represent the acquisition and extinction of response over time. To represent human behavior in an agent-based computer environment, we proposed an adaptation of Epstein’s Agent Zero Structure [9]. The selection of this approach was based on the robustness with which it was built using neurocognitive theories and the acceptation the model has in the agent-based community for modeling human behavior. For representing the occurrence of homicides based on an individual’s behavior, we used a micro behavior definition of crime proposed by routine activity. In this process, we got feedback from subject matter experts in ABM, Psychology, and Criminology. Their feedback was included in each step of the model development.

For verification and white-box validation, we performed regression and correlation analysis to ensure that the SLA agents learned behavior under the Rescorla-Wagner Model on time. The test was performed to verify that the learning rates resemble the learning rates exhibited by the Rescorla-Wagner Model, including non-linear rates. Also, the learning patterns
must exhibit higher learning rates for individuals with low values of learning and lower learning rates for individuals with high values of learning. Another characteristic that the learning patterns must exhibit is positive learning rates in the presence of stimuli and negative learning rates in the absence of stimuli.

Black-box validation was performed to ensure that the computer model and the real system under the same conditions provide statistically the same response. Because of the randomness of the model, we ran the model multiple times to get a mean number of homicides, which was compared with the number of homicides reported on the One Vision One Life Program using confidence intervals.

The remainder of this section describes the construction of the confidence intervals and the analysis of patterns of learning.

4.3.1 Confidence Intervals

A confidence interval is an interval estimate from the sample data. It is associated with a confidence level or the probability that using the same method to collect a different sample, we expect to get the parameter falling within the interval. The most common value used for the confidence level is 95%. The degrees of freedom are related to the number of samples, N, collected. The p-value measures the significance of the test of hypothesis statistically.

The use of confidence intervals allowed calculating an interval for the number of homicides per year in each environment that must include the number of homicides reported by the One Vision One Life program. Using confidence intervals, we also ensure that the replication of the experiment will give values for the number of homicides within the confidence interval.
To construct the confidence intervals, first, we collected simulated data by performing multiple runs in each computer environment (Northside, Hill District, and Southside). Because of the randomness in the variables and outputs in the environment, we run the experiment multiple times to calculate a mean value for the number of homicides. We started with 30 runs getting a bigger confidence interval. Then, we increased the runs to 50, 100, and 120. With 120 runs, we got better precision and accuracy in the number of homicides and a smaller confidence interval. We set the number of runs to 120, even when this meant an increase in simulation time. Then, the confidence interval per each computer environment was constructed using equation 18 below where the confidence level was set to 95% and the degrees of freedom was set to N-1, where N is the number of runs.

\[
CI = \bar{X} \pm t_{n,\alpha/2} \frac{\sigma}{\sqrt{N-1}}
\]

(18)

**Northside Computer Environment**

First, we set the parameters for estimating the confidence interval, the confidence level was set on 95%, and the number of experiments or runs was set to 120. The simulation time was approximately 15 mins per each set of 120 runs. Next, we calculated the mean = 15.30 and the standard deviation = 5.19 for the 120 runs outputs (number of homicides). Using equation 18, we calculated the lower = 14.37 and the upper = 16.23 values. The confidence interval calculated for the number of homicides in the Northside computer environment was [14.37, 16.23]. The calculated p-value was 0.000, so we can conclude that our results are statistically significant. For the Northside neighborhood, the number of homicides reported by the One Vision One Life Intervention program was 15, a value that is included in this interval.
Figure 29 below summarizes our results. The red line represents the confidence interval constructed based on the simulated data for the number of homicides occurring in the Northside computer environment. The red point represents the number of homicides reported by the One Vision One Life Program before the intervention in the Northside neighborhood.

Fig. 29. Confidence Interval - Northside Computer Environment.

**Hill District Computer Environment**

First, we set the parameters for estimating the confidence intervals; the confidence level was set on 95%, and the number of experiments was set to 120. The simulation time was approximately 6 mins per each set of 120 runs. Next, we calculated the mean = 8.16 and the standard deviation = 4.80 for the 120 run outputs (number of homicides). Using equation 18, we calculated the lower = 7.29 and the upper = 9.03 values. The confidence interval calculated for the number of homicides in the Hill District computer environment was [7.29, 9.03]. The calculated p-value was 0.000, so we can conclude that our results are statistically significant. For the Hill District neighborhood, the number of homicides reported by the One Vision One Life Intervention program was 8, a value that is included in this interval.
Figure 30 below summarizes our results. The green line represents the confidence interval constructed based on the simulated data for the number of homicides occurring in the Hill District computer environment. The green point represents the number of homicides reported by the One Vision One Life Program before the intervention in the Hill District neighborhood.

