IMPLEMENTING A COMPLEX SOCIAL SIMULATION OF THE VIOLENT OFFENDING PROCESS: THE PROMISE OF A SYNTHETIC OFFENDER

by

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DEDICATION

This dissertation is dedicated to my daughters, Mira and Ella, who inspire me to be a better person, and to my wife and best friend, Vanessa, who has taught me that life is about the journey, not the destination. I can think of no one I would rather take that journey with.

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GLOSSARY OF TERMS

adaptation………….. *(in the integrated model) change in the tactical plan intended to enable a successful resolution to a current state of dissonance (see Section 2.1.6.3)*

access………………. *(in the integrated model) action undertaken by the subject to approach and engage with the target. In the case of a dominant action, access also includes control. (see Section 2.1.6.2)*

accountable time…… *temporal constraints on a subject that shape spatial offending patterns (see Section 2.1.7.3)*

acquisitional goal…... *(in the integrated model) a goal that results from the subject's needs accumulation breaching the inhibitory threshold. The acquisitional goal drives action toward satisfying the need* (Ward, Hudson, & Keenan, 1998; Polaschek, Hudson, Ward, & Siegert, 2001)*. (see Section2.1.5)*

activity-space……… *geospatial bounds of an individual's normal activity* (Cohen & Felson, 1979) *(see Section2.1.7)*

anchor-point……….. *geospatial locations that tether an individual to his/her activity-space. Anchor-points generally include an individual's home, work and free-time locations* (Rossmo, 1995a). *(see Section 2.1.7)*

burn-in………………*(in the integrated model) a pre-designated period of time to run the simulation prior to collecting data. This allows the integrated model to create a more realistic representation of a subject by pre-loading him with experience. (see Section 2.2.8)*

centroid…………….. *a calculation to determine the spatial "center-of-gravity" of a group of locations. Within crime analysis, a centroid gives the "center-of-gravity" of series event-sites* (Elnekave, Last, & Maimon, 2007; Buscema, Breda, Grossi, Catzola, & Sacco, 2013).

centroid-path……….. *(in the integrated model) a path of triangle centroids (of sequential event-sites) used to create a dynamic measure of series "movement." (see Section 2.4.2.2)*

cognitive landscape…*(in the integrated model) the overall endogenous backdrop in which the subject utilizes his bounded perception of reality in the* *perception landscape and simulates actions to overcome and adapt to inhibitors in the simulation landscape. (see Section 2.1.6.2)*

cognitive resources… *(in the integrated model) resources utilized by the subject to navigate his simulation landscape. His cognitive resources are density, paths, depth, and focus. (see Section 2.2.7.2)*

comfort…………….. *(in the integrated model) the subject's spatial awareness (see Section 2.2.4)*

days-between-hits….. *the number of days between events in a series.*

dbh…………………. *days-between-hits*

density……………… *(in the integrated model) one of the subject's cognitive resources. Density determines what percent of the inhibitors in the perception landscape the subject will represent in his simulation landscape. (see Section 2.2.7.2)*

depth……………..… *(in the integrated model) one of the subject's cognitive resources. Depth determines how many rows deep the panels in the cognitive landscapes will be. (see Section 2.2.7.2)*

dissonance…………. *(in the integrated model) a condition that occurs when the subject encounters an inhibitor in his perception landscape that he has not tactically planned for. Generally, encountering dissonance will require the subject to adapt. (see Section 2.1.6.3)*

egress………………. *(in the integrated model) action undertaken by the subject to extricate himself from offending circumstances. (see Section 2.1.6.2)*

event-chain…………*(in the integrated model) a sequence of states that provide a cohesive view of the subject's progression through the violent offending process from acquisitional goal development to an output or end state.*

event-site……………*(in the integrated model) geospatial location at which the subject has changed states. Event-sites include development of an acquisitional goal, tactical plan, access, extraction, collaboration, egress, failure and retreat. The interpretation of event sites produces contextual labels. For instance, an access site for a subject using a dominant strategy can be interpreted as an abduction site, or an extraction site can be interpreted as a kill-site.*

extract……………… *(in the integrated model) action undertaken by the subject to directly satisfy his acquisitional goal. If he is pursuing a collaborative strategy, this would entail a collaboration. If he is* *pursuing a dominant strategy, this would entail the intended offense (i.e., the actual murder). (see Section 2.1.6.2)*

focus……………….. *(in the integrated model) one of the subject's cognitive resources. Focus determines what percent of time the subject will re-orient toward the acquisitional goal when searching for a path through the simulation landscape. (see Section 2.2.7.2)*

homicide…………… *killing of one person by another. Homicide may include criminal and non-criminal circumstances, as well as, manslaughter, justifiable homicide or killing during times of war.*

in silico……………...*in a computational setting or via a computer simulation*

inhibitory goal………*(in the integrated model) a goal that keeps an individual from pursuing a need* (Ward, Hudson, & Keenan, 1998; Polaschek, Hudson, Ward, & Siegert, 2001).*(see Section 2.1.5)*

inhibitory threshold... *(in the integrated model) defines the accumulated needs value below which the subject will not seek to satisfy the need and above which the subject will pursue the need via an acquisitional goal. (see Section 2.1.5)*

inhibitor……………. *(in the integrated model) a feature of the environment that the subject perceives to be an obstacle to achieving his acquisitional goal. Inhibitors are experienced in the subject's perception landscape.*

maze-running………. *(in the integrated model) the process of utilizing the cognitive landscapes to detect inhibitors, simulate a navigation path through the inhibitors, and adapt to unforeseen inhibitors. Maze-running represents tactical planning and adaptation as a problem solved in navigable space. (see Section 2.2.7)*

minutes-per-tick…….*(in the integrated model) the number of minutes represented by one time-step in the integrated model. (see Section 2.2.3.1)*

mpt…………………. *(in the integrated model) minutes-per-tick*

murder………………*killing of one person by another in violation of an established criminal code. Generally, murder requires criminal intent to harm.*

needs-accumulator..... *(in the integrated model) a variable that changes over-time and is constantly compared to a corresponding inhibitory threshold value. This is a key component of the integrated model's driven threshold system because when the needs value breaches the threshold suppressing the need, the subject's state changes to one in which he now pursues the need. (see Section 2.1.5)* panel………………...*(in the integrated model) navigable sub-spaces, or contiguous sets of rows, within the subject's cognitive landscapes. A panel is used to depict the subject's access, extraction, or egress problem space. Panels are defined by a start position and an end position that connects to other panels. (see Section 2.2.3)*

paths………..……… *(in the integrated model) one of the subject's cognitive resources. Paths determines how many probes the subject will use to navigate the simulation landscape. (see Section 2.2.7.2)*

perception landscape..*(in the integrated model) one of the two cognitive landscapes. The perception landscape is where the subject experiences inhibitors to his acquisitional goal. (see Section 2.1.6.2)*

politogenesis……….. *the process by which a unit of organized social cohesion comes into being and evolves* (Cioffi-Revilla, 2005). *(see Section 2.1.1)*

polity……………….. *a unit of organized social cohesion* (Cioffi-Revilla, 2005). *(see Section 2.1.1)*

primed……………… *(in the integrated model) a condition in which the subject has overcome inhibitory goals and developed an acquisitional goal. Primed generally refers to a continuum from building interest to active engagement in an activity. (see Section 2.1.2)*

privacy………………*(in the integrated model) varying degrees of isolation from public scrutiny (see Section 2.2.4)*

problem space……… *(in the integrated model) a cognitive construct where the subject's reality is created and where he anticipates inhibitors that must be overcome to successfully achieve the acquisitional goal (see Section 2.1.6.2)*

referent system……... *a real-world system that is abstracted and represented in a model*

satisficing…………... *the tendency to select the first solution perceived to be adequate as opposed to continuing to search for the optimal solution*

scheduling………….. *(in the integrated model) a method of defining when agents have accountable time and where they should be during the simulation when not actively pursuing an acquisitional goal (see Section 2.2.6.1).*

series……………….. *an accumulation of events (usually of the same type) that are attributed to one individual or group of individuals working in apparent consort*

simulation landscape..*(in the integrated model) an accumulation of the inhibitors that the individual can (or thinks he can) predict. The simulation landscape is where the subject develops a tactical plan and adaptations. (see Section 2.1.6.2)* spatial awareness…… *knowledge of an environment (see Section 2.1.7.2)*

stimuli……………… *(in the integrated model) environmental features that affect the subject's needs*

subject……………… *(in the integrated model) focus of the modeling effort, a potential offender*

tactical planning……. *(in the integrated model) developing a set of expectations for how to initiate an interaction (access), how this interaction will achieve a goal (extraction), and how to leave the interaction (egress) (see Section 2.1.6)*

target……………….. *(in the integrated model) an object with which the subject wishes to interact*

vector………………. *represents an ordered set such that the position in the order has meaning*

victim………………. *(in the integrated model) an object that the subject wishes to dominate*

violent offending…… *actions taken by an individual to commit a violent crime*

ABSTRACT

IMPLEMENTING A COMPLEX SOCIAL SIMULATION OF THE VIOLENT OFFENDING PROCESS: THE PROMISE OF A SYNTHETIC OFFENDER

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There are limitations to traditional methods of capturing the dynamics of violent interactions. These limitations are due to outcome driven approaches, data sampling issues, and inadequate means to capture, express, and explore the complexity of behavioral processes. To address these challenges, it is proposed that "violent offending" be re-framed as an emergent feature of a complex adaptive social system. This dissertation abstracts and computationally implements a theoretical framework that forms the basis of a complex social simulation of the violent offending process. The primary outcome of this effort is a viable synthetic offender that emerges from simulated interactions between potential offenders (subjects) and potential victims (targets) within an environment. The results of calibrating this model to a real-world murder series are discussed, as well as, the comparison metrics used to assess goodness-of-fit of simulated and real-world event-sites. A synthetic offender promises valuable insights into

individual offending trajectories, offender tactical processes, and the emergence of geospatial and temporal behaviors. Furthermore, this approach is capable of reproducing the violent offending process with sufficient detail to contribute new scientific understanding and insights to criminology and the social sciences.

CHAPTER 1: INTRODUCTION

1.1 Motivation

The sociological community has been engaged for centuries in comprehending violent behavior in its many forms (Reiss & Roth, 1993). More specifically, many criminological research efforts have focused on a variety of different theories and efforts to explain, understand, and (attempt) to predict **violent offending**.[1]

Yet, the following questions have been significant and enduring puzzles in the study of violent behavior: Can "offenders" be identified prior to an attack? Is it possible to discover and/or predict violent offending trajectories? How does offending depend on micro-level cognitive features of offenders? How can hidden attributes and features of violent offenders be effectively examined?

A fundamental problem in addressing these questions is that they have high dimensionality, because they involve many more variables than can be managed by traditional statistical and criminological approaches. This research addresses these problems by exploring violent offending behavior using a computational modeling approach capable of reproducing the violent offending process with sufficient detail to

[1] Violent offending refers to actions taken by an individual to commit a violent crime. "Violent crime is composed of four offenses: murder and nonnegligent manslaughter, forcible rape, robbery, and aggravated assault. Violent crimes are defined in the UCR Program as those offenses which involve force or threat of force." (Uniform Crime Reports, 2014).

contribute new scientific understanding and insights to the criminological and sociological community.

There are several practical outcomes to the academic study of violent offending. Some research seeks to generate insights that can inform investigative efforts to identify and capture violent offenders. By studying the behavioral attributes of crime scene and post-event offender behaviors, some have assumed that the “why” of the offense can be inferred and will lead to “who” committed the act (Douglas & Munn, 1992; Knight, Warren, Reboussin, & Soley, 1998; Petee & Jarvis, 2000). A central goal of these efforts is the development of relatively implicit classification systems and taxonomies of the “types” of offenders who display certain “behaviors” that can serve as operational heuristics during an investigation (Alison, Bennell, Mokros, & Ormerod, 2002). Essentially, the assumption is that “the offender’s personality will be reflected in the way he carries out his crime” (Godwin, 2002, p. 9). This approach has been generally referred to as “offender profiling,” “criminal investigative analysis,” “investigative psychology,” or “behavioral assessment” within the law enforcement community and social sciences (Douglas & Burgess, 1986; Pinizzotto & Finkel, 1990; Canter, 2004; Ainsworth, 2009).

While there has been a significant amount of experiential and empirical research to explore the relationship between crime scene attributes and offender characteristics (Ressler, Burgess, Douglas, Hartman, & D'Agostino, 1986; Davies & Dale, 1995; Kocsis, Cooksey, & Irwin, 2002; Dahbur & Muscarello, 2003; Woodhams, Grant, & Price, 2007; Canter & Youngs, 2009; Douglas J. E., Burgess, Burgess, & Ressler, 2013) there still remain questions about the applicability of “offender profiling” as a general practice

(Scherer & Jarvis, 2014a; 2014b; 2014c; 2014d). Specifically, Godwin (2002) points out that the assumption that crime scene behaviors are a reflection of offender personality "sees motivation and personality as the same process, and neglects that emphasis that each explanation may have for different individuals." (p. 9). Furthermore, he challenges the processes used to generate statements about offender personality and characteristics, and the forensic applicability of "profiling" methods due to implicit biases and a general lack of methods to address significant corollary relationships. Godwin is not alone in his critique and his assertions are reflected by a number other researchers (Alison, Bennell, Mokros, & Ormerod, 2002; Alison, Smith, Eastman, & Rainbow, 2003; Snook, Cullen, Bennell, Taylor, & Gendreau, 2008).

Other violent offending research seeks to provide meaningful insights about cognitive and social attributes that are most likely to lead to violence. For instance, Davies & Dale (2013) have explored the use of behavioral indicators as a means to detect or anticipate violent acts, especially those involving terroristic motivation. The goal of this type of research is to determine offender attributes and pathways that provide law enforcement and other community resources with implicit models that can presumably lead to intervention and/or preventative measures. These research efforts can include large aggregated cross-sectional or longitudinal studies of specific offense types like **homicide** (Block, 1976; Block, 1979), theoretical treatises on biological, psychological, and environmental causes of violence in general (Reiss & Roth, 1993), or research directed toward building relatively implicit pathway trajectory models of specific offending outcomes (Meloy, Hoffmann, Guldimann, & James, 2011). All of these "tripwire" or policy-directed efforts tend to focus on implications of various conditions and are inexorably tied to threat assessment of an individual or group of "potential" offenders.

A significant amount of violence research (regardless of whether focused on prevention or capture) concentrates on endogenous features of the offender specifically in terms of psychology (Cornell, et al., 1996; Ainsworth, 2009; Canter & Youngs, 2009), speculation about motivation (National Center for the Analysis of Violent Crime, 1990; 1993; 2007; Douglas J. E., Burgess, Burgess, & Ressler, 2013), and factors of criminal repetition (Ressler, Burgess, Douglas, Hartman, & D'Agostino, 1986; Hazelwood & Warren, 2004; Bateman & Salfati, 2007; Salfati & Bateman, 2005). Other avenues of research emphasize criminal and environmental opportunity with minimal consideration of the offender's explicit internal drivers. For instance, Brantingham & Brantingham (1993) focus on the relationship between crime and environment from a situational routine perspective while Eck *et al,* (2005) focus on identification and exploitation of spatial and temporal patterns in crime data.

Still other violence research is informed by both internal (to the offender) and external features (of the environment) and emphasizes the interactional components of the violent event. These research veins tend to focus on relevant features of a crime scene as the cross-section between the victim and the offender (Warren, et al., 1999; Santtila, Canter, Elfgreen, & Häkkänen, 2001), regard violent activity as a result of conflict-driven social interaction (Black, 2010; Felson & Steadman, 1983), or as a situational transaction (Luckenbill, 1977; Miethe & Drass, 1999; Labuschagne, 2000b).

While it is widely acknowledged among researchers that violent interactions can be viewed to varying degrees as complex and dynamic events (Wolfgang, 1957; Luckenbill, 1977; Felson & Steadman, 1983; Salfati & Taylor, 2006; Beauregard, Proulx, Rossmo, Leclerc, & Allaire, 2007; Woodhams, Grant, & Price, 2007), there are limitations to traditional methods of capturing the complexity of these events. These limitations are due, in part, to outcome-driven approaches to research, sampling issues within data collection efforts, and inadequate methodological solutions to capturing, expressing, and exploring the complexity of behavioral processes that culminate in offending (Johnson & Groff, 2014).

Violence research relies on three primary categories of source materials: interviews, official files, and other secondary materials like newspaper reports (Eck & LaVigne, 1994; Blackman, Leggett, Olson, & Jarvis, 2000; Maxfield & Babbie, 2009). Most criminological research does not involve direct observation of violent criminal offending by the researcher. Instead, each of these sources tend to involve secondary collection of data (often, as is the case with an investigative file, based on second- or even third-hand information) (Maxfield & Babbie, 2009). In addition, these data tend to be collected predicated on the expression of specific offenses (*i.e.*, "**murder**," or "rape").

Yet, the tendency to focus on an outcome is problematic because it is "largely nonsituationist in its belief that behavior is thought to remain stable in the face of different environmental influences" (Alison, Bennell, Mokros, & Ormerod, 2002, p. 117). For instance, focusing on the outcome of "rape" as a specific expression of violence does not necessarily take into account that under different circumstances the same underlying process that led to rape may result in very different outcomes like murder or assault. A significant drawback to relying on outcome as a unit of analysis is that outcomes are socially and legally defined and require evidence and documentation of behavior. Focusing on the outcome, and not the process behind the outcome, limits the ability of researchers to fully understand the build up to, and result of, violence in explicit terms (Pinizzotto & Finkel, 1990; Alison, Bennell, Mokros, & Ormerod, 2002; Dover, 2010). This ultimately restricts the exploratory and explanatory value of traditional methods and reduces the overall predictive significance of research findings.

Furthermore, to produce viable research on violent offenders, there must be a large enough (and representative enough) sample to generalize findings to the population of violent offenders. Yet the low base-rate of violence and relative inaccessibility of data about violent offenders (and even less accessible data on "potential" offenders) means that researchers are generally relying on smaller study samples (Ressler, Burgess, & Douglas, 1988). Thus, research that is aimed at understanding violent offending (especially murder), often lacks the ability to provide viable conclusions about probability of violent outcomes (Johnson & Groff, 2014). This also means that a study population of, for instance "murder offenders," is limited to individuals who have been identified as such and excludes those who have not been identified. This is a source of biased sampling and (potentially biased) extrapolation when trying to apply findings to unknown offenders or speculate about causative factors of violence. This is especially problematic considering that current crime data tends to be unrepresentative of the true levels of crime (Birks, Donkin, & Wellsmith, 2008).

Yet, from an investigative standpoint, it is the offenders who have not been identified that are often the most relevant, and the least understood.[2] While a significant amount of violence research is descriptive, without a baseline understanding of the offender attributes in unknown offender and non-offender populations, there is limited diagnostic value to the results (Alison, Smith, Eastman, & Rainbow, 2003; Johnson & Groff, 2014). Additionally, researchers do not understand the scope or nature of populations that come close to offending but never actually do (Malamuth, 1981; Polaschek, Hudson, Ward, & Siegert, 2001). While this "**primed**" but non-offending population is less relevant to prosecutorial elements of the legal system, it is extremely important in understanding issues of offense prediction and prevention (Reiss & Roth, 1993; Eck & Liu, 2008). Both unknown offenders and "primed" but non-offenders constitute hidden populations that are under-explored and clearly pose significant gaps in criminological insight.

A comprehensive and pervasive way to understand individual criminal offending is through interviews and case studies (Polaschek, Hudson, Ward, & Siegert, 2001). As a result, a significant amount of research on violent offending is based on these two data collection strategies which can produce detailed retrospective evaluations of offender personal, social, and psychological attributes within the backdrop of the criminal event (Ressler, Burgess, & Douglas, 1988; Hickey, 1991; Cornell, et al., 1996; Hazelwood & Warren, 2004; Kraemer, Lord, & Heilbrun, 2004). However, even though this type of research can produce non-trivial case-based findings, it is limited in generalizability

[2] For example, the most recent national figure indicates that in 2014, 35.5% of murders in the United States were unsolved (Uniform Crime Reports, 2014).

precisely because it relies on small and/or non-probability samples of outcome-driven events (Johnson & Groff, 2014).

It is often costly and time consuming to interview violent offenders, victims, or witnesses. Furthermore, interviews are comprised of subjects who volunteer for treatment or are willing to participate in research (Godwin, 2002). For instance, the development of fantasy (a relatively hidden and internal concept) and its role in targeting a victim is highly dependent on disclosures during an offender interview (Ressler, Burgess, & Douglas, 1988). This can be complicated by self-report bias (Babbie, 2006) and the propensity of some subjects to lie, be evasive, or lack introspection. It is precisely because of these issues that "there remain formidable obstacles to conducting research, in particular, prospective research into the covert elements of offending behavior." (Polaschek, Hudson, Ward, & Siegert, 2001, p. 541).

There is no shortage of implicit[3] theory about violence in the behavioral sciences. However, challenges in violent offender research have led to a dearth of explicit[4] models to test theoretical assumptions. This is exacerbated by significant deficits in the availability of data to test theory, and the underlying difficulties of exploring non-linear complex adaptive systems with traditional statistical methods (Johnson & Groff, 2014).

Some criminological research on violent offending does use inferential statistical methods to better understand relationships within the data. For instance, Salfati & Taylor (2005) utilized smallest space analysis to derive classifications of expressive and

[3] Abstract and/or relatively unspecified

[4] Specified and clearly expressed

instrumental homicide scene behaviors and Kocsis *et al* (2002) utilize Facet Theory in their empirical examination of sexual murder. However, criminological research within an operational context[5] tends to be focused on strictly descriptive studies of violent outcomes. For instance, a number of research studies used to drive investigative decisions about "offender profiles" (McNamara & Morton, 2004; Morton, Tillman, & Gaines, Serial Murder: Pathways for Investigation, 2014; National Center for the Analysis of Violent Crime, 1990; 1993; 2007) focus almost entirely on generating frequencies of offender attributes and behaviors. This strain of research and analysis tends to rely heavily on experience-based assumptions about corollary complexities (Arkes & Kajdasz, 2011).

To address these methodological challenges, it is suggested that violent offending be re-framed not as the product of offender, victim, or environmental attributes, but rather as the results of conflict-driven social interactions (Black, 2010) and dynamic adaptations within those interactions (Dover, 2010). Furthermore, it is important to "view a violent event as the outcome of a long chain of preceding events" (Roth, 1994, p. 6). From this perspective, violence is regarded as an emergent feature of a complex adaptive social system. Unfortunately, exploring these types of high dimensional, non-linear systems can become unmanageable with traditional statistical methods (Johnson & Groff, 2014).

One way to address this complexity is through the use of computational modeling and simulation as a means to augment criminological research. In this type of approach "models are primarily seen as surrogate systems that facilitate the examination of real-

[5] "Criminological research within an operational context" is used here to denote research outputs immediately utilized in investigative activities.

world situations and phenomenology that are too complex or uncontrollable to study and control directly." (Frank A. B., 2012, p. 18) This is accomplished by abstracting the **referent system**, developing these abstractions into concepts and then implementing those concepts into an explicit formalization (Cioffi-Revilla, 2014a).

Computational models can take on many arrangements and vary in scale and formalization.[6] However, regardless of the implementation, "the traditional role of a model in the social sciences is a translation of theory into a form whereby it can be tested and refined" (Crooks, Castle, & Batty, 2008, p. 418). This can be further underscored by the notion that "if a theory is valid, then a formal implementation of it should be able to ‘‘grow’’ the outcomes the theory was developed to explain" (Johnson & Groff, 2014, p. 4).

The use of computational algorithms has produced a significant opportunity for researchers in a variety of fields to represent complex systems as abstracted and more accessible assortments of interacting and dynamic objects. Within the scientific community "this has facilitated interdisciplinary research that crosses multiple problem domains, linking micro and macro levels of systems where emergent properties, phase transitions, path dependencies, feedback, hysteresis, and other dynamics occur." (Frank A. B., 2012, p. 2)

Within the criminological and computational communities, significant modeling and simulation efforts have been used to not only test criminological theory (Johnson & Groff, 2014), but to also address the complexities of geospatial offending patterns

[6] For a discussion of computational models see Cioffi-Revilla's (2014a) comprehensive review of computational social science methodologies.

(Brantingham, Glasser, Kinney, Singh, & Vajihollahi, 2005; Liu & Eck, 2008; Malleson, 2012; Malleson, Heppenstall, See, & Evans, 2013), focus on event clustering and hotspots (Barnes, 2003; Groff, 2007; Bosse & Gerritsen, 2008), and explore issues of **series**[7] tempo (Simkin & Roychowdhury, 2014). In addition, computational methods have begun to shed light on criminal connectivity especially in terms of social networks of terrorist activity (Ressler S. , 2006; Tsvetovat & Latek, 2009; Perlinger & Pedahzur, 2011) and gang rivalries (Radii, Flint, & Tita, 2010; Hegemann, et al., 2012). Furthermore, recent efforts in insider threat research have looked to combine disparate modeling approaches as a comprehensive and multi-faceted glimpse of insider threat activity (Moore, Kennedy, & Dover, 2016). The models highlighted above have started to effectively define the field of computational criminology (Berk, 2008; Brantingham, 2011) and provide researchers with a set of new methodological tools to better understand how and why actors interact in the "big picture."

Many computational criminology efforts tend to focus on macro-level understanding of complex systems (Frank A. B., 2012). However, when representations of individual actors are implemented, for example in an agent-based model (ABM) [8], there is a general tendency to represent entities with relatively simple rule sets that <u>imitate</u> behavior and regard specific social developmental characteristics of the individual as secondary (or untenable) (Epstein J. , 2014). Yet, there has been interesting research in other computational fields (non-offending context) that looks more specifically at how

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[7] A "series" is generally defined as an accumulation of events (usually of the same type) that are attributed to one individual or group of individuals working in apparent consort.

[8] Agent-based models will be discussed in greater detail in the Implementation Section 2.2

computational methods can also shed light on an endogenous features of decision-making (Sun, 2009), the use and application of heuristics (Kennedy, 2012), and even a holistic approach toward the development of a generative cognitive agent (Epstein J. , 2014).

From a criminological perspective, if one is to identify emerging offenders prior to observable violent behavior, or understand possible trajectories prior to offending, then it is important to devise a means to conceptually understand the micro-level structures of an offender's internal complexities. To focus on a simulated violent offender, therefore, it is necessary to address how the offender's internal micro-system is reinforced by external factors of the environmentally-based macro-system in which he interacts and further explore how these interactions may (or may not) culminate in an outcome of violent action.

1.2 Goal and Objectives

It is important to note that this dissertation is exploratory, not predictive.[9] It will focus on exploring the violent offending process from a computational criminology perspective to generate a more complete understanding of the emergence of violent criminal behavior. The overall goal for this dissertation is *to explore if implementation of the violent offending process as a computationally expressed complex social simulation provides meaningful insights[10] into the internal and external drivers of offending*. This requires

[9] For a comprehensive discussion of non-prediction applications of modeling see Epstein's (2008) discourse on the matter.

[10] For instance, a deeper understanding of offender-targeting decisions or opportunity-driven dependencies.

incremental steps toward building and implementing a series of computational models to conceptually represent and test various aspects of the offending process.

Achieving this goal necessitates the abstraction and implementation of a theoretical framework as the basis of a complex and dynamic social simulation. “Offending behavior” will be framed as *one of many manifestations of boundedly rational* (Simon, 1955) *decision-making that emerges from an individual’s interpretation of needs, goals and* ***targets***. Furthermore, from a computational perspective, “behavior” (including criminal behavior) will be viewed as *the outcome of multiple complex and adaptive processes in which the individual participates as a social actor, and in which the individual is, as well, the manifestation of a complex adaptive system of competing needs goals and resources* (Slade, 1994).

To attend to this goal, this dissertation will address four objectives; (1) the phased creation of a prototype integrated model of the violent offending process, (2) a viable means to establish internal validation of the model, (3) application of the integrated model to a real-world series[11] of violent offenses, and (4) the development of a method to determine the model’s efficacy in producing qualitatively realistic temporal and spatial outcomes.[12,13]

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[11] A series of real-world events will provide an opportunity to calibrate the model using temporal and spatial outcomes. For further discussion on the calibration of the integrated model, see the Calibration Procedures Section 2.4.1.

[12] For further discussion on the relevance of temporal and spatial elements of offending see the Spatial and Temporal Factors Section 2.1.7.

[13] For further discussion of the temporal and spatial metrics used, see the Comparison Metrics Section 2.4.2.

1.3 Research Contribution

This dissertation makes four main scientific contributions. First, it demonstrates the value of computational social science in the domain of criminology (this is among the earliest computational criminology investigations, with more advanced features than earlier models); second, it provides a new simulation model of violent offending behavior, basing it on a model of cognitive foundations that assumes bounded rationality; third, it uses a specific real-world case to demonstrate how the model can generate insights beyond those available through traditional criminological methods; finally, the compound event approach to offending is demonstrably effective and opens new and powerful directions for further investigation.

Growing and studying an offender *in silico*[14] will allow researchers to move away from outcome-driven research, explore offending as a process-driven compound event (Cioffi-Revilla, 2014a, pp. 147-152, 174-184), and provide unique insights regarding internal and external factors that contribute to the emergence of violent behavior. Viewing violent offending as a compound event opens new and powerful analytical possibilities that add value to assessments. Additionally, the explicit implementation of cognition and goal-setting can provide valuable conceptual insights into individual offending trajectories, variability of offender adaptations, responses to **stimuli**, and offender strategic and tactical processes. The emergence of geospatial and temporal behaviors can be used to inform investigative efforts to understand violent offenders (*i.e.*, victim selection or possible triggers for violent interactions) in the real-world and craft

[14] In a computational setting or via a computer simulation

practices directed toward prevention and interdiction (Groff & Mazerolle, 2008; Johnson & Groff, 2014).

The computational implementation of a synthetic offender does not replace the necessity for collecting criminological data via traditional methods (*i.e.*, police records, case files, or interviews), but instead complements it. This is analogous to the use of lab work in conjunction with epidemiological studies in virology. Criminological research will benefit from the ability to computationally "grow" offenders to supplement and understand empirical offending data. In some cases, the cultivation of a synthetic offender will provide researchers with the ability to quickly and inexpensively test and proto-type theory and/or explore large populations of agent-based synthetic offenders. This can be done without the necessity of large resource expenditures or traditional concerns regarding health and safety of human subjects usually under the purview of Internal Review Board (IRB) approvals. Additionally, model outcomes and relevant process features can be quickly and efficiently documented and collected as data, thereby eliminating significant resource expenditures (and potential error) on multiple data collection and data entry trials.

1.4 Dissertation Overview

This dissertation follows the Computational Social Science (CSS) methodology based on Motivation-Design-Implementation-Verification-Validation-Analysis (MDIVVA) (Cioffi-Revilla, 2014a, pp. 232-238). Accordingly, Chapter 1 addresses research motivation, Chapter 2 addresses design, implementation, verification and validation, and Chapter 3 addresses analysis.

In Chapter 1, Section 1.1, the current state of traditional violent offending research is discussed and a number of limitations are highlighted. It is suggested that computational methodologies offer a significant opportunity to address these challenges and several examples are given. Next, in Section 1.2 the overall goal of this dissertation is conveyed as the implementation of the violent offending process as a computationally expressed complex social simulation. Four objectives toward this goal, (1) phased creation of a prototype integrated model of the violent offending process, (2) internal validation of the model, (3) application of the integrated model to a real-world series, and (4), evaluating the model's ability to produce realistic temporal and spatial outcomes are introduced. In Section 1.3, the advantages and projected research contributions of this dissertation are discussed.

Chapter 2, Section 2.1 addresses this dissertation's first objective and presents theoretical and structural design elements used for scientific understanding of the violent offending process. Next, in Section 2.2, a specification of an integrated model is provided with a focus on the implementation of an offender's endogenous tactical and adaptive features, representation of exogenous environmental stimuli, and the interactions between the offender and environment that result in outcome behaviors and feedback.

Section 2.3 addresses the second objective of this dissertation by discussing verification in significant detail and focusing on internal validation of model specifications and parameters. Chapter 2 ends with a discussion of theoretical and structural validation in Section 2.4 and proposes a process by which the integrated model can be calibrated to a real-world series to further strengthen behavioral validation of model outputs.

The third objective of this dissertation is addressed in the first part of Chapter 3 which focuses on the analysis and results of calibration to a real-world series of murders. The first part of this chapter, Section 3.1, describes the series scenario. Section 3.2 highlights specific details of the series that can be used to configure parameters during calibration.

The second part of Chapter 3 addresses the fourth objective of this dissertation. Section 3.3 reports the findings of a comparison between the real-world series and simulated outputs generated by the integrated model. Chapter 4 continues to address the fourth objective by discussing the findings from Chapter 3. Section 4.1 focuses on spatial and temporal methods for generating comparisons, the specific value of those findings, and broader implications of the integrated model as a whole. In Section 4.2 model limitations and methods to overcome these limitations, as well as, ways to further extend the model and implications for future research are discussed.

Chapter 5 summarizes and discusses the objectives of the dissertation and assesses implementation success and insights into the internal and external drivers of offending. This chapter also lays the foundations for further work in computational social science and computational criminology.

Several Appendices are used to provide supplemental documentation of significant processes and results without detracting from the prose of this dissertation.

Appendix A provides a screen-capture of the integrated model interface and lists interface parameters and their specific uses. Due to the size of the interface, close-up views of functional areas are provided as additional screen captures (A1, A2, A3, and A4). Appendix A is referred to throughout this dissertation when discussing parameters on the interface. Appendix B provides a diagram of the variables (and their mathematical expressions) that are contained within the integrated model. Appendix B is referred to with some regularity in Chapter 2, Section 2.2, during the discussion of model implementation. Appendix C contains ten diagrams that show ***subject***[15] ***event-chain*** outcomes of the violent offending process, the causal-path of the *event-chain* expressed as a compound event, and constructed *event-chain* narratives as described in the discussion on model output narrative in Chapter 2, Section 2.2.9. Appendix D contains aggregated code profiles that were used during verification of the integrated model to monitor procedure calls (as described in Chapter 2, Section 2.3.7). Appendix E presents examples of spatial markers captured during integrated model configuration runs (as described in Chapter 3, Section 3.3.3). Appendix F contains the defense presentation slides for this dissertation.

[15] Within the remainder of this dissertation the primary focus of the modeling effort will be on a "potential offender" who will be referred to as a *subject*. Additionally, for ease of use and because in 2014 79.8% of offenders arrested for a violent crime and 88.6% of offenders arrested for murder and non-negligent manslaughter were male (Uniform Crime Reports, 2014), the pronoun "he" will also be used in reference to the *subject*.

CHAPTER 2: METHODOLOGY

This chapter begins by discussing the conceptual design elements that contribute to understanding and abstracting the violent offending process[16]. In Section 2.1 these design elements are abstracted and formalized as compound events and associated causal processes generated by offender agents in a given environment and then implemented as an explicit integrated model in Section 2.2. Once the formal model is specified, Section 2.3 addresses verification of the model and initial parameter tests provide significant internal validity. Finally, in Section 2.4 issues of validation are discussed in terms of calibrating the model to a specific case scenario and comparing simulated action outcomes to real-world results.

In this chapter, a number of different but related figures are discussed in detail. In Section 2.1, several figures are used to abstract the overall offending process. Figures in Sections 2.1.5 through 2.1.9 focus on conceptualization of the violent offending process and culminate in a fully realized diagram of necessary components. This diagram is further used to breakdown the conceptual underpinnings of each implementation stage. Additionally, Section 2.1.8 includes supplemental figures to illustrate key points about offending and non-offending path-dependent outcomes.

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[16] This discussion will follow the MDIVVA methodology referenced in Chapter 1

Throughout Section 2.2 a number of figures are used to illustrate key features of implementation. However, Figure 35, Figure 36, Figure 39 and Figure 42 are used to show gradual, stage-based implementation of the violent offending process as a cohesive computational model. In addition, throughout Section 2.2 there are a number of equations that describe internal and external interactions and endogenous *subject* features. These equations and their structural placement in the integrated model are, for clarification, further depicted in Appendix B.

2.1 Design

Given that organisms exist in a constantly changing environment, exposures to stimuli induce a necessity to adapt. Therefore, at the core of the current modeling effort is the notion that "behavior" is the manifestation of boundedly rational decision-making that emerges from the interpretation of stimuli and internal necessity to adapt (Simon, 1996; Miller & Page, 2007). This requires significant focus not only on endogenous features of a potential offender or *subject*, but also on how that *subject* reacts to, and interacts with, the environment. To encapsulate this dynamic process in the dissertation, computational implementation of the violent offending process requires a theoretical framework that can be used to represent the changing components of problem-solving and social interaction.

2.1.1 Problem-solving

While there are a number of ways to approach problem-solving (Perlman, 1957; Boyd, 1976; Salvucci & Anderson, 2001), a particularly useful way to address problem-solving through adaptation is found in the literature on **politogenesis** and the emergence of social complexity. In particular, the so-called fast process of the *Canonical Theory* (Cioffi-Revilla, 2005)[17] describes necessary conditions for the emergence of collective adaptation in a **polity**. According to the theory, complexity (within a society) is based on a series of sequential phases that must occur to address new challenges (both threats and opportunities).

First and foremost, the polity must not only experience significant change, but also perceive that the change poses a threat that is persistent and can be addressed through action. Second, there must be a desire to address the challenge, as well as the means to do so. Ultimately, action must be undertaken and this action may or may not be successful. If there is a failure at any one of the steps outlined in the fast process, the polity will fail to meet the challenge and fail to engage in effective adaptation. Importantly, the outcome space of the fast process consists of compound events generated by various alternative causal paths containing probabilistic contingencies.

Similar to the fast process, but focused on an individual offender-based model, the *Offender Interaction Process Model* (OIPM) (Dover, 2010) has been developed as a means to explore dynamic problem-solving elements in a (potential) murder offender. The OIPM proposes structuring offender-victim interactions as a task-oriented process and outlines the conceptual steps that an offender passes through to reach the outcome of murder or other end-states. The *OIPM* consists of four primary phases: *strategic*, *tactical*, *execution*, and *evaluation* (Dover, 2010). These phases can be summarized as

[17] A similar process is also used to explore individual radicalization or terrorists (Cioffi-Revilla, 2012a). However, as a model of "problem-solving" the fast process from the Canonical Theory is more appropriate.

the development of a need (*strategic*), the method for satisfying the need (*tactical*), the actual action toward satisfying the need (*execution*), and determining what happens next (*evaluation*).

The phases of the OIPM are isomorphic with those of the fast process in the Canonical Theory, as per the following mapping of corresponding events: a need for taking action arises and must be recognized, as a result of some public issue causing societal stress (equivalent to the *strategic* phase in the OIPM); a course of action is chosen (*tactical* phase); the action is undertaken (*execution* phase); and the action either works or fails, depending on factors and contingencies pertinent to the society and issues involved (*evaluation* phase). Accordingly, the offender cycle of the OIPM is akin to the fast process of the Canonical Theory. The OIPM offers a relatively simple but sufficiently precise and rigorous model with which to structure the subject's interactions with his environment. Importantly, like the fast process, it can be formalized using causal logic and probability to develop theory and implement a computational model that can be demonstrated below.

Borrowing similar visualization from the fast process (Cioffi-Revilla, 2005, pp. 138-140), Figure 1 portrays the *OIPM* re-formulated as a forward branching model with a sample-space of process outcomes (Ω) and serves as an initial means to abstract the violent offending process.

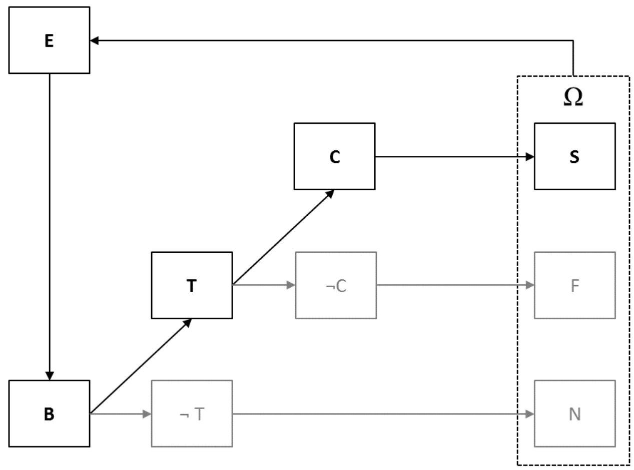

Figure 1: OIPM formalized as a forward-branching model.

Presenting the violent offending process in this way provides a more explicit conceptualization of the main events in the process as denoted by *strategic* (B), *tactical* (T), *execution* (C), and *evaluation* (E), and corresponding failures[18] ($\neg T$) and ($\neg C$). The general path-dependent outcomes of the OIPM can then be illustrated in the sample-space (Ω) as success (S), attempt but failure (F), and no attempt (N). Importantly, (1) each event in the offender cycle of the OIPM results from contingencies; (2) each of the three outcomes is a compound event as an end-state of a prior process, not a simple "out-of-the-blue" occurrence without priors (Cioffi-Revilla, 2012a). These features have analytical significance.

The highest level causal-path of success (S in Ω) is expressed as:

$$S \Leftarrow \langle (B) \wedge (T|B) \wedge (C|T) \rangle \tag{1}$$

[18] The importance of integrating "failure" states into the offending process is further discussed in the Outcomes Section 2.1.8 and Model Outputs Section 2.2.9

where the letters denote events in the offender cyclical process of the *OIPM* and the brackets show a sequential (*i.e.*, ordinal) conjunction of these conditional events. Clearly, *S* is a compound event (along with *F* and *N* in Ω), so this formulation for creating a simulation model also provides a mathematical object that can be analyzed using logic and probability, including formal analysis through multivariate calculus.[19] Also, note that *evaluation* (*E)* is excluded from equation 1 as it does not have a first-order role in the occurrence of *S*. Instead, *evaluation* is a reflective aspect of the model that feeds forward the results from the sample-space to the next cycle of the OIPM.

2.1.2 "Primed" Behavior

A significant feature of Figure 1 is the designation of outcomes in terms of offending behaviors. Figure 2 further abstracts this notion and shows that outcome *S* (an executed tactical plan, *i.e.*, completed murder) and outcome *F* (failed attempt to execute a tactical plan, *i.e.*, attempted murder) both result in "offending" behavior by the *subject*. Thus, it is the attempt to execute a tactical plan that defines the boundary between a *subject* who does and does not commit to offending.

The notion of offending is socially defined (Biderman & Reiss, 1967; Reiss & Roth, 1993; Black, 2010) and thereby requires observation of the offending behavior. However, in Figure 2, the *subject's* commitment to executing an offense can, in fact, be observed as the transition from *tactical* to *execution*. This dissertation does not focus on offending solely as an outcome behavior, but rather as a process (regardless of successful

[19] The goal here is a computational model, so mathematical aspects are reserved for the discussion in Chapter 4 in terms of broader theoretical implications.

execution). Therefore, the *subject's* commitment to offending, or the attempt to offend (whether socially observed or not), is regarded as the first step of offending.

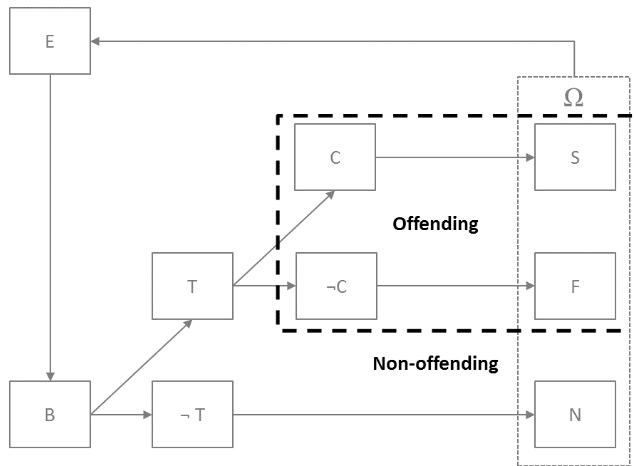

Figure 2: OIPM forward-branching model with offending and non-offending outcomes.

The notion of a "primed" state can be seen as the transitory zone of culminating interest that exists between a state of no interest and state of acting on the interest. In an offending context, a *subject* in a "primed, non-offending" state has an interest in "offending" action. However, he has not committed to that action (outcome *N* or perpetual state *T*).[20]

A "primed" state can represent transitory interest which may or may not be sustained. If sustained, lack of opportunity for a *subject* in a "primed" state may result in eventual offending when an opportunity does occur. Conversely, if the accumulated

[20] Perpetual existence in a *tactical* state without action is similar to the notion of persistence in the fast process as described by Cioffi-Revilla (2005).

interest that is instrumental to the “primed” state dissipates over time, reversion to a “non-primed” state can result. This means that when a *subject* is in a “primed” state, there are no assurances that this state will always lead to “offending.” This also means that, because the “primed, non-offending” state is endogenous to the *subject*, its observation requires either self-report by a “primed” *subject* or significant evidence of preparatory, but non-criminal activity. Thus, the “primed, non-offender” state defines a relatively hidden population of potential (but not certain) offenders.

Malamuth (1981) discussed the concept of primed behavior as “relative propensity.” He attempted to understand its prevalence in terms of rape through a series of studies that surveyed male college students. While the results of each study varied, Malamuth found with surprising consistency that approximately 35% of the subjects self-reported some likelihood[21] to commit rape[22] given absolute certainty of not getting caught. While this number is uncomfortably high, it is even more problematic when one considers that there is likely a self-report bias in the *subject* responses. The number reported by Malamuth (1981) only represents those individuals in the studies who were willing to admit interest in carrying out what is essentially a socially abhorrent act.[23] Yet, there is no evidence reported by Malamuth (1981) to suggest that any of the subjects ever committed a rape before or after the surveys.

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[21] Respondents were asked to indicate interest in committing rape on a five point Likert scale ranging from (1) “not at all likely” to (5) “very likely”. The 35% of respondents who indicated some likelihood of committing rape responded with a value of 2 or above (Malamuth, 1981).

[22] These studies did not differentiate between rape typologies or circumstances *(i.e.,* “stranger” versus “acquaintance”).

[23] Malamuth (1981) offers two alternative explanations for the reported levels of rape proclivity. 1) Some of his subjects may assume that they have a proclivity to commit rape because they have an interest in violent pornography. However, he argues, this may be evidence of the subjects over-estimating their own potential to turn fantasy into action. 2) The reported rape proclivity among college males may actually reflect confusion about “rape” due to evolving social definitions and attitudes.

Malamuth's findings lend credence to the notion that, at least in terms of rape, there is a significant population of "primed" non-offenders who are relatively undetected because they never actually offend.[24] Consequently, given the "dark figure" of crime (Biderman & Reiss, 1967) it is reasonable to suspect there are similar "primed, non-offenders" for other types of criminality. For example, this may be true for murder given the variety of documented murder "motivations" that arise from relatively common human interactions (Dover, 2010; Douglas J. E., Burgess, Burgess, & Ressler, 2013). This provides a compelling argument that to create a convincing implementation of the violent offending process, the specified model should be able to not only produce the emergence of violent offending behavior, but also track escalating and de-escalating transitions between "primed, non-offending" and "primed, offending" states.[25]

The notion of a "primed, non-offending" state also helps establish a clarification of terms. Thus, for the purpose of this dissertation, the operational definition of "offending" will be the commitment to an action (regardless of the success of that action) that is socially defined as violent criminality. Under this definition the "primed, non-offending" *subject*, while he may be contemplating a violent criminal act, is still considered a non-offender because his interest and planning have not been translated into action. The *subject* has not effectively turned the "criminal corner." In the same respect, once the "primed" *subject* has attempted to put a plan for violent offending into action (regardless of the success of that action) he enters an active "offending" state.

[24] Some of these primed non-offenders may have actually offended, but were either never identified or, given the circumstance of the rape, the offense may never have been reported to the authorities.

[25] This will be formalized in a detailed forward branching model in the Outcomes Section 2.1.8

2.1.3 Conceptualizing the Violent Offending Process

The previous two sections have focused on using a framework to abstract problem-solving and generate considerations of "primed" behavior in violent offending. However, devising a more formalized conceptualization of decision-making in the violent offending process necessitates focusing on two different domains: (1) the internal decision-making process of the *subject* independent (but not ignorant) of social outcomes, and (2) the social interpretation, ecological effects, and feedback that result from the *subject's* decision-making process (Dover, 2010). Figure 3 illustrates that the *subject* affects the environment by generating behavior, and in turn, is stimulated by environmental feedback. This serves as a conceptual starting point for discussing internal and external interactions of the violent offending process.

Thus, fully understanding and capturing the violent offending process requires not only understanding the boundary between emergent "offending" and "non-offending" behaviors, but also decision-making within the context of interaction. This necessitates abstracting the drivers of decision-making, focusing on the spatial and temporal contexts in which decisions take place, and using a fully conceptualized framework to create an integrated model.

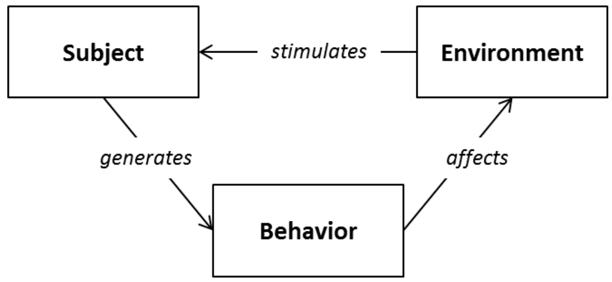

Figure 3: Class diagram of the abstracted role of behavior in subject-environment interaction that frames the violent offending process.

2.1.4 Decision-making

All organisms must make "decisions" in order to effectively leverage resources and exploit the environment in which they exist. Yet, these decisions are based on a limited and boundedly rational understanding of the environment (Simon, 1972). For this reason, implementing the violent offending process is an exercise in applying strategies to reproduce human decision-making within a bounded context.

Prospect theory (Kahneman & Tversky, 1979) posits that human decision-making does not seek optimized utility of outcomes, but rather involves evaluating potential loss and gain when compared to a baseline. The baseline is highly dependent not only on the current perceptions of the *subject*, but also the prior experience and reality the *subject* brings to the problem. Flawed decision-making, according to *Prospect theory,* exists because of innate human susceptibility to framing effects and errors in probability assessment. From this perspective, a *subject* not only perceives and internalizes exogenous stimuli, but also does so in ways that will shape endogenous drivers of behavior (see Figure 3). In modeling the violent offending process, *Prospect theory* offers significant conceptual guidance in the assessment of utility associated with action, and lays a foundation for behavior as a mechanism of feedback to ecologically relevant conditions.

2.1.5 Needs and Goals

In my theory, the internal drivers that motivate a *subject* to make-decisions are characterized as shifting drive states or *needs* (Schank & Abelson, 1975; 1977; Slade, 1994; Sun, 2009). Furthermore, motivation is generalized as the needs-driven balancing of internal states through external problem-solving (Abelson, 1959; Rouly, 2015). Specifically, a change in the subject's internal state creates an endogenous imbalance. If the change is significant enough or enough imbalances have accumulated to necessitate action, then the individual sets *goals* that are anticipated to satisfy the emerging *need* and re-balance the individual (Slade, 1994; Ward, Hudson, & Keenan, 1998; Polaschek, Hudson, Ward, & Siegert, 2001). Note that a key word here is "anticipated" which does not guarantee re-balancing nor does it guarantee that an optimal solution is pursued. Establishing a stimuli-driven *need* for re-balancing (or drive state) is tied to the perception (not realities) of the stimuli and subsequent *goals*.

> "(explicit) goals (such as "finding food") of an agent may be generated based on (past and current) internal drive states (for example, "being hungry") of the agent…This explicit

> representation of goals derives from, and hinges upon, (implicit) drive states." (Sun, 2009, p. 6)

Generating a *goal*, while an important part of problem-solving, is not an end-state, but rather instrumental, as a mechanism toward an end-state.

This implies that as an individual accumulates specific *needs; goals* are generated by significant breaches of equilibrium. As further discussed by Sun (2009), there are important differences between *goals* and *needs* (which he refers to as "drives"). First, multiple *needs* can exist at any one time (a parallel structure), but these *needs* are being pursued, generally, one *goal* at a time (a serial structure). Second, *needs* are much less focused than *goals* because *goals* are the explicit means to address implicit *needs*. Third, *needs* are bounded by "hard-wired" drives (Maslow, 1943), whereas, *goals* represent means to achieve *needs* externally, and as such, necessitate adaptive and flexible methodology.

Schank and Abelson (1975; 1977) address the notion of *goals* as motivational factors within a script, or a frequently recurring "sequence of actions." Their conception of *goals* is embodied as various specialized, although not entirely discrete, classifications. Each of these *goal* types: *Satisfaction*, *Enjoyment*, *Achievement*, *Preservation*, *Crisis*, *Instrumental*, and *Delta* have a nuanced part to play in changing the current state of an individual to a desired state. A notable part of this process is the *Delta goal* which serves as a specialized *Instrumental goal* that is not tied to a script per se, but serves in a much more generalized capacity to affect a plan for change. For this reason, *Delta goals* tend to deal with novelty and produce adaptation[26] both of which require reformulation of current understanding about a circumstance and intentionality.

According to Slade (1994), a *goal* is “a state of the world which an agent explicitly desires to achieve, preserve, avoid or destroy” (p. 49). It is further posited by Slade that, in terms of choosing between multiple options, it is not *goals* that are in a state of conflict, but rather the limited amount of viable resources that are available to the decision-maker. Thus, it is not *goals* that cause variations in behavior, but it is the means by which they are achieved. This argument can be made in an offending context as well. For example, it is not the goal of “control” that is problematic; it is the ensuing rape that is meant to achieve that *goal* that becomes violent and criminal behavior.

Figure 4 shows a class diagram outlining the relationship between *needs* and *goals*. In this dissertation, as a way to simplify the concept, *goals* are further conceptualized as underlying intentions that provide a foundation for action (Polaschek, Hudson, Ward, & Siegert, 2001) and can be divided into two categories: *goals* that keep an individual from doing something are considered *inhibitory*[27], and *goals* that emphasize satisfying a *need* are considered *acquisitional* (Ward, Hudson, & Keenan, 1998). ***Acquisitional goals*** focus on the attainment of a physical object (*i.e.*, money or a weapon) or an abstract feeling or state (*i.e.*, sexual satisfaction, power, or control). From this perspective, to successfully “pursue” ***inhibitory goals***, the individual must essentially do nothing (or restrain himself from doing something), and to achieve an *acquisitional goal,* the individual must dynamically pursue action.

[26] The need to adapt will be further explored in the Adaptation Section 2.1.6.3

[27] For additional discussion on inhibitions in killing as they relate to radicalization, see Cioffi-Revilla (2012a)

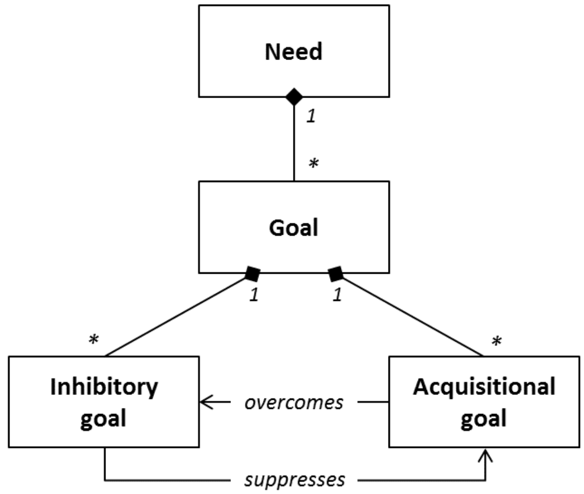

Figure 4: Class diagram showing the relationship between a need, goal (class), and acquisitional and inhibitory goals (objects).

Figure 4 further shows the interactions of *inhibitory* and *acquisitional goals*. An individual's *inhibitory goals* often take the form of a sense of morality, compassion, or fear of penalty (deterrence) and act as a means to deter or suppress abhorrent behavior. For example, *acquisitional goals* that lead to sex offending, then, are pursued by an individual who has overcome (or lacks) these *inhibitory goals* (Ward, Hudson, & Keenan, 1998; Cioffi-Revilla, 2012a).

Thus, in the context of the offending process, the assumption is that *goals* that lead to criminal behavior are primarily *acquisitional* (Ward, Hudson, & Keenan, 1998). From this perspective, *inhibitory goals* present a threshold to the individual's interest in pursuing an *acquisitional goal*. If the *subject's* interest remains below the threshold, then the *subject* is guided by the *inhibitory goal*. Figure 5 illustrates the process of transitioning toward a state in which an *acquisitional goal* guides subject behavior. The subject begins in a state in which *inhibitory goals* guide behavior. The *subject* experiences external stimuli which contribute to (or detract from) *needs* accumulation. If *needs* remain below the ***inhibitory threshold***, then *inhibitory goals* continue to guide behavior. If the accumulated *needs* exceed the current *inhibitory goal*, the *inhibitory threshold* is "breached," and the *acquisitional goal,* that was suppressed by the *inhibitory goal*, guides behavior. Effectively, the individual's interest in a *goal* has overcome the prohibitions against it.

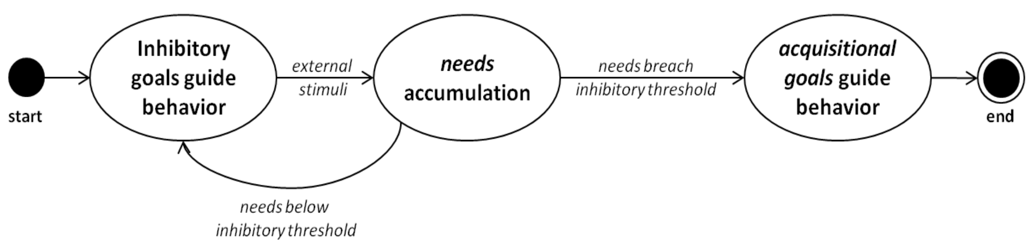

Figure 5: State diagram illustrating the process by which an acquisitional goal is generated through external stimuli.

In this dissertation, the process of overcoming *inhibitory goals* to pursue *acquisitional goals* is represented through an accumulator that relies on threshold-based rules. This notion of an accumulator acts as a driven threshold system (Rundle, et al., 2012) and is inspired by work in affect accumulation in marital processes (Gottman, et al., 1976; Gottman, 1998) and cognitive models of stimulus onset (Van Maanen & Van Rijn, 2007). In this dissertation, the emergence of an *acquisitional goal* α is expressed in terms of an accumulating *need* η that exceeds an *inhibitory goal* φ at any time t:

$$\alpha_t = \begin{cases} \eta_t - \varphi_t, & \eta_t - \varphi_t > 0 \\ 0, & \eta_t - \varphi_t \leq 0 \end{cases} \tag{2}$$

Figure 6 conceptually illustrates a ***needs-accumulator*** that represents changing *need* η over *time* t. In the figure, at t_1, the *subject's need* accumulator has not breached the threshold created by the *inhibitory goal* φ. Once the *need* does "breach" the threshold, at t_2, the *subject* develops an *acquisitional goal* α. The *acquisitional goal* is actively pursued at t_3 and is focused on satisfying (reducing) the *need*. Eventually at t_4, the *acquisitional goal* successfully satisfies the emergent *need* and pushes the *needs-accumulated* back below the *inhibitory goal*.

Change in the accumulation of *needs* is driven by environmental stimuli (*i.e.*, social interactions). *Inhibitory thresholds* are also driven by environmental stimuli (*i.e.*, location type or privacy). Thus, for example, if a *subject* gets into an argument with someone in a restaurant, the argument (social interaction) effects the *subject's need* accumulator and the environment (public restaurant) contributes to the *inhibitory threshold*. Given enough of a *need*, the *subject* may be less (or more[28]) inclined to act violently in a public location.

[28] Luckenbill (1977) found that public arguments may increase likelihood for violence if the subject is afraid of losing "face" in front of peers. For further discussion on social controls of conflict and violence, see Black (1990).

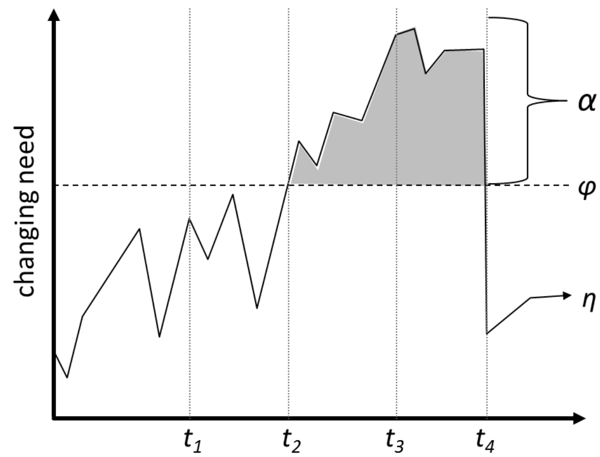

Figure 6: Conceptual representation of a needs-accumulator.

Figure 7 shows the initial consideration of a developing *acquisitional goal* in the larger conceptual context of the violent offending process. In this figure, and subsequent figures in following sections that build upon it, gray boxes indicate the elements described in the corresponding text. Environmental stimuli generate change in the *subject's* endogenous *needs* accumulation and *inhibitory threshold*. Regardless of the environmental circumstance, a *threshold* "breach" leads to an *acquisitional goal*.

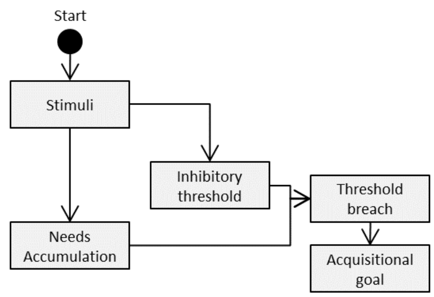

Figure 7: Environmental stimuli generate change in the subject's endogenous needs accumulation and inhibitory threshold, generating a threshold breach, and development of an acquisitional goal (elements discussed in the text are highlighted gray). This figure is extended in Figure 8.

2.1.6 Preferred Methods

To successfully achieve an *acquisitional goal*, the *subject* must (1) establish a *target*, and (2) devise a means to extract the *acquisitional goal* from (or with) the *target*. For this reason, the *subject* maintains a set of preferred methods that is comprised of previously successful methods used to achieve previous *goals*. As illustrated in Figure 8, once an *acquisitional goal* has emerged, the *subject* selects from a set of *preferred methods* to inform his understanding of available targets (targeting strategies) and create a tactical plan to address similar *goals.*

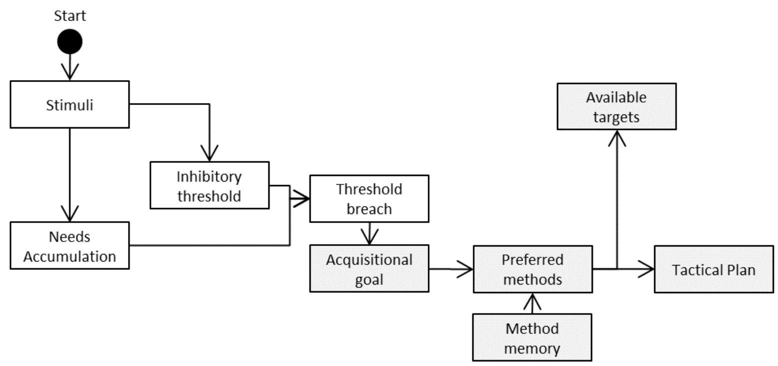

Figure 8: Once an acquisitional goal emerges, similar acquisitional goals and previously utilized methods are used to address those goals (elements discussed in the text are highlighted gray). This figure is extended from Figure 7 and further extended in Figure 11.

It is important to point out that both a *target*, and the means of using that *target* to achieve an *acquisitional goal* are conceptually entangled. Not only does the subject need to understand where to find available targets, but also how his method of extracting the *acquisitional goal* will affect the availability of those *targets*. As Figure 9 illustrates, the *target* is the vehicle through which the *subject* interacts (via a *method*) exogenously, creates a tactical plan, and achieves (or attempts to achieve) the *acquisitional goal*.

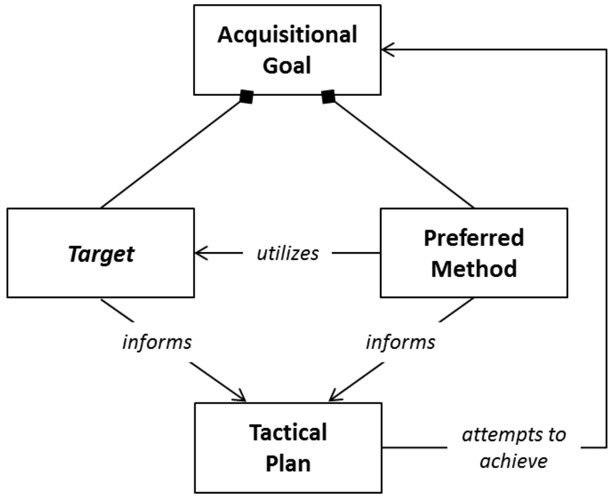

Figure 9: Class diagram showing interactions between the preferred methods, target, and tactical plan in achieving the acquisitional goal.

This is analogous to recognizing that a pothole in the road threatens the need for safety (*need*), perceiving that a viable way to address the problem is to fix the pothole (*goal*), and using gravel (*target*) to fill it (*method*). Table 1 shows this pothole example (in terms of *need*, *goal*, *target*, and *method*) and poses two other examples in the context of "esteem."[29] In both of these examples the subject lacks esteem (*need*), and in both cases the *subject* wishes to increase confidence (*goal*) by interacting with a person (*target*). Yet the method of interacting is very different. In one case he collaborates (dates the person), and the other method he dominates (rapes the person).

[29] For further discussion on different needs see Maslow (1943).

Table 1: Needs, goals, target, and method.

Need	***Goal***	***Target***	**Method**
safety	fix pothole	use gravel	fill pothole
esteem	increase confidence	person	collaborate (date person)
esteem	increase confidence	person	dominate (rape person)

Behavior is not determined by *needs* and subsequent *goals*, but rather by the methods by which those *needs* are satisfied (Slade, 1994). Therefore, variations in behavior emerge from the *subject's* tendency to engages in **satisficing**.[30] This is to say, preferred methods chosen by the *subject* may not be the optimal methods, but they are adequate methods that have succeeded in the past (as drawn from memory).[31]

2.1.6.1 Targeting

While an explicit *acquisitional goal* may be, for example, to get food to satisfy hunger, or rape a victim to feel control (Salfati & Taylor, 2006), there is still the matter of what food and what victim will be ultimately used as a means to meet the *goal* and fulfill the *need*. For this reason, *targeting* is an important part of the violent offending process (Beauregard, Proulx, Rossmo, Leclerc, & Allaire, 2007; Salfati & Taylor, 2006). *Targeting* provides a *subject* with something (or someone) that he perceives will, through his preferred method, satisfy his *acquisitional goal* and provides a bridge between goal-

[30] For further discussion of satisficing, see Simon (1972) and Schwartz, *et al* (2002).

[31] For discussion of further discussion on the implementation of *method memory*, see the Method Memory Section 2.2.8.2.

setting and ***tactical planning*** (Beauregard, Proulx, Rossmo, Leclerc, & Allaire, 2007). Without an identified *target*, there is no specific way to achieve the *acquisitional goal*. Thus, *targeting* also provides a direct and explicit link between the individual's internal *goals* and the external world in which the *target* exists.

It is important to note that a significant number of *subject* interactions with other individuals in the environment (*objects*), while responsive to emerging *acquisitional goals*, do not necessarily manifest as criminal behavior. Thus, for clarification of terms in this dissertation, Figure 10 shows that if the *subject* identifies an *object* that he wishes to interact with, this *object* becomes the *target* of the interaction. If the *subject* interacts with the *target* collaboratively (not as an offender), the *target* remains a *target*. If, however, the *subject* attempts to dominate the *target* (thereby offending against the *target*), then the *target* becomes a ***victim***. If the *subject*, however, fails to either collaborate with or dominate the *target* or *victim*, the *target* or *victim* will revert back to an *object* (unless further engaged by the *subject* in subsequent attempts to interact).

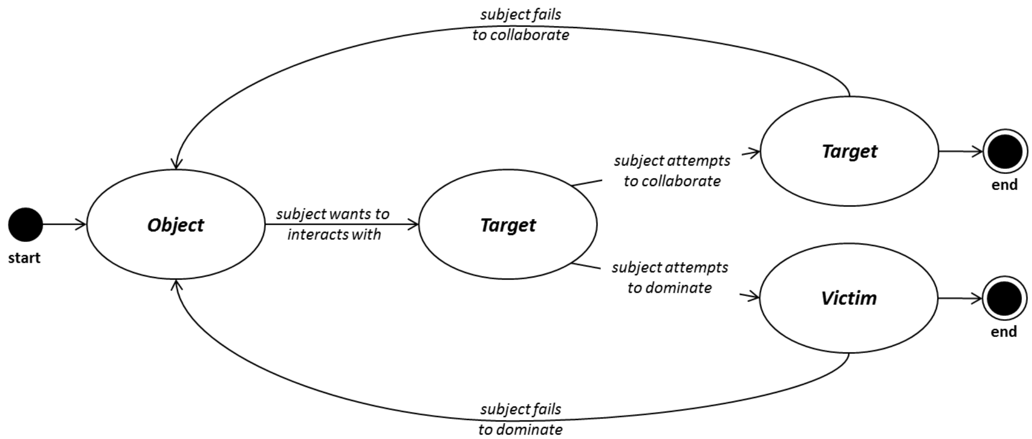

Figure 10: State diagram illustrating the transition of an object to target and/or victim given the subject's intentions.

Figure 11 shows that after an *acquisitional goal* emerges, the *subject's preferred methods* include *targeting strategies* for finding *available targets*. The *subject* may, for example, have access to *available targets* in his day-to-day routine, or he may have a specific "type" of *target* in mind and seek areas where those *targets* congregate (*i.e.*, children at a school or prostitutes at a prostitute "stroll"). Suitability of a specific *target* is a factor of a *subject's* assumptions that the *target* will satisfy the *acquisitional goal*. Thus, the *acquisitional goal* defines the *target attributes* that drive the *subject's* search for *available targets*.

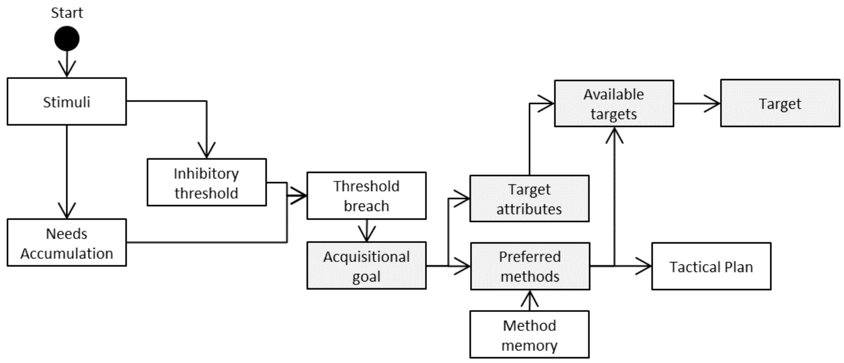

Figure 11: The subject's preferred methods include targeting strategies for finding available targets (elements discussed in the text are highlighted gray). This figure is extended from Figure 8 and further extended in Figure 12.

The correlation of *target attributes* (heterogeneous features or cues encapsulated in the *target* and perceived by the *subject*) with previous successful *goal* achievement involves framing future expectations of success based on past experience. Thus, while the *subject* may not have experience with a specific *target*, his previous experience with similar *targets* will frame expectations of successful strategies for achieving the current *acquisitional goal*. To return to the previous "pothole" analogy, using gravel may not objectively be the best way to fill a pothole (concrete or road-tar may be more viable). However, the selection of gravel as the means to achieve the *goal* may reflect what is currently available, or what has "worked" in the past.

2.1.6.2 Tactical Planning

Tactical planning is conditional on identifying a specific *target*. The *subject* must determine how to effectively (in his own estimation) **access** the *target*, **extract** the *acquisitional goal* from the *target*, and **egress** given a specific *target* (Willis, 2006; Beauregard, Proulx, Rossmo, Leclerc, & Allaire, 2007; Leclerc & Wortley, 2013). To understand why, consider how a *Special Weapons and Tactics* (SWAT) team operates. The SWAT team strategically plans for action by pursuing and maintaining skill sets associated with dangerous police actions (*i.e.*, shooting and breaching techniques). Yet, tactical planning for a specific operation cannot take place until the *target* has been identified. Only then can significant (and unique) circumstances associated with the specific *target* (*i.e.*, building layout, time-schedule, possible blind corners, potential for armed resistance, *etc.*) be understood and addressed.

Tactical planning involves (1) developing a set of expectations for how interaction with a specific *target* will occur and (2) how this interaction will achieve a *goal* (Dover, 2010). For this reason, in *tactical planning*, internally representing the environment is a necessary condition. This is especially true in a social context where the *subject* must (cognitively) model and simulate other individuals to generate expectations of successful interaction (Kennedy, 2012). Therefore, creating a tactical plan also depends a great deal on the *subject's* ability to perceive the *target* and (3) environment, (4) understand his own abilities, and (5) combine them into an abstract **problem space** (Osinga, 2013) within an endogenous cognitive representation (Rouly, 2015). Alternatively, success of the tactical plan (a different matter than creating a tactical plan) depends on how accurately the *subject's* cognitive representation depicts actual circumstances and his ability to adapt to differences.

In this dissertation, the problem space is a cognitive construct of the *subject*. This is where the *subject's* reality is created and where, once he identifies the *target*, the *subject* anticipates *inhibitors* or obstacles that must be overcome to create a successful (from his perspective) interaction that meets the *acquisitional goal*.[32] Furthermore, this problem space, because it involves *inhibitors* that must be navigated, is considered a traversable ***cognitive landscape***. As shown in Figure 12, this *cognitive landscape* can be conceptually divided into two primary areas: a ***perception landscape*** and ***simulation landscape***.

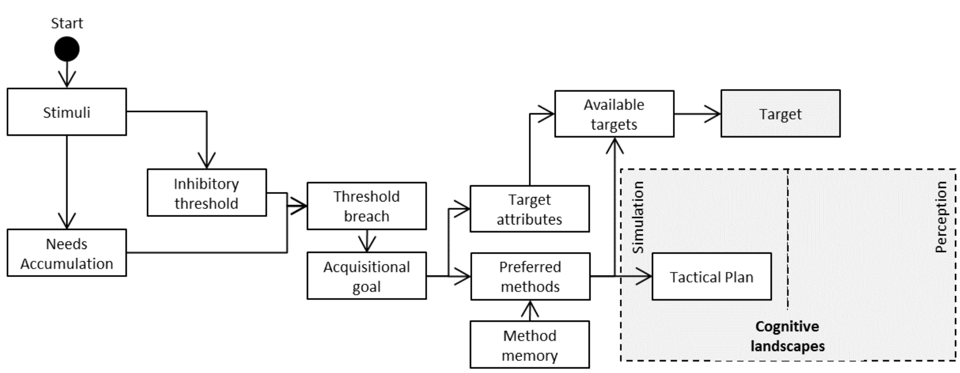

Figure 12: The cognitive landscape is divided into two regions, the simulated landscape and the perception landscape (elements discussed in the text are highlighted gray). This figure is extended from Figure 11 and further extended in Figure 13.

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[32] This is similar to Boyd's (1976) concept of "orientation" and is further discussed by Osinga (2013).

While a *perception landscape* and *simulation landscape* are both cognitive constructs of the *subject's* understanding of the world[33], they have very different purposes. The *perception landscape* encompasses the *subject's* interpretation of the world as he experiences it. This is to say, the *perception landscape* is constructed out of direct observation and experience with the environment. This is the closest thing to an objective reality within the *subject's cognitive landscapes*. On the other hand, the *simulated landscape* is constructed out of the *subject's* understanding of key aspects of the *perception landscape*. This is the landscape in which the *subject* plans for interactions and simulates solutions to known *inhibitors*.[34]

As illustrated in Figure 13 the *subject* first constructs the *perception landscape* in which he identifies and represents *inhibitors* to the *acquisitional goal*. This is to say, a *subject* who intends to rape a victim inside her home must overcome a lock on the door (*inhibitor*), or a *subject* who intends to assault a victim must account for the victim's ability to fight back (*inhibitor*). While the problem space is generally bounded by the *subject's* understanding of reality, *inhibitors* are elements within that reality that have an instrumental role in challenging the *subject's* ability to accomplish the *acquisitional goal*. *Inhibitors* change with each new *target* for which the *subject* devises a tactical plan.

[33] Interpretation of the problem space and constituent relationships within draws, in part, on the concept of belief systems as discussed by Abelson (1979) to construct the *cognitive landscapes*. However, the overall significance of the subject's interpretation is in understanding the necessary conditions (and challenges to overcome) to achieve the *acquisitional goal*.

[34] This process is formalized as *maze-running* and discussed in greater detail in the Stage 2: Tactical Planning and Adaptation Section 2.2.7.

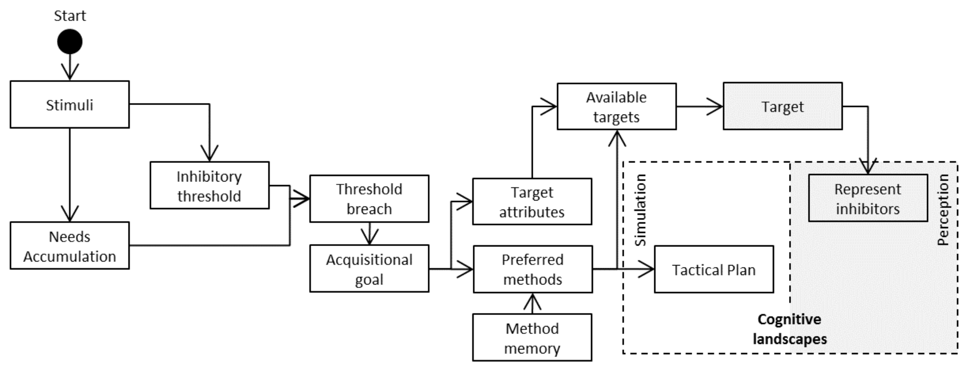

Figure 13: The subject understands the environment through the perception landscape where he identifies and represents inhibitors *to the acquisitional goal (elements discussed in the text are highlighted gray). This figure is extended from Figure 12 and further extended in Figure 14.*

The *simulation landscape* is an accumulation of the *inhibitors* that the individual can (or thinks he can) predict. However, it is an incomplete reproduction of the *perception landscape* which is itself an imperfect representation of reality. As shown in Figure 14, *tactical planning* takes place in the *simulation landscape.*

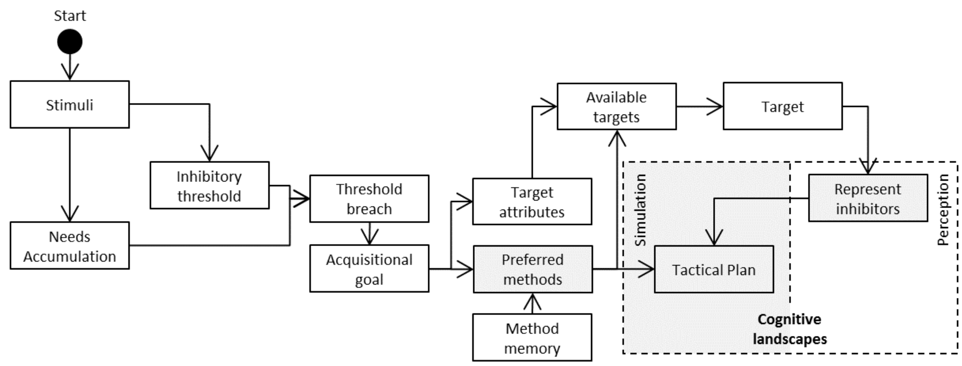

Figure 14: Tactical planning takes place in the simulation landscape *where the subject utilizes preferred methods of navigating identified obstacles (elements discussed in the text are highlighted gray). This figure is extended from Figure 14 and extended in Figure 15*.

In order to create a viable tactical plan, the *subject* must determine (1) how to access the *target*, (2) how to extract the *acquisitional goal* from the *target*, and (if a criminal event) (3) how to egress from the *target*.[35] Figure 15 illustrates a more detailed conceptual view of this *tactical planning* process. The *subject* starts by developing an *extraction plan* for how interacting with the *target* will meet the *acquisitional goal* in the first place. Next, the *subject* devises an *access plan* determining how to approach and control the *target*. Finally, the *subject* creates an *egress plan* to determine how, once the *acquisitional goal* has been extracted, the *subject* will determine he is free and clear of the offense.

[35] *Egress* is interpreted as the ability of the subject to extricate himself from the event, thus even in the case of a suicide accompanying a successful attack, the subject has successfully negotiated an *egress* (although further action is no longer possible). This type of event, further highlights that the problem space depends on the *subject's* own boundedly rational interpretation of reality and ability to assign meaning (and consequence) to his own actions.

If the *subject* is able to produce each of these sub-plans, then the *tactical plan* is determined by the *subject* to be viable – a "plan-of-plans" and significant compound event, by any measure. The *subject* then attempts action predicated on the success of the sub-plans. Thus, the *subject* attempts to access the *target* first, extract the *acquisitional goal* from the *target* next, and then egress from the interaction. These steps can be exemplified as: abducting a victim (*access*), raping and killing the victim (*extraction*), and then dumping the victim's body (*egress*).

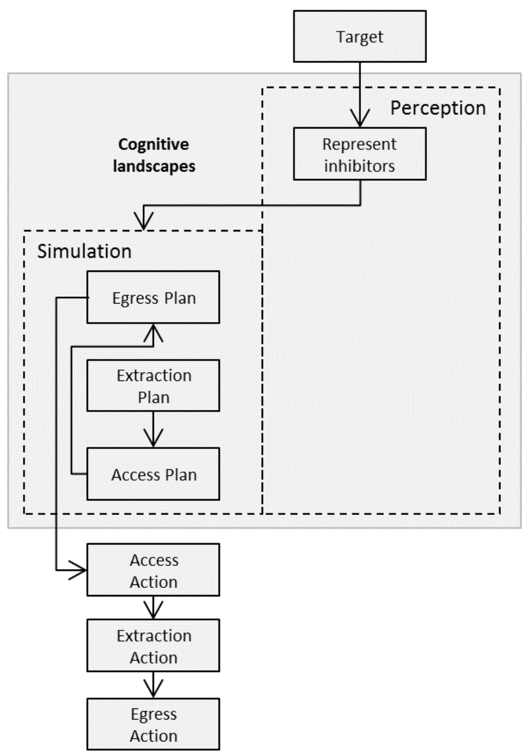

Figure 15: Detailed view of the tactical planning process (elements discussed in the text are highlighted gray). This figure is extended from Figure 14 and further extended in Figure 16.

As shown in Figure 16, a viable *tactical plan* leads to *action* so long as the *acquisitional goal* persists and the *subject* finds an environmentally viable opportunity to put the *tactical plan* into action.

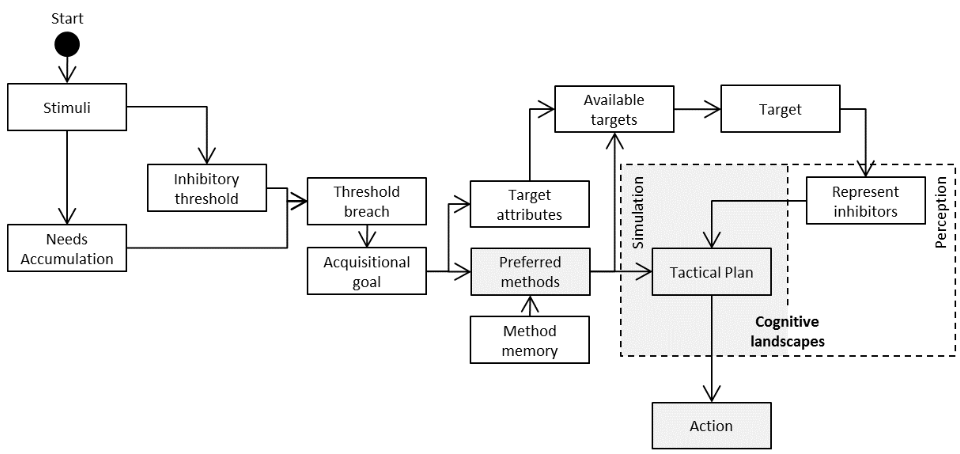

Figure 16: A viable tactical plan will, given viable environmental opportunity, ultimately lead to action (elements discussed in the text are highlighted gray). This figure is extended from Figure 15 and further extended in Figure 17.

2.1.6.3 Adaptation

There are often too many actual *inhibitors* for the *subject's* simplified *cognitive landscapes* to have accounted for them all. Thus, there is an inherent uncertainty associated with the problem space. For this reason, the *perception landscape* is an important part of identifying ***dissonance*** (unexpected *inhibitors*) during *action*. Therefore, once *action* ensues, the *perception landscape* is re-activated so that the *subject* can get feedback from the environment. The presence of *dissonance* between reality (as experienced in the *perception landscape*) and the initial *tactical plan* often necessitates an adjustment in *action* through ***adaptation***.[36]

Each sub-action (*access*, *extraction*, and *egress*) has its own set of *inhibitors* that produce *dissonance* and require *adaptation* by the *subject*. For instance, the *victim* may unexpectedly refuse to get into the *subject's* vehicle (*access dissonance*), the *subject* may not be physically able to strangle the *victim* (*extraction dissonance*), or the location where the *subject* was planning to dump the *victim* has unexpected visitors (*egress dissonance*). Figure 17 illustrates conceptually that as the *subject* translates his *tactical plan* into *action*, each of the sub-plans can produce *dissonance* that require returning to the *simulation landscape* to devise adaptive sub-plans.

[36] For a discussion on modes of resolving dissonance, see Abelson (1959).

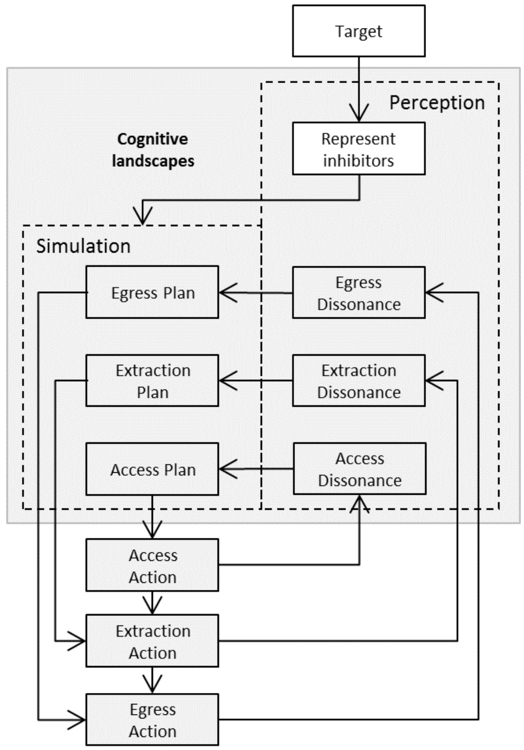

Figure 17: Detailed view of the adaptation process (elements discussed in the text are highlighted gray). This figure is extended from Figure 16 and extended in Figure 18.

Figure 18 places this process of *adaptation* in the larger context of the conceptual model. To adapt, the *subject* essentially creates a new tactical plan. This new tactical plan, if viable, is then used to define new *action*. The *subject* repeats this cycle of *adaptation* until either successfully achieving the *goal*, or reaching a point where he can no longer adapt.

The *subject's* ability to derive adaptive solutions is dependent on the cognitive resources that he can invest in the *simulation landscape*. Cognitive load under some circumstances (*i.e.*, divided attention, or duress) may far outweigh the capacity for the individual to create a viable adaptive tactical plan. In other circumstances, if enough cognitive resources are available for *adaptation*, the individual's reliance on adaptive tactical plans (essentially "flying by the seat of his pants" rather than careful planning) might become a successful and flexible strategy for achieving *acquisitional goals* in a highly uncertain environment.[37]

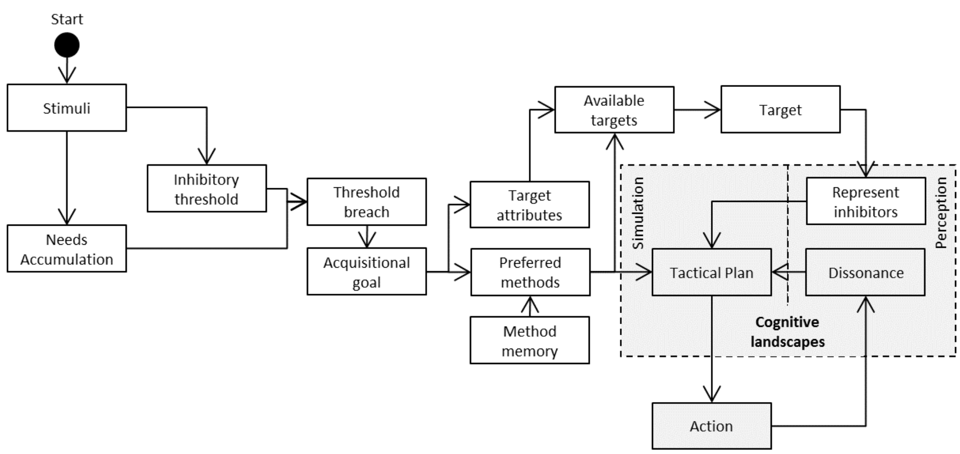

Figure 18: The process of adaptation is based on dissonance found in the perception landscape after the tactical plan has been applied as action (elements discussed in the text are highlighted gray). This figure is extended from Figure 17 and further extended in Figure 22.

2.1.7 Spatial and Temporal Factors

Implementing a complex adaptive social simulation of the violent offending process requires not only a well-abstracted representation of human decision-making, but also a viable representation of related spatial and temporal factors. Specifically, these factors

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[37] This process of adaptation is implemented as *maze-running* and discussed in more detail in the Stage 2: Tactical Planning and Adaptation Section 2.2.7.

include the *subject's* ***activity-space*** in which he encounters stimuli, the presence of available *targets*, and spatially relevant *action* outcomes (Cohen & Felson, 1979).

2.1.7.1 Activity-Space

Endogenous *cognitive landscapes* used by the *subject* form mental mazes of abstracted *inhibitors*[38] (*perception landscape*) and are utilized to create plans and adaptations (*simulation landscape*). However, the *subject's cognitive landscapes* run parallel to (and are informed by) what the *subject* spatially and temporally knows (or thinks he knows) about his physical surroundings which constitutes a mental map of the environment. Within this context, spatial factors related to violent offending rely heavily on the *subject's activity-space* (Cohen & Felson, 1979; Brantingham & Brantingham, 1993; Beauregard, Proulx, Rossmo, Leclerc, & Allaire, 2007). *Activity-space* refers to the area that defines an individual's geographic reach[39]. Within the violent offending process, the *subject's activity-space* provides a stimuli-rich environment that affects the *subject's needs*, *inhibitory thresholds*, and opportunities for *targeting* (Ratcliffe, 2006).

The boundaries of a *subject's activity-space* are defined by locations that are spatially relevant to the *subject*. These boundaries are comprised of ***anchor-points*** (Rossmo, 1995b) or significant locations that spatially tether an individual's activities, and the travel routes that connect them. Within this dissertation, the *subject's* home location(s), work location(s), and area(s) where he spends free time (*i.e.*, a specific bar or nightclub) are all considered *anchor-points* for his unique *activity-space* (Cohen &

[38] These *inhibitors* can include, but are not limited to, spatial or temporal factors.

[39] This is similar to the space-time prism concept explored by H. J. Miller (2007).

Felson, 1979). This *activity-space* defines the *subject's* routine mobility. Any additional exploration outside of this area provides a *subject* with an opportunity to increase his *activity-space* (Beauregard, Proulx, Rossmo, Leclerc, & Allaire, 2007).

The abstraction, conceptualization, and design of the model's environment must facilitate *subject* travel and interaction with environmental features. This is because when a *subject* pursues an *acquisitional goal*, spatial decisions are driven by intersections between the *subject* and other *objects,* or locations that he considers viable mediums in achieving his *goal*. This sentiment relies heavily on interactional theories of crime like *Situated Transaction* (Luckenbill, 1977) and the more spatially developed *Routine Activities* (Cohen & Felson, 1979) both of which recognize criminal activity as the spatial and temporal intersection of offenders and victims within a context. Ideally, this context involves additional aggravating factors like high-energy crowds during a fight (Luckenbill, 1977) or mitigating factors like visible security cameras or police to provide capable guardianship (Cohen & Felson, 1979).

Focusing on the spatial and temporal realizations of a *subject* emphasizes Hägerstrand's (1967) notion of disaggregating time and space (Pred, 1977; Corbett, 2015) as a way to better understand individualized human movement and boundaries. Thus, in order to understand human mobility, the purposes and bounds of that mobility must be considered as individualized choices. This approach leads to understanding and defining the offender's spatial choices as a "journey" to crime (Brantingham & Brantingham, 1984; 1993) that is augmented by context and rational script construction in criminal targeting and hunting patterns (Beauregard, Proulx, Rossmo, Leclerc, &

Allaire, 2007). Therefore, the reason why the offender and victim happen to be in the same place at the same time is regarded as a function of repetitive cycles of human movement.