![Confidence Interval - Hill District Computer Environment](image)

**Fig. 30. Confidence Interval - Hill District Computer Environment.**

**Southside Computer Environment**

First, we set the parameters for estimating the confidence intervals; the confidence level was set on 95%, and the number of experiments was set to 120. The simulation time was approximately 8 mins per each set of 120 runs. Next, we calculated the mean = 0.32 and the standard deviation = 0.71 for the 120 run outputs (number of homicides). Using equation 18, we calculated the lower = 0.19 and the upper = 0.44 values. The confidence interval calculated for the number of homicides in the Southside computer environment was [0.19, 0.44]. The calculated p-value was 0.000, so we can conclude that our results are statistically significant. For
the Southside neighborhood, the number of homicides reported by the One Vision One Life Intervention program was 1, a value that is not included in this interval.

Figure 31 below summarizes our results. The blue line represents the confidence interval constructed based on the simulated data for the number of homicides occurring in the Southside computer environment. The blue point represents the number of homicides reported by the One Vision One Life Program before the intervention in the Southside neighborhood.

Fig. 31. Confidence Interval - Southside Computer Environment.

**Comparison between Computer Environments**

Our computer model was able to replicate the emergence of homicides within the three target neighborhoods. In the Northside computer environment, the confidence interval calculated was [14.37, 16.23] for the number of homicides, while the One Vision One Life Program reported 15 homicides. In the Hill District computer environment, the confidence interval calculated was [7.29, 9.03] for the number of homicides, while the One Vision One Life Program reported 8 homicides. In the Southside computer environment, we had lower accuracy and higher
precision compared to the other two target neighborhoods. The confidence interval calculated was [0.19, 0.44] while the One Vision One Life Program reported 1 homicide.

From our results, we can conclude that the Northside and Hill District computer environments had a high precision and accuracy in representing the number of homicides and gave us confidence intervals that included the number of homicides reported by One Vision One Life Report. The Southside computer environment gave us higher precision but lower accuracy in representing the number of homicides and gave us a confidence interval with the number of homicides lower than the One Vision One Life Report. The lower stimuli for learning, lower number of offenders and the low percent of gang affiliation in the Southside neighborhood could be a reason for the lower number of homicides compared to the number of homicides reported in the One Vision one Life program. Table 2 below summarizes simulation results.

### Table 2. Confidence Intervals for the Number of Homicides.

<table>
<thead>
<tr>
<th>Validation</th>
<th>Northside</th>
<th>Hill District</th>
<th>Southside</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Confidence Intervals from Simulated Data</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Runs</td>
<td>120</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>Mean</td>
<td>15.30</td>
<td>8.16</td>
<td>0.32</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>5.19</td>
<td>4.80</td>
<td>0.71</td>
</tr>
<tr>
<td>Lower</td>
<td>14.37</td>
<td>7.29</td>
<td>0.19</td>
</tr>
<tr>
<td>Upper</td>
<td>16.23</td>
<td>9.03</td>
<td>0.44</td>
</tr>
<tr>
<td>p-Value</td>
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<table>
<thead>
<tr>
<th>One Vision One Life Report</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Homicides</td>
</tr>
<tr>
<td>15</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>1</td>
</tr>
</tbody>
</table>

#### 4.3.2 Analyzing Patterns of Learning

The variable learning represents how SLAs learn a behavior over time. It could increase when SLAs have positive stimuli from the environment, such as positive reinforcement or direct
observation. It could decrease because of the lack of stimuli from the environment. The analysis of learning patterns must show that in the presence of stimuli, SLAs are learning over time and this learning is higher for SLAs with lower levels of learning and lower for SLAs with higher levels of learning. This analysis also must show that in the absence of stimuli, SLAs must decrease their learning levels and vice versa. We hypothesize that SLAs learn on time with a logarithmic model. To assess this hypothesis, we performed a correlation and regression analysis. The analysis was performed per each target Neighborhood: Northside, Hill District, and Southside.

Because of the randomness in the variables and outputs in the environment, we ran the experiment multiple times to get a mean value for learning per time. We started with 30 runs getting high variation in the variable learning. Then we increased this number to 50, 100, and 120. We got better precision and accuracy for the mean of learning with 120 runs; then we set the number of runs to 120, even when this meant an increase in simulation time.