2.1.7.2 Spatial Awareness

"Awareness" is a concept that relies on a *subject's* cognitive realization or understanding (Rhodes, 2000). ***Spatial awareness*** depends upon travel and movement to increase comfort and spatial understanding (Hägerstrand, 1967; Brantingham & Brantingham, Patterns in Crime, 1984; Rossmo, 1995b; Felson M. , 2002). Knowledge of an environment, when coupled with temporal features, lays a foundation of possible travel within a specific spatial environment during a given time frame (Pred, 1977; Kwan, 1998; Miller H. J., 2007). Thus, in a spatial model it is imperative to represent the *subject's* temporal awareness to effectively bound his *activity-space*.

2.1.7.3 Time

Time acts as a bounding factor that defines the extent of the *subject's* reach, as well as, spatially relevant commitments (Pred, 1977; Miller H. J., 2007). As such, temporal periods for the subject can be seen as times during which he is either accountable or non-accountable to daily obligations. Thus, ***accountable time*** is used in this dissertation to refer to Ratcliffe's (2006) notion that there are temporal constraints on a *subject* that shape spatial offending patterns. For instance, if a *subject* has a job, he is expected to spend time working. This means that the *subject* must be at a specific location during a specific time (or he will likely lose the job) and, unless offending at work, the subject is not available to offend elsewhere.

The pursuit of needs-based spatial and temporal activities relies on the *subject's* ability to navigate an incompletely understood landscape. While the *subject* may have a sense of the temporal and spatial environment, it is ultimately the nature and outcome of the interactions within the environment that creates behavior (Brantingham & Brantingham, 1984; Simon, 1996; Ratcliffe, 2006). Thus, introducing *needs* and *goals* as the drivers of spatial decisions is an important part of creating a *subject's* environmental interactions. In terms of a *subject's* spatial and temporal constraints, *inhibitory goals* (Polaschek, Hudson, Ward, & Siegert, 2001) are reinforced by *accountable time*. The pursuit of emerging *acquisitional goals*, then, is due to the absence or the supersession of *accountable time*.

2.1.7.4 Spatial Targeting

Once an *acquisitional goal* has emerged, the search for a *target* to achieve the *goal* is bounded by the *subject's activity-space*. For instance, if the *subject* is hungry, the *need* will be satisfied by acquiring food which the *subject* must locate somewhere within his *activity-space*. If he cannot locate a desired "food" *target* within his *activity-space*, then the *subject* must expand his *spatial awareness* to encompass less familiar areas or expand his *temporal awareness* to encompass less familiar times (if the *need* can be temporarily deferred). The act of changing or evolving his own spatial and temporal awareness to accommodate emerging *needs* is a significant form of adaptation.[40]

Once the *subject* begins to *target*, he seeks available *targets* in the environment. The *subject* (through previous experience) associates favorable *target attributes* with a specific location (*i.e.*, he can find prostitutes in a "red-light" district) or identifies a specific *target* (through other non-targeting interactions) that he wishes to interact with. In either case, targeting involves not only anticipating *targets* that will satisfy an *acquisitional goal*, but also where and when the *target* can be exploited. Through exploration of the *subject's activity-space*, he begins to understand not only spatial information, but also information about potential *targets* (Ratcliffe, 2006).

Furthermore, independent of the *subject's* influence, potential *targets* also have *activity-spaces* (Ratcliffe, 2006). These areas of *spatial awareness* overlap with and diverge from the *subject's activity-space*. Thus, the *subject* must not only identify a *target*, but once he creates a viable tactical plan, create an opportunity to put that plan in motion. This involves spatially and temporally synchronizing (at least temporarily) his *activity-space* to the *target's activity-space* in order to situate himself within reach of the *target*.

Behaviorally driven factors behind the *subject's activity-space* increase understanding of not only how a *subject* offends, but also how he is spatially and temporally engaged when not offending. While behavior can be framed as the manifestation of boundedly rational decision-making that emerges from an individual's

[40] *Tactical planning* and *adaptation* in the *subject's cognitive landscapes* inform (and are informed by) the *subject's targeting* decisions.

interpretation of *needs*, *goals* and *targets*, a significant part of how behavior emerges is spatially and temporally defined (Brantingham & Brantingham, 1993).

2.1.8 Outcomes

Thus far, the discussion of conceptually designing the violent offending process has focused on the way that a *subject* develops an *acquisitional goal* from an accumulated *need*, identifies the means to achieve this *goal* through a *target*, and tactically plans and adapts to reach the *acquisitional goal*. In less esoteric terms, this implies a *subject* develops a motive, identifies a victim, plans to kill the victim, and adapts his methods to achieve the murder.

The path-dependent outcome of successful violent offending (*S*) is expressed in Figure 19. [41,42] An *acquisitional goal* is created when the accumulating needs of a *subject* without an *acquisitional goal* (¬α) *breaches* the *inhibitory threshold* thereby creating an *acquisitional goal (α)*.[43] Creation of a viable *tactical plan* (*T*) to exploit a *target* is put into action in terms of *access* (*A*), *extraction* (*K*), and *egress* (*D*). The causal-path of *success* (*S* in Ω) is expressed as:

$$S \Leftarrow \langle (\alpha|\neg\alpha) \wedge (T|\alpha) \wedge (A|T) \wedge (K|A) \wedge (D|K) \rangle \tag{3}$$

[41] This figure is similar to, and has several elements in common with, the formalized forward-branching model of the OIPM Figure 1 in the Problem-solving Section 2.1.1. However, for continuity, *execution* (C) is now broken down into access (A), extraction (K) and egress (D).

[42] This figure provides further basis for understanding the outcomes discussed in the Model Outputs Section 2.2.9.

[43] Equation 2 in the Needs and Goals Section 2.1.5 establishes the breach of an *inhibitory goal* by the *needs-accumulator* as an *acquisitional goal* α. Therefore, the absence of an *acquisitional goal* is represented as ¬α. This representation is carried forward for consistency.

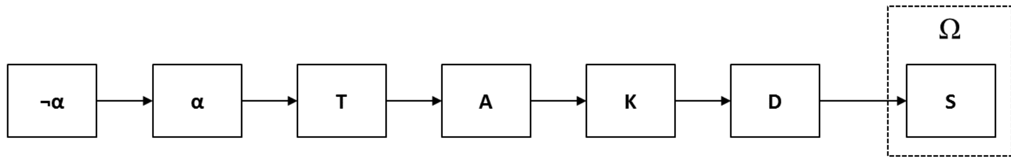

Figure 19: Path-dependent outcome of successful violent offending (extended in Figure 20).

Figure 20 extends Figure 19 to include failure states (¬*α*, ¬*T*, ¬*A*, ¬*K*, and ¬*D)* and their respective outcomes (*N*, P_1, P_2, F_1, F_2). This figure also provides the possibility of a persistent failure to produce an *acquisitional goal(¬α)*,[44] thereby producing outcome *N*. This outcome constitutes a *subject* who has no interest in offending. Outcome P_1 represents a *subject* that has breached the *inhibitory threshold* and developed an *acquisitional goal* but cannot formulate a viable *tactical plan*. Outcome P_2 represents a *subject* who has formulated a viable *tactical plan*, but has not yet had the opportunity to put that plan into action. Finally, F_1 and F_2 represent the *subject's* inability to successfully *access* a *target* or *extract* the *acquisitional goal* from the *target*, respectively, once a *tactical plan* is put into motion.

[44] While it seems counter-intuitive to refer to lack of interest in offending (¬α) as a failure, it could also be regarded as a "complementary event." Within a social and preventative perspective, this is the most coveted of successes. However, in the context of this dissertation, lack of interest in offending (¬α) constitutes a "failure" to initiate the violent offending process.

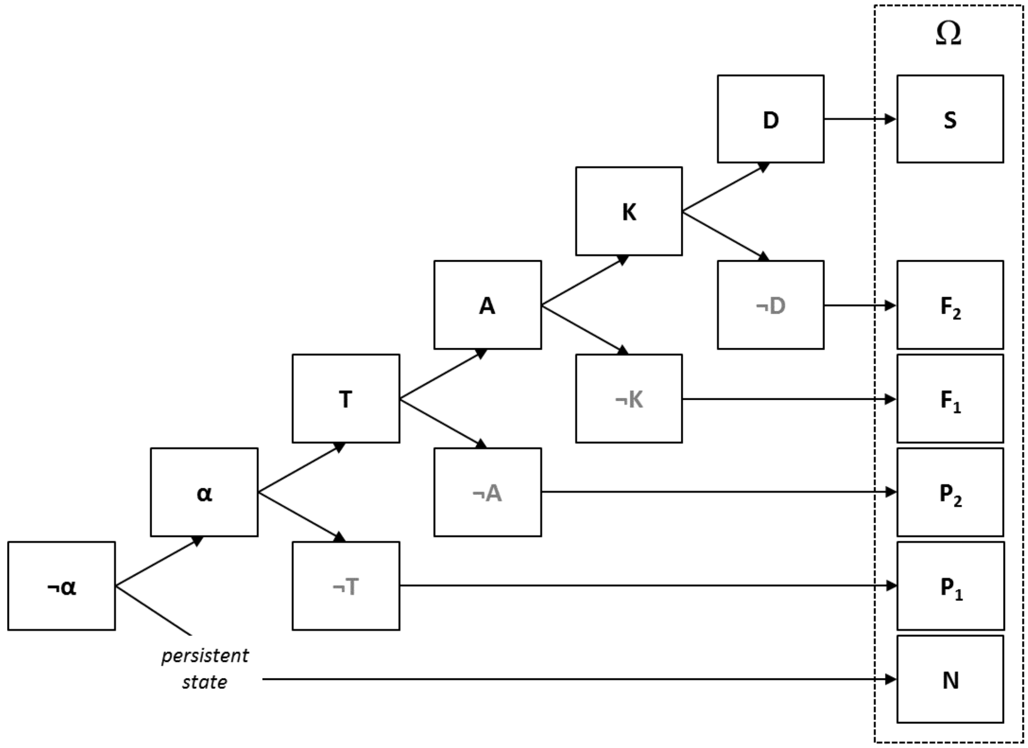

Figure 20: Path-dependent outcomes of the violent offending process including failure states and their respective outcomes (extended from Figure 19 and further extended in Figure 21).

"Offending" action begins when the *subject* attempts to *access* (*A*) the *target*. Inability to successfully transition from *access (A)* to *extraction (K)* constitutes failure to *access* and control the *target (¬K)*. It also represents a failed attempt to offend that must now be actively adapted into a successful retreat by the *subject*. To conceptualize this process, failures identified as F_1 and F_2 in Figure 20 are actually failures to successfully retreat and are consolidated and represented as *F* in Figure 21. Furthermore, Figure 21 shows that a new outcome, *retreat (R)*, emerges if the *subject* fails to address the *acquisitional goal*, but succeeds in egressing from that failed attempt.

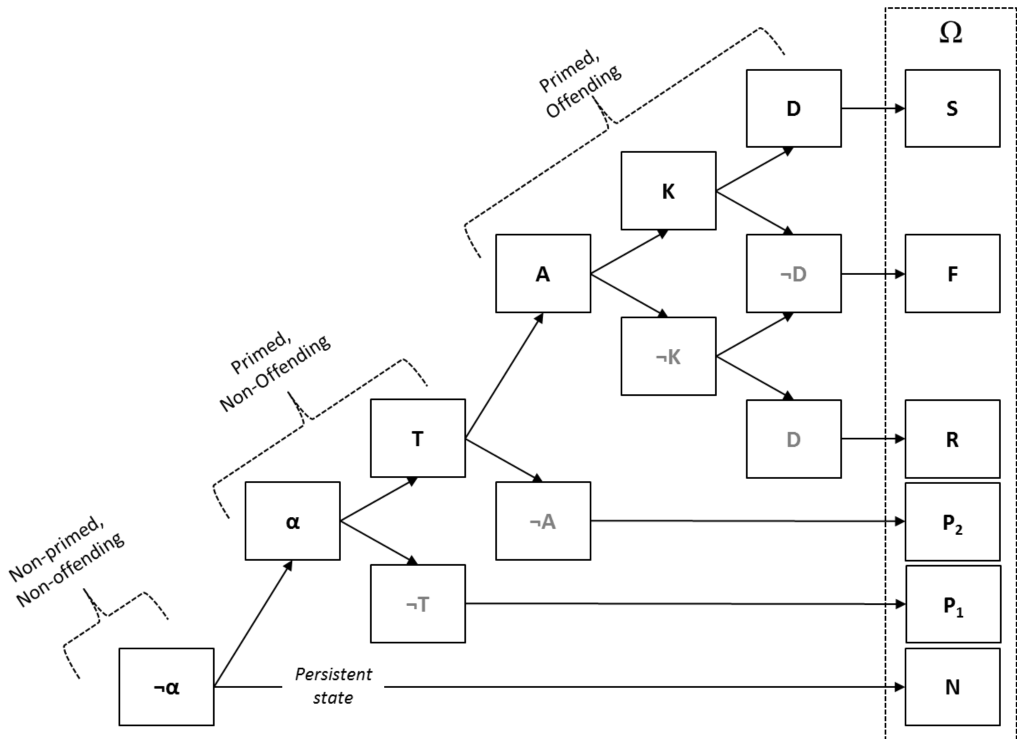

Figure 21: First-order path-dependencies in the violent offending process define significant emergent outcomes of the process (extended from Figure 20).

Figure 21 offers a way to conceptualize "non-primed, non-offending" subjects as those who do not have an interest in offending (N) and "primed, non-offending" subjects as those who have varying degrees of interest in offending but have not/cannot formulate a viable tactical plan or have not encountered an opportunity to put the tactical plan in motion (P_1 & P_2). Thus, "primed, non-offending", although defining a hidden population, can be conceptualized and formalized as a compound event. Furthermore,

Figure 21 also illustrates that once a tactical plan is put into action, regardless of outcome, the subject is "primed" and engaged in "offending."

Yet Figure 21 illustrates only one cycle of path-dependencies in what is truly an iterative and cumulative process (Dover, 2010). Given the *subject's* success in achieving an *acquisitional goal* (violent offending), the resulting outcomes defined in the sample space must still be integrated into the offending process to inform future activity through feedback. This constitutes the integration of an evaluation phase in the violent offending process (Dover, 2010).

Figure 22 illustrates that the *utility* of a successful action outcome hinges on the sufficiency of using the *target* to reduce the *needs accumulation*.[45]

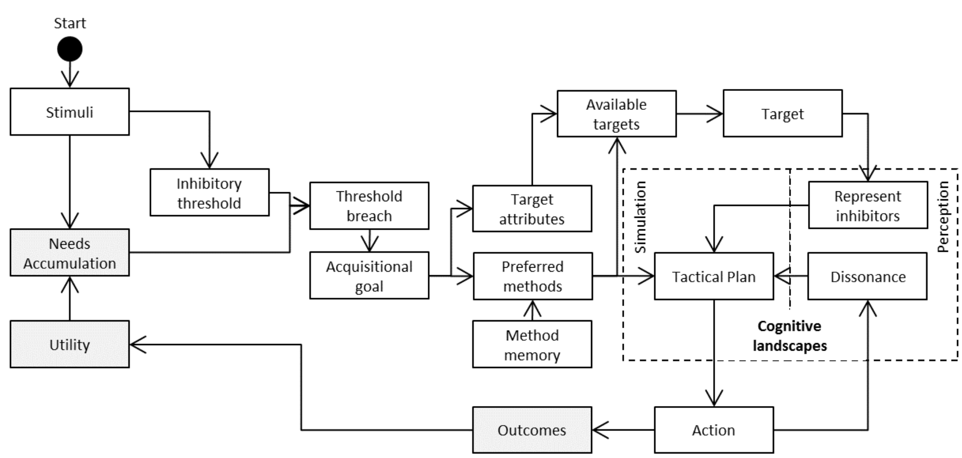

Figure 22: Utility of the target must be assessed in terms of reducing the needs-accumulation (elements discussed in the text are highlighted gray). This figure is extended from Figure 18 and further extended in Figure 23.

[45] This is further conceptualized by re-examining Figure 6 (see the Needs and Goals Section 2.1.5. The action outcome is illustrated at t_4, when the *acquisitional goal* (through the *target*'s *utility*) drives the emergent *needs* below the *inhibitory goal* and restores balance.

Figure 23 highlights that a successful outcome is added to the *subject's preferred-methods* of goal-seeking strategies that are stored as *method-memory* and can be leveraged given future *acquisitional goals*.

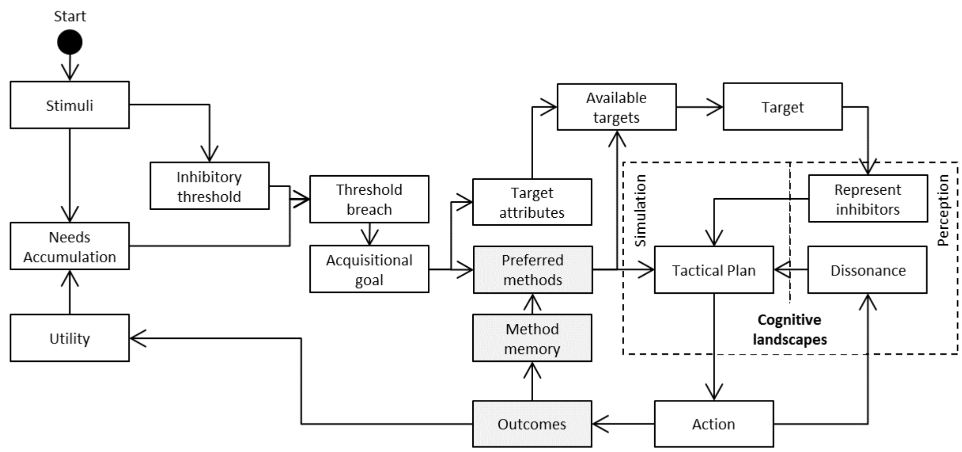

Figure 23: A successful outcome increases the subject's method memory of effective targeting, planning, and adaptation strategies so that those strategies can be considered when the subject encounters a similar acquisitional goal (elements discussed in the text are highlighted gray). This figure is extended from Figure 22 and extended in Figure 24.

This notion draws conceptually from Simon (1996) with regard to how a *subject* learns from the environment,

> "The information associated with familiar patterns may include knowledge about what to do when the pattern is encountered. Thus, the experienced chess player who recognizes the feature called an *open file* thinks immediately of the possibility of moving

> a rook to that file. The move may or may not be the best one, but it is one that should be considered whenever an open file is present." (p. 89)

Within the context of planning action, learning relies on a combination of boundedly rational behavior and satisficing — if it has worked in the past, then without an obvious better solution, it should work again. For this reason, successful methods contribute to future *preferred methods*.

As shown in Figure 24, a third product of interaction in general (this time regardless of success or failure) is augmentation of the *subject's activity-space*. This has a significant influence on the *subject's* spatial awareness and impacts encounters with future stimuli, *need* accumulation, and *inhibitory thresholds*.

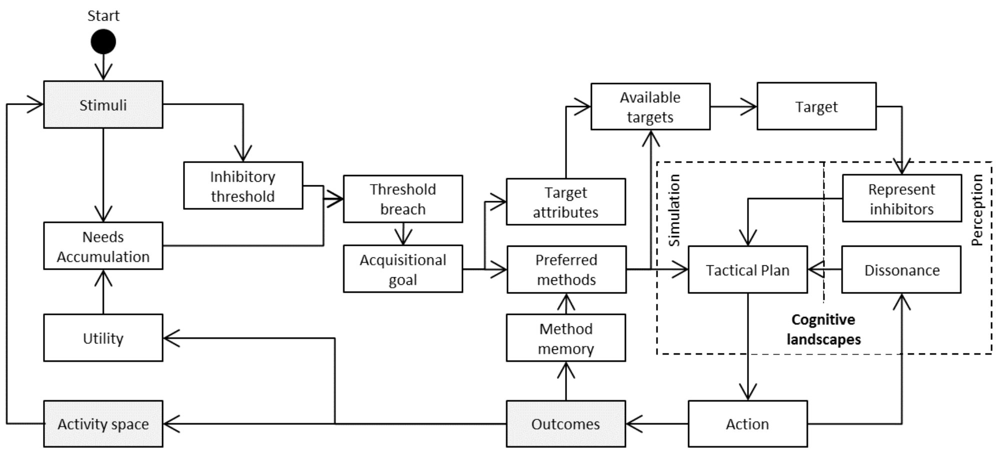

Figure 24: Any action outcome (regardless of success) augments the subject's activity-space and increases the subject's spatial awareness (elements discussed in the text are highlighted gray). This figure is extended from Figure 23.

Additionally, the *subject's* action outcomes are manifested spatially as physically located sites. Thus, where the *subject* successfully accesses a *target* constitutes an *access-site* or *abduction-site*, where the *subject* successfully extracts the *acquisitional goal* from the *target* is an *extraction-site* or *kill-site*, and where the *subject* successfully egresses from the *target* is an *egress-site* or *dump-site*.

These action outcome sites are an important part of understanding the *subject's spatial awareness* and constitute theoretically observable sites created by, but thereafter independent of, the *subject*.[46] Each of these action outcome sites also can be temporally placed within the environment. They are discrete moments in time that provide a significant amount of understanding of the *subject's* temporal awareness, *accountable time*, and offending intervals (Simkin & Roychowdhury, 2014).

[46] Most notably, if the subject has offended, as crime scenes.

2.1.9 The Integrated Model

The complexity of human behavior can be found not only in the endogenous rule-sets that govern interaction and reaction to stimuli, but also the inherent path-dependencies that follow from interacting exogenously. For this reason, the implementation of an integrated model of violent offending must involve implementing both internal and external factors that reasonably approximate a series of interdependent systems. Figure 25 illustrates the overall conceptual design of the violent offending process, as previously discussed, and serves to guide further implementation.

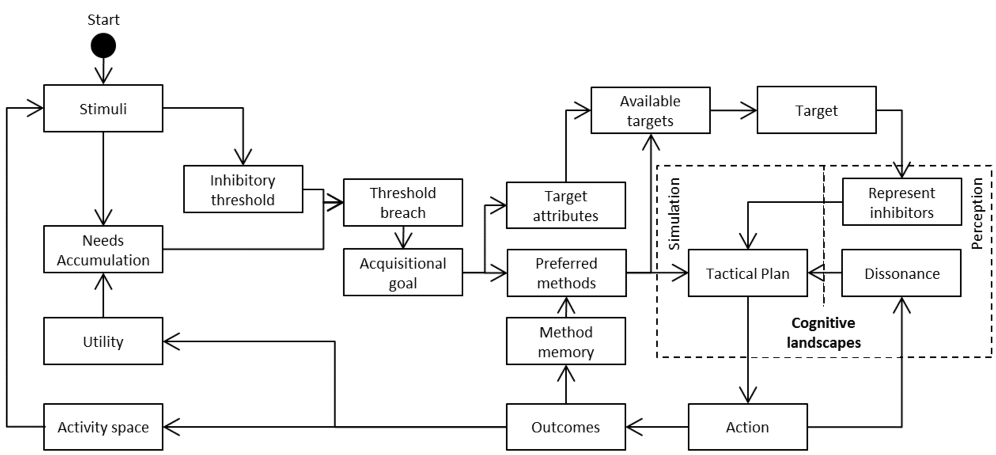

Figure 25: Integration of the violent offending process. The drivers of decision-making are expressed in terms of needs, goals, targeting, tactical planning, adaptation, and action outcomes.

To create a complex social simulation, a multi-stage process "must be carefully designed in order to provide cumulative insights as work proceeds toward the final model" (Cioffi-Revilla, 2014a, p. 245). The conceptual model from Figure 25 represents the integration of three primary stages; (1) interactions between the *subject* and his environment, (2) features of *tactical planning* and *adaptation*, and (3) re-incorporating process outcomes to inform future processes. Implementing these stages provide a basis for not only logically constructing an explicit representation of the offending process, but also conveniently identifies overlaps between each stage. These overlaps highlight conceptual bridges between stages and emphasize inter-stage feedback.

Figure 26 illustrates the first integrative stage (Stage 1, outlined in red), and shows that inputs are generated from environmental stimuli, accumulated *needs*, and preferred problem-solving methods. Consequently, given internal processes, the overall output of this first stage is an identified *target*.[47]

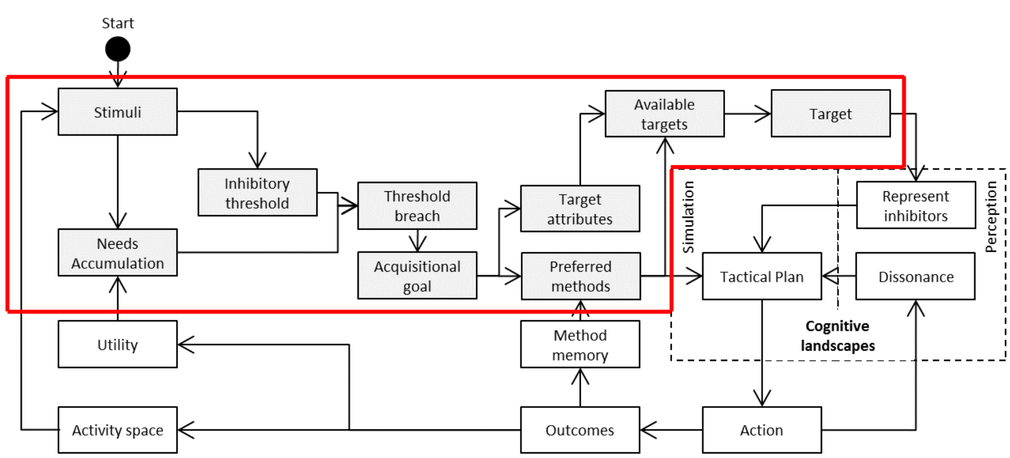

Figure 26: Stage 1 of the integrated model focuses on interactions between the subject and the environment (Stage 1 is outlined in red and elements discussed in the text are highlighted gray).

[47] For a detailed discussion on Stage 1, see the Stage 1: Interactions Section 2.2.6.

Figure 27 illustrates the next stage of the conceptual design with a focus on *tactical planning* and *adaptation* (Stage 2, outlined in red). In this stage, primary input comes from the features and attributes of the identified *target*, the preferred planning methods/capabilities of the *subject*, and feedback from the environment during action. The primary output of this stage is the final action outcomes that results from the string of actions pursued by the *subject*.[48].

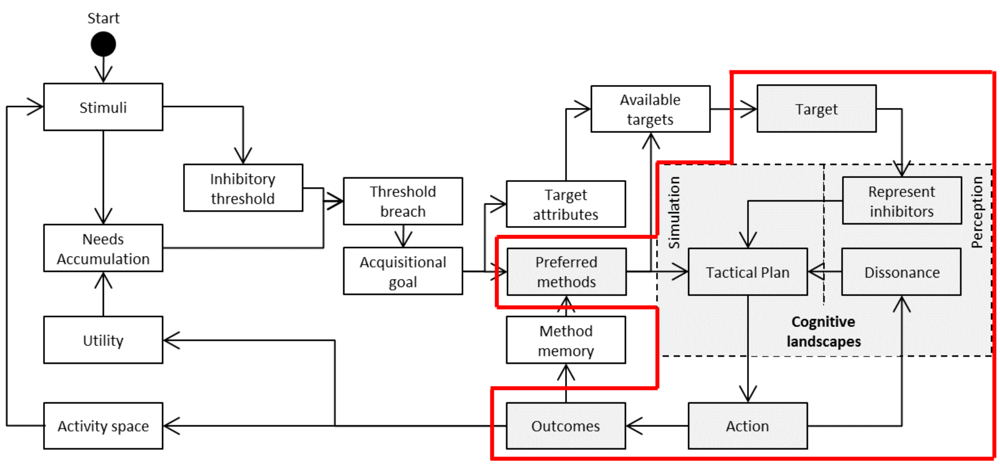

Figure 27: Stage 2 of the integrated model focuses on the subject's processes of tactical planning and adaption (Stage 2 is outlined in red and elements discussed in the text are highlighted gray).

Figure 28 illustrates the third stage of the design (Stage 3, outlined in red) in which the final action outcomes are fed back into the model via, a simple *method memory*, outcome *utility* (in terms of *needs* reduction), and a refined *activity-space*.[49]

[48] For a detailed discussion on Stage 2, see the Stage 2: Tactical Planning and Adaptation Section 2.2.7.

[49] For a detailed discussion on Stage 2, see the Stage 2: Tactical Planning and Adaptation Section 2.2.7.

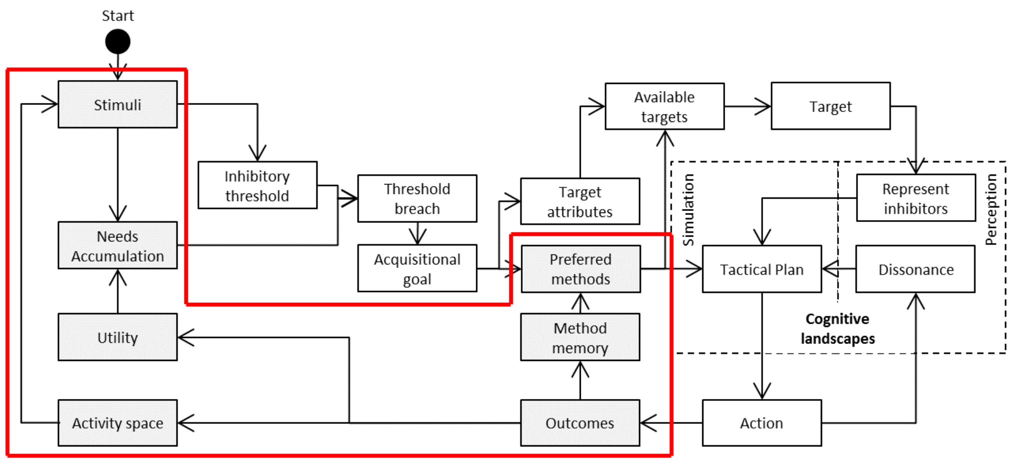

Figure 28: Stage 3 of the integrated model focuses on action outcomes and process feedback (Stage 3 is outlined in red and elements discussed in the text are highlighted gray).

2.2 Implementation

The conceptual design highlighted in Figures Figure 25 through Figure 28 is useful to visualize the overall integrated model. However, it is not explicit nor does it provide clear terms of realization. The practical implementation of the model, therefore, requires further specification.

There are a variety of modeling approaches that make up the current pantheon of simulation models from both a variable-oriented perspective (*i.e.*, system dynamics and queuing models) and an object-oriented perspective (*i.e.*, cellular automata, agent-based, and social network models)[50]. Each of these modeling approaches has significant advantages and disadvantages. For instance, a variable-oriented approach facilitates the

[50] For a comprehensive review of simulation models and their applications see Cioffi-Revilla (2014a).

study of system-wide attributes over-time (Cioffi-Revilla, 2014a; Moore, Kennedy, & Dover, 2016), whereas object-oriented approaches focus on emergent phenomena of interacting entities (Axtell & Epstein, 1994; Crooks & Heppenstall, 2012; Cioffi-Revilla, 2014a). Within a criminological context, this object-oriented approach also provides an opportunity to study "crime at the event level, and consider the necessary ecological conditions for a crime to occur at a particular place and time." (Johnson & Groff, 2014, p. 10)

As previously stated, this dissertation necessitates focusing on two different domains: (1) the social interpretation, ecological effects, and feedback that result from the *subject's* decision-making process, and (2) the internal decision-making process of the *subject* independent (but not ignorant) of social outcomes.[51] Thus, this dissertation takes a hybrid perspective[52] and utilizes both an object-oriented approach (to satisfy the first domain and a portion of the second domain) and a variable-oriented approach (to express the other portion of the second domain). Figure 29 illustrates the hybrid approach as discussed below.

The first domain focuses on the subject as an entity that interacts with other entities and requires an object-oriented approach; an agent-based model (ABM) is used to "simulate the individual actions of diverse agents, and to measure the resulting system behavior and outcomes over time" (Crooks & Heppenstall, 2012, p. 86). This is achieved

[51] Previously discussed in Conceptualizing the Violent Offending Process, Section 2.1.3.

[52] This is a hybrid methodology utilized by a number of modeling efforts. For example, Epstein (2014) and Moore, Kennedy, and Dover (2016).

by regarding the *subject* and environment as part of a larger referent system and focusing on incorporating interactions *via* a *subject-environment ABM*[53] (see Figure 29).

In the second domain, the *subject* utilizes an object-oriented approach via an embedded *maze-running*[54] *ABM* to treat his internally expressed problem space as a referent system and produce *tactical planning* and *adaptation*.[55] Additionally, in the second domain, the integrated model focuses on the endogenous accumulation of *need*s as a driver of behavior.[56] Specifically, the integrated model uses a system dynamics (SD) approach to represent the *subject* (as a referent system unto himself) with internal feedforward and feedback dependencies. These dependencies rely on exogenous stimulation and constitute a *needs accumulation SD* model

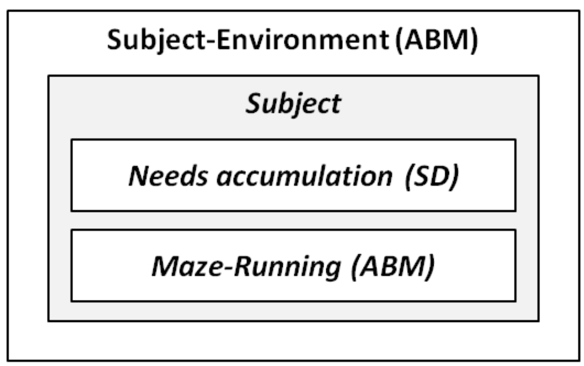

Figure 29: The violent offending process as an ABM of subject-environment interactions with ABM and SD models embedded in the subject.

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[53] See the discussion of targeting and spatial and temporal factors in Sections 2.1.6.1 and 2.1.7.

[54] *Maze-running* is discussed in detail in Section 2.2.7.

[55] See the discussion of tactical planning and adaptation in Sections 2.1.6.2 and 2.1.6.3.

[56] See the discussion of needs and goals in Section 2.1.5

The integrated model is implemented in NetLogo 5.2.0 (Wilensky, 1999). Screen captures of the interface and a list of the parameters on the interface and their specific uses are found in Appendix A.

2.2.1 Parameters

Throughout this dissertation, when literature supports assumptions about values or scale during parameterization, it will be so noted. However, where there is no clear evidence for particular parameter values or scales, due to either "the fact that assumptions and processes tend to outweigh the data available for complete assessment of their goodness of fit" (Crooks, Castle, & Batty, 2008, p. 419) or they are not adequately addressed in the literature, defaults will be imposed. Of course, simulation results could potentially be impacted by the default settings which is seen as an opportunity for further testing and validation in future applications of the model. Limitations to parameter values are further discussed in Chapter 4, Section 4.2.1 of this dissertation.

2.2.2 Agents

The integrated model focuses on two primary types of agents: *subject* and *object*. There is only one *subject* and it is the primary focus of the model. *Objects* represent items within the environment that the *subject* interacts with. In the current implementation, *objects* represent people. In the real-world, offenders must interact in non-offending ways to integrate (to some extent) with, and function in, society (Biderman & Reiss, 1967; Brantingham & Brantingham, 1993; Ratcliffe, 2006).

Aside from the *subject* and *objects*, the model also includes several other agents that are used for various navigation and visualization purposes. These include:

- *location agents* (used to mark the *subject's anchor-points*),
- *site agents* (used to mark significant ***event-sites***),
- *probe agents, TP-agents, and A-agents* (used to develop navigation paths throughout the *subject's* cognitive tactical planning and adaptation processes), and
- *comp-site agents* (used to represent *event-sites* from real-world incidents for comparison to simulated *event-sites*)

2.2.3 Model View

The integrated model "view" from the interface (see Appendix A) is shown in Figure 30. It is comprised of two regions that represent (1) the *subject's* internal *cognitive landscapes* and (2) external environmental perspective. The *subject's cognitive landscapes* are comprised of a *perception landscape* and a *simulation landscape*.[57] Each of these landscapes are further divided into three different **panels**;[58] an *access panel*, an *extract panel*, and an *egress panel*. These panels are used by the *subject* to tactically plan action and adapt to dissonance.

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[57] *Perception landscape* and *simulation landscape* are first introduced in this dissertation as the two *cognitive landscapes* that comprise the subject's problem space during *tactical planning* (see the Tactical Planning Section 2.1.6.2.

[58] Panels are navigable sub-spaces, or contiguous sets of rows, within the *subject's cognitive landscapes*. A panel is used to depict the *subject's access*, *extraction*, or *egress* problem space. Panels are defined by a start position and an end position that connects to other panels.

The *subject* navigates his external surroundings using the *environmental perspective* where he interacts with *locations* (*cells*) and *objects* on the same cell or within the Moore neighborhood (the eight surrounding *cells*). The *environmental perspective* also provides a means to depict spatially relevant features such as the *subject's activity-space* and *anchor-points*.[59]

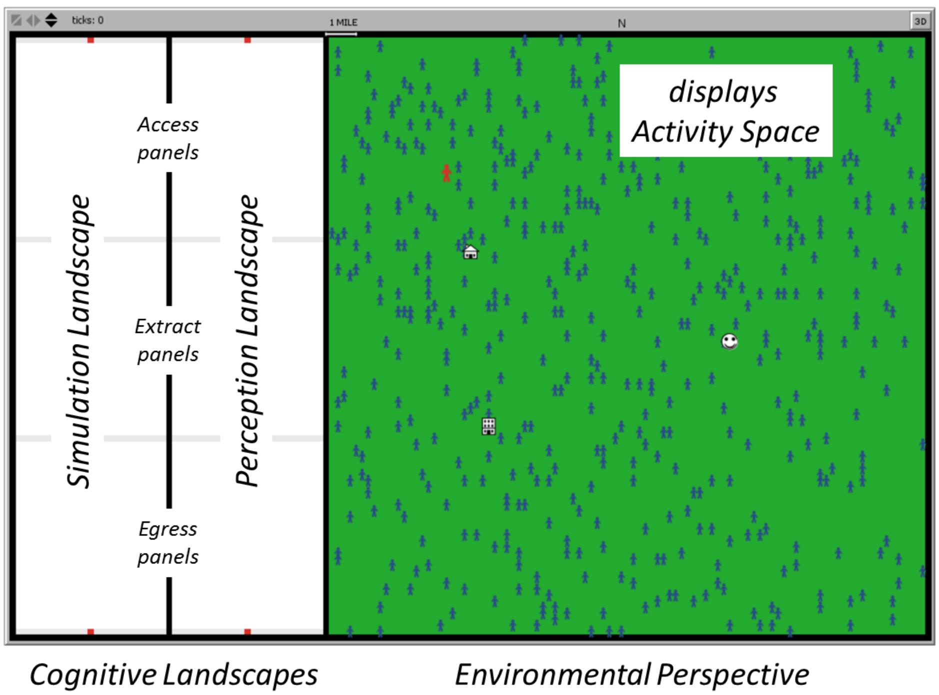

Figure 30: Integrated Model view showing the cognitive landscapes (simulation and perception), their respective panels, and the environmental perspective in which the subject's activity-space is displayed.

[59] As previously discussed in the Spatial and Temporal Factors Section 2.1.7.

2.2.3.1 Scale

The *subject* interacts within the *environmental perspective* at each discrete *time-step* of the model. For this reason, environmental interactions are sensitive to representations of spatial and temporal scale. For example, in Figure 31 the time scale for *subject A* is set to 5 ***minutes-per-tick*** (***mpt***), or one *time-step* for every five minutes. Over the course of ten minutes, *subject A* has three points at which he interacts exogenously (indicated with a red box): 0 minutes, 5 minutes, and 10 minutes. Alternatively, the time scale for *subject B* is set to 1 *mpt*, or one time-step for every minute. Over the course of ten minutes, *subject B* has eleven different discrete points of interaction.

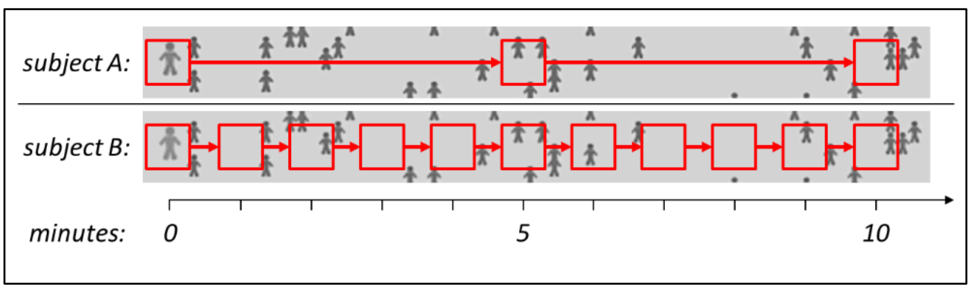

Figure 31: Comparison of interactions at two different time scales; one time-step every five minutes (subject A) versus one time-step every minute (subject B). Each red box denotes an interaction as the subject moves from left to right.

Given the same scale of environmental stimuli effecting both *subjects*, *subject A* does not have the same potential to develop emerging *acquisitional goals* as quickly as *subject B* simply because his *needs* will not accumulate and breach the same *inhibitory threshold* at the same rate. This provides an opportunity to explore magnitudes of effect experienced by the *subject* and adjust the model during calibration procedures when dealing with fixed spatial and temporal parameters. To facilitate this, the integrated model has adjustable spatial, temporal, *inhibitory threshold,* and environmental stimuli scaling via the model interface (see Appendix A). Specifically, the *min-per-tick* slider adjusts the time scale, *view-width* adjusts the spatial scale, the *base-threshold* slider[60] adjusts the base magnitude of the *inhibitory thresholds,* and the *object-effect* slider adjusts the scale of stimulus experienced by the subject when interacting with objects.[61]

2.2.4 Environmental Layers

Figure 32 illustrates the three primary layers for the *environmental perspective which resembles a geographic information system (GIS)*. The *navigation* layer is where *subject's anchor-points* are defined, *subjects* and *objects* navigate the environment, and *event-sites* are marked by the *subject*. The ***comfort*** layer defines the *subject's spatial awareness* and the ***privacy*** layer provides the *subject* with expectations of varying degrees of isolation.

[60] The *base-threshold* slider determines the value of the *subject's inhibitory threshold* at instantiation. For further discussion on the implementation of *inhibitory thresholds,* see the Inhibitory Thresholds Section 2.2.6.7.

[61] Settings for these parameters will be further discussed in the Verification Section 2.3 and the Calibration Procedures Section 2.4.1. The settings used during the real-world calibration are also discussed in the Configuring the GRK Series Section 3.2.

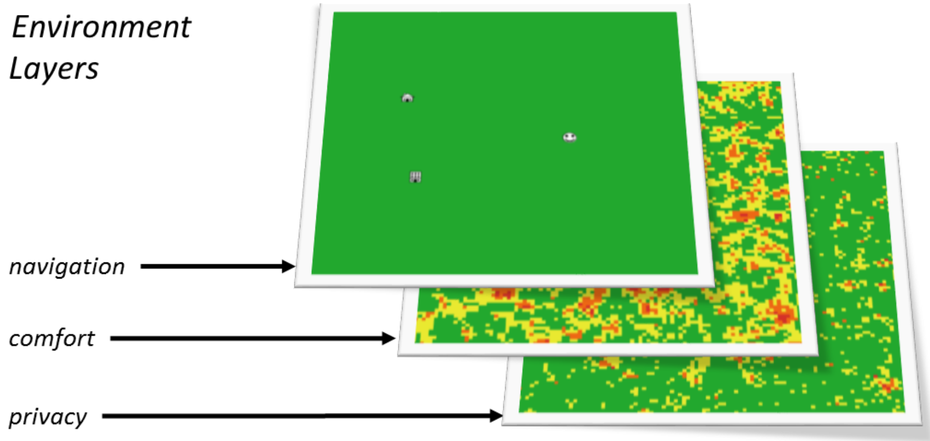

Figure 32: The three primary layers of the environmental perspective: navigation, comfort and privacy.

The navigation layer defines the initial *anchor-points* that tether the *subject* to his *activity-space* (Cohen & Felson, 1979). These locations are defined as *home*, *work*, and *play* (or free-time) locations and are instantiated at the model setup. The navigation layer is also used to display *subject* and *object* movement during the simulation run and display *event-sites* for relevant events. During calibration to a specific case,[62] this layer also defines geographic features and comparison *event-sites*.

The *subject* navigates the model "view" by first establishing a navigational target based on either ***scheduling*** or needs-based activity. Once he has established the location to which he will navigate, the *subject* determines the distance of the target location from his current location. If the *subject* is within a specified distance[63], he will walk to the

[62] Calibration to a specific case is further discussed in the Calibration Procedures Section 2.4.1.

[63] This distance is defaulted to 1 mile, but can be specified (in miles) with the *walk-tolerance* slider on the model interface (see Appendix A: A3). It is anticipated that most of the jurisdictions the model will be calibrated to use miles as a standard unit of distance.

location. It is assumed that the *subject* will drive to any locations that are further away than the specified distance. The *subject* then, based on method of navigation, walking or driving, establishes the maximum speed that he will travel.[64] The same navigation procedure is also used for each *object* (potential *target*).

Comfort and *privacy* have very different functions in the integrated model. *Comfort* defines areas that the *subject* is most familiar with and where he will go when seeking to interact.[65] *Privacy* defines areas in which the *subject* perceives significant degrees of isolation that will allow him to pursue secret activities.[66] It can be argued that most locations have areas that can provide significant *privacy* (*i.e.*, public bathrooms). However, in the integrated model, areas of the highest *privacy* offer the *subject* significant opportunity for prolonged activity shielded from public perception or scrutiny.

The *comfort* layer is defined by a *comfort value* assigned to each cell in the *environmental perspective*. *Comfort value* defines familiarity of the *subject* with a cell and is used to express locations in which the *subject* is liable to engage in certain activities like searching for a *target*. The higher the *comfort value*, the more comfortable the *subject* is with the specific location. At instantiation, the *comfort value* of the cell under an *anchor-point* is set to 10. All other cells are assigned a *comfort value* between 0

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[64] Maximum speed defaults to 5 mph if walking (Kennedy & Trafton, 2011). If driving, the maximum speed defaults to 30 mph to simulate navigating an urban environment with business districts. However, the speed assigned to the subject can be edited in the *distance-nav-target* procedure. Actual navigation speed is derived by generating a random float value between 0 and the designated speed. This accounts for stop-and-go traffic in a relatively urban location.

[65] The minimum score necessary for the subject to “feel comfortable” is defined by the *comfort-need* slider on the model interface (see Appendix A: A3).

[66] Significant privacy values are determined by the *privacy-need* slider on the interface (see Appendix A) and define areas the subject is most likely to commit a violent offense or dump a victim following a murder.

and 10.[67] All cells in the *environmental perspective* are then randomly activated and the *comfort value* is set to the mean score of the current cell and all cells in the current cell's Moore neighborhood.[68] Figure 33 shows an example of initial *comfort values* at *time–step* 0 (t = 0). Every time the *subject* interacts with a cell he increases the *comfort value* of the cell by a random value between 0 and 0.20. This is illustrated in Figure 33 where at *time-step* 28800 (t = 28800), the *subject's* navigation throughout the environment has generated increases in *comfort values* especially along travel routes.