**Northside Computer Environment**

Figure 32 below shows a scatter plot for the learning of SLAs over time in the Northside computer environment using the mean of 120 runs. The simulation time was approximately 15 mins per each set of 120 runs. From upper to lower, we have the mean of the leader or the SLA with the highest learning value, the mean of the SLAs associated with the gang, and the mean of the New Member or the SLA with the lowest learning value. We adjusted the values to a logarithmic function to perform a correlation and regression analysis.
The correlation analysis gave us values for correlation between the variables (R) of 0.9519, 0.97, and 0.9698 for the Leader, Mean and New Member cases; with these values being positive and near to one, we can conclude that there is a strong positive correlation between learning and the evolution of the system in time.

The regression analysis gave us values for the logarithmic rate of change of 0.0994, 0.1183, and 0.2329 for the Leader, Mean and New Member cases. From these values, we can conclude that there is a positive logarithmic rate of learning over time, being the biggest growth rate for the New Member case and the lowest growth rate for the Leader case. These results show us that for the Northside computer environment SLAs with lower learning have higher learning rates than SLAs with higher learning. The intercept gives us 3.81, 2.32, and 1.82 for the Leader, Mean, and New Member cases. From these values, we can conclude that the highest learning starting point corresponds to the Leader and the lowest learning starting point corresponds to the New Member. From the values for $R^2$ we can conclude that the variations in learning can be explained by evolution in time with 90.61%, 94.09%, and 94.06% for the Leader, Mean and New
Member cases. For the three cases, the p value is 0.000, meaning that the variable learning is statistically significant.

**Hill District Computer Environment**

Figure 33 below shows a scatter plot for the learning of SLAs over time in the Hill District computer environment using the mean of 120 runs. The simulation time was approximately 6 mins per each set of 120 runs. From upper to lower, we have the mean of the leader or the SLA with the highest learning value, the mean of the SLAs associated to the gang, and the mean of the New Member or the SLA with the lowest learning value. We adjusted the values to a logarithmic function to perform a correlation and regression analysis.

![Fig. 33. Learning over Time – Hill District Computer Environment.](image)

The correlation analysis gave us values for correlation between the variables (R) of 0.7325, 0.9498, and 0.9602 for the Leader, Mean, and New Member cases. Being that all these values are positive and near to one, we can conclude that there is a strong positive correlation between learning and the evolution of the system in time.
The regression analysis gave us values for the logarithmic rate of change of 0.0037, 0.1283, and 0.2377 for the Leader, Mean, and New Member cases. From these values, we can conclude that there is a positive logarithmic rate of change of learning over time, being the biggest growth rate for the New Member case and the lowest growth rate for the Leader case. These results show us that for the Hill District computer environment SLAs with lower learning have higher learning rates than SLAs with higher learning rates. The intercept with Learning gives us 3.79, 2.17, and 0.61 for the Leader, Mean, and New Member cases. From these values, we can conclude that the highest learning starting point corresponds to the Leader and the lowest learning starting point corresponds to the New Member. From the values for $R^2$ we can conclude that the variations in learning can be explained by evolution in time with 53.65%, 90.22%, and 92.20% for the Leader, Mean and New Member cases. For the three cases, the p value is 0.000, meaning that the variable learning is statistically significant.

_Southside Computer Environment_

Figure 34 below shows a scatter plot for the learning of SLAs over time in the Southside computer environment using the mean of 120 runs. The simulation time was approximately 8 mins per each set of 120 runs. From upper to lower, we have the mean of the leader or the SLA with the highest learning value, the mean of the SLAs associated with the gang, and the mean of the New Member or the SLA with the lowest learning value. We adjusted the values to a logarithmic function to perform a correlation and regression analysis.
Fig. 34. Learning over Time – Southside Computer Environment.

The correlation analysis gave us values for correlation between the variables (R) of 0.8960, 0.9498, and 0.9602 for the Leader, Mean, and New Member cases, being that all these values are positive and near to one, we can conclude that there is a strong positive correlation between learning and the evolution of the system in time.

The regression analysis gave us values for the logarithmic rate of change of -0.0350, -0.0090, and 0.0125 for the Leader, Mean, and New Member cases. From these values, we can conclude that there is a negative growth rate of learning over time for the Leader and the SLAs associated with the Social network cases, and there is a positive growth rate for the New Member case. These results show us that the Southside computer environment SLAs with lower learning have higher learning rates than SLAs with higher learning rates. It is important to notice that for this case, the lower number of homicides makes Southside a computer environment with low stimuli to learn and exhibit criminal and deviant behavior and that SLAs with high learning could decrease their learning rates because of the lack of stimuli from the environment. The intercept with Learning gives us 3.79, 2.57, and 1.27 for the Leader, Mean and New Member cases, from these values, we can conclude that the highest learning starting point corresponds to
the Leader and the lowest learning starting point corresponds to the New Member. From the values for $R^2$ we can conclude that the variations on learning can be explained by evolution on time with 80.28%, 85.16%, and 86.13% percent for the Leader, Mean, and New Member cases. For the three cases, the $p$ value is 0.000, meaning that the variable learning is statistically significant.