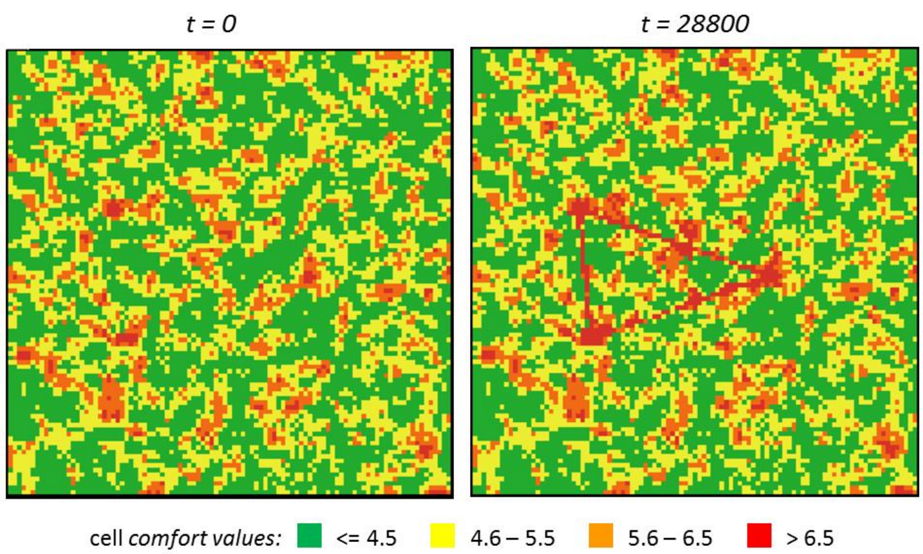

Figure 33: Evolving cell comfort values (range: 0-10) from time-step 0 to time-step 28800.

[67] Comfort values can be manually set via the scenario builder functionality in the integrated model. The user selects the *comfort* button and then manually locates the desired areas of highest *comfort*. A value of 10 will be assigned to the selected cells.

[68] This produces a distribution of *comfort values* that tend to be highest around the anchor-points, but creates other areas in which *comfort* is also quite high

Privacy value for each cell is calculated at instantiation by adding the cell's initial *comfort value* to a random value.[69] *Privacy values* range between 0 (completely public) and 10 (completely isolated). Figure 34 shows an example of *privacy values*. As this configuration depends on the underlying *comfort values*, it is also based in part on *anchor-site* locations. The notion here is that the *subject's comfort* with certain locations (including the *anchor-points*) affords him knowledge of significant private areas in those locations. *Privacy* for each cell is treated as a static value throughout the simulation and does not change.

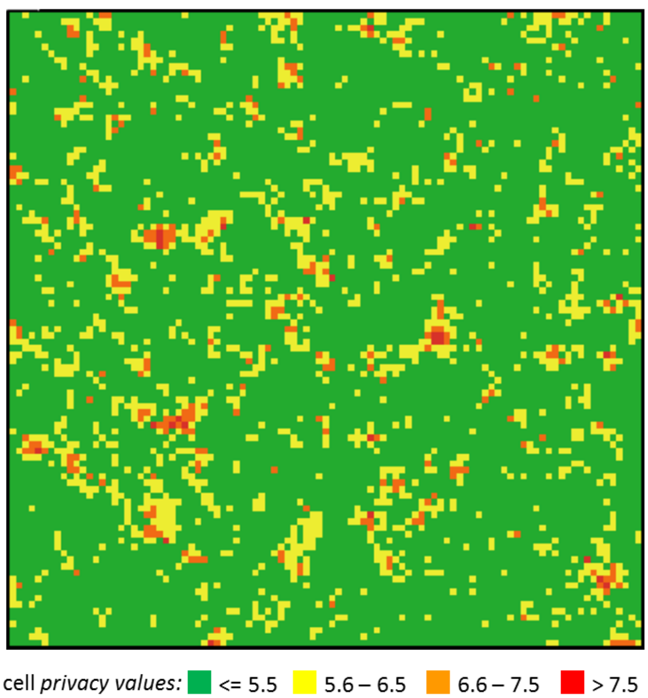

Figure 34: Cell privacy values (0-10).

[69] Random value for privacy is generated from a normal distribution with a mean of zero and a standard deviation of 0.5.

2.2.5 Stage Diagrams

As previously discussed in Section 2.1.9, the integrated model consists of three primary stages; (1) interactions between the *subject* and his environment, (2) features of *tactical planning* and *adaptation*, and (3) re-incorporating process outcomes to inform future processes. A number of figures are used to illustrate implementation of these stages. Stage 1 is described in Figure 35, Stage 2 is described in Figure 36 and Figure 39, and Stage 3 is described in Figure 42. These four figures build on each other and culminate in a comprehensive illustration of the violent offending process as an integrated model. The portions of the model discussed in the text are highlighted in gray in each diagram.

2.2.6 Stage 1: Interactions

Figure 35 shows the overall program logic of Stage 1. This stage focuses on interaction between the *subject* and environmental stimuli, the emergence of *acquisitional goals*, and the *subject's targeting strategies*. This stage culminates in the identification of a viable *target* (as perceived by the *subject*). Each of these factors is discussed in greater detail below.

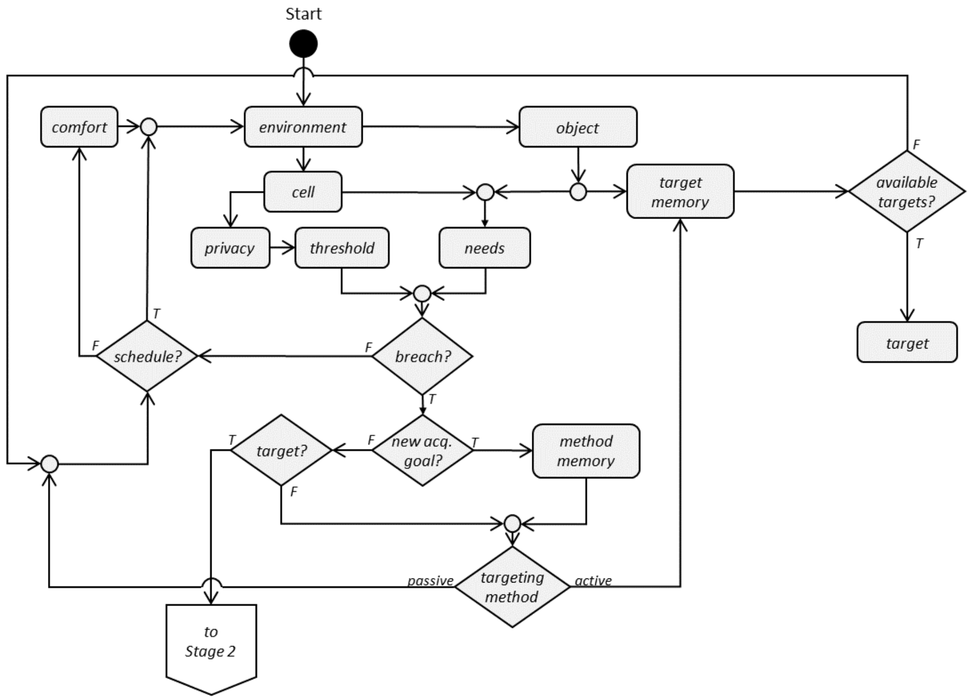

Figure 35: Stage 1 in the integrated model program logic showing the contribuition of environmental stimuli (derived from cell and object interactions) in the emergence of an acquisitional goal and subsequent targeting (elements discussed in the text are highlighted gray).

2.2.6.1 Scheduling

Interactions occur as a function of the *subject's* (and *objects'*) routine activities and *spatial awareness.*[70] For this reason, temporal and spatial constraints have a significant impact on creating opportunities to interact. *Accountable time* is represented through a schedule and is controlled via the *scheduling?* switch on the model interface (see Appendix A: A1). When *scheduling* is "on," the *subject* uses a preset itinerary to determine where he should be at certain times of the day (*i.e.*, he must be at work

[70] As discussed in the Spatial and Temporal Factors Section 2.1.7.

between 8:00 am and 5:00 pm). *Scheduling* has a similar effect on 90%[71] of the *objects* in the model. However, each *object* has its own randomly generated set of *anchor-points* to travel among.[72] If *scheduling* is "off," instead of following a schedule, the *subject* and *objects* wander between *anchor-points* with stochastically generated pauses at each destination.

2.2.6.2 Clustering

The integrated model represents *objects'* tendencies to gravitate toward specific locations by setting a percent[73] of *objects* to share an *anchor-point* with the *subject* and setting a percent[74] of these *objects* to also have relatively similar attributes to each other.[75] This increases the propensity of relatively homogenous *objects* to cluster around areas that are "comfortable" to the *subject*.

---

[71] The US Bureau of Labor Statistics (http://data.bls.gov/timeseries/LNS14000000) shows that from 2005 to 2015 the mean January unemployment rate was 6.8%. It was reasoned, therefore, that this population, in addition to a slight margin of people between jobs, truant from school, *etc.* could be rounded to 10%, leaving approximately 90% of the population following some form of a schedule.

[72] Object *anchor-points* are represented as lists of three to five cells for each object.

[73] The default percent is 20% of the *objects* following a schedule and the default *anchor-point* is one of the *subject's* "play" locations. This value was selected as a means to create ample opportunity for the *subject* to encounter potential targets in his *activity-space*. These values can be manually changed using the *target-percent* slider and *location-shared* chooser, respectively, on the model interface (Appendix A: A3).

[74] The default percent is 80% of the population that shares one of the *subject's anchor-points* but can be manually changed using the *pref-percent* slider on the model interface (see Appendix A: A3). The value of 80% was selected as a means to create a tendency for homogeneity of attributes with some slight variation.

[75] Clustering is set with two parameter switches on the interface: *obj-share-loc?* and *object-pref?* (see Appendix A: A3)

2.2.6.3 Implementing Needs and Goals

The *subject's* interest in pursuing *acquisitional goals* is driven by accumulators that track his **vector** of nominal *needs* $\boldsymbol{c}$ where specific *needs* c are nominal values that are referenced based on their position within the vector of *needs*:[76]

$$\boldsymbol{c} = (c_1, c_2, \dots, c_n) \tag{4}$$

A separate vector of corresponding dynamic *need values* $\boldsymbol{\eta}$ is associated with the nominal *needs* $\boldsymbol{c}$ and serve as a way to track *needs* accumulation. Thus, the vector of *need values* at *time-step t* is expressed as:

$$\boldsymbol{\eta}_t = (\eta_1, \eta_2, \dots, \eta_n) \tag{5}$$

Each specific *need value* changes independent of the other *need values* in the vector. In this way, the integrated model can be used to track *needs* based on *need values*. Table 2 shows how *needs* and *need values* differ and Appendix B illustrates how these *subject* attributes interact endogenously and exogenously within the model.

[76] This dissertation utilizes vector notation because a vector represents an ordered set such that the position in the order has meaning.

Table 2: Needs and need values.

		Type	Example
Need	$\boldsymbol{c}$	vector	(A, B, C…)
	c	string	A
Need Value	$\boldsymbol{\eta}$	vector	(0.1, -3.5, 26.4…)
	η	ratio	0.1

There is a declining usefulness in data that is over-fit to a dynamic system (Boyd, 1976). Thus, it was reasoned, that labeling specific *needs*[77] has the potential to constrain the overall process and may not be particularly useful in defining the emerging behavior. However, the deconstruction of a *need* into basic components and subsequent re-construction of new (albeit abstract) combinations of *needs*, referred to by Boyd (1976) as the process of "destructive deduction" and "constructive induction", provides a useful way to produce adaptable and dynamic representation of diverse and emergent *goals*. Additionally, abstracting *needs* in this way, leaves open the possibility that different combinations of *needs*, can result in similar behavioral outcomes.

As the *subject* interacts with the environment, he experiences stimuli. These stimuli take on two forms: *cell effects* and *object effects*. Both of these stimuli contribute to the *subject's* dynamic set of *need values*. In addition, cells encountered by the *subject* contribute to the *subject's* level of *privacy* and, thereby, affect his current *threshold* values. Furthermore, cells and *objects* that the *subject* encounters contribute to his growing understanding of available *targets*.

[77] Per Maslow (1943).

2.2.6.4 Cell Effect

Cells that the *subject* encounters affect his *need values* through their *cell effect values*. *Cell effect values* are instantiated[78] for each cell during setup by assigning the cell a random value[79] that corresponds to specific *needs* within the vector of nominal *needs*. *Cell effect values* for each cell are different, but they are not dynamic since the value does not change over the course of the simulation run. Thus, for a specific *cell* at any time the vector of *cell effect values* $\boldsymbol{v}$ are expressed as:

$$\boldsymbol{v} = (v_1, v_2, \dots, v_n) \tag{6}$$

For a visual depiction of how this environmental attribute contributes to interactions endogenous and exogenous to the *subject*, see Appendix B.

2.2.6.5 Object effect

The *attention* value determines the probability of the *subject* noticing an *object*.[80] If there are *objects* in the Moore neighborhood of the *subject*, depending on the *subject's* level of *attention*, one of the *objects* may affect the *subject's needs* accumulation through the its *object effect values*. *Object effect values* are instantiated

[78] Set prior to running an instance of the simulation.

[79] From a distribution with a mean of 0 and a standard deviation of 1

[80] The *subject's* attention is determined at instantiation and is calculated as a random number between 10 and 90. When the subject encounters an object he will pick a number between 0 and 100. If the number is less than the attention value, the subject "pays attention", if not, the subject ignores the object.

for each *object* during setup by assigning a random value[81] that corresponds to each *need* in the vector of nominal *needs*. The vector of *object effect values* $\boldsymbol{o}$ for each *object* are different but not dynamic. Thus, for a specific *object* at any time, the vector of *object effect values is* expressed as:

$$\boldsymbol{o} = (o_1, o_2, \dots o_n) \tag{7}$$

For a visual depiction of how this *object* attribute contributes to interactions endogenous and exogenous to the *subject*, see Appendix B.

2.2.6.6 Need Accumulation

At each new *time-step t* of the model the specific *cell effect values* υ of the cell on which the *subject* resides and the specific *object effect values o* of any *object* that the *subject* pays *attention* to are added to the *subject's* corresponding *need values* η from the previous *time-step (t-1)*:

$$\eta_t = \eta_{t-1} + \upsilon + o \tag{8}$$

Appendix B illustrates the contribution of this exogenous interaction to the *subject's* endogenous attributes.

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[81] From a distribution with a mean of 0 and a standard deviation of 15. This parameter setting has been tuned to represent the diversity of the measure.

2.2.6.7 Inhibitory Thresholds

As with the *subject's need values*, the *subject* also compiles *inhibitory threshold values* for each *need* in the vector of *needs* and stores them as vector of dynamic *threshold values*. The vector of *threshold values* $\boldsymbol{\varphi}$ at *time-step t* is expressed as:

$$\boldsymbol{\varphi_t} = (\varphi_1, \varphi_2, \dots, \varphi_n) \tag{9}$$

For a visual depiction of how this *object* attribute contributes to interactions endogenous and exogenous to the *subject*, see Appendix B.

The *subject's inhibitory thresholds* are affected by the privacy of the current location (*cell*). The *privacy value* has an effect on the *subject's inhibitory thresholds*. For instance, when the *privacy value* of a cell is relatively "high," the *subject* is in a relatively private location and his *inhibitory threshold* is relatively "low." Consequently, the cell's *privacy value p* is incorporated in the *subject's* evolving *inhibitory threshold*. This process is described in Equation 11 wherein a new specific *threshold value* φ at *time-step (t+1)* is calculated based on changes to the current specific *threshold value* φ at *time-step t*:

$$\varphi_{t+1} = \varphi_t + \left(\frac{-5p+25}{100}\right)\varphi_t \tag{10}$$

Appendix B further shows how this external interaction contributes to the *subject's* endogenous *inhibitory threshold values*.

Thus, for example, if *privacy value* of the current cell is set to 5 (theoretically average),[82] the new specific *threshold value* does not change. However, a *privacy value* of 0 (very public) results in a 125% increase in the new *threshold value* and the *subject* requires significantly higher *need values* to pursue an *acquisitional goal*. Conversely, *privacy value* of 10 (complete isolation) results in a 50% decrease in the new *threshold value* and requires significantly lower *need values* to pursue an *acquisitional goal.*

2.2.6.8 Developing an Acquisitional Goal

Ultimately, when any of the *subject's* specific *need values* η from the vector of *needs* $\boldsymbol{\eta}$ exceeds the corresponding *inhibitor value* φ that regulates it, an *acquisitional goal* α is either created or (if already created) perpetuated. At every *time-step* of a model run, the *subject's* accumulating set of *need values* are compared to his dynamic set of *inhibitor values*. If specific *need value* does not exceed the corresponding specific *threshold value*, then no *acquisitional goal* has emerged for that *need*. If a specific *need value* exceeds a corresponding specific *threshold value*, then the *subject* generates an *acquisitional goal value* α for the specific nominal *need* that *need* represents the strength of the *need*. This is expressed as:

$$\alpha_t = \begin{cases} \eta_t - \varphi_t, & \eta_t - \varphi_t > 0 \\ 0, & \eta_t - \varphi_t \leq 0 \end{cases} \tag{11}$$

[82] The static privacy values of cells range from 0 to 10. The values were chosen as a relatively easy to conceptualize scale. For further discussion, see the Chapter 4, limitations to parameter values 4.2.1.

Thus, each specific *need value* η is evaluated with respect to its corresponding *threshold value* φ to generate a vector of *acquisitional goal values* $\boldsymbol{\alpha}$ at *time-step t*:

$$\boldsymbol{\alpha}_t = (\alpha_1, \alpha_2, \dots, \alpha_n) \tag{12}$$

For a visual depiction of how this *subject* attribute is derived from, and contributes to, interactions endogenous and exogenous to the *subject*, see Appendix B.

The current *acquisitional goal* g represents the set of active nominal *needs* that the *subject* is currently attempting to satisfy. In equation 13, a specific nominal *acquisitional goal* g corresponds to specific *need c* from the vector of nominal *needs* (if the *acquisitional goal value* α for that *need c* is greater than zero) or zero (if the *acquisitional goal value* α for that *need c* is less than or equal to zero):

$$g_t = \begin{cases} c, & \alpha_t > 0 \\ 0, & \alpha_t \leq 0 \end{cases} \tag{13}$$

Thus, the vector for nominal *acquisitional goals* $\boldsymbol{g}$ at *time-step t* is expressed as:

$$\boldsymbol{g}_t = (g_1, g_2, \dots, g_n) \tag{14}$$

This *subject* attribute is referenced in Appendix B.

The process of *needs* accumulation and *acquisitional goal* development is further illustrated in the following example. Given vector ***c*** of five nominal *needs*, a vector of accumulated *need values* $\boldsymbol{\eta}$, and a vector of *threshold values* $\boldsymbol{\varphi}$ corresponding to those *needs* at *time-step* ***t***:

$$\boldsymbol{c} = (A, B, C, D, E), \text{ and} \tag{15}$$

$$\boldsymbol{\eta}_t = (10, 5, 20, 32, 46), \text{ and} \tag{16}$$

$$\boldsymbol{\varphi}_t = (12, 12, 15, 10, 20), \tag{17}$$

the following vectors of *acquisitional goal values* $\boldsymbol{\alpha}$ and nominal *acquisitional goal* $\boldsymbol{g}$ develop at *time-step t*:

$$\boldsymbol{\alpha}_t = (0, 0, 5, 22, 26) \tag{18}$$

$$\boldsymbol{g}_t = (0, 0, C, D, E) \tag{19}$$

Thus, in the above example (Equations 15-19), the *subject* has developed an *acquisitional goal* at *time-step t* that is a combination of specific *needs*: *C*, *D*, and *E*. In addition, each of these nominal *needs* has a corresponding *acquisitional goal value*: 5, 22, and 26 respectively, which describes its strength.

The primary reason to identify the emerging nominal *acquisitional goal* independent of associated *acquisitional goal values* is to provide a general nominal *goal* configuration that can be used to identify similar emergent circumstances in the future. While the strengths of *acquisitional goal values* may be different for future *acquisitional goal* configurations, the configuration itself *(i.e.*, $(0, 0, C, D, E)$) provides a nominal comparison when looking for similar problems that have been previously addressed. Once a problem-set has been defined via the *goal* configuration, the *acquisitional goal values* determine the minimum utility necessary to satisfy each *need* within the *goal*.

If the accumulated *needs* when compared to the *inhibitory thresholds* do not create an *acquisitional goal* ($\boldsymbol{\alpha}_t = (0, 0, 0, 0, 0)$), then the *subject* is not "primed." Essentially, while the *subject* may be thinking about the emerging *needs*, his *inhibitory goals* are sufficient to suppress any interest in pursuing those *needs* as an *acquisitional goal* at the current *time-step*.

2.2.6.9 Target-Memory

If the *subject* attends to an *object*, then the *subject* also records the interaction with that *object* into his *target-memory* (see Figure 35). *Target memory* acts as an associative memory for the subject in which *objects* and/or *locations* are indexed based on *object-attributes* that the subject encounters (Rhodes, 2000; Park, Shobe, & Kihlstrom, 2005; Suzuki, 2005). An *object's* vector of *attributes* ***b*** are values associated with the *object* that correspond to the *subject's* vector of nominal *needs* ***c***:

$$\boldsymbol{b} = (b_1, b_2, \dots, b_n) \tag{20}$$

These *object attribute values* represent the *subject's* interpretation (which is not necessarily accurate) of how the *object* could satisfy each of his respective *specific acquisitional goals*.

Target-memory provides the *subject* with a list of available *targets* and/or target-rich locations that he can refer to when he is interested in interacting in pursuit of an *acquisitional goal*. Thus, *target-memory* at *time-step t* is expressed as a vector ***tm***:

$$\boldsymbol{tm_t} = (tm_1, tm_2, \dots, tm_n) \tag{21}$$

where a target-memory entry is expressed as:

$$tm = (\boldsymbol{b}, [0 \ \vee object], [0 \ \vee cell]) \tag{22}$$

in which the first item is the vector of *attributes* ***b*** for the encountered *object*, the second entry is either 0 or the *object ID* for the *object* with *attributes* ***b***, and the third entry is either 0 or the *cell ID* for where the *object* with *attributes* ***b*** was encountered.[83] For a visual depiction of the components of the *subject's* target memory, see Appendix B.

In some circumstances the *subject* is more interested in *target attributes* than a specific *target* (Ratcliffe, 2006). In these situations, the *subject* engages in targeting that is focused on a location. For instance, the *subject* may go to a "red-light district" to find a prostitute or go to a school to find a child. In the integrated model, this feature is implemented as *location-based targeting*.[84] If *location-based targeting* is "on", the

[83] Attention is used to determine if the object ID, the location cell, or both are associated with the attributes and captured in *target memory*. If both object and cell entries are 0, then the memory is not retained.

[84] The location-based *targeting* parameter is a switch (*loc-based-target?*) on the model interface (see Appendix A: A3).

subject only records a location associated with *object-attributes* (as opposed to the *object* itself) into the *target-memory*. This means when the *subject* pursues an *acquisitional goal*, he goes where he has, in the past, encountered an *object* with the requisite attributes (Eacott & Heywood, 1994).

2.2.6.10 Targeting Methods

At every *time-step* the *subject* repeats the Stage 1 process outlined in Figure 35. As a result, the *subject* constantly encounters stimuli in the environment that change his accumulated *need values*. Therefore, it is possible that the *subject* will develop additional *needs* that change the current *acquisitional goal*. If the current *acquisitional goal* is a new *goal*, the *subject* refers to his *method memory*, which is an accumulation of past successful actions,[85] to identify a successful *targeting strategy*.

If the *subject* chooses an "active" *targeting strategy*, he will search for suitable *targets* in his *target-memory*. If the *subject* finds an *object* with an *attribute* entry that satisfies his current *acquisitional goal*, then he will select the listed *object* as a *target*.[86] If the *subject* does not find a suitable *target* but has found a location in his *target memory* that satisfies his current *acquisitional goal*, then he will move toward the location at which he expects to find a suitable *target*. If the *subject* does not find any suitable *targets*

[85] For further discussion of *method-memory* construction, see the Method Memory Section 2.2.8.2.

[86] If there are multiple target memory entries that could satisfy the emerging acquisitional goal, the *subject* will select the *object* or location that is closest to his current geo-spatial position.

or locations in *target memory*, the *subject* will move toward a location with sufficient *comfort value*.[87]

If the *subject* chooses a "passive" *targeting strategy*, he will continue to follow any *schedule* that he currently observes or (if not following a schedule) travel to areas of significant *comfort.* During these routine activities, the *subject* will interact with the environment and remain hyper-aware of his surroundings (100% *attention*). At each *time-step*, the *subject* will check the *attributes* of all *objects* at his position and within the Moore neighborhood and select the first *object* that fits his *acquisitional goal* as a *target*.

2.2.7 Stage 2: Tactical Planning and Adaptation

The previous section, 2.2.6, addresses the first stage of implementing the violent offending process. This section addresses the second stage. Once a *target* has been identified, the *subject* initiates Stage 2 of the integrated model. In this stage, the *subject* employs *tactical planning* to determine how he can exploit the *target* and achieve his *acquisitional goal*. If the *subject* has not yet devised a tactical plan (*i.e.*, this is a new *goal*), he will attempt to formulate one that allows him to interact with the *target*. Figure 36 illustrates the program flow for the beginning of Stage 2 which necessitates that the *subject* understands the emerging problem space[88] to identify viable *tactical planning* methods and resources.

[87] As determined by the *comfort-need* slider on the model interface

[88] Problem space was previously discussed in the Tactical Planning Section 2.1.6.2

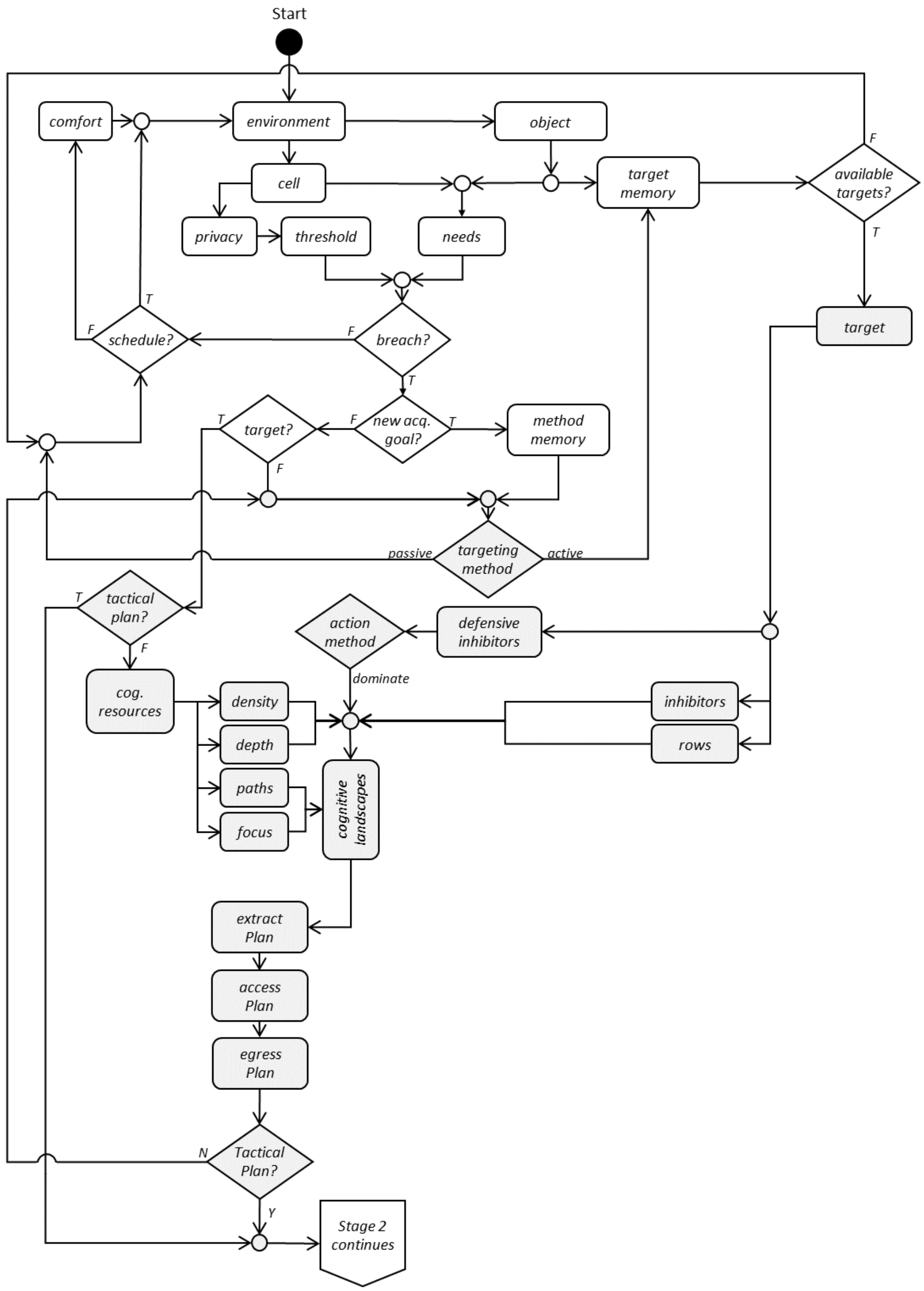

Figure 36: Stage 2 (part 1) in the integrated model program logic showing features involved in preparing the cognitive landscape for tactical planning (elements discussed in the text are highlighted gray).

2.2.7.1 Setting-up the Cognitive Landscape

To initiate tactical planning, the *subject* constructs his perception of the problem-space in the *perception landscape* of the model view. The panels of the *perception landscape* address the *subject's* requirements to access the *target* (*access panel*), extract the current *acquisitional goal* from the *target* (*extract panel*), and egress from the *target* once he is done (*egress panel*).

The integrated model implements tactical planning (and subsequent adaptation) as an analog to building and navigating a "maze" of obstacles or *inhibitors*. The *target's row* variables[89] define the number of rows assigned to each panel in the *subject's perception landscape*.[90] The *target's inhibitor* variables[91] define the density of *inhibitors* (as a percent of the cells in the panel) for each panel.[92] As these features, *rows* and *inhibitors* are unique to each individual *target*, the "maze" of *inhibitors* constructed in the *subject's perception landscape* changes with each new *target*.

Inhibitors presented by the *target* are also dependent on the *action strategy* selected by the *subject*. The *action strategy* is selected from the *subject's method-memory*[93] and can be either "dominant" or "collaborative." If the *subject* is using a

[89]These variables, *a_rows*, *ex_ rows*, and *eg_rows*, are associated with the *target* and automatically adjusted on the model interface (see Appendix A: A4)

[90] These three row variables for each object are assigned at instantiation as random values between 1 and 32 because each panel in the *conceptual landscapes* could be a maximum of 32 cells high. This is a limitation of the model view.

[91]The variables, *a_inhibitors*, *ex_inhibitors*, and *eg_inhibitors*, are associated with the *target* and automatically adjusted on the model interface (see Appendix A: A4)

[92] These variables are defined at instantiation for each object as a random value between 5 and 25. This range was chosen based on experimentation with the parameters.

[93] If there is no *method-memory* entry that is similar to the current circumstance, the *subject* will randomly choose an action method: either "dominant" or "collaborative." If the methods are manually specified, the action method is manually selected using the action chooser on the model interface (see Appendix A: A3) at instantiation.

“dominant” *strategy*,[94] the *target* presents a significantly higher number of *inhibitors* to the *subject* via additional *defensive inhibitors*. These additional *defensive inhibitors* significantly increase the density of the *inhibitors* in the *perception landscape* panels by between 5% and 30%.[95]

Inhibitors are specific to a *target*. Therefore, *target* “risk” can easily be implemented via the *target risk* parameter[96] which uses the *target inhibitor* and *row* variables to predefine *targets* at “high-” or “low-risk”. A *target* is at a “high-risk” if it presents relatively few *inhibitors* and *rows* in the *subject’s perception landscape*. A *target* is at a “low-risk” if it imposes a higher number of *inhibitors* and *rows* (Wheeler, 2010).

Figure 37 illustrates an example “maze” in the *subject’s perception landscape* (right side). The height of each panel in the cognitive landscapes is determined by the current *target’s* corresponding *row value*. *Inhibitors* are represented as green cells that are randomly distributed in the corresponding panels of the *perception landscape* based on the current *target’s inhibitor values*.

---

[94] The subject intends to forcibly extract the *acquisitional goal* from the target. This is by the definition offered in Section 1.1, violent action.

[95] This range was chosen based on experimentation with the parameters and was tuned to represent the diversity of the measure.

[96] *target-type?* switch on the model interface (see Appendix A: A3)

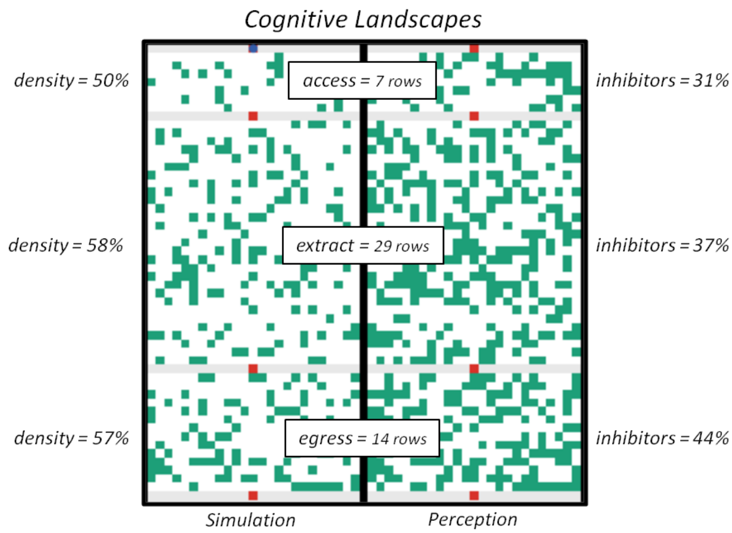

Figure 37: Generating the "mazes" in the cognitive landscape panels.

It is important to note, that while the *perception landscape* defines the "maze," it does not provide a solution to navigating the "maze." To determine how to navigate each of the panels, the *subject* produces a cognitive model of the "maze" in his *simulation landscape* (left side) so that he may run a series of navigation simulations for each panel. The "best" successful outcome of these simulated runs then constitutes a tactical plan.[97]

2.2.7.2 Cognitive Resources

Maze-running, or finding viable paths through the "maze" in the *simulation landscape* using *probe-agents*, is an endogenous ABM generated by the *subject* to derive "navigational" solutions as an analogy to *tactical planning*. To assist (and bound) the *subject's* understanding of the *simulation landscape*, the *subject* has several ***cognitive***

[97] For further discussion of the conceptual framework of the tactical planning implementation, see the Tactical Planning Section 2.1.6.2.

resources at his disposal: *density*, *paths*, *depth*, and *focus*. Each of these *cognitive resources* has an important part in defining and utilizing the *cognitive landscapes*.

As shown in Figure 37, *density* defines the percent of the inhibitors in the *perception landscape* that the *subject* accounts for in the *simulation landscape*. Generally speaking, underestimates in the *density* of the *inhibitors* presented by a *target* are a primary source of *dissonance* between the tactical plan and *action*. *Paths* correspond to the number of routes (concurrent simulation runs) that the *subject* can generate during tactical planning. This translates to the number of *probe-agents* that the *subject* will generate in the *simulation landscape* to find and record viable paths through each panel's inhibitor "maze." A *probe-agent* attempts to run from the red cell at the top of each panel (start) to the red cell at the bottom of each panel (finish) while avoiding *inhibitors*. *Depth* defines the number of moves that a *probe-agent* has at its disposal to navigate a panel from start to finish. This resource is dependent on the number of rows in the panel. *Focus* defines the tendency for the *probe-agents* to re-orient their respective courses through a panel toward the panel finish. It is implemented as the percent of the time that a *probe-agent* will adjust its course during its navigation through a panel.[98]

The tendency toward *high* (*H*), *medium* (*M*), or *low* (L) values for each of the four *cognitive resources* (*density*, *paths*, *depth*, and *focus*) comprise the *subject's tactical strategy* as derived from his *method memory* each time the *subject* selects a new *target*. The *subject's* choice of *tactical strategy* σ to address a specific *target* is expressed as:

[98] Mapping these *cognitive resources* to psychological principles or cognitive functioning is not the point here. These four factors are simply necessary to practically navigate an unknown landscape. Absence of any one of these resources will not allow success. For further discussion about implications of these parameters, see the limitations Section 4.2.1.

$$\sigma \Longrightarrow \begin{bmatrix} density & paths & depth & focus \\ \downarrow & \downarrow & \downarrow & \downarrow \\ H & H & H & H \\ M & M & M & M \\ L & L & L & L \end{bmatrix} \tag{23}$$

Designation as *H*, *M*, or *L* tendency means that the *subject* will generate a random *r* new resource value for the corresponding parameters:

$$density \Longrightarrow \begin{cases} H, & 60 \leq r \leq 90 \\ M, & 35 \leq r \leq 65 \\ L, & 10 \leq r \leq 40 \end{cases} \tag{24}$$

$$paths \Longrightarrow \begin{cases} H, & 7 \leq r \leq 10 \\ M, & 4 \leq r \leq 8 \\ L, & 1 \leq r \leq 5 \end{cases} \tag{25}$$

$$depth \Longrightarrow \begin{cases} H, & 6.25\,\lambda \leq r \leq (6.25\,\lambda + 3.75\,\lambda) \\ M, & 3.75\,\lambda \leq r \leq (3.75\,\lambda + 3.75\,\lambda) \\ L, & 1.25\,\lambda \leq r \leq (1.25\,\lambda + 3.75\,\lambda) \end{cases} \tag{26}$$

where in the *depth* calculation, λ is the number of rows in the specific panel,

$$focus \Longrightarrow \begin{cases} H, & 60 \leq r \leq 90 \\ M, & 35 \leq r \leq 65 \\ L, & 10 \leq r \leq 40 \end{cases} \tag{27}$$

Thus, even though tendencies (*H*, *M*, or *L*) for each *cognitive resource* in the *subject's tactical strategy* are generally defined, there is a significant level of variation in the specific *cognitive resource* parameter values within those tendencies.

The *subject* generates *cognitive resource* values (based on the above scheme) for each panel. For example, in Figure 37 the tendency for the *subject's density* is "*M*," however, the actual *density* in the *access panel* is 50%, in the *extraction panel*, it is 58%, and in the *egress panel*, it is 57%.

Once the *subject* has built his *perception landscape* for the *target* and prepared a *simulation landscape* based on that *perception landscape*, he must define a viable path through the "maze" of *inhibitors*. As shown in Figure 38, navigation is achieved by utilizing the *cognitive resources* discussed above for each panel and stringing the shortest derived paths into one cohesive path to represent the tactical plan.

The sequence of panels navigated to create the tactical plan is not linear. This is to say, the *subject* must first consider how the *acquisitional goal* can be extracted from the *target*, then determine how to access the *target*. Thus, in the tactical plan the first panel that is navigated is the *extraction panel*. If the *subject* successfully navigates this panel (creates a plan of how to exploit the *target*), then it is worth his time to consider how to access the *target* and given continued success (if he is using a "dominant" *action strategy*) how to egress from the *target*. The *egress panel* represents how the *subject* plans to "get away" with his offense and can include simply exiting the premise or (in some murders) moving a deceased victim to another location and dumping the body. Successful *tactical planning* is predicated on the *subject's* ability to navigate all three panels.

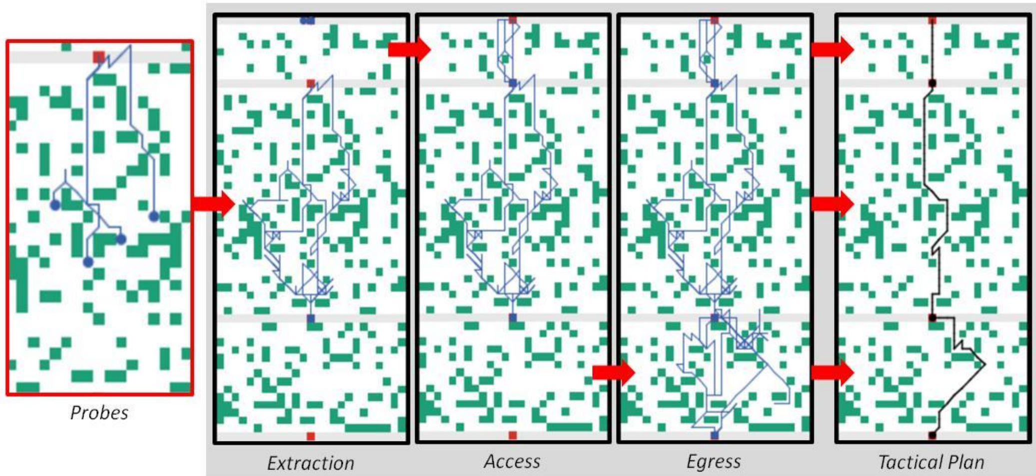

Figure 38: Navigating the simulation landscape starts with the extraction panel, then the access panel, and finally the egress panel. The subject strings a single path through all three panels and creates the cohesive tactical plan.

While Figure 38 showed the first part of Stage 2, Figure 39 illustrates the program flow for the remainder of Stage 2. If the *subject* is unable to produce a tactical plan, he reassesses his methods and re-initiates *targeting*.[99] Given the same *acquisitional goal*, his *tactical strategy* tendencies remain the same. However, actual *cognitive resource* values are recalculated with each new (or re-established) *target*. Thus, even if he selects the same *target* again, the *subject* will have a new set of circumstances which may lead (this time) to a tactical solution. Ultimately, the *subject* will continue to re-initiate *targeting* if he fails to produce a tactical plan until his *acquisitional goals* change or he achieves success.

[99] The *subject* can select the same *target* again.

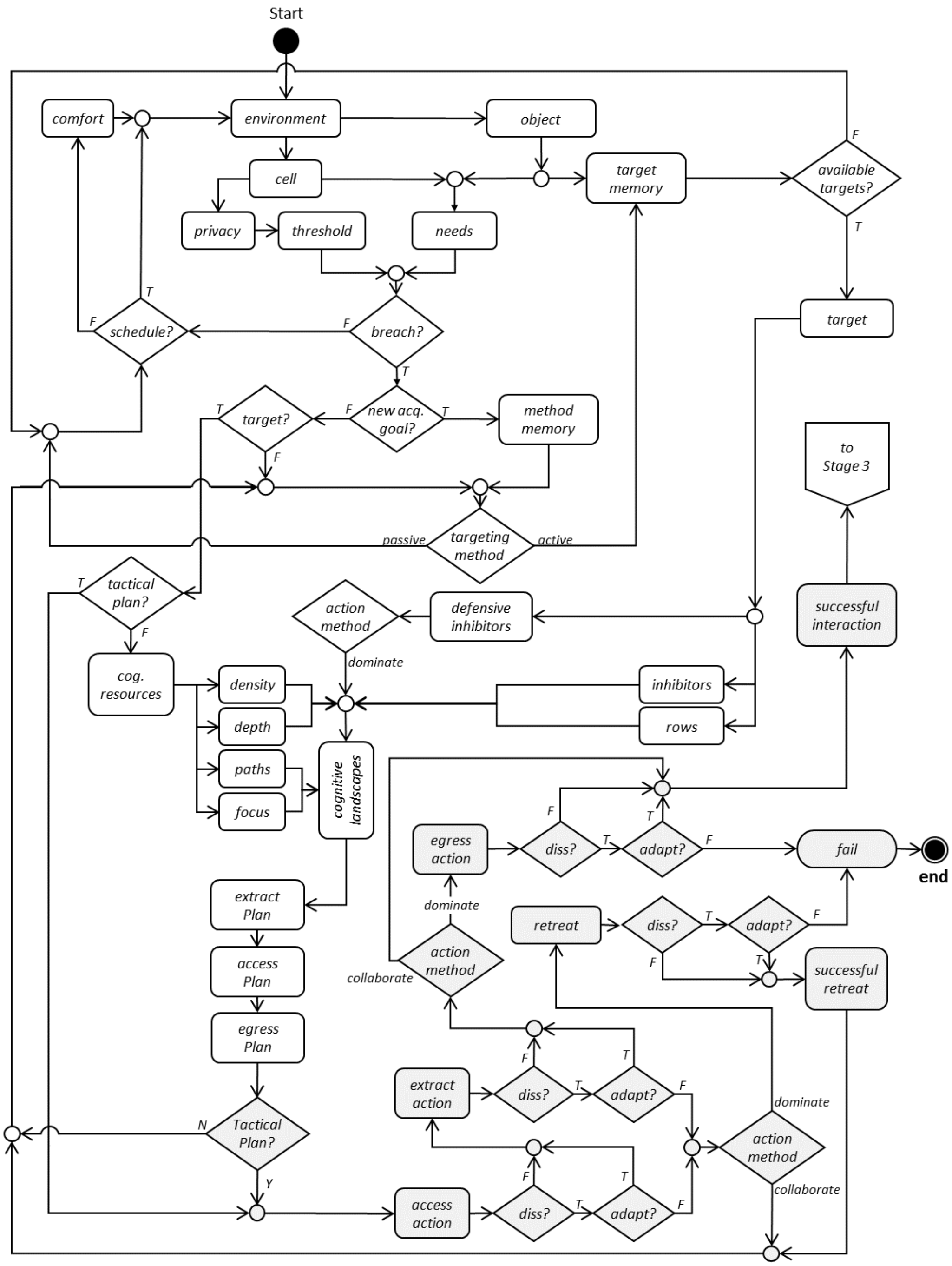

Figure 39: Stage 2 (part 2) of the integrated model program logic showing the utilization of the maze-running process to create a tactical plan, pursue action, and adapt to dissonance (elements discussed in the text are highlighted gray).

If the *subject* is able to create a tactical plan, he transfers his plan to the *perception landscape* to translate it into *action*. The *subject* approaches this part of the *maze-running* process in a linear manner. First he must access the *target*. The *subject* must then move/accompany the *target* to an appropriate private location.[100] Then he must exploit the *target*, and then he must egress.[101] If he is able to do all three without experiencing *dissonance*,[102] or un-foreseen *inhibitors*, then his tactical plan is sufficient for the task, and the *subject* will experience success.

It is important to note however, just because the *subject* is able to conceive of a tactical plan, does not mean that the plan is viable in reality. The creation of a tactical plan simply implies that the configuration of the *subject's cognitive resources* has led him to believe he will be successful. Yet, *inhibitors* represented in the *simulated landscape* are (by definition) a fraction of the *inhibitors* identified in the *perception landscape*. This underestimate leads to missing information in the *simulation landscape* and results in a significant potential for encountering un-foreseen *inhibitors* during action. These un-foreseen *inhibitors are* considered *dissonance* in the *maze-running* process. Thus, the *subject* is likely to create a tactical plan that, when put into action, leads to some level of *dissonance*. *Dissonance* in any of the three *perception landscape* panels requires that the *subject* adapt to be successful.