**Comparison between Computer Environments**

From the correlation and regression analysis, we can conclude that SLAs are learning over time according to the Rescorla-Wagner Model for Acquisition and Extinction of Response with a logarithmic function. By comparing the learning patterns for the Leader, the SLAs in the Social Network, and the New Member, we can conclude that the SLAs with lower learning levels have higher learning growth rates over time than SLAs with higher learning levels. From the comparison between the computer environments, we can conclude that computer environments with the higher number of homicides provide an environment with abundant stimuli for learning and computer environments with the lower number of homicides provide an environment with a lack of stimuli for learning. From the criminology point of view, results suggest that program interventions for violence reduction could have better impact in communities with a high number of homicides.

### 4.4 Policing and Decision Marking

For policing and decision making, we analyzed the gang size influence in the number of homicides in each computer environment. The gang affiliation represents the percent of clients affiliated with the gang. A low percentage means a low number of clients affiliated with the gang.
and a high percentage means a high number of offenders affiliated with the gang. We hypothesized that the larger the gang size, the higher the number of homicides. To test this hypothesis, we performed a correlation and regression analysis between the gang size and the number of homicides.

First, we designed a mono-factorial experimental design for the variable gang affiliation, varying its values randomly 30 times between -10% and +10%. Because of the randomness in the variables and outputs in the environment, we run the experiment multiple times to get a mean value for the number of homicides. We started with 30 runs and increased this number to 50, 100, and 120. We got better precision and accuracy for the mean of the number of homicides with 120 runs, then we set the number of runs to 120, even when this meant an increase in simulation time. Next, we performed 120 runs for each gang association value and recorded the mean of the number of homicides. The resultant values were used to perform a correlation and regression analysis between the variables number of homicides and gang affiliation.

Northside Computer Environment

Figure 35 below shows the scatter plot for the number of homicides and the gang affiliation in red. The values for gang affiliation were set between [43.8 – 10.00, 43.8 + 10.00] percent randomly. It means that we generated 30 random numbers between [33.8, 53.8] percent to set the gang affiliation parameter. Then, we ran each case for 120 times and recorded the mean of the number of homicides. The simulation times was approximately 15 mins. Finally, we performed a correlation and regression analysis.
The correlation analysis between the number of homicides and the gang affiliation gave us a correlation coefficient of 0.7028. Being that this value is positive and near to one, we could conclude that there is a strong positive correlation between the number of homicides and the gang affiliation.

The regression analysis gave us values for the linear rate of change of 0.0755. From this value, we can conclude that there is an increase in the number of homicides when the gang affiliation is increased. From the values for $R^2$ we can conclude that the gang affiliation can explain 49.40% of the variations on the number of homicides. The $p$ value is 0.000, then we can conclude that the variable gang association is statistically significant.

*Hill District Computer Environment*

Figure 36 below shows the scatter plot for the number of homicides and the gang affiliation. The values for gang affiliation were set between $[18.8 \pm 10.00, 18.8 + 10.00]$ percent randomly. It means that we generated 30 random numbers between $[8.8, 28.8]$ percent to set the gang affiliation parameter. Then, we ran each case for 120 times and recorded the mean of the
number of homicides. The simulation times was approximately 6 mins. Finally, we performed a correlation and regression analysis.

![Graph showing number of homicides per gang association.](image)

**Fig. 36. Number of Homicides per Gang Association – Hill District Computer Environment.**

The correlation analysis between the number of homicides and the gang affiliation gave us a correlation coefficient of 0.9865. Being that this value is positive and near one, we can conclude that there is a strong positive correlation between the number of homicides and gang affiliation.

The regression analysis gave us values for the linear rate of change of 0.3997. From this value, we can conclude that there is an increase in the number of homicides when gang affiliation is increased. From the values for $R^2$ we can conclude that the gang affiliation can explain 97.32% of the variations on the number of homicides. The $p$ value is 0.000, so we can conclude that the variable gang association is statistically significant.

**Southside Computer Environment**

Figure 37 below shows the scatter plot for the number of homicides and the gang affiliation. The values for gang affiliation were set between $[38.5 - 10.00, 38.5 + 10.00]$ percent...
randomly. It means that we generated 30 random numbers between [28.5, 48.5] percent to set the gang affiliation parameter. Then, we ran each case 120 times and recorded the mean of the number of homicides. The simulation times was approximately 8 mins. Finally, we performed a correlation and regression analysis.

![Graph showing number of homicides per gang association.](image)

Fig. 37. Number of Homicides per Gang Association – Southside Computer Environment.

The correlation analysis between the number of homicides and gang affiliation gave us a correlation coefficient of 0.3957. Being that this value is positive between zero and not near to zero, we can conclude that there is a weak positive correlation between the number of homicides and gang association.

The regression analysis gave us values for the linear rate of change of 0.0041. From this value, we can conclude that there is an increase in the number of homicides when gang affiliation is increased. From the values for $R^2$ we can conclude that gang affiliation can explain 15.66% of the variations on the number of homicides. The $p$ value is 0.000, so we can conclude that the variable gang association is statistically significant.
Comparison between Computer Environments

From the simulation results, we can conclude that the Northside and Hill District computer environments exhibit a more significant reduction in the number of homicides than the Southside District. These results support the configuration in which the Northside neighborhood and Hill District neighborhood have a large at-risk population and high stimuli for learning a behavior. The Southside neighborhood has a small at-risk population and low stimuli for learning a behavior that even leads to forgetting the learned behavior.
This dissertation proposed a model of social learning developed in a computer environment. Behavioral Psychology Theories and Social Learning Theories were used as an explanatory framework. An adaptation Agent Zero was used to represent the learning structure and the decision to exhibit a behavior.

Developing a use case allowed us to test the validity of the approach and its usefulness for policing and decision making. The use case represents youth gang homicides for three target neighborhoods in the city of Pittsburgh, PA. The model was constructed using the social learning structure developed in the methodology section. The occurrence of the shootings that lead to homicides was represented using a micro definition of crime proposed by routine activity to represent the congruence in time and space of a motivated offender, a suitable target, and the lack of guardianship. The model was set using demographic data from three target neighborhoods in the city of Pittsburgh, PA. The model measures the number of homicides as the output variable.

We calibrated the model using sensitivity analysis to ensure a good fit between the SLA’s threshold and the grid’s number of patches that gave us an output similar to the one reported in the One Vision One Life Intervention Program. For validation, we constructed confidence intervals that included the number of homicides in the One Vision One Life report and a correlation and regression analysis tested the significance of the variable learning over time statistically.
For policing and decision-making, we used correlation and regression analysis to test the effect of the social network size in the occurrence of homicides statistically. This section reports our major findings in each step of the process. It includes the conclusions of our work, recommendations to improve our findings, and future work that could be explored.

5.1 Conclusions

This dissertation developed a model of social learning. SLAs were provided with a social learning structure to represent the dynamics that lead to learning through social interactions and the environment. The proposed approach for social learning allowed our SLAs to learn and exhibit behavior over time by representing the occurrence of events in the environment. Behavioral Psychology Theories and Social Learning Theories were used as an explanatory framework. ABM allowed representing the influence of social processes and the environment in learning behavior using the Rescorla-Wagner Model to model the acquisition and extinction of response to the occurrence of events in the environment. An adaptation Agent Zero was used to represent the learning structure and the readiness to exhibit a behavior. The decision-making process was represented using threshold equations to represent the SLA’s motivation, or lack thereof, to exhibit behavior. The evolution in time of the model was able to capture and represent how SLAs learned and exhibited the behavior.

The development of a use case allowed us to test the validity of the approach and its usefulness for policing and decision making. The use case represents Youth Gang Homicides in three neighborhoods of Pittsburgh, PA. The ABM represents the city as a square grid of cellular automatons with two states white and red, where the white state represents a cell in which a homicide has not occurred, and the red state represents a cell in which at least one homicide has
occurred. The agents that populate the grid are people, clients (of the violence reduction program), and police officers. Agents are provided with a random-walk behavior rule to move within their local vision. In addition, clients are provided with an exhibit-behavior behavior rule that verifies whether the conditions to exhibit behavior hold using a micro definition of crime in the context of routine activity. The input variables number of people, number of clients, number of police officers, and percentage of gang affiliation were set using demographic data from the city of Pittsburgh, PA reported by the One Vision One Life Program. The number of homicides is calculated as the output variable, where the number of homicides is calculated as the count of red cells in the grid or the cells in which at least one homicide has occurred.