---

[100] If the subject pursues a "dominant" *action strategy*, he controls and moves the target to a cell with a privacy value greater than the *privacy-need* slider on the interface (see Appendix A: A3). If he pursues a "collaborative" *action strategy*, he accompanies the target to a cell with a *privacy* value greater than (*privacy need* slider - 1). In a "collaborative" strategy, the *subject* wants *privacy*, but does not require as much as he does for the "dominant" *action strategy*.

[101] If the subject pursues a "collaborative" *action strategy*, he does not egress because he has no need to "get-away" / retreat from offending.

[102] See the previous discussion on dissonance and its role in adaption in the Adaptation Section 2.1.6.3.

In order to adapt, the *subject* must first recognize that there is an *inhibitor* blocking his navigation in one of the panels. The *subject* will address the *inhibitor* by transferring its location from the *perception landscape* to a corresponding location in the *simulation landscape*. Once the *subject* has simulated the new *inhibitor's* location, he then uses his *cognitive resources* to adjust the current tactical plan by simulating a new path around the obstacle and integrating this new plan with the prior tactical plan.

This newly adapted plan may, or may not, be the most efficient way around the newly discovered *inhibitor*. This aspect of *maze-running* purposefully mimics imperfect decision-making. If the *subject* is able to work out an adapted path given his current *cognitive resources*, he selects the shortest solution, amends the tactical plan in the *perception landscape*, and continues the attempted *action*.

Figure 40 illustrates an example of the *adaptation* process by showing where the *subject* changed his tactical plan in the *simulation landscape* to adapt to unforeseen *inhibitors*. The left most panel illustrates the initial tactical plan that was created in the *simulation landscape* and then transferred to an *action-probe*[103] in the *perception landscape* (far right panel). The *action-probe* attempts to carry-out the plan in the *perception landscape*. However, if the *action-probe* encounters an *inhibitor*, it stops and the new *inhibitor* location is transferred to the *simulation landscape* where *probe-agents* attempt to create a navigational solution around the obstacle. If a solution is created, the solution is then transferred back to the *action-probe* and it navigates around the *inhibitor*.

[103] An *action-probe* is a specialized agent that uses the final path (tactical plan) created in the *simulation landscape* to navigate the *perception landscape*.

In the example shown in Figure 40, to be successful, the *subject* made fifteen *adaptations*[104] to the original tactical plan. A successful *action*, therefore, may involve a significantly different path than was initially planned. This highlights the point that successful *action* is in many cases only possible through successful *adaptation*.

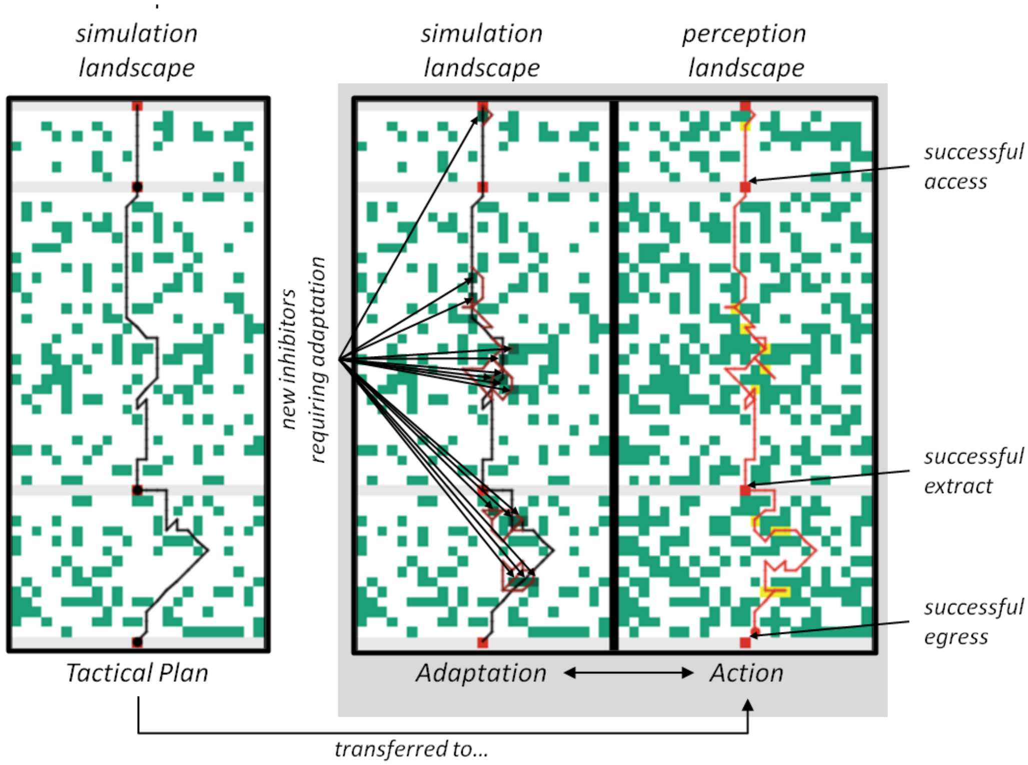

Figure 40: The initial tactical plan is transferred from the simulation landscape to the perception landscape for action and then re-adjusted in the simulation landscape when new inhibitors requiring adaptation are discovered.

[104] In the Integrated Model, dark green cells in the *simulation landscape* indicate *inhibitors* that are discovered in the *perception landscape* during *action*. These *inhibitors* are transferred to a corresponding location in the *simulation landscape* in order for the subject to revise his tactical plan (adapt).

If the *subject*, given attempts to *adapt*, is unable to successfully navigate the necessary panels in the *perception landscape*, then he has failed to achieve his *acquisitional goal*. If the *subject* is pursuing a "collaborative" *action strategy* and he fails to navigate either the *access* panel or *extract* panel, he will re-initiate *targeting*, build a new tactical plan for a new *target*, and try again.

However, if the *subject* is pursuing a "dominant" *action strategy* and he fails to navigate either the *access* or *extract panel* during action, he must shift his attention to extricating himself from the failed action. This requires that he initiate an attempt to navigate the *egress panel* to *retreat*. This process is illustrated in Figure 41 which shows an example of a *subject* that is able to successfully access the *target* in his *access panel*, but fails to *extract* (*i.e.*, kill the *target*) in his *extract panel*. In this example, the *subject* must now drop his primary *acquisitional goal* and create a new temporary *goal* – to egress without capture. Thus, the *subject* in Figure 41 fails to address his *acquisitional goal*, but because he is able to fully navigate the *egress panel*, he successfully retreats from the attempted murder.

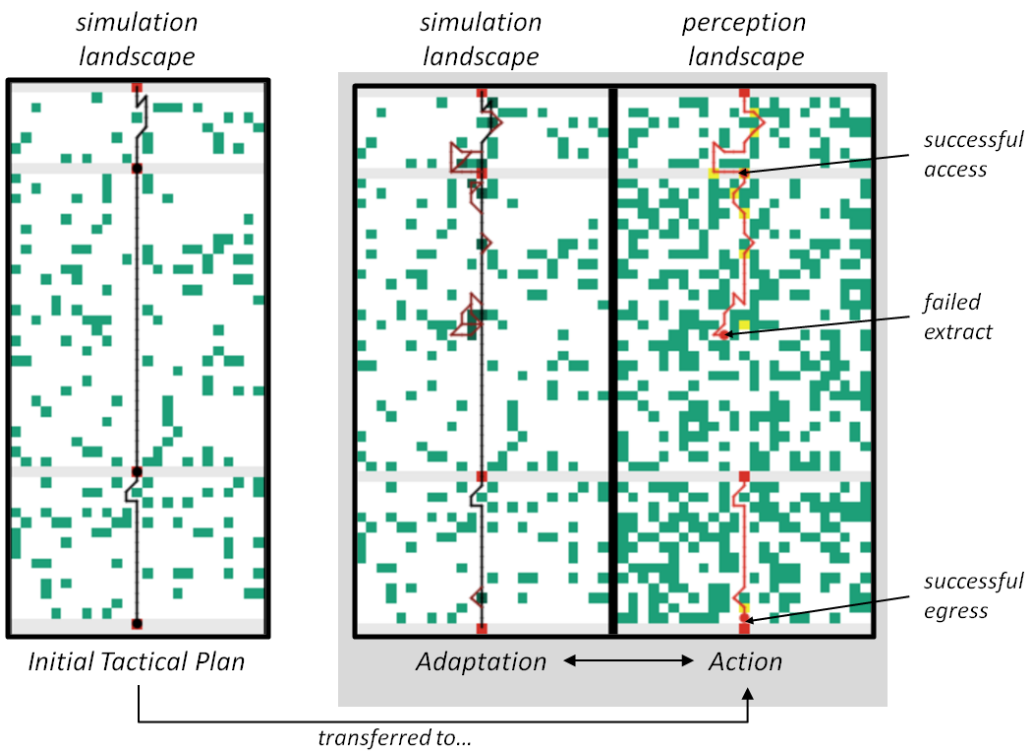

Figure 41: The subject is unable to adapt his initial tactical plan to navigate newly discovered inhibitors in the extract panel (unsuccessful offense). However, he is able to successfully egress (retreat).

The program flow in Figure 39 shows that failure to adapt while retreating from a failed attempt and failure to adapt while egressing from a successful offense both lead to overall failure. Failure to egress following a successful offense is interpreted as the *subject* being "caught after the act" with incriminating evidence *(i.e.*, the victim's body). Failure to retreat following a failed attempt can be interpreted as the *subject* is "caught in the act." In the integrated model, failure will stop the simulation run.

Alternatively, if the *subject* successfully retreats from a failed attempt, he will continue to pursue his *acquisitional goal* (if it is still active) by re-initiating *targeting* and going through the entire process of *tactical planning* and *adaptation* again. With each failed attempt but successful retreat, this cycle will continue until the *subject* is successful, his *acquisitional goal* changes or subsides, or he experiences failure to retreat and the simulation ends.

2.2.8 Stage 3: Learning and Burn-in

The previous section, 2.2.7, addresses the second stage of implementing the violent offending process. This section addresses the third stage. Figure 42 illustrates that in Stage 3 successful interaction feeds forward to the integrated model at several points: through the *utility* of successful interaction in satisfying *acquisitional goals*, by augmenting *subject method-memory*, and to inform the *subject's* spatial awareness.

2.2.8.1 Utility

Given successful interaction, the *subject* reduces his accumulated *needs* based on the *target's* vector of *utility values* $\boldsymbol{u}$.[105] *Target utility values* correspond to the *subject's* set of nominal *needs*. The vector of *utility values* is static and is expressed as:

$$\boldsymbol{u} = (u_1, u_2, \ldots, u_n) \tag{28}$$

[105] *Utility values* are drawn from a normal distribution with a mean that is determined by the *object-utility* slider on the model interface (see Appendix A: A3) and standard deviation of 0.15. This range was tuned to represent the diversity of the intended measure. Values are clamped between 0 and 1 and assigned at instantiation of each *target*. This value represents the percent decrease in needs that the *subject* will experience upon successfully extracting an *acquisitional goal* from the object.

These *utility values* specify percent reduction that is applied toward the *subject's acquisitional need*. Such that given specific *utility value u* and specific *need value* η at the previous *time-step t-1* and new environmental stimuli (*cell effect value* υ and *object effect value o*), the new *need value* η is calculated as:

$$\eta_t = (\eta_{t-1} - \eta_{t-1}u) + \upsilon + o \tag{29}$$

For a visual depiction of the contribution of an *object's utility value* on the *subject's* accumulated *need values*, see Appendix B.

If the *subject* has extracted the *utility* via a "dominant" *action strategy* the entire reduction is applied to the *subject's needs*. However, if the *subject* has extracted *utility* via a "collaborative" *action strategy*, he will only be able to apply up to 90% [106] of the reduction to his emerging *needs*. This implements the notion that the *subject* does not have the same amount of control over a "collaborative" interaction as he does over a "dominant" interaction.

It is also important to note that the *utility* of the interaction is independent of the intended *target's attributes*. This means the *subject* may believe that the *target* will satisfy an *acquisitional goal* based on his interpretation of the *target's attributes*. Yet, he may find that the *target's* true *utility* is very different and thereby more or less satisfying than expected.

[106] As determined by selecting a random number r: $0 \le r \le 90$. In a collaborative strategy, the subject does not dominate the interaction. It is, therefore, assumed that there is a significant variation that will occur in his ability to fully derive utility from the interaction.

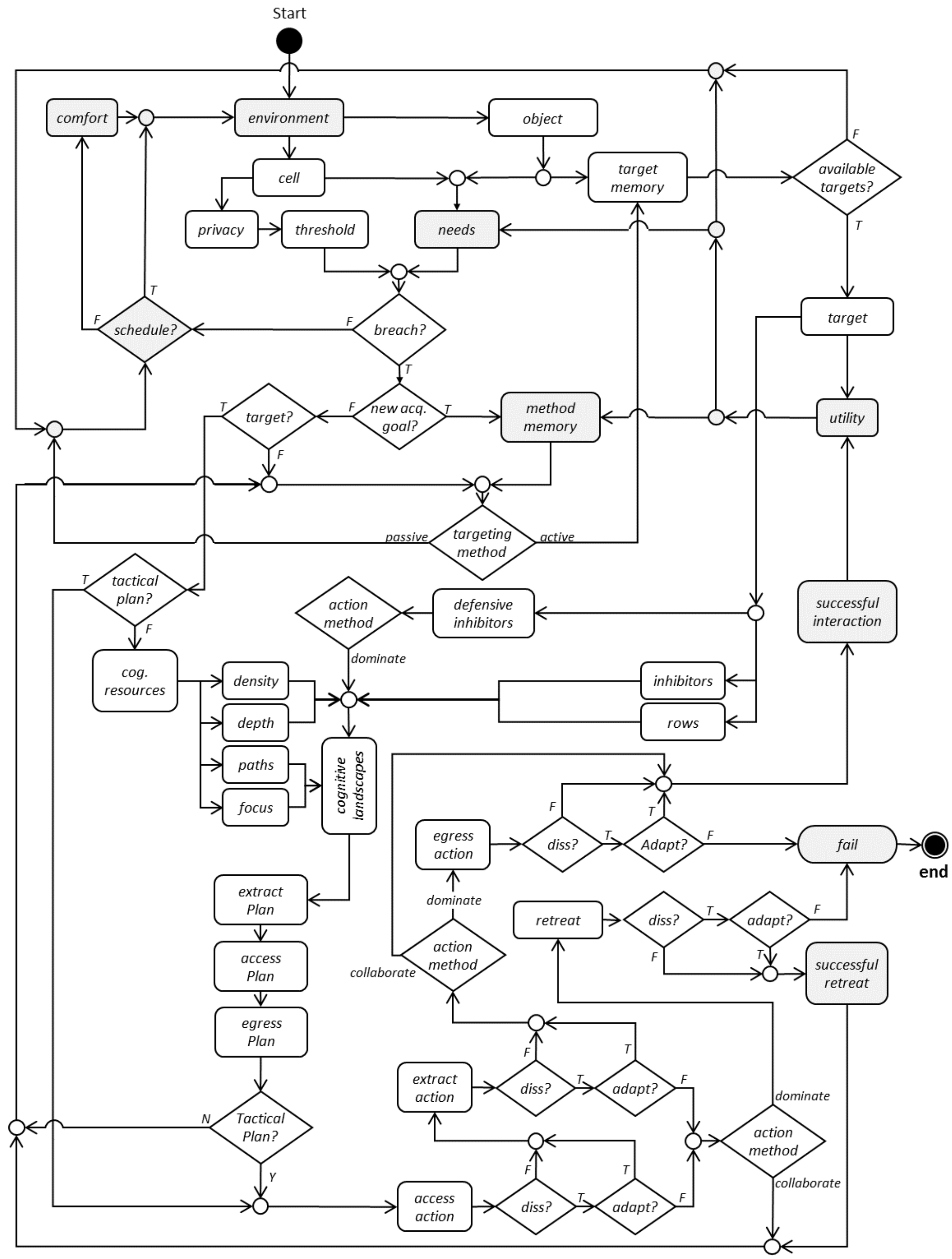

Figure 42: Stage 3 of the integrated model program logic showing the use of the target utility to reduce subject needs, integrate success into method-memory, and the subject's interaction with the environment (elements discussed in the text are highlighted gray).

This process can be further illustrated by re-visiting the example in Equations 15 through 19 discussed earlier in this chapter in which nominal *needs* $\boldsymbol{c}$, accumulated *need values* $\boldsymbol{\eta}$, *threshold values* $\boldsymbol{\varphi}$, *acquisitional goal values* $\boldsymbol{\alpha}$, and *acquisitional goals* $\boldsymbol{g}$ at *time-step t* are given as:

$$\boldsymbol{c} = (A, B, C, D, E) \tag{30}$$

$$\boldsymbol{\eta}_t = (10, 5, 20, 32, 46) \tag{31}$$

$$\boldsymbol{\varphi}_t = (12, 12, 15, 10, 20) \tag{32}$$

$$\boldsymbol{\alpha}_t = (0, 0, 5, 22, 26) \tag{33}$$

$$\boldsymbol{g}_t = (0, 0, C, D, E) \tag{34}$$

If successful “dominant” action against a *target* yields the following specific *utility values*:

$$\boldsymbol{u} = (0.32, 0.15, 0.65, 0.80, 0.56) \tag{35}$$

and the vectors for *cell effect values* $\boldsymbol{\upsilon}$ and current *object effect values* $\boldsymbol{o}$ at *time-step (t + 1)* are:

$$\boldsymbol{\upsilon} = (0, 0, 0.3, 0.8, -0.5) \tag{36}$$

$$\boldsymbol{o} = (5.2, -6.1, 10.6, 0.4, -3.0) \tag{37}$$

Then, according to Equation 29, each new *specific need value* η at the next *time-step* *(t + 1)* is calculated as:

$$\eta_{t+1} = (12, -1.85, 17.9, 7.6, 16.74) \quad (38)$$

Furthermore, given the same *threshold values* $\boldsymbol{\varphi}$ at *time-step* (t+1) as at *time-step* t:

$$\boldsymbol{\varphi}_{t+1} = (12, 12, 15, 10, 20) \quad (39)$$

The new vector of *acquisitional goal values* $\boldsymbol{\alpha}$ and new vector of *acquisitional goals* $\boldsymbol{g}$ for *time-step* (t+1) are:

$$\boldsymbol{\alpha}_{t+1} = (0, 0, 2.9, 0, 0), \quad (40)$$

$$\boldsymbol{g}_{t+1} = (0, 0, C, 0, 0) \quad (41)$$

Thus, in the above example, successful "dominant" action led to fully exploiting the *target's utility* and reduced all of the *subject's need values.* However, the success did not eliminate all of the *subject's acquisitional goals*.[107] In this circumstance, the *subject* will regard the remaining *acquisitional goal* as a new *goal* and begin looking for new *targets.*

[107] Primarily due to an object stimulus that intensified *need* "C."

2.2.8.2 Method Memory

The *subject* tracks successful "dominant" and successful "collaborative" interactions along with the *targeting*, *tactical*, and *action strategies* used to achieve that success in his *method-memory*. The *method-memory* provides the *subject* with a list of nominal *goal* configurations that he has encountered previously and how those *goals* were successfully met. This list is used to derive *preferred methods* for addressing similar emerging *acquisitional goals* (Einstein & McDaniel, 2005). Given successful interaction, the *subject* will add an entry into his *method-memory* that references the vector of nominal *needs* $\boldsymbol{c}$ and correspond to *the vector of utility values* $\boldsymbol{u}$. Thus, a specific *acquisitional goal* addressed by the *target's utility*, or *utility goal* ug, can be represented as:

$$ug = \begin{cases} c, & u > 0 \\ 0, & u \leq 0 \end{cases} \tag{42}$$

Thus, to create a vector of *utility goals* $\boldsymbol{ug}$:

$$\boldsymbol{ug} = (ug_1, ug_2, \dots, ug_n) \tag{43}$$

Appendix B shows the contribution of endogenous and exogenous elements toward the *subject's utility goals*.

The *subject* uses a specific *method-memory* entry *mm* to record the *utility goals* vector $\boldsymbol{ug}$, the *targeting strategy (tar)*[108], the *tactical strategy* to address cognitive resources σ[109], and the *action strategy (act)*[110]. Thus, a specific *method-memory entry* is expressed as:

$$mm = (\boldsymbol{ug}, tar, \sigma, act) \tag{44}$$

and the vector representing method-memory ***mm*** is expressed as:

$$\boldsymbol{mm} = (mm_1, mm_2, \dots, mm_n) \tag{45}$$

Tracking the *utility goal* (as opposed to the *subject's acquisitional goal* or the *targets attributes*) in *method memory* ensures that the *subject* is generating his memory not from what he <u>expects</u> to encounter, but from what he <u>actually</u> encounters. When seeking *preferred methods*, the *subject* compares his current *acquisitional goal* to the *utility goals* that correspond to previous successes and selects those memories that either satisfy or exceed the current *acquisitional goal*.

In addition, the *utility goal* may include additional *needs* that are not part of the *subject's* current *acquisitional goa*l (but are collaterally associated with the *utility* due to previous success). Thus, the *subject* has the potential to develop unintentional

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[108] "active" or "passive"

[109] H, M, or L associated with *density*, *paths*, *depth*, and *focus* (see Equation 25)

[110] "dominant" or "collaborative"

associations of success with additional spurious *needs*. This provides a potential that the *subject* will choose less than optimal methods to address *acquisitional goals* resulting in boundedly rational decision-making.

2.2.8.3 Spatial Awareness

After successful interaction, the *subject* may have satisfied his *acquisitional goal* in total, in part, or not at all. If he has satisfied the entire *acquisitional goal*, then the *subject* returns to his previous *schedule* (if he was following one) and/or travels among known areas of *comfort*. If the *subject* has not satisfied (or has only partially satisfied) the *acquisitional goal*, the *subject* returns to his *method-memory* to look for previous successes to satisfy the new *acquisitional goal*, develop a new set of methods, and proceed to address the *goal* through *tactical planning* and *adaptation*.

Additionally, if the *subject* has used a successful "dominant" *action strategy*, effectively killing the *target*, the *victim/target* is removed from the simulation and references to the *target* in *target-memory* are removed. This means that the *subject* will not consider the victim as a future viable *target*.

2.2.8.4 Model Memory and Burn-in

During implementation of the model, it was necessary to build limitations to the *subject's method-memory* size (for efficient operation). Therefore, it was determined that the *subject's method-memory* would be a fixed length.[111] When the *subject* reaches the

[111] This parameter is set via the *method-memory-size* slider on the interface (see Appendix A: A3).

memory limit, he will begin to over-write old memories in light of newer memories (Koechlin & Hyafil, 2007). For this reason, the *subject's method-memory* will change over the course of the model run, produce limited dynamic associative memories (Eacott & Heywood, 1994) and create an evolving offender that changes his methods (of operation) over-time (Ressler, Burgess, & Douglas, 1988; Salfati & Bateman, 2005).

The integrated model can start with a *subject* that has an empty *method-memory* and begins accumulating memories at the beginning of the model run. However, it was determined this strategy for building *method-memory* does not allow the *subject* to effectively utilize "experience" at the start of the simulation. Therefore, ***burn-in***,[112] is necessary to effectively implement *method-memory*.

To produce *burn-in*, the model can be set to begin preliminary *method-memory* build-up until a user-defined time-step. This initial build-up involves lowering the *subject's inhibitory threshold* and allowing the *need* accumulator to breach the threshold at high frequency. This produces a condensed barrage of cycles through the violent offending process. During *burn-in*, ending the simulation due to failure to egress or retreat is suspended.[113] While the *subject* does not gain *utility* from failed interactions, he will continue to interact and the simulation continues. At a user pre-defined *time-step*, the simulation pauses and current *method-memory*, location information, and spatial *comfort* and *privacy* are recorded. The model components are then reset with the recorded information and the actual model run begins.

[112] A pre-designated period of time to run the simulation prior to collecting data

[113] This is achieved by setting the *capture?* parameter on the model interface (see Appendix A: A1) to "off."

2.2.9 Model Outputs

The integrated model contains a number of different outputs that provide means to evaluate the model for verification and calibration as a viable representation of the violent offending process. Tests using these outputs will be discussed in greater detail in the Verification Section 2.3. However, it is important to discuss how these model outputs were addressed as part of the model implementation.

In the integrated model, the *subject* can transition through ten different states. These states are: *Acq. Goal (α)*, *Tactical Plan (T)*, *Access (A)*, *Extract (K)*, *Egress (D)*, *Fail Action (X)*, *Collaboration (C)*, *Fail/Capture (F)*, *Retreat (R)*, and *No Acq. Goal (¬α)*. Each of these states is defined in Table 3 and can be used to track the *subject* status within the current cycle of the violent offending process.

Table 3: Integrated Model States and definitions.

State		Definition
Acq. Goal	α	The subject has developed an acquisitional goal, but not yet developed a tactical plan.
Tactical Plan	T	The subject has developed a tactical plan but not yet had an opportunity to access the target.
Access	A	The subject has successfully accessed the target (collaborate) or victim (dominate).
Collaboration	C	The subject has collaborated with the target
Extract	K	The subject has extracted the acquisitional goal from the victim, but he has not yet successfully egressed.
Egress	D	The subject has successfully egressed.
Fail Action	X	The subject has failed to access and/or extract the acquisitional goal from the victim and must now attempt to retreat.
Fail/Capture	F	The subject has failed to retreat.
Retreat	R	Although the subject has failed to access and/or extract the acquisitional goal from the victim, he has successfully retreated.
No Acq. Goal	¬α	The subject's acquisitional goal did not persist.

The $\neg\alpha$, C, D, and R states are end states for the cycle because they result in the *subject* re-engaging in the environment and potentially initiating a new cycle of the violent offending process. F is an end state because it ends the simulation. Figure 43 illustrates the ten states listed above:

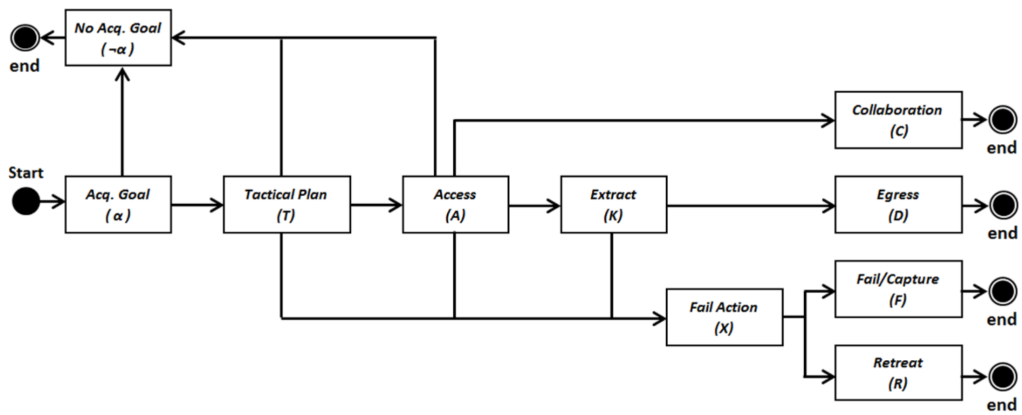

Figure 43: Subject states in the violent offending process.

The number of times the *subject* transitions to each state is counted over the course of the simulation run. These counts are then used to evaluate first order transition probabilities to each state. State counts offer an explicit means to verify the model because the number of transitions into a state equal the number of transitions out of a state and both are equal to the state count. Thus, the number of times the individual is in state i is the sum of the number of times the individual transitioned to state i which is also equal to the sum of the number of times the individual transitioned from state i (unless state i is a terminal state).

Transitions can also be verified by calculating the probabilities of first-order transitions from the current state i to another state j. This can be done in the model, again using the state counts. The probability of transitioning to state j from state i is $P(j|i)$, and can be calculated using the new state counts $c(j)$ and the prior state counts $c(i)$:

$$P(j|i) = {c(j)}/{c(i)} \tag{46}$$

As the *subject* enters various states of the model (with the exception of the *Fail Action* state)[114], the model places a *site-marker* that represents the specific state in the navigation layer of the model "view." This allows spatial configurations of state transitions to be used with various spatial metrics. Additionally, given appropriate temporal scaling of the model during calibration, days can be modeled and utilized, in conjunction with state transitions, for ***days-between-hit*** (***dbh***) metrics and comparisons. Spatial and temporal outputs and their utility in calibrating and validating the model will be further discussed in the Validation Section 2.4.

The integrated model can be set to collect an entire cycle of the violent offending process. Within the integrated model this is referred to as a "narrative" (Auble, 2015) and constitutes a series of directly related events (as illustrated in Figure 43). This function records the *subject's* chain of transitions from development of a tactical plan[115]

[114] The subject does not place a site-marker when he fails to successfully act. This is because this state does not specifically correspond to a physical site.

[115] The model generates frequent *acquisitional goals* that revert back to no *acquisitional goal*. To keep the narratives manageable, the model will only start recording a chain of events once the subject has successfully developed a tactical plan.

to output and notes the methods used, *time-step*, and spatial location of each event. This "narrative" is not only invaluable during verification procedures, but it also provides the means to contextualize events during interpretation of integrated model outputs.

An important part of utilizing the model outputs is in how the outputs are to be contextualized and interpreted. This entails having some idea of what the outputs "mean" (Auble, 2015). Thus, while Figure 43 shows possible states, the interpretation of those states in terms of actual violent offending gives a better sense of how these states can tell a story or script violent offending outcomes (Schank & Abelson, 1975; Beauregard, Proulx, Rossmo, Leclerc, & Allaire, 2007; Leclerc & Wortley, 2013). Table 4 shows the integrated model states and examples of interpretations for each in an analysis of potential "sexual murder" outcomes (Kocsis, Cooksey, & Irwin, 2002; Salfati, James, & Ferguson, 2008; Dover, 2010). The scenario offered by this example will be revisited during verification tests (see Section 2.3) and when calibrating to a real-world series in Chapter 3, Section 3.2.

Table 4: Integrated Model States and an example interpretation.

State		Example Interpretation…(Sexual Murder)
Acq. Goal	α	The subject has developed an interest in exerting control and/or having a sexual experience.
Tactical Plan	T	The subject has developed a tactical plan to either engage the services of a prostitute (collaborate) or abduct a female victim (dominate).
Access	A	The subject has successfully secured the services of a prostitute (collaborate) or abducted a female (dominate).
Collaboration	C	The subject has successfully engaged in sexual interaction with a prostitute (target).
Extract	K	The subject has successfully raped and/or killed the female victim.
Egress	D	The subject has successfully dumped the female victim's body.
Fail Action	X	The subject has failed in his attempt to abduct and/or rape/kill the female victim and must now retreat without being detected or captured.
Fail/Capture	F	The subject has failed to retreat and is either arrested or killed.
Retreat	R	Although the subject has failed in his attempt to abduct and/or rape/kill the female victim, he has successfully avoided detection or capture.
No Acq. Goal	¬α	The subject's interest in exerting control and/or having a sexual experience did not persist.

Given the interpretations assigned to each state in Table 4, a sequence of states, like those found in Table 5, provides cohesive *event-chains* to further analyze.[116]

Event-chains 1, 2 and 3 all result in the subject reverting to a non-acquisitional goal state prior to offending. However, in *event-chain* 5, the *subject* successfully commits a "sexual murder."[117] In *event-chain* 4 the *subject* does not commit a violent offense, but instead employs the services of a prostitute. In *event-chains* 6 through 10,

[116] These *event-chain* narratives are further depicted in Appendix C, along with the causal-path of the event-chain expressed and a state diagram illustrating the *subject's* trajectory through the violent offending process.

[117] The definition of "sexual murder" used here does not differentiate between a murder committed as part of a sexual experience or a rape committed in conjunction with an instrumental murder. For further differentiation between these two types of murder, see Dover (2010).

the *subject* fails at various points during the violent offending process, but gets away in *event-chains* 6 and 8, and he is arrested in *event-chains* 7, 9 and 10.

Table 5: Event-chains and interpretations in a "sexual murder" series.

event-chain 1	**α** The subject has developed an interest in exerting control and having a sexual experience.	**¬α** The subject has lost interest in exerting control and having a sexual experience.	**end**				
event-chain 2	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to abduct a female victim (dominate) or engage the services of a prostitute (collaborate).	**¬α** The subject has lost interest in exerting control and having a sexual experience.	**end**			
event-chain 3	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to abduct a female victim (dominate).	**A** The subject has successfully secured the services of a prostitute (collaborate).	**¬α** The subject has lost interest in exerting control and having a sexual experience.	**end**		
event-chain 4	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to engage the services of a prostitute (collaborate)	**A** The subject has successfully secured the services of a prostitute (collaborate).	**C** The subject has successfully engaged in sexual interaction with a prostitute.	**end**		
event-chain 5	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to abduct a female victim (dominate).	**A** The subject has successfully abducted a female (dominate).	**K** The subject has successfully raped and killed the female victim.	**D** The subject has successfully dumped the female victim's body.	**end**	
event-chain 6	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to abduct a female victim (dominate).	**X** The subject has failed in his attempt to abduct a female victim and must now retreat without being detected or captured.	**R** The subject has successfully avoided detection and arrest.	**end**		
event-chain 7	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to abduct a female victim (dominate).	**X** The subject has failed in his attempt to abduct a female victim and must now retreat without being detected or captured.	**F** The subject has failed to retreat and is arrested.	**end**		
event-chain 8	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to abduct a female victim (dominate).	**A** The subject has successfully abducted a female victim (dominate).	**X** The subject has failed in his attempt rape and kill the female victim and must now retreat without being detected or captured.	**R** The subject has successfully avoided detection and arrest.	**end**	
event-chain 9	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to abduct a female victim (dominate).	**A** The subject has successfully abducted a female victim (dominate).	**X** The subject has failed in his attempt rape and kill the female victim and must now retreat without being detected or captured.	**F** The subject has failed to retreat and is arrested.	**end**	
event-chain 10	**α** The subject has developed an interest in exerting control and having a sexual experience.	**T** The subject has developed a tactical plan to abduct a female victim (dominate).	**A** The subject has successfully abducted a female victim (dominate).	**K** The subject has successfully raped and killed the female victim.	**X** The subject has failed in his attempt to dump the victim's body	**F** The subject has failed to successfully egress and is arrested.	**end**

2.3 Verification

Verification (sometimes referred to as internal validity) "is the process of making sure that an implemented model matches its design" (Crooks, Castle, & Batty, 2008, p. 419). In this dissertation, this was established through a number of verification procedures. Throughout the implementation process, the model code was subjected to incremental tests of functionality and annotation. Once the code was completed, a line-by-line walk-though was performed accompanied by logging procedures to the model *output* field for review. This procedure identified several key coding and logic errors that were corrected.

Verification also included testing parameters associated with the three different stages of the violent offending process as they relate to an established baseline of the integrated model. This was followed by a profile analysis of code procedures, as suggested by Cioffi-Revilla (2014a), to ensure call volumes were appropriate given parameter settings. These two procedures, stage-based testing and profiling, are described in greater detail below.

2.3.1 Stage Parameter Tests

Stage tests had two primary purposes. First, these tests were a form of model verification to ensure that parameters behaved consistently with underlying abstraction and coding of the model. Second, the stage tests were used as sensitivity tests to understand how each set of parameters contribute to outcomes in the model. Table 6 provides a list of the stages, configurations, and parameters tested.

Table 6: Stages tested, test configuration names, and the parameters tested.[118]

	Test Configuration	Parameter(s) Tested
Stage 1: Interactions	Scheduling	*Schedule?*
	Object clustering	*Obj-share-loc?*
		Object-pref?
	Location-based Targeting	*Loc-based-target?*
Stage 2: Tactical Planning & Adaptation	Target Risk	*Target-type?*
		preset-target-type
	Methods	*Manual-method?*
		Variation
Stage 3: Learning & burn-in	Learning	*Use-memory?*
	Burn-in	*Start-sim*

Stage 1 verification tests examined interactions between the *subject* and *targets* within the model "view" and focused on parameters that constrain the *subject's* targeting capacity. By concentrating on *scheduling*, *object clustering*, *and location-based targeting*, these tests assessed the effectiveness of routine activities and spatial awareness on driving *subject* output behavior. Stage 2 verification tests examined the *subject's* internal *tactical planning* and *adaptation* capabilities and focused on parameters associated with constructing and navigating the *subject's cognitive landscapes*. This series of tests evaluated the effects of *target risk* and the *subject's preferred methods* on output behaviors. Stage 3 verification tests examined learning and experience by focusing on *method-memory* and *burn-in*.

The integrated model states for the verification tests were all interpreted in terms of a series of "sexual murders" (see Table 4). In addition, to ensure the verification tests were not affected by issues of scale (see the discussion about scale in Section 2.2.3.1) the following parameters on the interface (see Appendix A: A3) were set to the following

[118] See Appendix A

defaults for all verification tests: *view-width* = 20 miles, *minutes-per-tick* = 1, base-threshold = 1000, and object-effect = 15. These settings are selected based on preliminary testing of the integrated model.

2.3.2 Model Baseline Configuration

To facilitate verification tests, a *model baseline* was run to provide a reference point from which to gauge the efficacy of changes in stage-specific parameters. The *model baseline* configuration is shown in Table 7.

Table 7: Parameters for the model baseline configuration.

Parameter(s) Tested		**Baseline**
Schedule?		OFF
Obj-share-loc?	*contingent on… Schedule? = True*	OFF
Object-pref?		OFF
Target-type?	*contingent on… Obj-share-loc = True& Object-pref? = True*	--
preset-target-type	*contingent on… Target-type? = True*	--
Loc-based-target?		OFF
Manual-method?		OFF
Targeting	*contingent on… Manual-method? = True*	--
Density		--
Paths		--
Moves		--
Focus		--
Action		--
Variation		--
Use-memory?		OFF
Start-sim		0

The *model baseline* configuration was run for 14,400 *time-steps* (equivalent of 10 days), 100 times.[119,120] As shown in Figure 44, transition between each state was calculated and displayed in a Markov model to illustrate *model baseline* first-order transition probabilities.

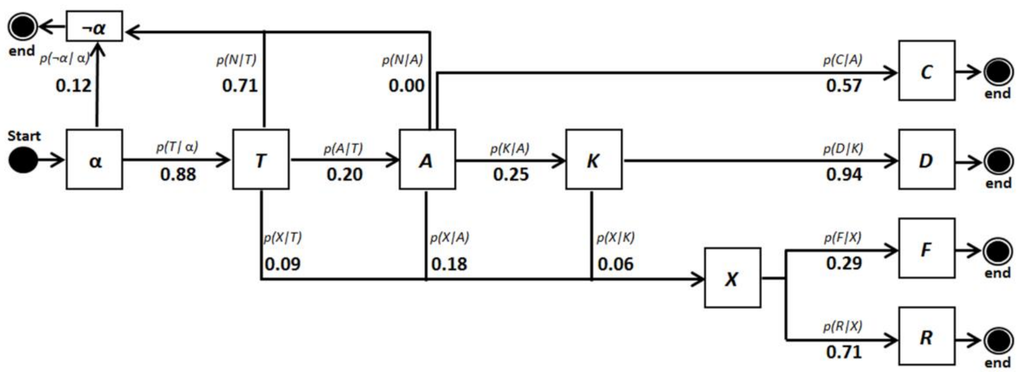

Figure 44: Model baseline first order transition probability p(i|j) between states.

2.3.3 Testing Procedure

The stage-based testing configurations are listed in Table 8. Each of the test configurations consists of the baseline configuration with parameter variation. The parameters used in each stage are located on the integrated model interface illustrated and further described Appendix A.

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119 With variations in the model random seed

120 The subject's *need* accumulator is always active. It is acknowledged that this may not be a "realistic" representation of developing needs because it does not appear to account for sleep. However, there is some research that suggests cognitive processes (Mueller & Dyer, 1985; Stark & Squire, 2001; Schott, et al., 2004; Suzuki, 2005) and *needs*, as "hard-wired" and implicit drives (Slade, 1994; Sun, 2009), do not always operate at a conscious level. For this reason, and because the subject is constantly stimulated by the environment regardless of schedule, the subject's needs were allowed to accumulate at all times.

In the Stage 1 verification tests, the *Scheduling* configuration set the *schedule?* parameter to “on”. The *Object clustering* configuration set the *obj-share-loc?* and *object-pref?* parameters to “on”. The *Location-based targeting* configuration set the *loc-based-target?* parameter to “on”.

In the Stage 2 verification tests, the *Object risk* configuration set *object clustering* and *target-type?* parameters to “on” and tested the *preset-target-types* parameter set to “high-risk” and “low-risk”. The *Methods* configuration set the *manual-methods?* parameter to “on,” *targeting strategy* to “active,” the *density*, *paths*, *moves*, and *focus* resources to “M”, *action strategy* to “dominant,” and tested variation parameter at 0%, 25%, and 50%.

In the Stage 3 verification tests, the *Learning* configuration set the *use-memory?* parameter to “on.” The *Burn-in* configuration set the *use-memory?* parameter to “on” and set the s*tart-sim* parameter to 14,400 time-steps.[121]

[121] The *Burn-in* configuration runs from 0 to 14,400 *time-steps* during *burn-in* and then from 14,400 to 28,800 *time-steps* during the substantive simulation.

Table 8: Stage-based testing configurations.

		Stage 1: Interactions			Stage 2: Tactical Planning & Adaptation		Stage 3: Learn & Burn-in	
Parameter(s) Tested		**Scheduling**	**Object Clustering**	**Location-based Targeting**	**Object risk**	**Methods**	**Learning**	**Burn-in**
Schedule?		**ON**	OFF	OFF	OFF	OFF	OFF	OFF
Obj-share-loc?	*contingent on… Schedule? = True*	OFF	**ON**	OFF	**ON**	OFF	OFF	OFF
Object-pref?		OFF	**ON**	OFF	**ON**	OFF	OFF	OFF
Target-type?	*contingent on… Obj-share-loc = True& Object-pref? = True*	--	--	--	**ON**	--	--	--
preset-target-type	*contingent on… Target-type? = True*	--	--	--	**high/low**	--	--	--
Loc-based-target?		OFF	OFF	**ON**	OFF	OFF	OFF	OFF
Manual-method?		OFF	OFF	OFF	OFF	**ON**	OFF	OFF
Targeting	*contingent on… Manual-method? = True*	--	--	--	--	**"active"**	--	--
Density		--	--	--	--	**M**	--	--
Paths		--	--	--	--	**M**	--	--
Moves		--	--	--	--	**M**	--	--
Focus		--	--	--	--	**M**	--	--
Action		--	--	--	--	**"dominate"**	--	--
Variation		--	--	--	--	**0/25/50**	--	--
Use-memory?		OFF	OFF	OFF	OFF	OFF	**ON**	**ON**
Start-sim		0	0	0	0	0	0	**14400**

Each configuration was run for 14,400 *time-steps* (to simulate 10 days), 100 times. As with the model baseline, a Markov model was used to map first-order transition probabilities from each state i to the next j. For each Markov model, the mean difference *(deltas)* between transition probabilities of the test configuration *(P_1)* and the *model baseline (P_2)* were calculated as $\Delta\bar{P}$:

$$\Delta\bar{P}(j|i) = \bar{P}_1(j|i) - \bar{P}_2(j|i) \tag{47}$$

As shown in Figure 45, *delta* transition probabilities were captured and displayed on a *delta* Markov model to understand how test configuration probability outcomes changed from the baseline. Differences were measured using a *t-score* and significance was determined by calculating two-tailed *p-values*. Significant findings are reported with either * ($p < 0.05$) or ** ($p < 0.01$). The results of these stage-based verification tests are shown and discussed below.

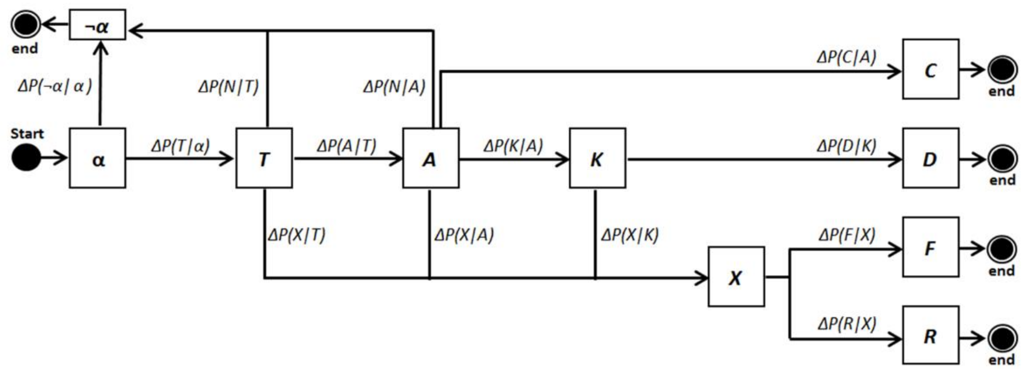

Figure 45: A delta (Δ) Markov model is used to illustrate the difference between test and baseline configuration first order transition probabilities (PΔ).

2.3.4 Stage 1 Verification

The first stage focused on testing exogenous interactions between the *subject* and *objects* within the environment. The environment of the stage-based tests offered significant opportunity to create a variety of different spatial arrangements between the *subject's* routine-based *anchor-points* and movement while pursuing *needs-based goals*. As the verification test results inform calibration of the model, the *delta* transition probabilities are discussed in terms of significant and/or interesting findings.

2.3.4.1 Scheduling

As Figure 46 illustrates, turning *scheduling* “on” significantly improves the *subject’s* probability of *accessing* a *target* (0.17**), reduces his probability of not being able to create a tactical plan (-0.14*), and increases his propensity to successfully collaborate (0.15*).

It is possible that *scheduling* creates an environment in which the *subject* has a better chance of identifying *targets* and locations he has encountered in the past, and is likely to repeatedly encounter due to his routine *activity-space*. Storing these *targets* (or *target* locations) in his *target-memory* leads to relatively quick selection of a potential *target*, *tactical planning*, and attempted *action*. Thus, *scheduling* seems to facilitate *target-memory* and is an important consideration when calibrating the model.