The calibration of the model allowed us to set the parameters SLA’s threshold and grid’s number of patches. First, we constructed a surface response that plotted the input variables SLA’s threshold and cell’s number of patches and the output variable number of homicides. The process of calibration showed a surface response according to the model inputs and restrictions. The model outputs did not exhibit unexpected values such as out of range values, peaks, nor depressions. The sensitivity analysis allowed us to explore the dynamics that lead to the emergence of behavior. We found that a high concentration of agents in the grid or a low concentration of agents in the grid will not produce any emergent phenomena or homicide. Only when the grid is not underpopulated or overpopulated, would we be able to observe the emergence of behavior. We also found an inverse relationship between the number of homicides (emergent phenomena) and the threshold, meaning that low values of threshold lead to the emergence of behavior.

The calibration process also showed three computer environments able to exhibit the emergence of homicides. The characteristics of each computer environment made them unique.
The Northside computer environment was the biggest in population with 48,102 habitants and the highest number of homicides with 15 homicides per year. The maximum number of homicides recorded with the sensitivity analysis was 21 homicides. The Hill District computer environment was the smallest in population with 18,276 habitants and 8 homicides per year. The maximum number of homicides recorded was 74. The Southside computer environment had 27,054 habitants and the lowest number of homicides with 1 homicide per year. The maximum number of homicides recorded was less than 1. These results suggest the Hill District as the computer environment with high potential for disputes and confrontation to emerge and escalate to shootings. Results also suggest the Southside neighborhood being a computer environment with low opportunities for disputes and confrontation to emerge, and less likelihood for shootings. The calibration process revealed that demographic differences in neighborhoods could lead to differences in homicide patterns, as postulated by Akers’ Social Learning and Social Structure Theory [55]. These results suggest that programs and interventions for homicide reduction could have different impacts on the target neighborhoods depending on their demographic configurations.

To ensure that the model and the One Vision One Life Program have similar outputs, confidence intervals were constructed for each computer environment and compared to the number of homicides reported by the One Vision One Life Report. In the Northside computer environment, the confidence interval calculated was [14.37, 16.23] for the number of homicides, while the One Vision One Life Program reported 15 homicides. These results show high precision and accuracy in both measures. In the Hill District computer environment, the confidence interval calculated was [7.29, 9.03] for the number of homicides while the One Vision One Life Program reported 8 homicides. These results show high precision and accuracy
in both measures. In the Southside computer environment, the confidence interval calculated was [0.19, 0.44] while the One Vision One Life Program reported 1 homicide. In this neighborhood, we had lower accuracy and a higher precision compared to the other two target neighborhoods. One reason for this finding could be the small at-risk population and the low stimuli for the acquisition of response that this environment offers, being that homicides are rare events.

The analysis of learning patterns tested the hypothesis that agents will learn behavior over time according to the Rescorla-Wagner Model for acquisition and extinction of response. For testing this hypothesis, we performed correlation and regression analysis adjusting the outputs to a logarithmic function for the variables learning and time. The correlation and regression analysis gave us positive learning rates for the Northside and Hill District computer environments and negative learning rates for the Southside computer environment with a significant p-value. The analysis of learning patterns showed a high rate of learning for SLAs with lower values of learning and lower rates of learning for SLAs with high levels of learning when processes of stimuli-response are present in the neighborhood. These results suggest that neighborhoods with high homicide rates provide abundant stimuli for learning behavior, and neighborhoods with low homicide rates provide an environment with a lack of stimuli from learning a behavior. Our results support the implementation of intervention programs for homicide reduction in target cities with high homicide rates compared to the national media. Some examples of these implemented programs include CeaseFire Chicago, One Vision One Life, Safe Streets Baltimore, Project Safe Neighborhoods Stockton.

Decision-making policies for homicide reduction were tested in our computer ABM. We tested the hypothesis that gang affiliation was positively correlated with the number of homicides. The correlation analysis gave us a positive correlation between the variables gang
affiliation and number of homicides with a significant p-value, where the variable gang affiliation represents the percentage of clients associated with a gang. Results suggest that neighborhoods with a large at-risk population and gang affiliation could lead to the occurrence of a high number of homicides. From these results, we could highlight the positive impact of violence reduction programs in communities with high crime rates, such as the One Vision One Life, CeaseFire Chicago, Safe Streets Baltimore, and Project Safe Neighborhoods Stockton. These violence reduction programs were focused on removing gang members from the streets by incarceration or by rehabilitation. Some of the support clients received was aimed at helping re-introduce people into society by providing counseling, support, school reenrollment, and job opportunities.