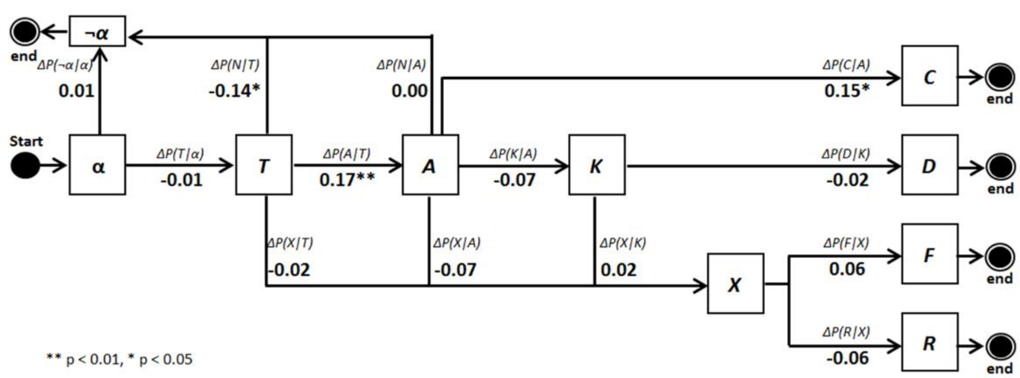

Figure 46: Scheduling (on) change in transition probability from Model baseline (ΔP).

2.3.4.2 Object Clustering

Figure 47 shows that when *object clustering* is "on" there is a significant increase in the *subject's* probability to successfully access a *target* (0.37**). Additionally, the *subject* is significantly more likely to pursue a "collaborative" *action strategy* (0.28**) and significantly less likely (-0.17**) to pursue a "dominant" *action strategy*. Both of these factors significantly decrease the *subject's* likelihood of failing to access a *target* (-0.07*) overall, or kill a *target* (-0.11*) when pursuing a "dominant" *action strategy*.

These results verify that clustering has a significant effect on the *subject's* efficacy in targeting. There also appears to be a greater propensity to incorporate a "collaborative" *action strategy* which is a significant consideration for model calibration. This is especially true if a comparison series involves a target-rich environment.

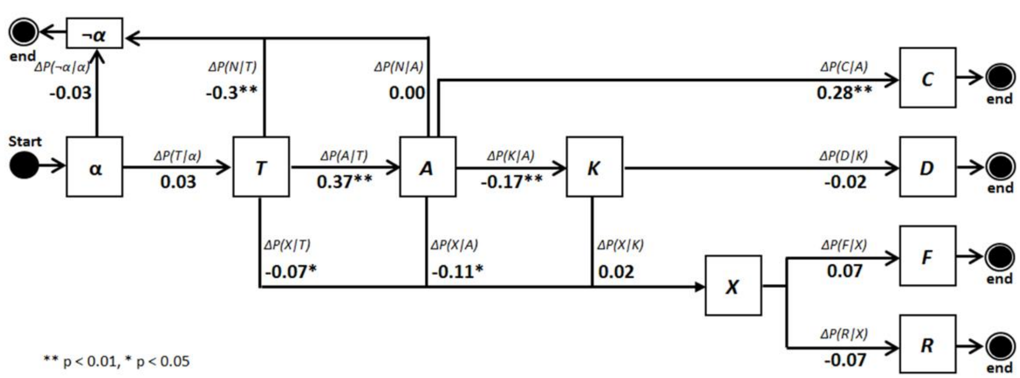

Figure 47: Cluster (on) change in transition probability from Model baseline (ΔP).

2.3.4.3 Location-based Targeting

As indicated in Figure 48, the location-based targeting test configuration did not produce significant results when compared to the *model baseline*. This may be due to the *subject's* tendency to frequent areas that are already *anchor-points* for a significant number of *objects*. Thus, the *subject* may be likely to encounter an *object* with desired attributes in the same general areas as originally recorded in *target-memory*. This could obfuscate whether the *subject* was targeting the location or the *object*. In conjunction with *object clustering*, however, *location-based targeting* may be useful to configure a *subject's* specific victim selection preferences to target-rich areas. For this reason, location-based targeting may still prove to be useful during calibration.

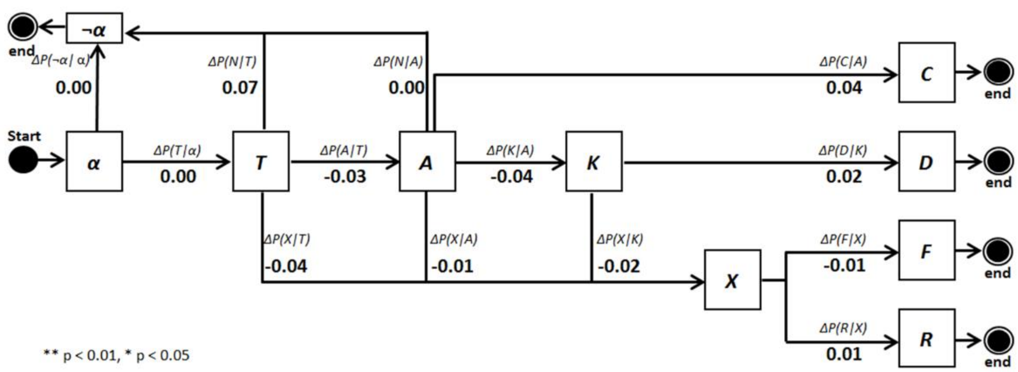

Figure 48: Location-based (on) change in transition probability from Model baseline (ΔP).

2.3.5 Stage 2: Verification

The second stage focuses on testing endogenous factors of *tactical planning* and *adaptation* within the *subject's* cognitive landscapes.

2.3.5.1 Risk

In Figure 49, a “high-risk” *target* configuration significantly increases the *subject’s* probability of successfully accessing a *target* (0.30**) and significantly reduces the *subject’s* failure to create a tactical plan (-0.25**). Additionally, a “high-risk” configuration significantly increases the *subject’s* propensity to be successful if pursuing a “collaborative” *action strategy* (0.22**), and decreases his tendency to fail to kill a victim if pursuing a “dominant” *action strategy* (-0.13**).

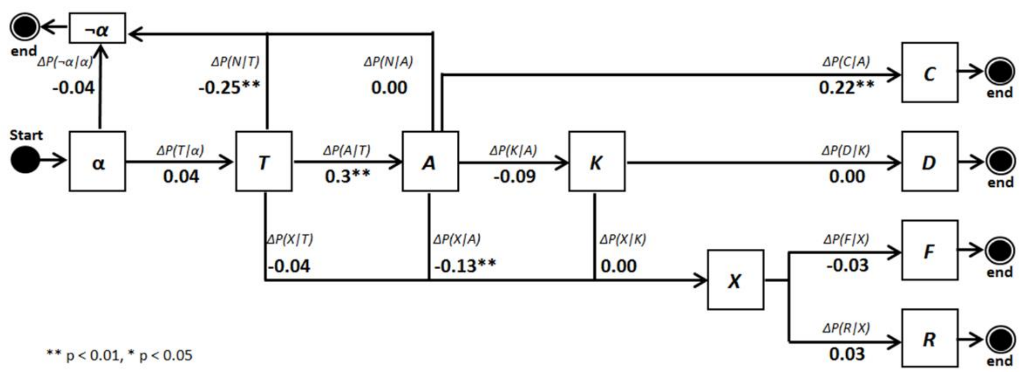

Figure 49: “High-risk” target change in transition probability from Model baseline (ΔP).

In Figure 50, a “low-risk” *target* configuration significantly increases the *subject’s* probability of successfully accessing a *target* (0.37**) and significantly reduces the *subject’s* failure to create a tactical plan (-0.30**). Additionally, a “low-risk” configuration significantly increases the *subject’s* propensity to be successful if pursuing a “collaborative” *action strategy* (0.27**). This configuration also significantly reduces the *subject’s* tendency to <u>attempt</u> to kill a victim (-0.17**) but decrease his tendency to fail when doing so (-0.10*) indicating an overall reduction in the *subject's* tendency to select a "dominant" *action strategy*, but effective implementation of the "dominant" *action strategy* when utilized.

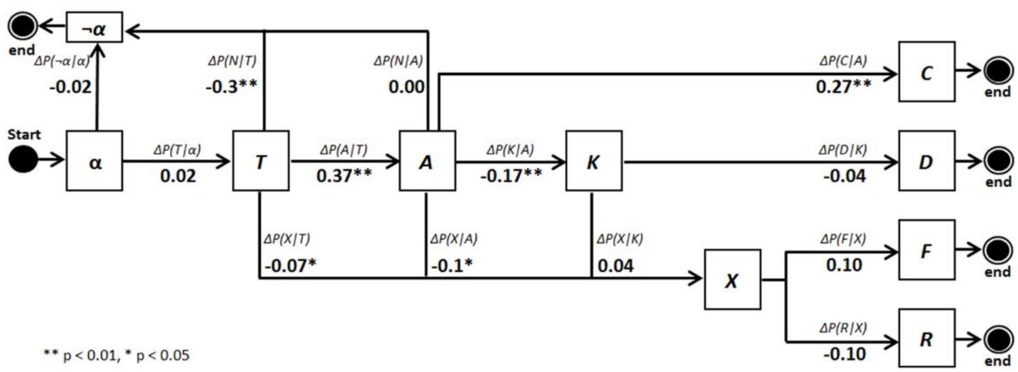

Figure 50: "Low-risk" target change in transition probability from Model baseline (ΔP).

Both the "high-risk" and "low-risk" configurations increase the *subject's* ability to access a *target*, decrease failures in creating a tactical plan, increase collaborations, and decrease tendencies toward a "dominant" *action strategy*. This is likely because both configurations utilize *object clustering*. Thus, some of these findings are likely conflated with the effects of *object clustering*.

However, if the "high-risk" and "low-risk" configurations are compared to each other (effectively controlling for *object clustering*), as in Figure 51, there is a higher tendency in a "high-risk" configuration for the *subject* to kill a victim (0.09*) and if he fails an attempted offense, to successfully retreat (0.14*). This makes sense given that *targets* at "high-risk" pose fewer inhibitors to a *subject* than *targets* at "low-risk".

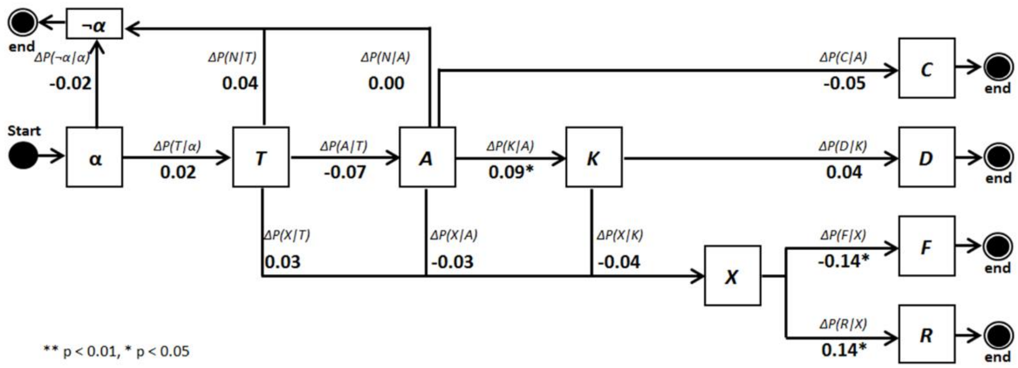

Figure 51: "High-risk" victim v. "Low-risk" victim change in transition probability (ΔP).

2.3.5.2 Methods

The baseline configuration selects *preferred methods* based on a random selection from a (flat) distribution of methods. The *Method* configuration tests the efficacy of variations in the *manual-methods* settings. All possible *manual-method* configurations are not tested.[122] However *variation* is tested. The expectation, then, is that when *variation* is set to 0%, (no variation from the default *manual-method* settings) there will be a significant difference from the baseline and no significant difference when *variation* is set to 50%.

In the method variation tests (Figure 52 – Figure 54) the default action method is set to "dominant" (Ressler, Burgess, & Douglas, 1988; Reiss & Roth, 1993; Stone, 2001; Kocsis, Cooksey, & Irwin, 2002; Salfati & Taylor, 2006; National Center for the Analysis of Violent Crime, 2007). Thus, the *subject* will select a "dominant" *action*

[122] Testing all manual-method configurations (without variation) would entail 324 separate test configurations.

strategy with the designated amount of *variation*. This means when *variation* is set to 0%, the *subject* should always select a "dominant" *action strategy*. As this variation slides toward 50%, the *subject's* tendency to favor a "dominant" *action strategy* should become much less pronounced until at 50%, he is just as likely to select a "collaborative" *action strategy*.

As illustrated in Figure 52, if *variation* is set to 0%, the *subject* is significantly more likely to create a tactical plan after developing an *acquisitional goal* (0.11**), but less likely to access a *target* (-0.16**) and more likely to return to a non-breach state (0.19**). If the *subject* does access a *target*, then he is significantly more likely to kill the *target* (0.44**) or fail while attempting to kill a *target* (0.13*) indicating that the *subject* is much more likely in general to pursue a "dominant" *action strategy*.

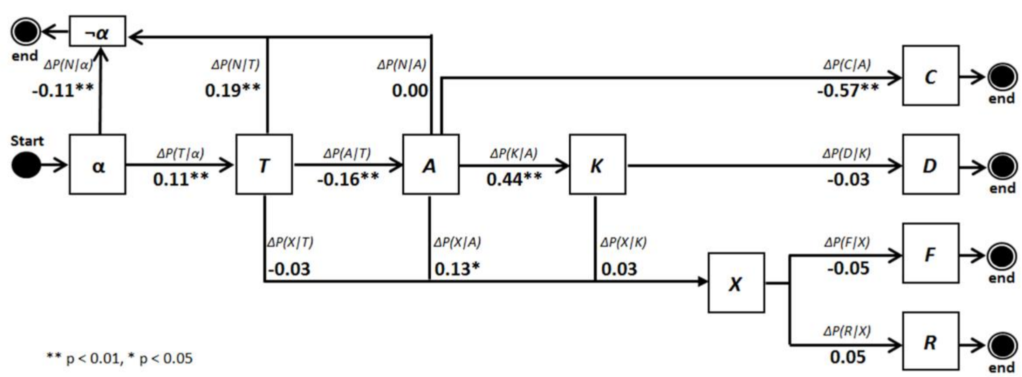

Figure 52: Method variation (0%) change in transition probability from Model baseline (ΔP).

Figure 53 illustrates that when variation is set to 25% the *subject* still has a significantly higher tendency than the baseline configuration to kill the *target* (0.13*) and a lower tendency to collaborate (-0.19*). This is, like the previous configuration (*variation* = 0%), an artifact of the *subject's* tendency to vary from a "dominant" *action strategy* 25% of the time.

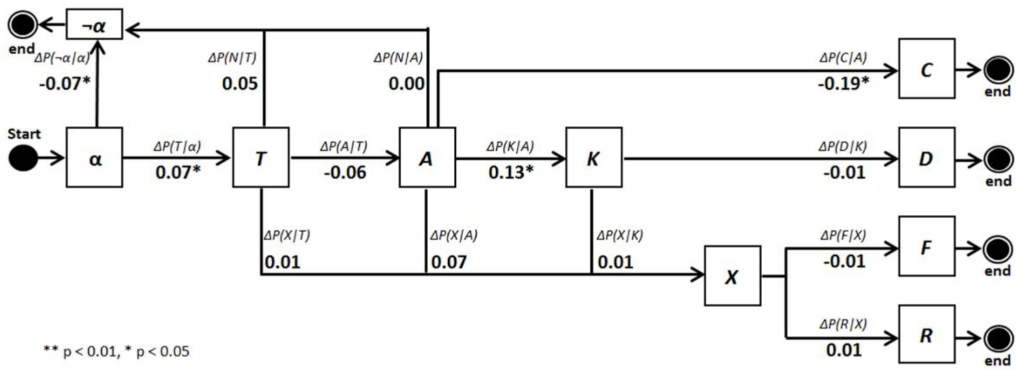

Figure 53: Method variation (25%) change in transition probability from Model baseline (ΔP).

Figure 54 illustrates that, as expected, there is no significant difference between the method configuration when variation equals 50% and the baseline configuration. The overall results from the Method tests (Figure 52-Figure 54) appear to verify the underlying functionality of the variation parameter.

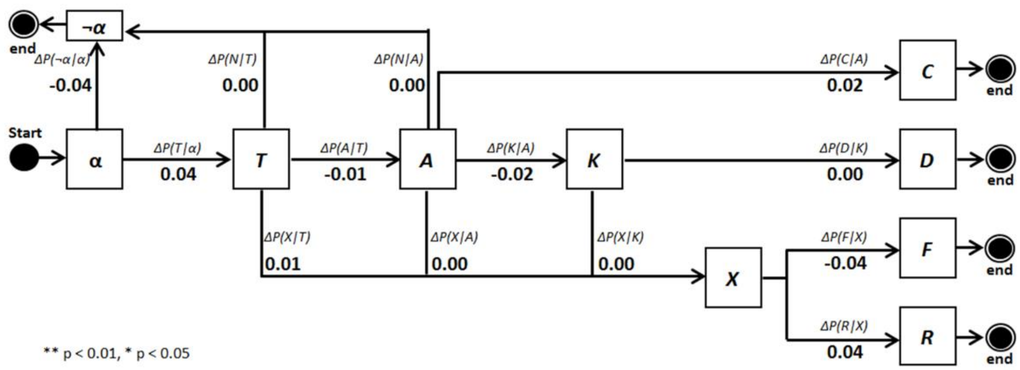

Figure 54: Method variation (50%) change in transition probability from Model baseline (ΔP).

2.3.6 Stage 3: Verification

The third stage focused on testing the *subject's* ability to learn from previous experience and successful methods for achieving *goals*. This relies on feedback from integrated model outputs and the incorporation of successful methods in the *subject's method-memory*.

2.3.6.1 Learning

The learning test configuration involved implementing *method-memory* in lieu of the *manual methods* tested in Stage 2. As is illustrated in Figure 55, *method-memory* alone did not produce significant differences in transition probabilities over the model baseline. This was not unexpected and is likely because the model runs were relatively short and did not allow the *subject* sufficient time or enough experiences to noticeably learn from interactions.

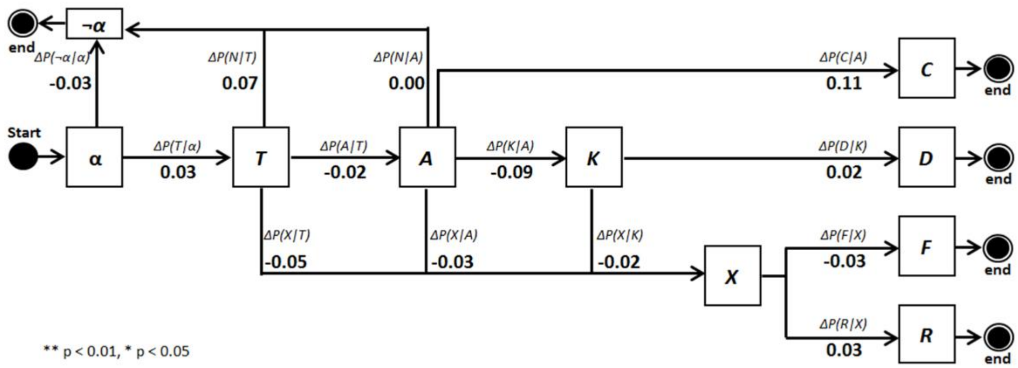

Figure 55: Delta Method-memory (on) change in transition probability from Model baseline (ΔP).

2.3.6.2 Burn-in

When the *subject* is allowed *burn-in* time (10 days) and intense exposure to *goal* development, Figure 56 shows that there is an increases in the probability of successful tactical planning (0.08*) and "collaborative" *action strategy* (0.30**), but a significant decrease in the probability of killing the *target* (-0.23**). This implies that *burn-in* leads to a more likely choice of "collaboration" as a successful *action strategy*. This is useful information for calibrating the model to a real-world comparison series.[123]

[123] see Chapter 3, Configuring the GRK Series Section 3.2.

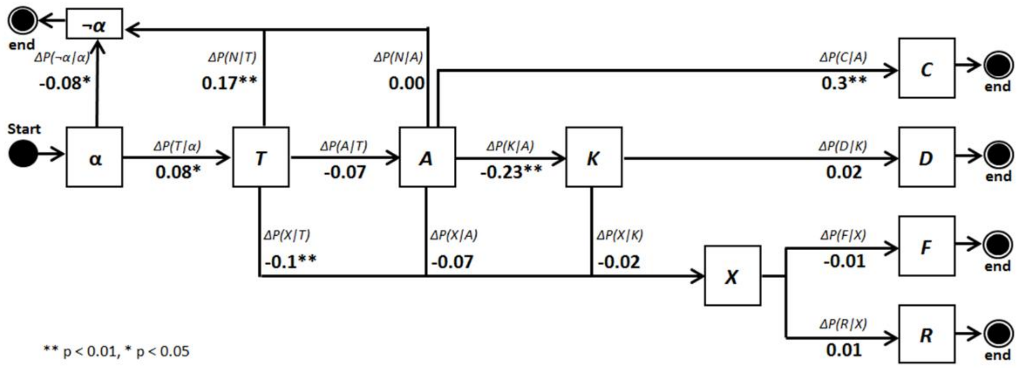

Figure 56: Burn-in (10 days) and Method-memory (on) change in transition probability from Model baseline (ΔP).

2.3.7 Code Profiles

For each stage-based verification test, three runs were profiled to ensure the frequency of called procedures made sense. The code profiles were aggregated and a mean profile for each test configuration was produced. These aggregated code profiles can be found in Appendix D.

There were 52 procedures called among all of the profiled simulation runs. Five of these procedures were related to *burn-in*[124] and were only called during the *burn-in* configuration tests. Of the remaining 47 procedures, 16 are only called once per time-step and 1 is called once per time-step with an additional call upon simulation end. The most frequently called procedures involved in *object* navigation and scheduling.[125] The third most common procedure called is used to reset a series of internal switches that

[124] These procedures control other procedures dedicated to saving *method-memory* and location information and resetting the model during transition from *burn-in* to actual simulation

[125] Although *scheduling* was only turned "on" during one of the tests, *objects* actually set a schedule at each time-step. The *scheduling* parameter only determines whether or not the *objects* follow their schedule. This procedure operates in the background so that *scheduling* can be turned "on" during a simulation run.

keep track of *subject* states. Given the context of the verification tests, code profiling revealed that all procedures are being called appropriately. There are no discrepancies or abnormalities noted.

2.4 Validation

External validation involves structural and behavioral (how the model behaves) validity (Cioffi-Revilla, 2014a). Structural validity focuses on theoretical and empirical examination and “refers to internal features of the model, including main assumptions concerning relevant agent attributes, interaction rules, and environments” (Cioffi-Revilla, 2014a, p. 297). Behavioral validation focuses on how well the model approximates the referent system it was implemented to represent (Crooks, Castle, & Batty, 2008). The key to behavioral validation is the comparison of empirical data to simulation outputs to determine “whether simulated spatial patterns generated by an ABM [or other model] correspond to known empirical patterns in its referent system” (Cioffi-Revilla, 2014a, p. 299)

In this dissertation, structural validation is achieved in Chapter 2 (Section 2.2 and Section 2.3) through the abstraction and specification of implicit theoretical concepts behind model elements and the implementation of those abstractions within explicit program logic.

Behavioral validation is an ongoing procedure that is important in understanding the integrated model’s practical application to real-world circumstances. However, because this model focuses, in part, on internal features of the violent offending process, data to empirically validate this model are not readily available. In fact, one of the proposed contributions of this modeling effort is to create a mechanism to generate synthetic data for hidden features.

To explore whether or not the integrated model provides meaningful insights into the internal and external drivers of offending behavior, it will be calibrated to a real-world murder series. While beyond the scope of this dissertation, the violent offending process implemented in the integrated model does not apply exclusively to serial violence (Dover, 2010). In fact, the implemented model is quite capable of producing a subject who does not offend or offends only once. However, there are significant advantages to calibrating the integrated model to a series of murders.

From 2010 to 2014, there were approximately 14,000 to 15,000 murders in the United States per year (Uniform Crime Reports, 2014). There is a general sense that only a fraction of these murders are part of a series (Douglas & Burgess, 1986; Egger, 1990; Petee & Jarvis, 2000). Yet, there are no well-supported estimates of the occurrence of serial murder primarily because the phenomenon presents a conundrum; *how do you definitively determine whether unsolved murders are committed by the same offender unless that offender is in custody or forensic evidence links the cases?* Some estimates state that “there are between twenty-five and fifty serial killers operating throughout the U.S. at any given time” (Bonn, 2014, p. 2). However, these estimates are based on known serial murders or linked cases. Thus, researchers are not entirely aware of how many unsolved or unlinked cases should, in fact, be linked to a series. This presents a prime example of a hidden population of offenders. For a comprehensive exploration of the challenges facing research on violent serial offending, see Petee and Jarvis (2000).

Additionally, applying the integrated model to a series of murders, because it incorporates "primed, non-offending" and "primed, offending" outcomes, provides potential insight into the role of internal and external subject features in series longevity and tempo. Thus, calibrating the integrated model to a murder series will provide an empirical comparison of how well the model can reasonably and consistently approximate a real-world scenario.[126]

2.4.1 Calibration Procedures

"Calibration involves fine-tuning the model to a particular context and this means establishing a unique set of parameters that dimension the model to its data. This is not validation per se but calibration can often involve validation because the parameters are often chosen so that performance of the model related to data is optimal in some way, in terms of some criterion of goodness of fit." (Crooks, Castle, & Batty, 2008, p. 419)

The "Scenario Builder" on the integrated model interface is designed to assist in configuring the model to a specific series. This entails identifying the geospatial and temporal scale and back-drop of the scenario, identifying *anchor-points* for the offender, and locating known *event-sites* (*i.e.*, *abduction-sites* or *kill-sites*) for comparison to simulated sites. The simulation setup then uses these *anchor-points* and known *event-*

[126] For a discussion of a similar process used to validate a model of households in East Africa see Kennedy, Cotla, Gulden, Coletti, & Cioffi-Revilla (2014).

sites to create a simulated *activity-space* that is utilized by the *subject* during the simulation run.

In addition, qualitative details of the series are reviewed to understand what combinations of integrated model parameter settings are likely to be the most appropriate. During configuration, the following are considered: *comfort*, *privacy*, *scheduling*, *location-based targeting*, *object clustering*, *preferred methods*, *target risk*, and *learning methods*. After reviewing the real-world series details, it is possible that multiple model configurations may be developed and tested.

2.4.2 Comparison Metrics

It is important to note that once the model has been configured, the purpose of simulation runs is to reproduce aspects of the real-world scenario. Thus, there must be careful consideration as to how the simulation runs will be compared to the real-world scenario. Comparisons are made based on temporal metrics, spatial metrics, and qualitative matching criteria. These comparison metrics provide ad hoc goodness of fit measures that are based on qualitatively observable and quantitatively measurable model and real-world outputs.

2.4.2.1 Temporal Metrics

Temporal comparisons are made by collecting the *time-step* (converted to day) that a specific type of event takes place and calculating the number of days until the next one.

This is referred to as *days-between-hits* and can be applied to accesses (abductions) or kills depending on the specific comparison series.[127]

To better understand the tendency for a simulated series to match *dbh* spacing of a comparison series, a metric was developed that calculates the mean distance of each hit-day from the mid-point between the preceding and following hit-days. This *dbh-score S* is calculated as follows:

$$S = \sqrt{\sum_{i=2}^{n} \left(\frac{p_i - \frac{p_{i+1} - p_{i-1}}{2}}{n} \right)^2} \tag{48}$$

where *p* represents a hit-day in the series of hit-days. Note that the calculation requires at least three hit-days, *(i)*, *(i-1)*, and *(i+1)*. The closer the *dbh-score* is to zero, the more regular the *dbh* spacing in the series.

For example, Figure 57 illustrates the *dbh-score* with 10 example hit-days. In *series A* hit-days are clustered around the first and last days of the series (S = 0.25). In *series B* three hit-days cluster at the beginning and end of the series while there is a cluster of four hit-days in the middle (S = 0.14). *Series C* indicates slightly more regular hit-day spacing (S = 0.05), and in *series D* the hit-days are evenly distributed across the whole series (S = 0.000).

[127] In some series, *access* or abduction dates might be more appropriate if the kill dates are not known.

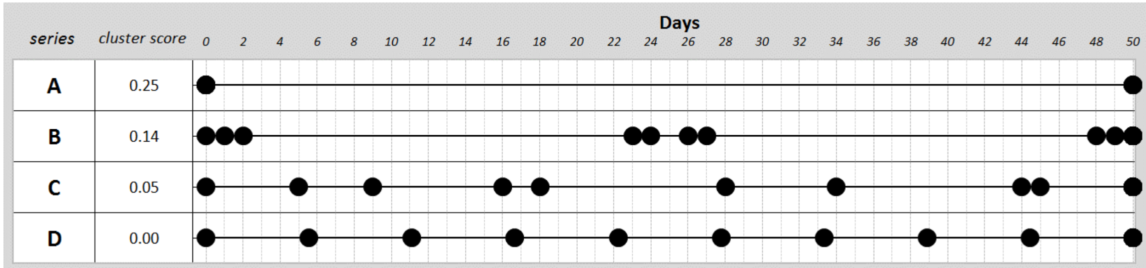

Figure 57: Timelines illustrating the dbh-score (S) as applied to four series with 10 example hit-days each.

2.4.2.2 Spatial Metrics

It is important to have a clear idea of what *event-sites* offer relevant spatial *comparison-sites*. In some series, *kill-sites*, if known, may provide the best *comparison-sites*. However, in other series, especially if the *kill-sites* are unknown and different from body *dump-sites*, *dump-sites* may be the more appropriate *comparison-sites*.

Spatial comparisons can be made using two metrics that are calculated at the end of each simulation run. First, the mean distance of specified[128] *simulated-sites*[129] from the closest known *comparison-site*[130] is calculated. This is referred to as the *comparison location score*. The closer the score is to zero, the closer the match to comparison *event-sites*. Second, the proportion of *comparison-sites* that are accounted for by *simulated-sites* is calculated. This is referred to as the *comparison completeness score*. The closer the score is to 1, the closer the simulated output has come to accounting for all *comparison-sites*.

[128] Specific type of site *(i.e., kill-site* or *dump-site*) being used for comparison in the scenario.

[129] *Simulation-sites* are the simulated *event-sites*.

[130] *Comparison-sites* are the comparison *event-sites* of the real-world scenario.

In addition, ***centroid*** calculations for the "series" spatial center-of-gravity are also helpful (Elnekave, Last, & Maimon, 2007; Buscema, Breda, Grossi, Catzola, & Sacco, 2013). To understand dynamic directionality of events, *x* and *y* coordinates for sequential triads of *dump-sites* are used to produce triangle *centroids A(x,y)*:

$$A(x, y) = \left(\frac{x_i + x_{i-1} + x_{i-2}}{3}, \frac{y_i + y_{i-1} + y_{i-2}}{3}\right) \quad (49)$$

Simulation-site centroids are used to create series-specific ***centroid-paths*** for different simulation configurations. These paths are then compared to the centroid-path of the scenario *comparison-sites* to better understand how the simulated series spatially evolves when compared to the real-world series.

2.4.2.3 Qualitative Matching Criteria

A set of matching criteria is developed to assess how well simulation outputs reproduce the comparison series. In addition, to the spatial metrics and the temporal metrics discussed above, other metrics the like length of the comparison series (in days) and the number of events are used to make non-trivial comparisons. Appropriate qualitative matching criteria are series-specific and require extracting suitable comparison criteria from the real-world scenario.

CHAPTER 3: ANALYSIS & RESULTS

Chapter 2 abstracts and implements an integrated model of the violent offending process and conducts a number of verification tests to ensure internal validity. The chapter concludes by offering a procedure to calibrate the model and compare outputs to a real-world series of violent offenses. This chapter will focus on describing the application of this calibration procedure to a specific series (Section 3.1), testing the procedure for configuring the model to a real-world series (Section 3.2), and the results of a comparison between this series and simulated results from the integrated model (Section 3.3).

3.1 Series Scenario

The real-world comparison series selected is The Green River Killings (GRK) in the Pacific Northwest of the United States. This series was chosen because it is well documented, it was solved with the arrest of the offender (Gary Ridgway), and because there is a significant amount of open-source spatial and temporal information about the series available outside of law enforcement sources.

The 49 murders that Gary Ridgway is known to be responsible for took place from 1982 to 1998 and were centered around the Seattle-Tacoma Metropolitan area in Washington State. The majority of the victims were taken from International Boulevard along the east side of the Sea-Tac International Airport. This area was well known as a prostitute “stroll,” and Ridgway’s victims were young women that frequented the area.

The victims were solicited for prostitution by Ridgway and taken in his vehicle either to secluded areas or to his home (which was in a nearby neighborhood) where Ridgway would engage the victims (sometimes consensually and sometimes non-consensually) in sexual intercourse. After killing a victim, Ridgway would drive to a secluded area where he would dump her nude or partially clothed body. Ridgway was known to return to these locations to watch the victims decompose and/or to have sex with the body (Lackey, Jones, & Johnson, 2015). Many of the victims' decomposed and/or skeletonized remains were not found until weeks, or even years later.

Ridgway was married three times and his wives/girlfriends indicated that he was hyper-sexual, often demanding sex several times a day and frequently using the services of prostitutes (Lackey, Jones, & Johnson, 2015). After leaving the Navy, Ridgway worked as a truck painter at the Kenworth Truck Company in Renton, Washington, approximately four miles northeast of the Sea-Tac International Airport. His address was less than a mile southeast of the Sea-Tac International Airport (Montaldo, 2011).

3.2 Configuring the GRK Series

The GRK series and Ridgway's personal and social behaviors provide a number of data points that can be significantly represented in the integrated model. Although the entire GRK series involved at least 49 murders, it was decided that the current comparison would focus on the first nine murders. The first nine incidents were consolidated to an area within King's County (within the Seattle-Tacoma Metropolitan area), and occurred within the first 74 days of the series between July 8, 1982 and September 20, 1982. This provides a focused set of spatial (consolidated within the model view) and temporal outcomes to drive model configuration. While the tenth abduction occurred 6 days after the ninth, the tenth and eleventh victims were recovered in regions significantly outside of the Kings County area.[131]

The GRK series involved sexual murders. Therefore, integrated model states for the verification tests were all interpreted in terms of a series of "sexual murders" (see Table 4). In addition, the view-width was set 20 miles to match the scale of the reference maps, *minutes-per-tick* was set to 1 to ensure significant opportunities for the subject to interact in the environment, and base-threshold was set to1000 to ensure the model was instantiated with a subject who would not immediately begin developing acquisitional goals (prior to building a *target-memory*). These parameter values were held constant across all GRK calibrations.

3.2.1 Model "View"

Several maps of the GRK victim *dump-sites* were located online from a variety of sources.[132] These maps were used to identify relevant spatial locations on a street map view of the same area from the MapQuest website[133] and then imported into the integrated model. The model scale was matched to the scale of the imported maps (20 miles by 20 miles). Spatial features including water areas, *anchor-sites*, and the first nine

[131] see Chapter 4, Section 4.1.1 for a discussion of the spatial findings.

[132] seattletimes.nwsource.com/art/news/local/greenriver/graphics/grbodies.gif
seattletimes.nwsource.com/art/news/local/greenriver/graphics/bodymap06.gif
seattletimes.nwsource.com/art/news/local/greenriver/graphics/grresidences.gif
www.asesinos-en-serie.com/new/wp-content/uploads/2012/08/gary-ridgway-victimas-asesinatos-maps-of-killings.jpg

[133] www.mapquest.com

victim *dump-sites* were manually located and marked in the model “view”. *Anchor-points* defined in the model were Ridgway’s home prior to 1987 (“*home”*), Kenworth Truck Company in Renton (“*work”*), and the north boundary, middle, and south boundary of the International Boulevard prostitute “stroll” (“*play”*). Figure 58 shows the original GRK series map and spatially relevant sites used to configure the integrated model. *Dump-sites* 1, 3, 4, 5, and 6 are along the Green River. *Dump-sites* 2 and 8 are in the prostitute “stroll” area.

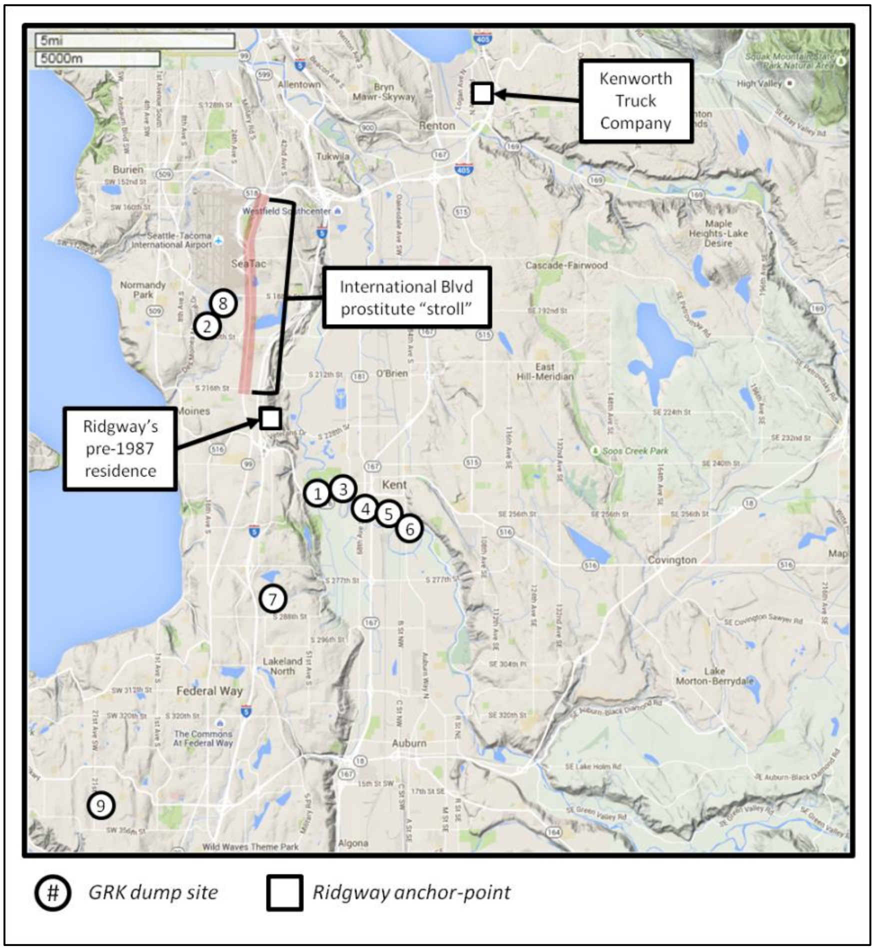

Figure 58: The first nine Green River Killings associated with Gary Ridgway. Most of the victims were abducted from the International Boulevard prostitute “stroll.” Also shown are Ridgway’s home and work anchor-points.

Figure 59 illustrates the configuration of the GRK series *dump-sites* and Ridgeway’s *anchor-points* in the integrated model “view.”

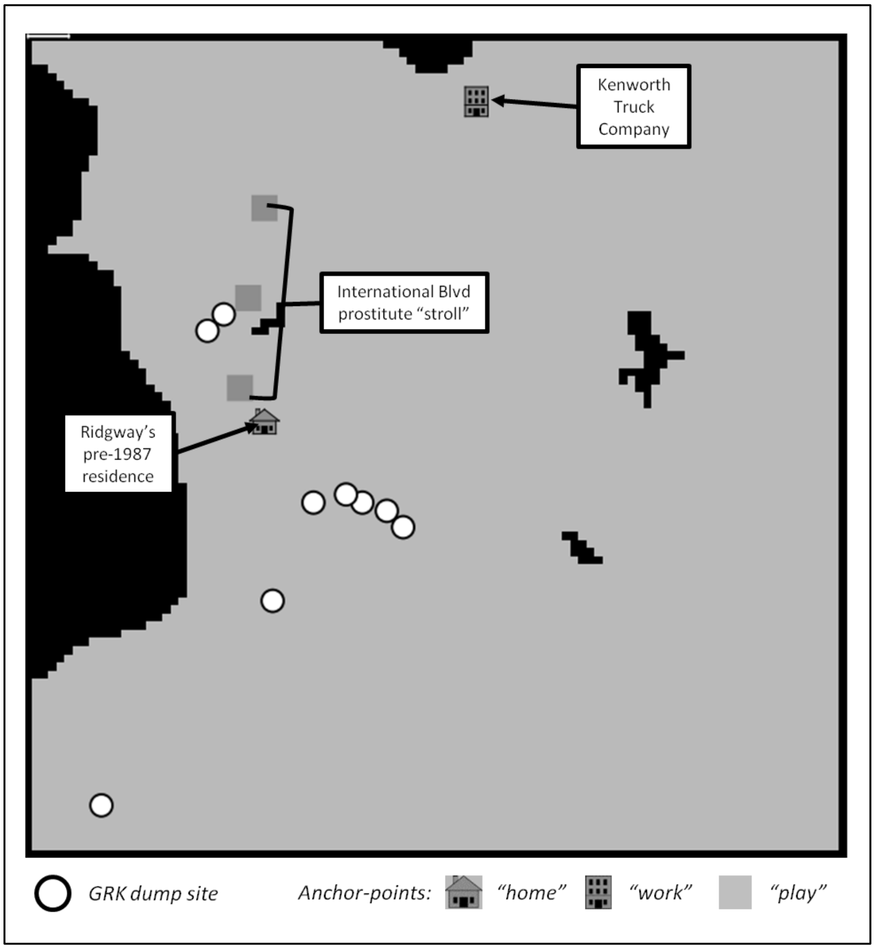

Figure 59: The first nine body dump-sites from the GRK series are implemented in the integrated model as comparison-sites. The integrated model also includes anchor-points associated with Gary Ridgway.

3.2.2 Comfort and Privacy

In the integrated model, the *subject's* initial areas of significant *comfort* were defined by Ridgway's *anchor-points*. *Comfort*, at a much lower level, was stochastically generated for other locations in the model to provide a back-ground *comfort* for the region. It was reasoned that, by selecting certain areas to kill and dump bodies, Ridgway self-defined his areas of most significant *privacy*. Therefore, the highest areas of *privacy* in the model were defined as the nine real-world *dump-sites* in the GRK series and Ridgway's home.

3.2.3 Schedule

Ridgway's accountable time was not discernible from the open source materials consulted. However, it was assumed, because he worked for a business as a truck painter, that he did have a schedule. In the integrated model, the *subject's* work schedule follows normal work/business hours. Therefore, from 7:00 am to 5:00 pm the *subject* is scheduled to be at (or on his way to/from) "work," from 5:00 pm to midnight he is scheduled to be at "home" or "play," and from midnight to 7:00 am he is scheduled to be at "home." This schedule does not account for weekends.

3.2.4 Location-based Targeting

Ridgway targeted victims based on their presence at a prostitute "stroll." This indicates that he hunted in areas he knew to be target-rich, as opposed to following or tracking-down specific victims. For this reason, implementing the GRK series involved *location-based targeting* to represent a tendency for the *subject*, while targeting, to be more interested in specific locations rather than specific *targets*.

3.2.5 Object Parameters

The integrated model was instantiated with a stochastically generated population of *objects*. However, Ridgway specifically targeted women who frequented a known prostitute “stroll.” This level of location-based specificity was not only a factor of *location-based targeting* on the part of Ridgway, but also a by-product of the exogenous features of the environment and *object* population itself. Therefore, in the integrated model *object clustering* was utilized.

Based on the default settings laid-out in the clustering discussion in the Methodology Section (2.2.6.2), it was estimated that approximately 90% (~450) of the individuals that Ridgway was likely to encounter would follow a schedule and approximately 20% (~90) of these would gravitate toward Ridgway’s “play” locations along the International Boulevard during part of that schedule. Of these individuals it was further estimated that 80% (~72) would have attributes that Ridgway might consider attractive and useful for achieving a *goal* with either “collaborative” or “dominant” action. These parameters were viewed as practical assumptions that gave the *subject* a reasonable population of suitable *targets* that would congregate in areas that he frequented.

Ridgway’s *targets*, prostitutes and teenage runaways, constituted a vulnerable population at risk of victimization. This was due to the ease of sexual access to these individuals, their involvement in criminal activity (and therefore reluctance to report victimization to the police), and their marginalization by the rest of society. Effectively, this meant there were relatively few inhibitors for Ridgway to overcome in order to access and victimize the women he preyed upon. For this reason, *target risk*, when used in the model, was implemented with a preset of “high-risk”.

Prostitutes both repulsed and stimulated Ridgway creating a confluence of aggression and sexual arousal (Lackey, Jones, & Johnson, 2015). Consequently, the attributes of *target* vulnerability, sexual attraction, and (at the same time) social repulsion drove his *target* selection. Additionally, Ridgway found arousal and satisfaction in murdering his victims (Lackey, Jones, & Johnson, 2015). These are factors that can be expressed in the integrated model via *object-effect* (the potential *target's* effect over the *subject's needs-accumulator*)[134], *object-attributes* (the *subject's* perception that the potential *target* has useful attributes for satisfying a *goal*)[135], and *object-utility* (the actual utility toward the *subject's goal*)[136]. The impact of these parameters were considered and utilized to fine tune calibration of the model to the GRK series.

3.2.6 Tactical Planning and Adaptation Methods

During calibration, one configuration used *manual-methods* to explore the *subject's* tactical planning and adaptation. In this configuration, *targeting* was set to "active" because, in the GRK series, Ridgway sought out *targets* at locations and during times that were in conflict with his *scheduling* constraints.

It was reasoned that successful victimization (due to vulnerability in *targets*) did not necessitate more than a low ("L") setting for the *density* (perception of inhibitors) and *paths* (number of cognitive navigations) parameters. The *subject's depth* (number of moves) and *focus* were not highly resourced. However, within the model these settings

[134] As discussed in the Chapter2, Scale Section 2.2.3.1.

[135] As discussed in the Chapter 2, Target Memory Section of 2.2.6.9.

[136] As discussed in the Chapter 2, Utility Section of 2.2.8.1.

are related to the *subject's* time to tactically plan and adapt and his ability to stay on task, respectively. Based on the series scenario, there is no indication that Ridgway was lacking time or focus. Therefore, these settings were left as the default baseline medium ("M").

Ridgway's frequent use of prostitutes (without murder), hyper-sexual activity with compliant wives and/or girlfriends, and necrophilic activities with previously dumped bodies all constitute a "collaborative" action in which Ridgway was satisfying *needs*.[137] This appears to have been happening more frequently than the killings themselves. While Ridgway was a very prolific serial murderer, he more frequently seems to have used "collaborative" action to satisfy emerging *needs*. Thus, when using the *manual methods*, the *action strategy* was set to "collaborative" and *variation* was set to 15%.

3.2.7 Learning

As an alternative to *manual-methods*, the ability to organically produce a viable method for tactical planning and adaptation was implemented using *method-memory*. Additionally, *burn-in* to pre-configure evolving methods was explored with and without the tendency (67%) to use a "dominant" *action strategy* when no reference memory exists[138].

[137]Engaging in necrophilic activities with a victim that he had previously killed and dumped was a matter of "economics and convenience" (Lackey, Jones, & Johnson, 2015) for Ridgway to satisfy emerging needs without expending energy to first "dominate" a non-compliant victim.