In conclusion, this dissertation has developed an agent-based computer model of social learning that allows agents to exhibit behavior learned from social interactions and the environment and developed a use case to represent Youth Gang Homicides. The computer ABM was able to capture the emergence of complex social human behavior, specifically homicides for the environments tested, and the use case provided a way to test the validity of the approach and its use for policy and decision making.

5.2 Recommendations

Our computer ABM was able to show the emergence of homicides in the three target neighborhoods Northside, Hill District, and Southside. While it was accurate in representing homicide rates as reported in the One Vision One Life intervention program, we consider that it represents our understanding of the system for the processes that we were modeling. However, we simplified some aspects of the real system.
First, we considered the topology of the cities as a square grid. We could implement some improvements to this approach. The use of GPS grids could give a more accurate representation of each city configuration. This addition could also lead to performing hot spot analysis.

Second, we considered a random walk pattern of movement. Using different patterns of movement could lead to a better understanding of the occurrence of homicides and where they occur.

Third, we did not include population dynamics such as joining rate or leaving rate for the social network. The addition of these dynamics could lead to analyzing gang reduction policies.

Fourth and finally, the model lacks incarceration processes. Guardians lack the ability to apprehend an offender. The addition of a behavior rule for apprehension and incarceration could lead to analyzing the effects of deterrence and learning by negative reinforcement.

5.3 Future Work

This section includes possible future work to extend this research. We consider the next possible topics to extend this research: improving the human behavior modeling, implementing different decision-making algorithms, deterrence policies, reduction policies, and hot spot analysis.

5.3.1 Human Behavior Modeling

We used Behavioral Psychology Theories and Social Learning Theories to represent the processes of learning. While an advantage of Behavioral Psychology Theories is its ability to define behavior clearly and measure changes in behavior by introducing stimuli-response trials,
it only provides a partial model of human behavior. Essential factors like emotions, expectations, and motivations, among others, are not considered.

For future work to improve the processes of learning, we propose to account for what Bandura called the mediational processes that lead to exhibiting behavior. Bandura stated that observational learning occurs because of cognitive processes; individuals do not automatically observe the behavior and imitate it. There is some thought before imitation, and these processes are called Mediational Processes [41]. The mediational processes are attention, retention, reproduction, and motivation. Attention is the extent to which an individual is exposed to or notices the behavior. Retention is how well the behavior is remembered. Reproduction is the individual’s ability to perform the behavior. Motivation is the will to perform the behavior. If perceived rewards outweigh perceived punishments, then the behavior is more likely to be repeated. The addition of the mediational processes could enrich the decision-making process of our SLAs by adding the mediational processes that lead to learning.

The approach of Ardiles-Cruz et al. [10] for modeling Insider Threat using an ABM represents the disposition of employees to commit a threat or not based on precursors of behavior such as initial predisposition, access to the system, skills, and level of disgruntlement. This approach attempts to represent emotions, expectations, and motivations that lead to a disposition to commit a threat while the model lacks the learning processes. We propose to join both pieces of research to propose a broader approach for modeling of human behavior.

5.3.2 Decision-Making Algorithm

The decision-making process for our SLAs was implemented using threshold equations to represent the readiness of SLAs to exhibit behavior. The SLA’s motivated? attribute is binary
where zero represents no behavior exhibited, and one represents the SLA’s readiness to exhibit the behavior. A threshold equation sets the motivated? attribute to one when the SLA’s learning attribute exceeds a given threshold. We propose to implement other decision-making algorithms, such as rational choice [107] and game theory [110] approaches for decision-making. A comparative analysis of these decision-making algorithms could lead to finding the approach that better represents the decision-making processes.

5.3.3 Deterrence Policies

Deterrence is a theory from Behavioral Psychology focused on preventing behavior through fear of punishment or retribution. In the criminal justice system, deterrence is a basis for the incarceration system.

We propose to implement a got caught behavior rule. Got caught could be a behavior rule implemented in the context of deterrence for police officers. When a client commits a homicide, there is a probability that a police officer could apprehend him, because the guardians’ local vision must be bigger than the clients’ local vision. Our current approach does not model the police officer agent. This modeling must include a bigger local vision and a behavior rule to apprehend offenders (Got_Caught). The behavior rule Got_Caught must include negative reinforcement that allows the extinction of response for all clients in the social network when somebody is apprehended. Epstein’s Civil Violence ABM suggests a jail term drawn from $U(0,J_{max})$ generated randomly, to remove agents from the model for a given random time to analyze the effects of deterrence in the model [8]. Figure 38 below provides a possible implementation of the event Got_Caught.
The algorithm below provides the possible steps to implement the behavior rule Got_Caught.

```java
void Got_Caught() {
    // verify if there is a homicide in guardian's local vision
    IF (Exhibit_Behavior = TRUE and SLA in PoliceOfficer LV)
    THEN
        // assign jail term
        Ask SLA [ set JailTerm = \max(0, J) ]
        // decrease Reinforcement
        Ask SLAs in SN [ set \( R(t) = R(t-1) - \alpha \beta R(t-1) \) ]
}
```

The addition of this behavior rule in the environment could allow us to explore some dynamics and policies of deterrence. We can analyze the response on the environment when the local vision for guardians is increased using different local vision configurations. For this case scenario, we hypothesize that the increase in local vision and the negative reinforcement for clients in the SN will lead to less crime. We can also analyze the effect on the environment of different learning rates to avoid punishment. For this case scenario, we hypothesize that larger learning rates will lead to lower homicide rates. Finally, we can analyze the effect on the
environment of different jail times set constant and random. For this case scenario, we hypothesize that longer jail times will lead to fewer homicides.

5.3.4 Reduction Policies

According to the FBI, 33,000 violent street gangs, motorcycle gangs, and prison gangs are active in the US. Gangs use violence to control neighborhoods and for illegal activities such as robbery, drug and gun trafficking, prostitution and human trafficking, and fraud. The FBI has implemented programs dedicated to investigating, disrupting, and dismantling the most significant gangs.

Government and community efforts were implemented to address gang-related activities across the US, such as the Project Safe Neighborhoods (PSN) and the Pulling Levers Intervention. Project Safe Neighborhoods (PSN) was developed by the US Department of Justice to combat gun crimes during the 1980s and 1990s. PSN proposes strategies to turn gang members away from gangs. PSN was implemented in various districts of Chicago with the name of Boston Gun Project’s Operation Cease Fire and later in California, Massachusetts, the District of Columbia, Nebraska, Illinois, Missouri, and New York [94].

Many intervention programs were implemented as initiatives for crime reduction including the One Vision One Life Program, the Pulling Levers deterrence strategy, the Safe Streets Baltimore program, and the Ceasefire Chicago program. These initiatives were focused on removing individuals at risk of committing crimes by incarceration or by helping them to leave the streets.

We propose to implement a Leave_SN behavior rule, to represent individuals leaving the gang because of unexpected events or social interventions aimed at reducing homicides such as
moving to another place, getting a job, starting a family, and being incarcerated. For modeling this event, we propose to develop a new method to remove the SLA’s link to the gang randomly. This method proposes to analyze the effect of reducing the number of clients associated with the gang dynamically in time and providing negative reinforcement for the remaining clients associated with the gang. Figure 39 below provides the steps used for implementing the event Leave_SN.

![Behavior Rule Leave_SN](image)

The algorithm below provides the steps to implement the behavior rule Leave_SN.

```java
void Leave_SN() {
    // select randomly a SLA and remove SLA from the SN
    Ask any SLA in SN
    [ remove link to Leader
    set A_i(t) = 0 ]
    // decrease reinforcement
    Ask SLAs in SN [ set R_i(t) = R_i(t-1) - \alpha \beta R_i(t-1) ]
}
```

The addition of this behavior rule in the environment could allow us to explore some dynamics and policies for violence reduction. We can analyze the effect of negative reinforcement and the response on the environment when the number of offenders in the social
network is decreased dynamically over time. For this case scenario, we hypothesize that the reduction in the social network size will lead to fewer homicides.

5.3.5 Hot Spots Analysis

According to Eck, Chainey, and Wilson [111], crime is not spread evenly across an area; it is concentrated in some areas and absent in others, and people use this knowledge in their daily activities to avoid some places and seek out others. In some places, people lock their cars and secure their belongings while in other places they do not. This behavior suggests that people understand that crime is not evenly distributed and that the risk of being a victim is not geographically the same.

Hot spots are areas within a city where many crimes occur. These areas have a higher than average number of criminal events, and people in these areas have a higher than average risk of victimization. Hot spots can be located near services such as bus stations, bars, stores, ATMs, and others.

To perform hot spot analysis in our virtual computer environment, we suggest using a GPS grid instead of a \((n \times n)\) squared grid to capture the geographic configuration of the target area to study. This addition could lead to analyzing the location of hot spots. Also, using different patterns of movement and more than two different states for the cellular automaton can lead to a better understanding of the dynamics that lead to the emergence and displacement of hot spots.
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