[138] The *dom-tendency?* switch on the model interface (see Appendix A: A3) was implemented as a means to de-conflict when there are no *method-memory* entries available for the current *goal* configuration.

3.2.8 Running the Integrated Model

The model was instantiated with 500 objects (potential *targets*). The *minute-per-tick (mpt)* parameter was set to one *mpt* (each *time-step* in the model represents one minute). If the *subject* did not kill a victim within the first ten days (14,400 *time-steps*), the simulation stopped. If he did commit a murder in the first ten days, then the model continued to run for 74 more days (time from first GRK abduction to ninth abduction) or until he failed to retreat from an attempted or completed murder and was captured.

During each run *access-sites*, *kill-sites*, *dump-sites*, and *collaboration*-sites were marked on the "view" and recorded. Additionally, a "narrative" showing the *event-chain* (from breach to success or failure), the *time-step*, and the location (cell) was captured to provide context to each sequence of events and allow specific run calculations. Spatial outputs were also recorded and included a break-down of *event-sites*, *event-chains*, and comparisons to real-world *dump-sites*.

First, the *Model Baseline* (MB) configuration as described in the Model Baseline Configuration Section 2.3.2 was run.[139] Second, a *Series Baseline* (SB) model was run in which *scheduling*, *location-based-targeting*, *object clustering*, and *target risk* were turned "on." The *Manual-Method* (MM) configuration utilized the SB configuration and manually set tactical planning and adaptation *methods* to reflect "active" *targeting strategy*, low ("L") *density*, low ("L") *paths*, medium ("M") *depth*, medium ("M") *focus*, "collaborative" *action*, and *variation* set to 15 (15% chance of each of these settings changing when a new *acquisitional goal* emerges). The final two configurations, *Burn-in*

[139] The same parameters were used except a *failure* was considered an arrest/capture and the simulation stopped.

1 (B1) and *Burn-in 2* (B2), used the SB configuration with *method-memory* turned "on," 10 days of *burn-in*, and variations on *object-effect*, *object-attributes*, *object-utility*, and *dominant tendency*. These five configurations are compared in Table 9.

Table 9: Integrated model test configurations for comparison to the GRK series.

Configuration Parameters	Model Baseline (MB)	Series Baseline (SB)	Manual-Method (MM)	Burn-in 1 (B1)	Burn-in 2 (B2)
Scheduling?	OFF	ON	ON	ON	ON
Loc-based-target?	OFF	ON	ON	ON	ON
Target-type?	OFF	ON	ON	ON	ON
Preset-target-type	--	"high risk"	"high risk"	"high risk"	"high risk"
Obj-share-location?	OFF	ON	ON	ON	ON
Object-pref?	OFF	ON	ON	ON	ON
Object-effect	0	0	0	0	15
Object-attributes	0	0	0	0	30
Object-utility	0.5	0.5	0.5	0.5	0.9
"Dominate" tendency	--	--	--	OFF	ON
Manual-method?	OFF	OFF	ON	OFF	OFF
Targeting (method)	--	--	"active"	--	--
Tactical (method)	--	--	L/L/M/M	--	--
Action (method)	--	--	"collaborate"	--	--
Variation (method)	--	--	15	--	--
Start-sim	0	0	0	14400	14400
Use-memory?	OFF	OFF	OFF	ON	ON

3.3 GRK Series Comparison Results

Each configuration was run 100 times. In this section, outputs for each run are compared across a set of GRK series matching criteria and compared to the real-world outcomes of the GRK series. The three closest matches to *dbh-score* from each configuration are compared to the GRK series on a timeline and aggregated spatial outputs are displayed for each configuration.

3.3.1 Matching Criteria

Match criteria were developed to assess how well simulation outputs reproduce the GRK series. From each simulation run, the spatial metrics (*comp_loc_score* and *comp_completeness*), temporal metrics (*dbh* and *dbh-score*), length of the series (in days), number of murders, and number of collaborations were compared.

Table 10 shows the 95% confidence interval ranges around the mean values (n=100) of each configuration for the GRK match elements. The GRK value for each criterion is listed in the right-most column of the table. While no configuration range matches the GRK value for *location-score* of 0, the MB configuration comes the closest with a range between 0.8 and 2.1. No configurations matched the GRK value for the *completeness-score* of 1. However, the SB and B2 configurations both were the closest to a match with ranges of 0.20 to 0.27 and 0.19 to 0.28, respectively. The GRK series had a mean of 9.3 *dbh*; the closest match was the B1 configuration with a range between 2.3 and 5.5 *dbh*. The SB and B2 configurations both produced ranges that contained the GRK *dbh-score* of 0.06. The portion of the GRK series tested was 74 days long. The B1 and B2 configurations produced, on average, the longest series with mean lengths between 8.3 and 14.6 days and between 9.5 and 14 days. The portion of the GRK series tested involved 9 murders. The closest match was the B2 configuration which produced a mean range between 3.2 and 5.8 murders. It was assumed the GRK series involved approximately 2 to 3 sexual experiences ("collaborations") a day.[140] The MB, SB, and B1 configurations produced ranges that encompassed this estimate.

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[140] Based on statements made by Ridgway's wives and girlfriends (Lackey, Jones, & Johnson, 2015)

Table 10: Mean (95% confidence interval) model outputs for GRK match elements for each model configuration.

GRK Match Elements	Model Baseline (MB)	Series Baseline (SB)	Manual-Method (MM)	Burn-in 1 (B1)	Burn-in 2 (B2)	GRK Value
location-score	**0.8 - 2.1**	2.1 - 3.4	1.3 - 2.6	1.2 - 2.5	2.0 - 3.4	**0.0**
completeness-score	0.09 - 0.14	**0.2 - 0.27**	0.12 - 0.19	0.11 - 0.18	**0.19 - 0.28**	**1.00**
avg. days-between-hits	0.9 - 1.5	0.6 - 1.1	1.6 - 2.6	**2.3 - 5.5**	1.6 - 2.9	**9.3**
dbh-score	0.01 - 0.04	**0.04 - 0.08**	0.02- 0.04	0.01 - 0.05	**0.03 - 0.07**	**0.06**
series length	2.9 - 4.5	2.8 - 6.2	5.5 - 9.1	**8.3 - 14.6**	**9.5 - 14**	**74.0**
count *kill-sites*	1.2 - 2	2.6 - 4	1.7 - 2.7	1.5 - 2.6	**3.2 - 5.8**	**9.0**
collaborations-per-day	**1.3 - 2.1**	**3 - 4.3**	4 - 5.6	**1.9 - 2.8**	4.9 - 6.3	**2.0 - 3.0**

All confidence ranges represent a 95% confidence interval

The GRK match elements from Table 10 were assessed and relaxed criteria ranges were derived from a qualitative review of model outputs. The GRK match elements, GRK output, and relaxed matching criteria are listed in Table 11

Table 11: GRK outputs that drive qualitative assessment criteria for the integrated model configurations.

GRK Match Elements	***GRK Output***	***Relaxed Matching Criteria***
location-score	0	*≤ 5.00 (count kill sites > 0)*
completeness-score	1	*≥ 0.40*
avg. days-between-hits	9.3	*range: 3 - 15*
dbh-score	0.06	range: 0.04 - 0.08
series length	74	≥ 45
count kill-sites	9	*range: 6 - 12*
collaborations-per-day	~2-3, unk	*range: 1 - 10*

Table 12 shows the number of runs from each of the different test configurations that matched the relaxed GRK criteria. The SB configuration produced 65 runs that fit the *location-score* criteria. SB and B2 both produced 21 runs that fit the *completeness-score*. The MM, B1, and B2 configurations each produced 14 runs that generated *days-between-hits* within the criteria range. The B2 configuration produced 6 runs and the B1 configuration produced 6 runs that had *dbh-scores* similar to the GRK series. The B1 configuration was able to produce 6 runs that lasted more than 45 days. In three of the B1 configurations and one of the SB configurations the subject was still active when the simulation ended. These four runs constitute unsolved series during the data collection period. Configuration B2 produced 16 runs that matched the *kill-sites* criteria. The SB, B2, and MM configurations all produced a significant number of runs that met the *collaborations-per-day* criteria (77, 76, and 75, respectively).

Table 12: Frequency of series from each test configuration that met the GRK match criteria.

GSK Match Criteria	Model Baseline (MB)	Series Baseline (SB)	Manual-Method (MM)	Burn-in 1 (B1)	Burn-in 2 (B2)
location-score *≤ 5.00 (count kill sites > 0)*	52	**65**	53	47	53
completeness-score *≥ 0.40*	5	**21**	13	10	**21**
days-between-hits *range: 3 - 15*	1	2	**14**	**14**	**14**
dbh-score *range: 0.04- 0.08*	1	4	2	**6**	**6**
length of series *≥ 45 days*	0	1	1	**6**	3
count kil-sites *range: 6 - 12*	6	14	11	11	**16**
collaborations-per-day *1 - 10*	53	**77**	75	66	76

As shown in Table 13, all five configurations produced a significant number of series with *kill-sites*. If only runs that produce at least one *kill-site* are considered,[141] the MB configuration has the highest percent of criteria matches for *location-score* (78.8%). However, B1 and/or B2 had higher percent matches on all other criteria.

Table 13: Percent of series (with at least one murder) from each test configuration that met GRK match criteria.

GSK Match Criteria	Model Baseline (MB)	Series Baseline (SB)	Manual-Method (MM)	Burn-in 1 (B1)	Burn-in 2 (B2)
location-score *≤ 5.00 (count kill sites > 0)*	**78.8%**	77.4%	71.6%	74.6%	70.7%
completeness-score *≥ 0.40*	7.6%	25.0%	17.6%	15.9%	**28.0%**
days-between-hits *range: 3 - 15*	1.5%	2.4%	18.9%	**22.2%**	18.7%
dbh-score *range: 0.0366 - 0.0766*	1.5%	4.8%	2.7%	**9.5%**	8.0%
count kil-sites *range: 6 - 12*	9.1%	16.7%	14.9%	17.5%	**21.3%**

Table 14 shows that none of the runs from any of the five configurations met all seven GRK match criteria during the simulations. Among all five configurations, two runs (one from the MM configuration and one from the B2 configuration) met six of the seven criteria. Among all five configurations, 18 runs met five of the seven criteria. Eleven of these runs used the B1or B2 configuration. None of the MB configuration runs met more than four of the seven criteria.

[141] Number of days and *collaborations-per-day* did not require that the series have any *kill-sites* and were not considered for this part of the analysis. Runs with at least one *kill-site*: MB (66), CB (84), MM (74), B1 (63), and B2 (75).

Table 14: Number of series from each configuration that met at least 1, 2, 3, 4, 5, 6, and 7 GRK match criteria.

GSK Match Criteria	Model Baseline (MB)	Series Baseline (SB)	Manual-Method (MM)	Burn-in 1 (B1)	Burn-in 2 (B2)
all 7 criteria	0	0	0	0	0
at least 6 criteria	0	0	**1**	0	**1**
at least 5 criteria	0	3	4	**6**	5
at least 4 criteria	2	10	9	**15**	11
at least 3 criteria	4	**23**	18	18	**21**
at least 2 criteria	35	**57**	49	42	41
at least 1 criteria	77	**91**	89	87	71

3.3.2 Days-Between-Hits

Figure 60 shows timeline comparisons for the three runs from each of the five configurations that were closest to the GRK *dbh-score*[142] (0.06). The closest matches from each configuration are run MB-2 (0.07) from the MB configuration, run SB-3 (0.06), from the SB configuration, run MM-3 (0.08) from the MM configuration, run B1-1 (0.05) and run B1-3 (0.05) from the B1 configuration, and run B2-1 (0.06) from the B2 configuration.

Overall, the nine closest *dbh-scores* came from SB, B1, and B2. Five of the six best matches were from B1 and B2. Although the runs represented in Figure 60, are the three closest matches to the GRK *dbh-score* from each configuration, only two of these runs (SB-3 and MM-3) were close to half as long as the GRK series.

[142] In this analysis, *dbh-score* refers to days between kills.

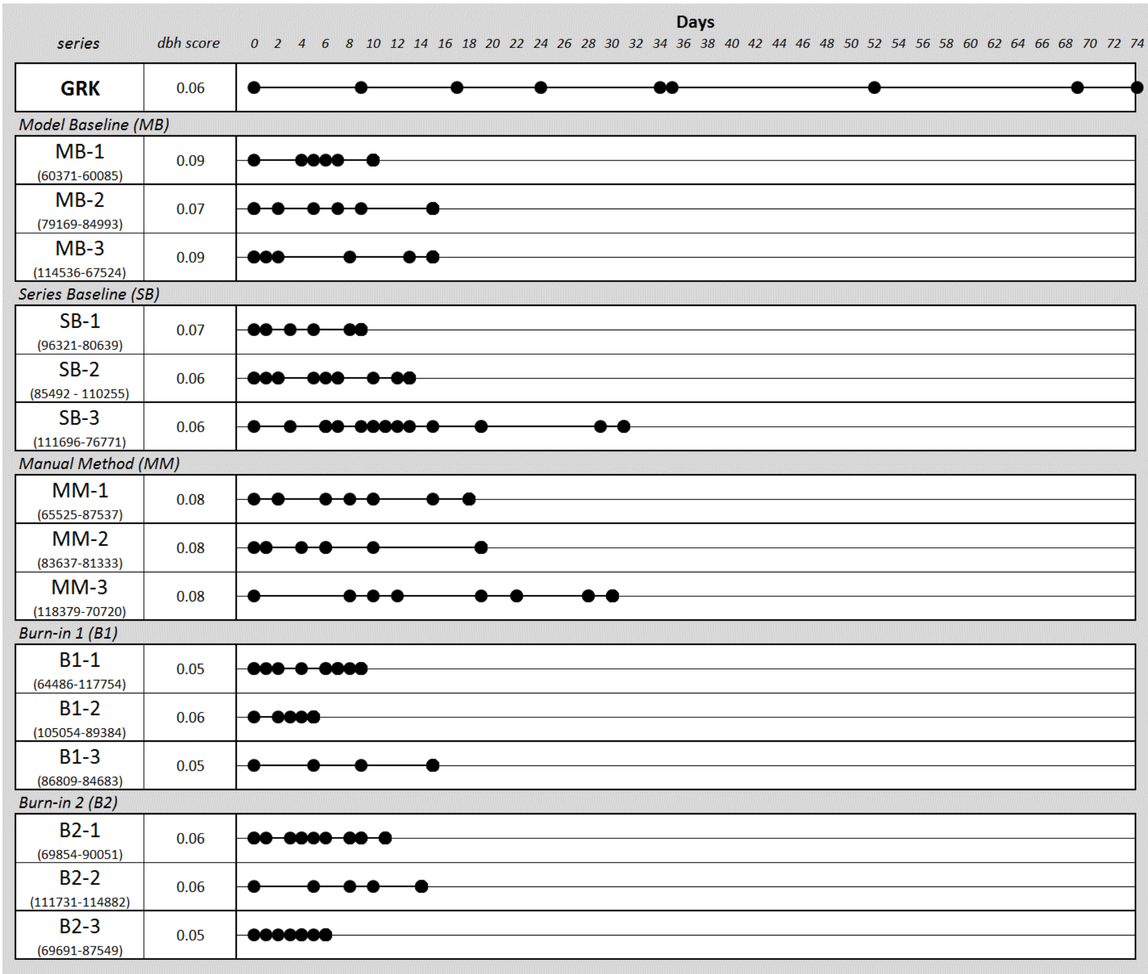

Figure 60: Timelines comparing abduction days from the GRK series to access (abduction) days from three examples of each of the configurations. Note cluster-score describes standardized clustering and does not reflect length of a series.

The *dbh-score* describes the clustering tendency, not length of the series or the number of events. Therefore, the runs from Figure 60 were re-plotted on a new set of timelines in Figure 61 and scaled to the same length (in days) as the GRK series. These new timelines illustrate that, with scaling there is much more qualitatively similar clustering to the GRK series. Figure 61 also includes the scaling factor used for each series.

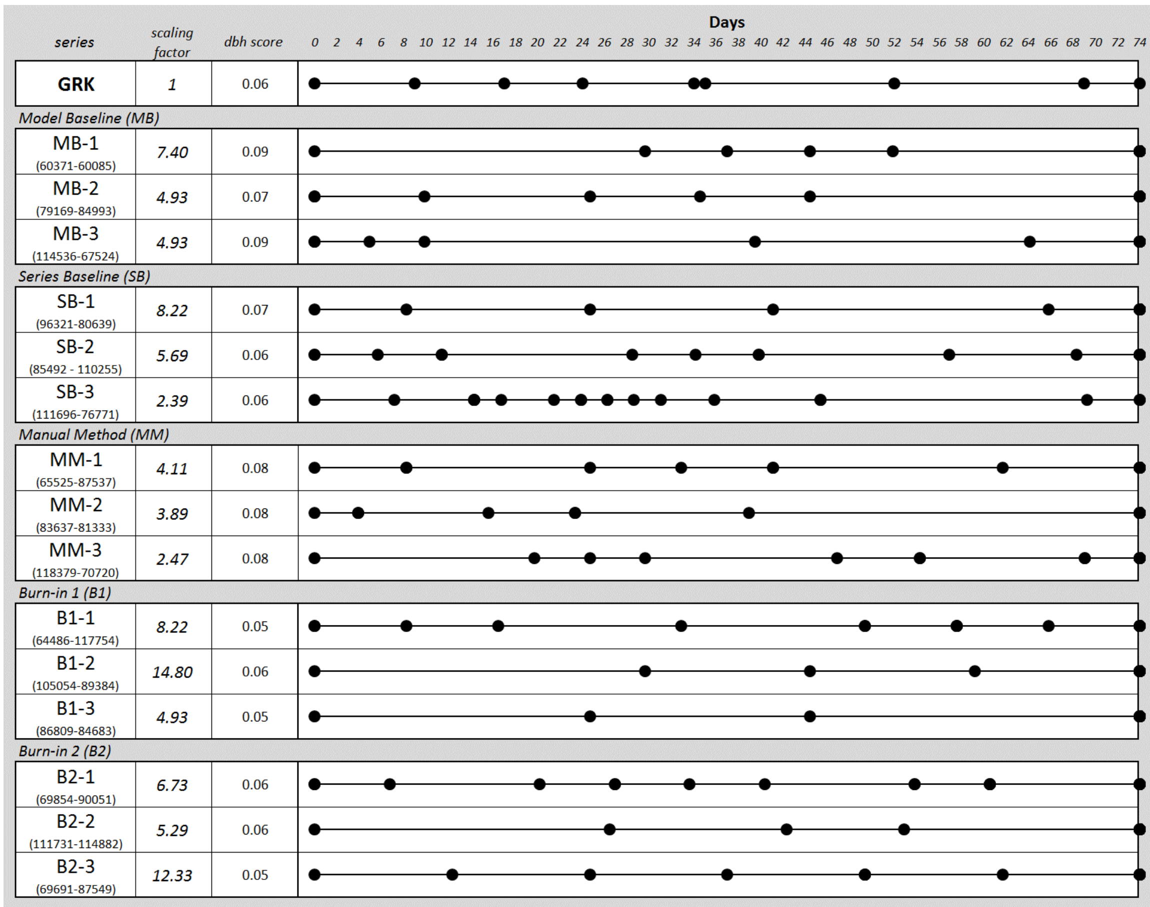

Figure 61: Timelines comparing the three closest matches to the GRK dbh-score from each configuration. The scaling factor for each run is also shown.

A second set of criteria (reduced from the original seven criteria in Table 12 to five weighted criteria) was used to further search each set of configuration runs for qualitatively similar runs to the GRK series. Weights were used to increase emphasis on matching series longevity and the number of *kill-sites*. These new criteria and weights are listed in Table 15.

Table 15: Adjusted and weighted GRK match criteria.

GRK Match Elements	***Relaxed Matching Criteria***	***Weight***
location-score	*< 5.00 (count kill sites > 0)*	1
completeness-score	*> 0.40*	1
avg. days-between-hits	*range: 3 - 15*	1
series length	> 45	2
count kill-sites	*range: 6 - 12*	2

Figure 62 shows the timelines for the "best fit" (based on the revised criteria and weights) from each configuration. The "best fit" for MB, SB, and MM were also found to be the best *dbh-score* fits previously identified. The "best fit" for B1 and B2, however, have higher *dbh-scores* than the GRK series and show significantly elevated tendency to cluster in comparison to the GRK series.

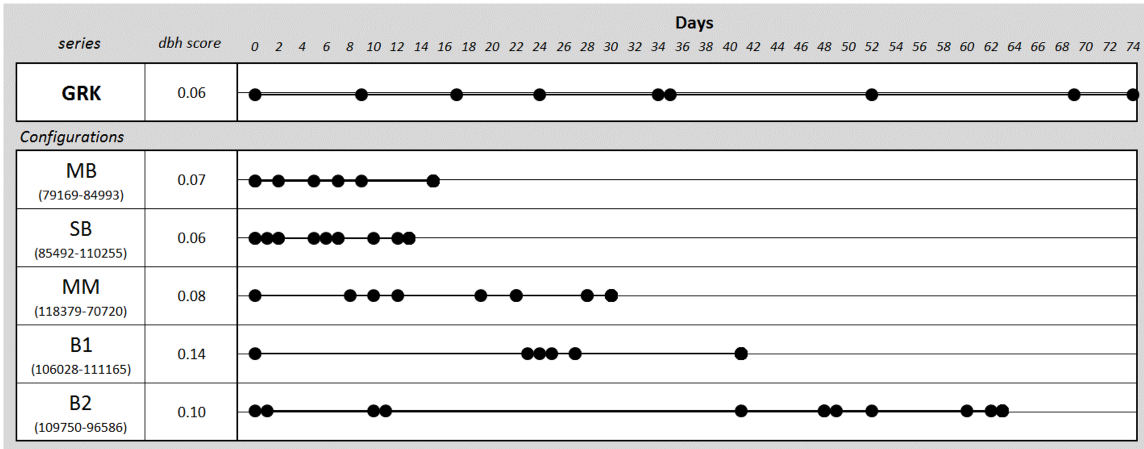

Figure 62: Timelines for the "best fit" (based on the revised criteria and weights) from each configuration.

Figure 63 shows, given scaling, MB, SB, and MM are visually closer matches to the GRK series clustering tendency than the B1 or B2 configurations.

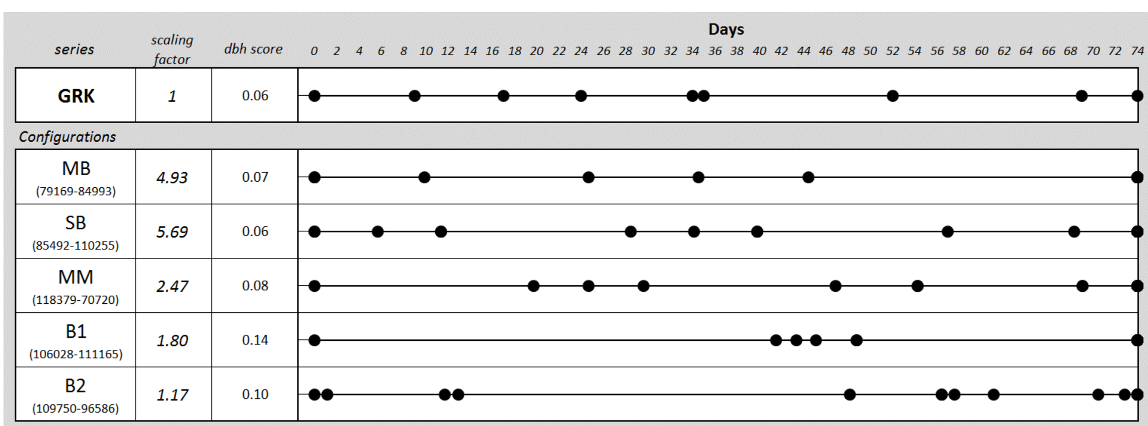

Figure 63: Scaled timelines for the "best fit" from each configuration.

3.3.3 Spatial Comparisons

Access-sites were expected to cluster around the International Boulevard prostitute "stroll." *Kill-sites* were expected to cluster around the prostitute "stroll," Ridgeway's home, and the GRK *dump-sites*. *Dump-sites* were expected to be found at the same locations as the GRK *dump-sites*. *Collaboration-sites* were expected to cluster around the prostitute "stroll," Ridgeway's home, and the GRK *dump-sites*.

Event-sites were collected for each configuration and aggregated for all 100 runs. They were then displayed as heat-maps to illustrate spatial tendencies[143] for each type of *event-site* for each of the five configurations. An example of *event-sites* captured during a run from each configuration can be found in Appendix E.

Figure 64 illustrates the aggregated spatial distribution of *access-sites, collaboration-sites*, *kill-sites,* and *dump-sites* for the MB configuration. *Access-sites* generally cluster around the *subject's* home, work, and the prostitute "stroll." *Collaboration-sites* were found near the *subject's* home, the middle of the prostitute "stroll," and in the vicinity of the Green River *dump-sites*. The *subject* primarily killed victims in the middle of the prostitute "stroll" and at his home. The *subject* primarily dumped bodies where he killed, although there was also a tendency to utilize the Green River *dump-site* locations.

[143] In this spatial analysis, "tendency" is defined as more than 10% of the maximum number of sites at any point over the course of 100 configuration runs. Effectively, this equates to at least an orange colored cell for the heat-maps.

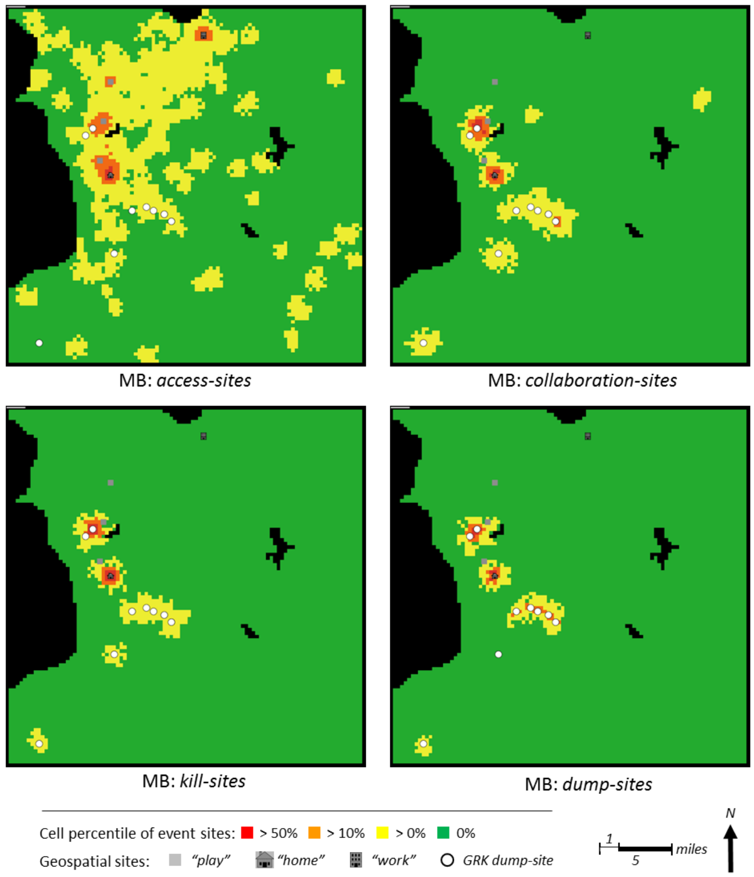

Figure 64: Aggregated spatial distribution of access-sites*,* collaboration-sites*,* kill-sites*, and* dump-sites *for the MB configuration.*

Figure 65 illustrates the aggregated spatial distribution of *access-sites*, *collaboration-sites*, *kill-sites*, and *dump-sites* for the SB configuration. *Access-sites* generally cluster around the *subject's* home, work, and the prostitute "stroll." *Collaboration-sites* were near the *subject's* home, the middle of the prostitute "stroll," and in the vicinity of the Green River *dump-sites*. The *subject* killed victims in the middle of the prostitute "stroll," at his home, and in the area of the Green River *dump-*

sites. The *subject* primarily dumped bodies where he killed, although he did utilize other GRK *dump-site* locations.

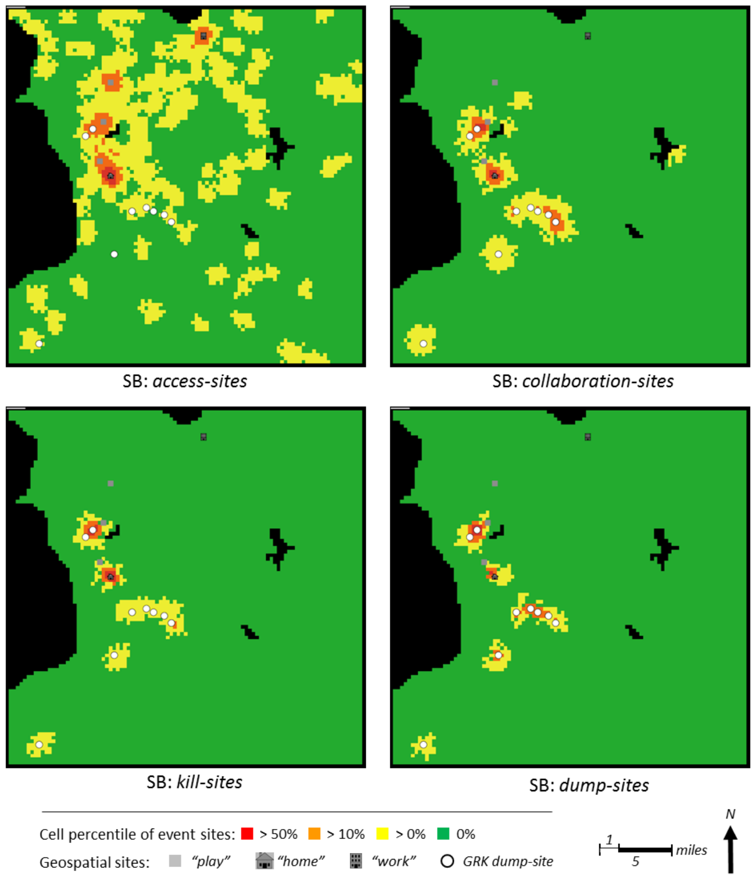

Figure 65: Aggregated spatial distribution of access-sites, collaboration-sites, kill-sites, and dump-sites for the SB configuration.

Figure 66 illustrates the aggregated spatial distribution of *access-sites*, *collaboration-sites*, *kill-sites*, and *dump-sites* for the MM configuration. *Access-sites* generally clustered around the *subject's* home, work, and the prostitute "stroll." *Collaboration-sites* were near the *subject's* home and the middle of the prostitute "stroll."

The *subject* killed victims in the middle of the prostitute "stroll" and at his home. The *subject* dumped bodies primarily where he killed, although there was also a tendency to utilize the Green River and other GRK *dump-site* locations.

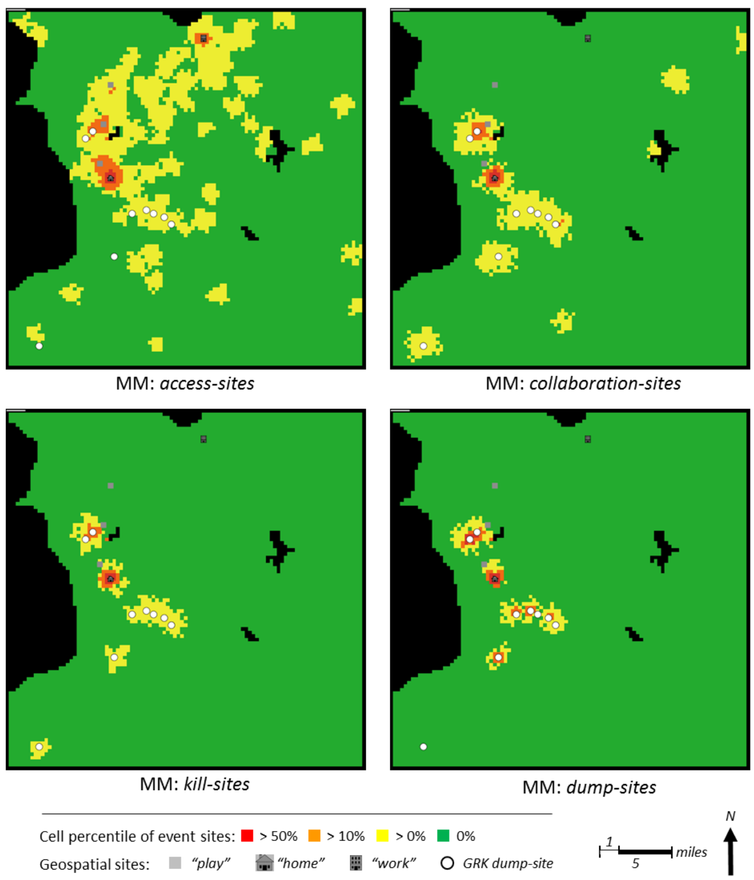

Figure 66: Aggregated spatial distribution of access-sites, collaboration-sites, kill-sites, and dump-sites for the MM configuration.

Figure 67 illustrates the aggregated spatial distribution of *access-sites*, *collaboration-sites*, *kill-sites*, and *dump-sites* for the B1 configuration. *Access-sites* generally clustered around the *subject's* home, work, and the prostitute "stroll." *Collaboration-sites* were near the *subject's* home and the middle of the prostitute "stroll."

The *subject* killed victims in the middle of the prostitute "stroll," at his home, and in the area of the Green River *dump-sites*. The *subject* dumped bodies primarily where he killed, although there was also a tendency to utilize other GRK *dump-site* locations.

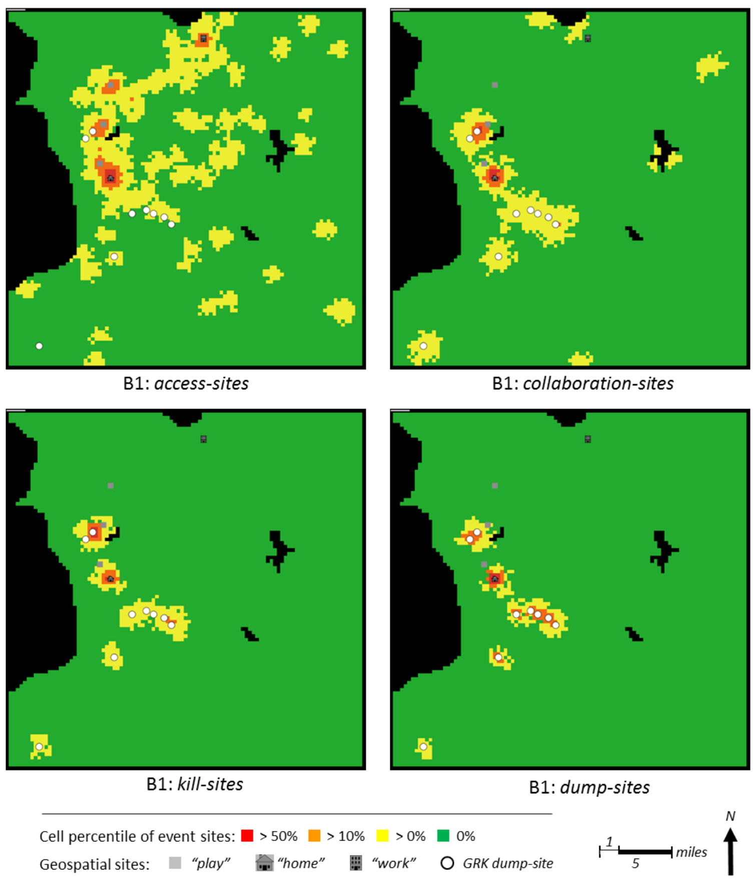

Figure 67 Aggregated spatial distribution of access-sites, collaboration-sites, kill-sites, and dump-sites for the B1 configuration.

Figure 68 illustrates the aggregated spatial distribution of *access-sites*, *collaboration-sites*, *kill-sites*, and *dump-sites* for the B2 configuration. *Access-sites* generally clustered around the *subject's* home and the prostitute "stroll." *Collaboration-*

sites were near the *subject's* home and the middle of the prostitute "stroll." The *subject* killed victims in the middle of the prostitute "stroll" and at his home. The *subject* dumped bodies primarily at the prostitute "stroll" and Green River *dump-site* locations.

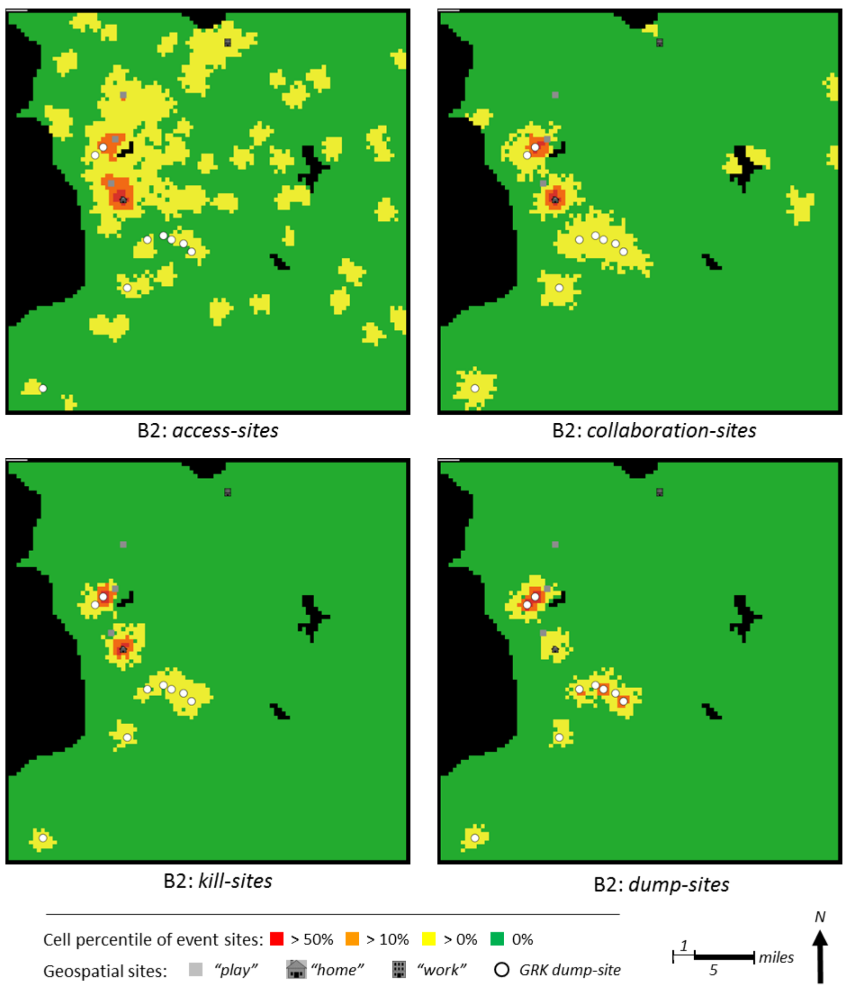

Figure 68: Aggregated spatial distribution of access-sites, collaboration-sites, kill-sites, and dump-sites for the B2 configuration.

The initial spatial expectations (with respect to each event-site) and aggregated tendencies for each of the five configurations are outlined in Table 16. Grey boxes in Table 16 indicate configuration tendencies that were not consistent with expectations of the GRK series.

Table 16: Initial spatial expectations (with respect to event-sites) and aggregated tendencies for each of the five configurations.

Event-Sites	Locations	Expectations	Model Baseline (MB)	Series Baseline (SB)	Manual-Method (MM)	Burn-in 1 (B1)	Burn-in 2 (B2)
access-sites	home		X	X	X	X	X
	work		X	X	X	X	
	prostitute "stroll"	X	X	X	X	X	X
kill-sites	home	X	X	X	X	X	X
	work						
	prostitute "stroll"/*dump-sites*	X	X	X	X	X	X
	Green River *dump-sites*	X	X	X		X	
	other GRK *dump-sites*	X					
dump-sites	home		X	X	X	X	
	work						
	prostitute "stroll"/*dump-sites*	X	X	X	X	X	X
	Green River *dump-sites*	X	X	X	X	X	X
	other GRK *dump-sites*	X		X	X	X	
collaboration-sites	home	X	X	X	X	X	X
	work						
	prostitute "stroll"/*dump-sites*	X	X	X	X	X	X
	Green River *dump-sites*	X	X	X	X	X	
	other GRK *dump-sites*	X					

All five configurations had tendencies toward *access-sites* near the prostitute “stroll” which is consistent with expectations. However, all of the configurations also had tendencies to create *access-sites* at the *subject’s* home and four of the five (excluding B2) tended to create *access-sites* near the *subject’s* work which is not consistent with expectations.

Each of the configurations created *kill-sites* at the *subject’s* home and near the prostitute “stroll” *dump-sites* which is consistent with expectations. However, only MB, SB, and B1 also had tendencies to create *kill-sites* near the Green River *dump-sites*, and none of the configurations consistently created *kill-sites* near the other GRK dump-sites.

Additionally, all of the configurations created *dump-sites* consistent with the prostitute "stroll" and Green River *dump-sites*. However, only SB, MM, and B1 also had tendencies to create *dump-sites* consistent with other GRK *dump-sites*. B2 was the only configuration that, consistent with the GRK *dump-sites*, did not have a tendency to create a *dump-site* at the *subject's* home.

Furthermore, all five configurations created *collaboration-sites* at the *subject's* home and near the prostitute "stroll" which is consistent with expectations. However, only four of the five configurations (excluding B2) had tendencies to create *collaboration-sites* at the Green River *dump-sites* and no configuration consistently created *collaboration-sites* near other GRK *dump-sites*.

3.3.4 Dump-site Centroids

The location and order of *dump-sites* created during a model run produce distinct *centroid-paths* that can be compared to the GRK dump-site *centroid-paths*. Thus, *dump-sites* from the "best fit" runs[144] for each configuration were used to calculate dynamic triangle *centroid-paths* over the course of the run. These *centroid-paths* were plotted and compared to the triangle *centroid path* for the GRK *dump-sites*.

[144] Using the modified and weighted criteria

Figure 69 illustrates the *centroid-path* for the MB configuration "best fit" run. While it seems to move in an opposite direction, the MB *centroid-path* remains in the same general area as the GRK path.

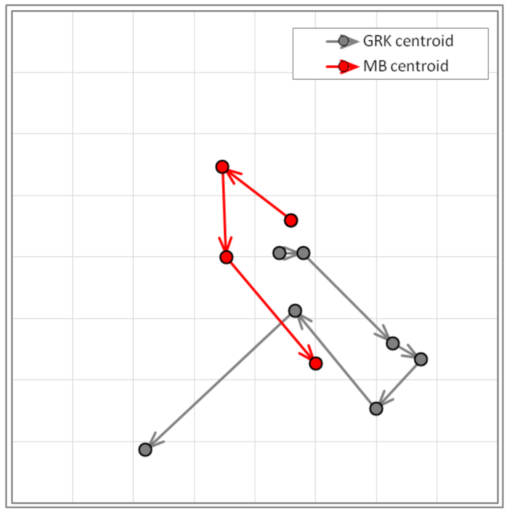

Figure 69: Centroid-path for the MB example.

As shown in Figure 70, the *centroid-path* for the SB configuration "best-fit" does not match the shape of the GRK *centroid-path*; however, it does follow the same general directionality at the beginning of the series and remains in the same general area over the course of the run.

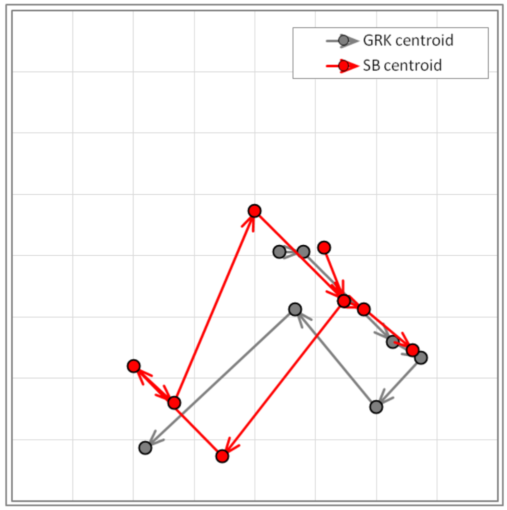

Figure 70: Centroid-path for the SB example.

Figure 71 illustrates that the *centroid-path* for the MM configuration “best-fit” closely matches the beginning of the GRK *centroid-path*. However, it never takes the southwest turn that the GRK series does and instead doubles back on itself.

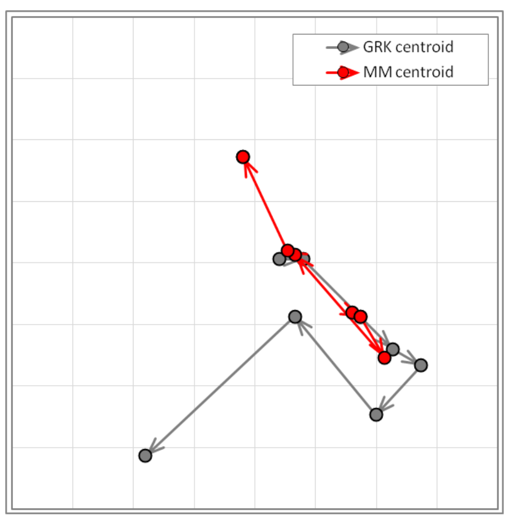

Figure 71: Centroid-path for the MM example.

Figure 72 shows the *centroid-path* for the B1 configuration "best fit". It moves in the opposite direction from the GRK *centroid-path*. However, it remains in the same general area.

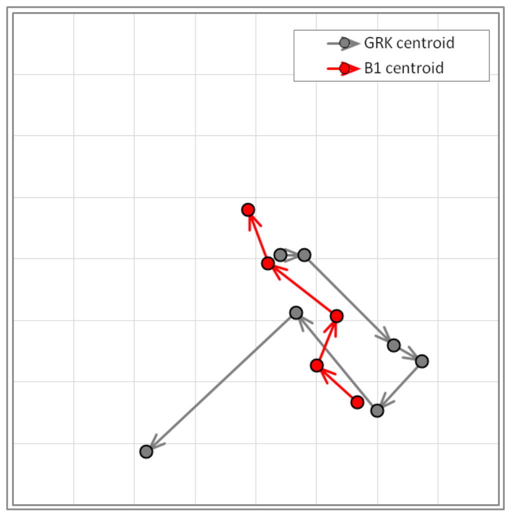

Figure 72: Centroid-path for the B1 example.

Figure 73 shows the *centroid-path* for the B2 configuration "best fit" example. This path remains significantly northwest of the GRK *centroid-path* for the majority of the run.

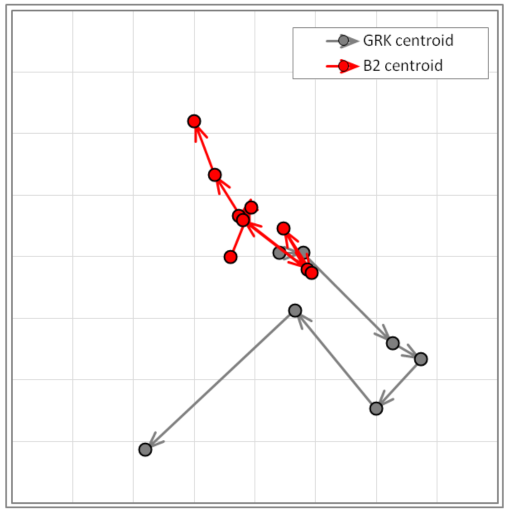

Figure 73: Centroid-path for the B2 example.

3.4 Summary

Section 3.1 provided a short synopsis of the Green River Killer (GRK) series in Seattle-Tacoma, Washington, and the relevant spatial, temporal and behavioral features that were used to test the configuration procedures for the integrated model.

Section 3.2 provided a review of how the integrated model was configured using open-source details about the series. Different configurations of the model were described. Section 3.3 reported findings of the comparison between the model configurations and the GRK series using weighted qualitative matching criteria, temporal analysis using *days-between-hit* data for selected configuration runs, and timeline visualizations. Finally, the configurations were compared to the real-world series by examining aggregated event-sites, and series *centroid-paths*. A significant amount of information was learned about the performance of the integrated model and the spatial and temporal dynamics of the comparison series. These findings will be further discussed in the larger context of the integrated model in the next chapter.

CHAPTER 4: DISCUSSION

4.1 Discussion of Findings

Measuring how well the integrated model "fits" the GRK series involves addressing comparisons between the real-world series and simulated model outputs based on spatial, temporal, and qualitative criteria. The findings from the previous chapter will be discussed in these terms. In addition, the integrated model will be further examined with regard to the implications of these findings and the larger context of using the integrated model to better understand the violent offending process.

4.1.1 Spatial Findings

At first blush, it appears that all configurations performed with relatively similar results in reproducing the *event-sites*. Generally speaking, the integrated model identified *access-sites*, *kill-sites*, *dump-sites*, and *collaboration-sites* where they would be expected to be, given calibration to the GRK series. Yet, the model is designed to utilize pre-defined areas of significant spatial *comfort* and *privacy* at instantiation. Thus, it should be no surprise that the *subject* tended toward accessing *targets* in areas that he had significant *comfort* ("work," "home," or "play") and killing and collaborating (sexually) in areas that he felt he had a sufficient level of *privacy* ("home" and GRK *dump-sites*).

For this reason, it is a foregone conclusion that the *subject* will dump a *victim* near or on GRK *dump-sites*. However, given expectations that the *subject* would utilize *privacy* and *comfort* areas to select certain sites for certain activity, what bears further examination is the general tendencies among these pre-defined locations for the subject to favor one area over another. While the simulated aggregated spatial outputs from Section 3.3.3 generally reproduce the GRK *dump-sites,* nuanced differences are based on the underlying implementation of temporal and spatial drivers.

It is important to note, that expectations of *access-site, kill-site,* and *collaboration-site* locations were not based on location data from the GRK series, but rather general statements. Thus, the expectation that *access-sites* are primarily in the area of the prostitute "stroll" is based on qualitative observations from open-source information that did not specify where along International Boulevard access took place, nor did it explicitly exclude accessing *targets* at other locations like the *subject's* "work" or "home." In fact, finding that the *subject* accessed *targets* near Ridgway's home during simulation may, in actuality, be consistent with the reality of the GRK series. Ridgeway lived just south of the prostitute "stroll" and often complained about prostitutes in his own neighborhood. Additionally, while it is clear that Ridgway would return to *dump-sites* to have sexual experiences with living and deceased victims, it is not clear which *dump-sites*. Thus, tendency for the absence of *collaboration-sites* and *kill-sites* at some *dump-sites* may not be altogether inconsistent with the known facts of the GRK series.

"Scheduling" tends to keep a *subject* close to locations involved in the schedule. Therefore, the *subject*, while following a schedule, does not travel far from his "home," “work” and “play” *anchor-points* unless he has a current *acquisitional goal* and is pursuing an “active” *targeting strategy*. In the GRK series, the prostitute “stroll” is the only location determined to be a “play” location for the *subject*. This limits the *subject’s* resulting *activity-space* and may exclude other relevant locations the *subject* frequents when not at “home” or “work.” In addition, over time it is logical to assume that the *subject* will incorporate changes not only in spatially relevant *anchor-points* but also scheduling and other temporal constraints. Notably missing from the integrated model is the incorporation of days that the regular “work” schedule does not apply. On a weekend, for instance, the *subject* may have more latitude to expand his spatial awareness due to relaxed time constraints.

Reliance on static spatial *privacy* is a limiting factor as well. If the *subject’s* spatial awareness evolves in terms of *comfort*, then his knowledge of areas that provide significant *privacy* should also evolve over time. Consequently, the discovery of a body and resulting investigative and media related activities are likely to significantly reduce the *privacy* of an area, at least during the short-term. Thus, the absence of reasons to temporarily avoid preferred private locations and lack of dynamic *privacy* may account for over- and under-represented tendencies toward certain *dump-sites*.

While the aggregation of *event-sites* across configurations is useful to understand the underlying context of spatial features, the use of *centroids* provides a significantly more constructive dynamic analysis. This type of comparison more deeply explains the relevance of dynamic spatial features and highlights that the sequence and number of *dump-sites* matters when comparing the integrated model to a real-world series.

In contrast to the aggregated spatial results that can appear qualitatively convincing, the simulated *centroid-paths* did not have the same dynamic spatial features as the GRK series. This highlights a deeper layer of understanding about the GRK series. While *privacy* and *comfort* are the primary drivers of the *event-sites* that are available, there are other important elements that have a significant impact on sequence and timing.

In a dynamic spatial comparison to a real-world series like the GRK, it is necessary, therefore, to consider additional factors not currently incorporated into the integrated model. These include (but are not limited to) the *subject's* spatial choices as they relate to avoiding investigation, evolving dynamic levels of *privacy*, and increased awareness of risk among potential *targets*. Thus, if the *subject* abducts from the prostitute "stroll" and dumps the *victim's* body next to the Green River, *target* and environmental circumstances affecting the viability of future *event-sites* are likely to (temporarily) change. For example, *targets* at the prostitute "stroll" may become more situationally aware, [145] thus forcing the *subject* to hunt in a new area, or the *subject* may need to find a new area to dump a body because media coverage surrounding previous *dump-sites* has brought too much attention to a previously private location.

4.1.2 Temporal Findings

The temporal findings from the previous chapter focus on two different, but related, outputs; series longevity and *days-between-hit* (*dbh*) clustering. In general, it was difficult to find a significant number of model runs that lasted as long as the GRK series.

[145] Temporarily changing potential *victims* from "high-risk" to "medium- "or "low-risk"

This is especially interesting considering that the GRK data only included the first nine of 49 total murders. Additionally, those runs that did come close to the length of the GRK series were not particularly good matches based on clustering characteristics as measured with *dbh score*. When model runs approached GRK *dbh-score*, the lengths of the runs were significantly shorter than the GRK series. The inability of the integrated model to generate series with concurrent longevity and clustering characteristics similar to the GRK series appears to be due to two factors; (1) the inability of the integrated model to produce a *subject* who successfully evades capture for a prolonged period of time, and (2) issues in temporal scaling.

It may be that the integrated model over-emphasizes the concept of "capture" following failure to *egress*. That is to say, in the integrated model, failure to *egress* from an attempted action involving *access* or *extraction* leads automatically to capture, whereas in a real-world series, failure to *egress* under the same circumstances may lead to evidence or a witness, but not necessarily immediate capture. In fact, barring being caught in the act or with the body (which would be considered failure to *egress* <u>after</u> the *extraction*), it may be more realistic to regard failure to *egress* not as capture, but rather as increased exposure to suspicion by law enforcement. In this way, if the *subject* regularly fails to *egress* from attempted action, over time he may accumulate enough law enforcement scrutiny to lead to capture. However, until then, he remains free and potentially active.

Findings in the previous chapter[146] indicate that the Series Baseline (SB), *Burn-in* 1 (B1), and *Burn-in* 2 (B2) configurations consistently produce the most GRK temporal clustering characteristic matches and B1 and B2 produce the most consistent longevity (albeit not concurrently with temporal clustering). Structurally speaking, SB, B1 and B2 incorporate significant representations of *target* clustering and risk. Additionally, B1 and B2 incorporate learning, via the *method-memory* and *burn-in* procedures, that appear to aid the *subject* in making useful and purposive decisions.

Conversely, Manual Method (MM) did not perform well in matching temporal cluster characteristics or longevity even though it too utilized significant representations of *target* clustering, risk, and cognitive decision-making. The primary difference between MM and the better performers (SB, B1, and B2) appears to be that MM uses preset assumptions about the *subject's preferred methods* with slight variation (15%), whereas the B1 and B2 configurations allows those *preferred methods* to emerge and the SB configuration creates random *action strategies*. Thus, it appears that increased variation (whether purposeful or not) in *preferred methods* tends to create underlying structural similarities to the GRK series. Also, strategies that are responsive to environmental realities increase potential for avoiding failure, thereby producing a greater potential for series longevity. Both of these points stress that endogenous variation and adaptability are key elements in reproducing temporal clustering characteristics and series longevity. This supports recent research that stresses a nuanced

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[146] See Matching Criteria, Section 3.3.1, and Days-Between-Hits, Section 3.3.2.

understanding of geospatial, temporal, and crime scene differentiation and consistency for serial offenders (Osborne & Salfati, 2015; Sorochinski, 2015).

4.1.3 Criteria-based Matching

Criteria-based matching was used with the intention of quickly identifying "best fit" runs produced by the various integrated model configurations. However, none of the five configurations was able to adequately match the GRK series on all seven criteria. Even when the seven criteria are relaxed to relatively liberal ranges, the best that any configuration could muster was three runs that match six of the seven criteria; two from B2 and one from MM.

After further examination, however, it is apparent that the integrated model was capable of reproducing some of the individual criteria with regularity. Specifically, more than 50% of the runs in all five configurations generated *collaborations-per-day* that matched the relaxed criteria for the GRK series. This tendency significantly increases to 74% when the Model Baseline (MB) is excluded from the comparison.

Additionally, some of the criteria were only valid if the *subject* killed at least once. Among all configurations, an average of 72% of the runs concluded with at least one murder. Thus, while the integrated model provides potential for violence, it is not a foregone conclusion that every run will result in violent offending[147] which automatically precludes several of the GRK criteria. When the *subject* did kill, the *location-score*, *completeness-score*, and *kill-site* count met GRK outcomes (based on relaxed criteria

[147] This is, in itself, an interesting finding that supports the notion of "non-primed, non-offenders" and "primed, non-offenders" discussed in Chapter 2, "Primed" Behavior, Section 2.1.2.

ranges) with much more regularity. Ability to satisfy criteria that address *event-site* locations, however, is not a surprise considering that *dump-sites* generated by the integrated model are dependent on pre-determined *privacy* and *comfort* derived from the GRK series.

Criteria-based matching also highlights useful differences between configurations in temporal factors (*mean dbh* and *dbh-score*). Although none of the configurations overwhelmingly matched the GRK series, Table 12 shows that MM, B1 and B2 significantly out-performed the MB and SB configurations in matching *days-between-hits (dbh)*, and B1 and B2 were much more effective at matching *dbh-score*. The *dbh-score* criterion is based on temporal clustering characteristics and, given differences in the configuration matches and superior performance of B1 and B2, points to a potential relationship between the integrated model's endogenous features of adaptability and series tempo (which is relatively unaddressed in the literature).

Furthermore, the location criteria (*location-score* and *completeness-score*) are not particularly diagnostic of a "fit" to the GRK series simply because they are already biased toward the GRK *dump-site* locations. In fact, these location criteria are probably better addressed in terms of dynamic sequence through the use of *centroids*. Thus, to enhance the notion of a criteria-based "best fit", it would be beneficial to re-examine the spatial metrics used and perhaps replace them with a more useful means to measure the differences between *centroids* generated by the integrated model and the GRK series *centroid*.

4.2 Discussion of Broader Implications

This dissertation has been the first to explore the efficacy of computationally implementing the violent offending process and has incorporated a number of significant steps toward representing exogenous and endogenous subject features. Central to this research is the question; *can the violent offending process be computationally expressed as a complex social simulation?* The findings in this dissertation suggest that, indeed, it can be.

In general, the integrated model provides theoretically and structurally sound representation of violent offending as an emergent feature of decision-making and ecologically relevant interactions. The integration of needs-driven behavior with agent-based environmental interactions provides an interesting and viable means to represent *inhibitory thresholds*, the development of *acquisitional goals*, and satisficing through preferred endogenous tactical and adaptation strategies. Furthermore, the incorporation of two different types of subject memory (target-memory and method-memory), and their integration with the subject's ability to explore his environment and learn from experience represent significant scientific contributions to the emerging field of computational criminology.

The introduction of *maze-running* in Section 2.2.7.2 highlights an effective means to tether the relatively esoteric concepts of *tactical planning* and *adaptation* to the analogy of navigating traversable space. This provides a means to leverage a cognitive landscape to better understand ecological realities not only from a dynamic perspective, but also from a larger understanding of an individual bounded reality. In essence, *maze-*

running provides a significant advancement toward, and interesting realization of, “the whirl of reorientation, mismatches, analyses/synthesis over and over again *ad infinitum* as a basis to comprehend, shape and adapt to an unfolding, evolving reality that remains uncertain, ever-changing, unpredictable.” (Boyd, 1992, p. 33).

Significantly, a number of the interactions that emerge in the model do not involve violent offending. For this reason, the integrated model’s features are not limited solely to violent offending and appear to have application across decision-making and ecologically relevant interaction in general.

In addition, these first steps toward creating a viable synthetic offender have established the relevance of the stages necessary to create qualitatively convincing interactions that result in violent outcomes. The interaction of these stages in the integrated model cement the notion that the emergence of violent behavior, like many other human behaviors, is in reality the interaction of endogenous processes with exogenous stimuli reinforced by bounded learning and satisficing (Simon, 1972).

The introduction of “narratives”[148] into the model enables the tracking of pre-and post-behaviors for each *event-site* and in doing so, provides an invaluable means to contextualize many of the findings. Thus, not only does the integrated model record a *kill-site*, but it also connects it to the initial *breach* that developed the *acquisitional goal*, the *tactical planning*, and *access* that came before the *killing*, and the *dump* or failure to *egress* that followed. This does not mean that the *breach* or *tactical planning* events offer explicit spatial data, but rather, the model, by tracking these events, creates *event-*

[148] As discussed in Chapter 2, Model Outputs, Section 2.2.9 and Chapter 3, Running the Integrated Model, Section 3.2.8.

chains that describe the overall progression from a "non-primed, non-offender," to a "primed, offender."[149]

It is important to note that, the integrated model defines an "offender" in terms of current state. This does not reduce the criminal culpability of the *subject* for a murder-event, but it does address the dynamic transition of the *subject* between offending and non-offending states throughout the series. It also further highlights that, even for a *subject* who is a prolific serial killer like Ridgway, the majority of his time is spent in a "non-primed, non-offending" or "primed, non-offending" state. Practically speaking, this means that it behooves the investigative community to understand (and potentially exploit) the counter-intuitive reality that murder offenders mostly engage (even throughout an active series) in non-offending activity.

The integrated model, therefore, has the potential to provide significant insight into hidden behaviors that drive the development of offending outcomes. Thus an important overall implication to consider is that, with further calibration and validation, the creation of a synthetic offender can offer a significant contribution to understanding how the violent offending process evolves, or does not evolve, given significant internal conditions and external stimuli. For instance, this type of effort can explore targeting decisions, opportunity-based spatial offending (Ratcliffe, 2006), or limitations to offender adaptability.

[149] The incorporation of *event-chains* provides an interesting form of data imputation (derivation of missing values). While imputation generally is achieved via statistical methods, the integrated model provides an alternative method of actually building a form of contextual imputation.

A logical second question then, is: *if the efficacy of the integrated model is predicated on further calibration and validation, can it be calibrated to a specific series?*[150] The answer appears to be a qualified "yes." While calibrating the integrated model to a specific series may be possible, this first step in doing so with the GRK series has highlighted a number of issues and challenges. Overcoming these challenges will require further addressing temporal scaling, dynamic *comfort* and *privacy*, and the ecological impact of the *subject's* violent activities.

The complexity of the violent offending process prohibits exact "duplication" of a real-world series. Yet, if the underlying process is consistent with the underlying process of real-world events, it is important to have an understanding of what the specific outputs actually mean. As an analogy, if an apple seed is planted in the earth, the expectation is that, given favorable environmental conditions and time, an apple tree will grow. It is understood that given certain inputs, certain outputs will follow. The expectation of output does not, however, include exact expectations of fruit yield or branch configuration and no two seeds will produce exactly the same tree. Non-deterministic modeling of the violent offending process is similar to planting an apple seed. The potential for violent behavior exists, and given a certain set of cultivating environmental conditions, the model can encourage that behavior to emerge. However, the nature and yield of that emergence are not solely determined by the potential of the *subject*, but also the interactions of the *subject's* potential with the specifics of a dynamic environment.

[150] It is interesting to note that any one run of the integrated model is an accumulation of interactions. Thus, every run constitutes a series of interactions that may, or may not, be defined as violent offending. Given this perspective, it appears that the notion of calibration to a specific violent offending event versus a series of violent offending events depends on how the outcome events in the model run are eventually defined.

Thus, certain things are relatively predictable. For instance, given stimuli, behavior will emerge. Probability-wise, the *subject* may have greater tendencies toward certain strategies for dealing with *acquisitional goals*. However, the more specifically one would like to reproduce an explicit outcome of a specific series of events; the more significantly the *subject's* potential (and environment) must be bounded. Thus, how and with whom he interacts, where he goes and what happens when he gets there must be highly defined. Unless the *subject* is completely bounded to a specific real-world series, the expectations of predictably reconstructing the behavior are unreasonable. The most we can hope for is approximations.

So then the question is*; what insights* <u>*can*</u> *the integrated model provide when applied to a specific series?* The integrated model has significant potential to provide spatial and temporal insights primarily because there is value in understanding where the theoretically and structurally informed assumptions put forth in the model diverge from observable reality. This can provide a viable theory of the offender's behavior that could lead to earlier opportunities for interdiction.

For instance, it is easy to conclude that the underlying assumptions having to do with *privacy* and *comfort* in the integrated model account for *event-site* placement across aggregated runs. However, these factors do not account for spatial discrepancies evidenced in each of the specific model runs. Thus, in a specific series, there is value in further examining the spatial dynamics of the series by highlighting other ecologically relevant factors like investigation and its dynamic impact on *comfort* and *privacy*. It may very well be that *privacy* and *comfort* are responsible for driving <u>potential</u> site locations, but dynamic social factors are responsible for the choice of actual *event-sites*. This supports dynamic models of opportunity-based offending (Ratcliffe, 2006) and routine activities (Cohen & Felson, 1979).

This type of refinement highlights those features that provide meaningful insights into the internal and external drivers of violent offending in general. For instance, application of the integrated model to the GRK series suggests that while the underlying temporal structure of the configuration runs is similar to the GRK series, the scale of component parameters needs to be adjusted. This finding further suggests that there may be structural process similarities between events that occur at very different tempos like serial murder and mass murder. The main difference between these types of events might essentially be the temporal scale at which they are expressed.

4.2.1 Limitations

While this project provides a viable means to model the violent offending process, it highlights several of the challenges encountered in this endeavor. It is important to examine these limitations and how they were addressed and/or can be overcome to understand their impact on the functioning and overall efficacy of the integrated model, as well as, provide guidance for further implementation and research.

Configuring the integrated model to the GRK series proved relatively straight-forward given known and readily available series details. Spatial, temporal, and investigative details were fairly well-documented and available via open-source information. However, there were some challenges during configuration that bear further examination. These challenges were driven by assumptions about linked cases, geospatial representation of speed and travel routes, and occasionally conflicting or absent open-source information.

While the GRK series officially connects Ridgway to 49 murders, there is speculation that he may be responsible for as many as 71 murders spanning from 1974 to 1998 (Montaldo, 2011). This could certainly pose complications in any comparison, especially if suspected cases are temporally and spatially interspersed among officially connected cases. To this point, the comparison of the integrated model to a real-world scenario like the GRK series is only as "good" as what is currently known about the extent of offending. Reliance on officially connected and/or adjudicated cases may, in fact, provide an incomplete understanding of the series.

This is a particular issue in the GRK series because while it is assumed that the integrated model was configured and compared to the first nine murders, there is a possibility that there was (based upon the aforementioned speculation) an additional murder committed by Ridgway within the 74-day time-frame, and four unaccounted-for murders before the official series began. However, the choice was made during this analysis to exclude these five potentially confounding cases because they were not part of the official record. Their attribution to Ridgway is only speculation at the time of this writing.

Speed is represented as a function in which maximum walking speed is 5 miles per hour and maximum driving (or alternative transportation method) speed is 30 miles per hour. While the limits to these speeds is adjustable, it is recognized that the speed function as implemented does not allow for particularly realistic geo-spatially determined variations (*i.e.*, urban versus rural). By defining speed zones (in future implementations of the model) it is suggested that speed can be more realistically represented by making speed an attribute of the cells within respective zones and basing agent (*subject* and *object*) movement on speed curves or distributions within those zones.

Travel routes *(i.e.*, roads and paths) are not utilized in the *subject's* spatial representation. Although major road systems are present on the reference maps, the integrated model is not a traffic model and is not intended to simulate or identify travel routes. It is instead intended to present the *subject's* cognitive representation of the environment and key locations. Therefore, while it is acknowledged that travel routes are an important part of an individual's *activity-space*, it was decided that generating road-based navigation routes would have the effect of appearing more spatially granular than the model warranted and generally over-complicate matters. For this reason, clustering around anchor-points and incident sites (that are driven by *comfort* and *privacy*) is more representative than travel between these sites and *targets* encountered. Furthermore, breaches experienced <u>between</u> locations and *event-sites* cannot be interpreted as literal locations.

As with any open-source data, accuracy is a concern. To this point, while the GRK data used to configure the model was widely reported in multiple sources, there were still issues that required some clarification. For instance, there was some confusion about where Ridgway's pre-1987 home was located. Several news sources confused his three different residences (one from pre-1987, one from 1987 – 1997, and one post-

1997). The first nine officially connected killings took place in 1982. Therefore, the only residence that was relevant to the current configurations was the pre-1987 residence. The residence location selected during configuration was the location that had the most support for being the pre-1987 residence.

Additionally, as already noted in the discussion on spatial findings in Section 4.1.1, the expectations of *access-site*, *kill-site*, and *collaboration-site* locations in the GRK series were not based on well-defined location data. This is not as much a limitation to the model as it is a caveat in the interpretation and comparison of these simulated event-sites to speculated event-sites in a real-world case.

As previously noted in the discussion on model memory in Section 2.2.8.4, due to computational resource limitations, the sizes of *method-memory* and *target-memory* were restricted. While this could have an effect on resources available to the *subject* during decision-making, it was reasoned that newer memories would have a greater impact on the *subject* than older memories (Koechlin & Hyafil, 2007). For this reason, if the *subject* reaches a memory limit, he will replace the oldest memory with the newer one.

As previously noted in the discussion on parameters in Section 2.2.1 many of the values for parameters are not associated with standard units of measure. For instance, *needs accumulation* is based in values that do not have real-world defined units. Nor is there a corresponding real-world value, for instance, that measures *inhibitory threshold* that can be used when calibrating to a real-world series. However, these "unit-less" values were generated as relative parameter values within the model itself. When possible, "unit-less" parameters were calibrated using reasonable assumptions about accumulation in relation to time and distance (which did have standard transferable units). Additionally, given the same parameter across configurations of the model, "unit-less" values can be compared across model runs and findings are couched in statements of relativity.

Cognitive resources (*density*, *paths*, *depth*, and *focus*) were developed as necessary elements to navigate the cognitive landscape panels during *maze-running*. For this reason, while there may be interesting parallels, attempting to equate them to psychological or neurological concepts or principles is not validated in the integrated model at this time and presents an opportunity for further investigation and research.

Scheduling is implemented without weekends, variations, or deviations. Scheduling was implemented this way to simplify the model and, in the absence of detailed and nuanced scheduling information, avoid making unwarranted or extraneous assumptions about variations in the *subject's* temporal or spatial constraints.

The integrated model has been calibrated to one real-world case (GRK). Although this comparison involved multiple configurations, there is still more validation to the model that must take place. For this reason, generalizability of the findings or statements about the model must be understood to be preliminary and based on limited findings. Ultimately, more cases are needed to validate the integrated model and its implementation of the violent offending process.

4.2.2 Implications for Further Research

This project has built and tested a complex social simulation of the violent offending process. Yet, this is only the start. The integrated model offers significant and exciting opportunities for further development and research that can be divided into two categories; (1) suggestions for improving the integrated model itself and (2) ideas for further computational and criminological research. Both are discussed below.

4.2.2.1 Further Development of the Integrated Model

Currently, the integrated model can incorporate multiple evolving *needs*. These *needs* were initially implemented to be relatively abstract so as not to over-complicate the integrated model during development. However, explicit representation of *needs* could be an important part of creating well-defined and interpreted *acquisitional goals*. This can provide a useful means to generate compound actions and a more nuanced understanding of offending and non-offending outputs. [151]

As previously discussed in this chapter, it is proposed that incorporating the *subject's* adaptive responses to emerging investigations and social circumstances will improve the ability of the integrated model to reproduce dynamic and temporal aspects of a real-world series. For instance, by integrating the concept of accumulated suspicion by law enforcement (as opposed to capture) when the *subject* fails to egress, it is suggested that series longevity will be increased. Furthermore, emerging social effects that likely have an impact on the *subject* would include detrimental effects on *privacy* following the

[151] See further discussion on the interpretation of model outputs using "narratives" in Chapter 2, Section 2.2.9.

recovery of a *victim* or increased situational awareness of potential *targets*. Addressing these factors will contribute significantly to generating qualitatively convincing spatial and temporal dynamics by effectively pushing the *subject* to expand his *activity-space* and spatial awareness.

It will also be beneficial to develop a means to automate procedures to refine configuration of the integrated model during calibration. One possible method may be the use of a genetic algorithm to utilize refined criteria-based matching and "evolve" the most viable matching configurations. This automation will also necessitate establishing new metrics to measure dynamic *centroid* variation (*i.e.*, cosine similarity) and should include the means to also automate *centroid* calculations.

4.2.2.2 Further Computational, Social, and Criminological Research

This dissertation suggests a new role for computational research in criminology and the social sciences that focus on the integration of endogenous subject features of decision-making and learning within environmental interactions. This type of research agenda includes further validation of the model, exploration of further analytical methods, and addressing general and specific research questions.

The GRK comparison represented a proof-of-concept for the integrated model. However, further research must include an effort to calibrate the integrated model across a significant number of real-world series. This is an important step toward empirical validation of the integrated model through spatial and temporal comparisons. For example, calibrating the integrated model to other real-world murder series (sexual murders and non-sexual murders), rape series, and robbery series will provide additional opportunities to refine comparison metrics, devise selection criteria for default parameter values, and highlight parameters that are (and are not) significant. This will also provide an opportunity to better understand variations in model configuration during calibration and establish a more robust understanding of the divergences of real-world series from the integrated model's proposed violent offending process.

The integrated model produces iterative cycles of interaction that span from development of the *acquisitional goal* (*inhibitory threshold* breach) to interaction "outcome." Aggregating transitions between states across all iterations of the violent offending process allows one to calculate first-order transition probabilities. Given future validation and refinement, first order transition probabilities have the potential to provide a basis for useful causal-path analysis for aggregated, as well as specific, events (see Appendix C).

Other methods of analyzing integrated model outcomes should also be examined. For instance, temporal analysis of aggregated runs may provide opportunities to apply hazard force analysis (in which intensity is measured as *dbh* within any given series) to simulated data. Once the integrated model has been validated, coupling hazard force analysis with power law analysis may provide significant insights about tempo and severity of violent events (Cioffi-Revilla, 2014b). Furthermore, given structural similarities of "priming" with the concepts of criticality and "metastability" in bifurcation theory in conflict analysis, the integrated model may provide unique insights "into situations that are deceptively stable but in fact are fully capable of generating extreme events that will surprise decision makers." (Cioffi-Revilla, 2012b, p. 207).

The integrated model can be used to address specific research questions. For instance, it can offer insights toward the exploration of events with similar structure but different time scale (*i.e.*, serial murder versus mass murder) or explore the relationships between offender adaptability, criminal series longevity, and tempo (a topic that is relatively unaddressed in the literature). These research efforts can go a long way toward understanding the violent offending process as having multiple layers of application throughout social and criminological research. For this reason, examining and further testing the robustness of event structure across temporal scale within the context of the integrated model provides a promising focus for future study.

In addition, the integrated model, due to its foundational incorporation of threshold-based drivers and resultant compound events, offers an interesting and unique way to integrate the concept of "loss of killing inhibition" (as applied to individual radicalization) into the violent offending process (Cioffi-Revilla, 2012a). Not only will incorporating the notions of *distancing* and *differentiation* provide insight into criminal violence, but it will also move toward using of the integrated model to enhance current understanding of the dynamics of radicalization in terrorism (Cioffi-Revilla, 2012a).

The integrated model can also be used to explore specific issues of social interaction and investigative relevance. For instance, if an offender has a tendency to be absent during accountable time, under certain conditions it may be possible to infer negative social effects on the offender's lifestyle *(i.e.*, he is absent a lot from work and therefore he cannot hold down a job). The repercussions of this type of analysis could offer non-trivial insights for investigative leads.

Another set of dynamic questions that could be explored are the interplay of *action strategies* with target–rich environments. For instance, when an offender selects a *victim* from a target-rich environment for "dominant" action, the integrated model appears to show (as a function of *comfort* and *privacy*) that he is also likely to have a significant number of "collaborative" encounters in the same location. Further validation of the model using real-world events will create a greater understanding of this dynamic and will go a long way toward addressing (and supporting) practical investigative assumptions.

The specification of "primed" and "non-primed" behaviors also has the potential to be the first step toward establishing a set of guiding principles of primed behavior. Paramount to this effort is the determination that state of "priming" and state of "action" are two separate features that complement each other. As such, within an offending context, a subject can be a "non-primed, non-offender," a "primed, non-offender," and a "primed, offender." This also means that there is a potential fourth condition of "non-primed, offender" that is not addressed in this dissertation but does pose an interesting theoretical question for further investigation. For instance, *is there a condition under which a subject violently offends, but has no intentions throughout the event to commit a violent offense?* The theoretical implications of this fourth condition are ultimately dependent on the underlying social construction of what constitutes "violent offending," and are left for future investigation.

Ultimately, the development of the integrated model has long term implications for computational and criminological research in general. The ability to create an offender *in silico* to simulate the violent offending process can, given further validation of the integrated model, produce viable hidden populations of primed non-offender populations and synthetic data. This will help researchers to better understand transitions from non-offender to offender states and create a way to better address and define complex and dynamic aspects of violent offending.

4.3 Summary

This chapter begins in Section 4.1.1 by discussing findings from the spatial, temporal and criteria-based analyses in the previous chapter. In Section 4.1.1, it is found that the five different configurations of the model closely matched the GRK series with respect to aggregated spatial placement of event-sites. However, a deeper discussion of these findings highlights that the dynamic spatial quality, which depends on site sequencing, is not well matched. This spatial discrepancy is attributed to the lack of dynamic representation of *privacy* and the *subject's* lack of response to social circumstances that are, in the real-world, likely to drive an offender to new event-sites.

Temporal findings (see Section 4.1.2) are discussed in terms of *days-between-hits* and series longevity. It is found that the integrated model is effective at matching the GRK series when it comes to temporal clustering characteristics. However, the integrated model does not perform well in creating runs that had the same longevity as the real-world series. Interestingly, temporal findings seem to suggest that the more variation that a *subject* has in his preferred tactical planning and adaptation methods, the more the simulated series appears to be structurally similar to the GRK series. Furthermore, the more responsive the methods are to changing ecological conditions, the better chance the *subject* has of avoiding capture.

Criteria-based matching (see Section 4.1.3) is discussed as relatively ineffective at identifying a "best fit" configuration. However, it is also found that some of the criteria do show significant matching with the GRK series and the temporal criteria are fairly effective in identifying two configurations that emphasize adaptive learning as providing effective matches. However, the discussion notes that these findings simply reinforce the temporal findings.

Broader implications of the findings are discussed in Section 4.2. It is argued that the integrated model, while still in need of validation, is a significant step toward computationally expressing the violent offending process. Furthermore, it is asserted that calibration of the integrated model to a specific series is not only possible, but also necessary to further validate the model and provide deeper understanding of how specific instances of violent offending differ from the violent offending process as expressed in the integrated model.

A significant number of limitations to the integrated model (and strategies to overcome them) are discussed (see Section 4.2.1) in terms of configuration challenges, memory limitations, "unit-less" parameters, cognitive resources, scheduling and the necessity for further validation. Finally, implications for further research are discussed (see Section 4.2.2) in terms of further development of the integrated model and further suggestions for social and criminological research.

CHAPTER 5: CONCLUSIONS

This dissertation begins with four enduring questions about violent offending. The answers to these questions highlight how this research provides unique insights into the violent offending process. First, *can a violent "offender" be identified prior to attack?* The answer is "yes." The integrated model provides the opportunity to examine a "potential" violent offender's transitions from pre-offending states to active offending.

Second, *is it possible to discover and/or predict offending trajectories?* Again the answer is "yes." The integrated model represents the transitions in the violent offending process as compound events that can be discovered and formalized as a forward-branching process and contextualized via *event-chain* narratives. In addition, model outputs produce state transition probabilities that can inform causal-path analysis of specific offending trajectories. While the prediction of a particular subject's pathway through the process is still not tenable, the integrated model implements the means to discover and generally predict probability-driven trajectories.

Third, *how does offending depend on the micro-level features of the offender?* The representations of endogenous needs-driven decision-making, *tactical planning* and *adaptation*, associative memory, and experiential learning all contribute to the *subject's* outcome states. The integrated model can be used to understand variations in each of these factors and their effect on state transitions.

Fourth, *how can hidden attributes and features of violent offenders be effectively examined?* The integrated model provides a unique opportunity to examine endogenous subject features by allowing violent offending to become an emergent feature of the model. Furthermore, the integrated model provides a significant level of transparency in watching how features, that in the real-world are hidden from examination, interact and produce behavior. These outputs can then be collected directly, free from biases associated with data collection strategies, and give an accurate representation of explicit outcomes.

This dissertation is motivated by the need to apply new methodologies to violent offender research. This is not to say that traditional research is without merit. Instead, this dissertation seeks to address the "hard" problem of getting to hidden attributes of violent offending and the endogenous features that implicit theories of violence attempt to address. While general methods of social and behavioral research depend on observation of outcomes, the methods executed here find that additional focus on the underlying process of violent offending can produce interesting and insightful conclusions that may validate some current understanding of violent behavior and suggest deeper interconnectedness generated by the offender, victim, and environment interactions.

It is further suggested that this dissertation highlights useful analytical methodologies like formalization of forward-branching processes and transition probabilities that are used in interpreting states and generating causal-paths. These are extremely important considerations for analysts, investigators and policy-makers thinking about contingencies and interested in expanding their understanding of a problem space (Boyd, 1992; Kauffman, 2003).

The overall objective of this dissertation is *to explore if implementation of the violent offending process as a computationally expressed complex social simulation provides meaningful insights into the internal and external drivers of offending*. Achieving this primary goal necessitated the completion of four objectives; 1) phased creation of an integrated model of the violent offending process, 2) verification of the model, 3) calibration of the model to a real-world series of violent offenses, and 4) development of a way to determine the model's efficacy in producing qualitatively realistic temporal and spatial outcomes. As a result, this dissertation has produced a viable integrated model of the violent offending process with significant internal validation that can be calibrated to, and generate simulated outputs comparable with, a real-world series.

It is important to remember that this dissertation is exploratory, not predictive. Thus, the reason for its creation is not to find immediate opportunities for anticipating the trajectory of, or the next event within, a series of violent crimes. While in time this type of modeling effort may have predictive applications, prediction itself is outside the scope of this dissertation. However, "meaningful insight" does not imply the exercise of prediction (Epstein J. , 2008). In fact," meaningful insight" in this exploratory effort involves understanding the complexities of offending in a more sophisticated or nuanced way, re-enforcing or (in some cases) re-defining implicit theory, and even identifying useful analogies to better understand the overall complexities of decision-making within a dynamic social system. Additionally, this modeling effort should be seen as an opportunity to identify new questions that can enhance other research efforts.

In criminology and crime analysis, computational methodologies offer practical contributions to understanding the complexity of crime as a social phenomenon.[152] With increasing computational resources, expanding methods, and no shortage of "hard" problems to be addressed, there is a significant amount of momentum to be gained. This dissertation furthers the field of computational criminology by integrating macro-level subject-environment interactions with boundedly rational endogenous features of the violent offender himself. In this way, the integrated model adds to general discourse about crime trends and can also offer specific insights about offending behavior.

Thus, not only does this dissertation successfully prototype a computational expression of the violent offending process in Chapter 2, but it also produces "practical" findings in Chapter 3. Primary among these findings is the notion that a *subject's* ability to vary his methods and adapt are key elements in temporal clustering characteristics and series longevity. Additionally, while areas of *privacy* and *comfort* provide the *subject* with targeting and site <u>options</u>, dynamic interactional factors influence specific choices. Moreover, the development of *maze-running* as analogy to tactical planning and adaptation provides a unique way to better understand the dynamic circumstances in which decisions are made.

The integrated model as a whole highlights the possibility that there may be a process of violent interaction that can be applied to offending outcomes expressed at

[152] There is also an educational aspect to computational criminology (seeing traditional crime problems in new ways) that will likely play an important role in changing the mentality of analysts and investigators.

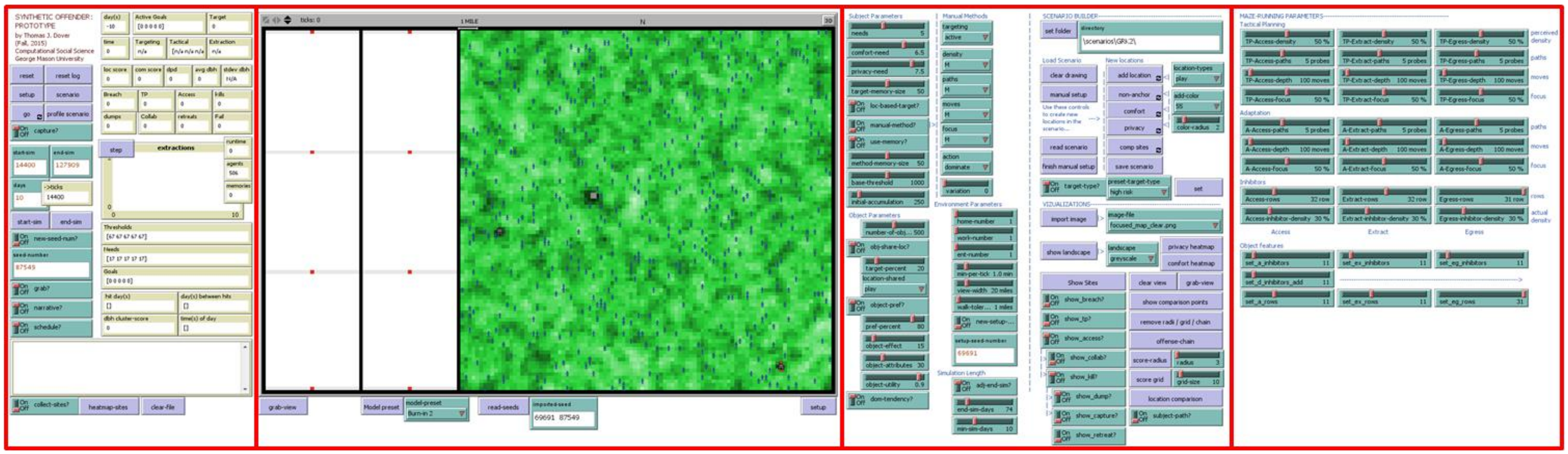
various temporal scales. Thus, given further modeling efforts, a useful model of interactions in general could be distilled from the integrated model. This is especially promising when one considers that the majority of the interactions organically allowed to evolve in the integrated model tend to be “collaborative” and not “dominant.” Thus, with a slight shift in perspective, the integrated model presents an interaction model.

In conclusion, the exercise of creating a complex model of the violent offending process necessitates the explicit examination of a diversity of factors involved in violent offending and decision-making. However, it also presents opportunities for research that extend far beyond the emergence of violence. The underlying theoretical and structural basis of the integrated model provides computationally explicit means to improve understanding of a variety of behavioral and political domains. In doing so, this integrated model presents the first step toward a much more comprehensive understanding of the dynamic endogenous and exogenous features of human interaction.

APPENDIX A

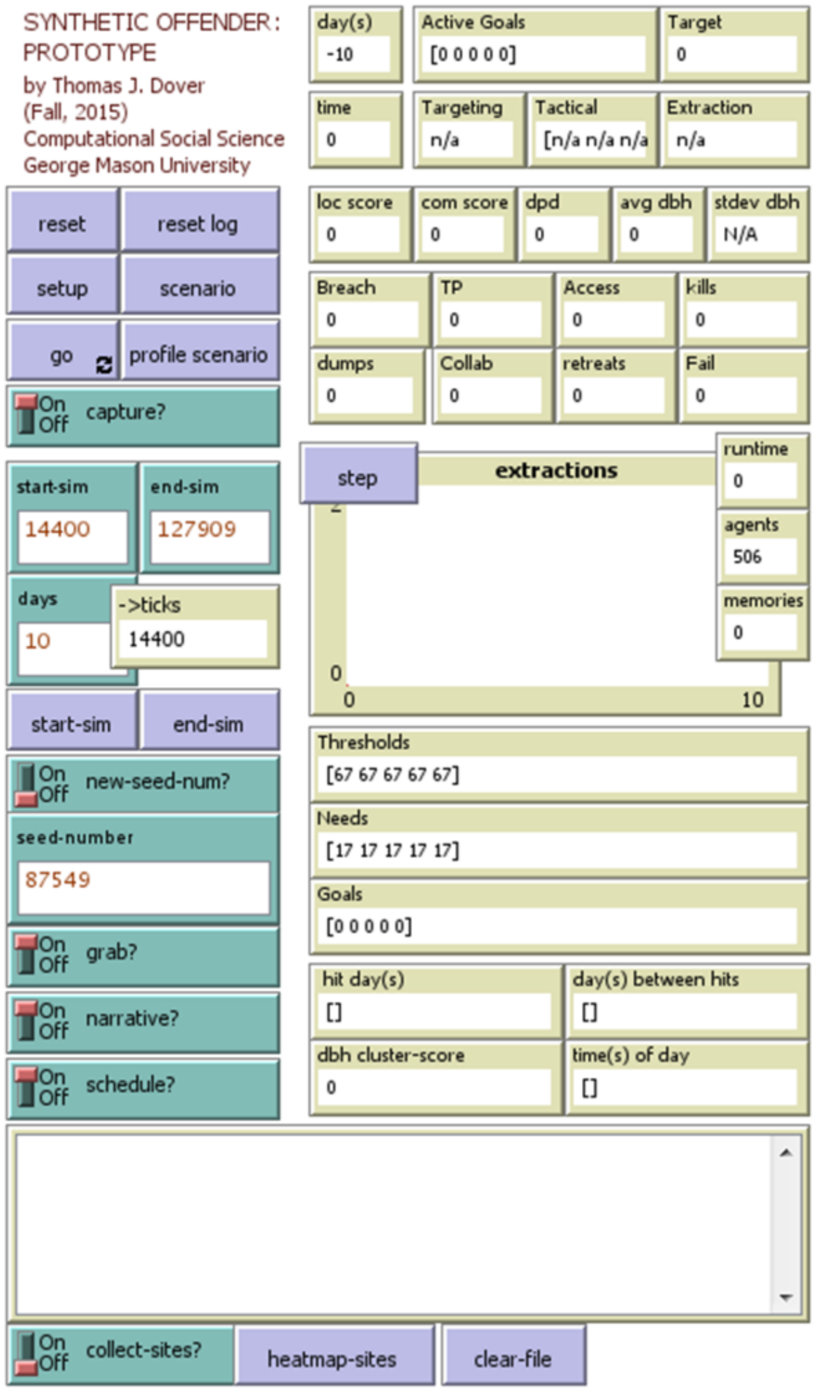
The integrated model interface is shown. Each area (A1, A2, A3, and A4), along with a description of the interface elements in the area, follow.

Integrated Model Interface



A1 A2 A3 A4

A1


SYNTHETIC OFFENDER : PROTOTYPE
by Thomas J. Dover
(Fall, 2015)
Computational Social Science
George Mason University
day(s)
-10
Active Goals
[0 0 0 0 0]
Target
0
time
0
Targeting
n/a
Tactical
[n/a n/a n/a
Extraction
n/a
reset
reset log
setup
scenario
go
profile scenario
loc score
0
com score
0
dpd
0
avg dbh
0
stdev dbh
N/A
Breach
0
TP
0
Access
0
kills
0
dumps
0
Collab
0
retreats
0
Fail
0
On
Off
capture?
start-sim
14400
end-sim
127909
step
extractions
runtime
0
agents
506
memories
0
days
10
->ticks
14400
0
0
10
start-sim
end-sim
Thresholds
[67 67 67 67 67]
On
Off
new-seed-num?
Needs
[17 17 17 17 17]
seed-number
87549
Goals
[0 0 0 0 0]
On
Off
grab?
hit day(s)
[]
day(s) between hits
[]
On
Off
narrative?
dbh cluster-score
0
time(s) of day
[]
On
Off
schedule?
On
Off
collect-sites?
heatmap-sites
clear-file

A1			
Type	**Label**	**Explanation**	**Note…**
BUTTON	reset	runs the RESET-INTERFACE procedure to reset maze-running parameters, object clustering and object number on the model interface.	procedure: reset-interface
BUTTON	reset log	runs code to reset "running-event-log.csv" which captures the specific methods used during tactical planning and adaptation for a specific target following a successful egress from a dominant action.	code: file-open "/logs/running-event-log.csv" file-print "end" file-close file-delete "/logs/running-event-log.csv" file-open "/logs/running-event-log.csv" file-print (word "targeting,density,paths,depth,focus,action,target,file") file-close
BUTTON	setup	runs the SETUP procedure to instantiate a stylized non-scenario-based simulation.	procedure: setup
BUTTON	scenario	runs the SETUP-CASE procedure to instantiate a specific "series" as defined through the *SCENARIO BUILDER elements*.	procedure: setup-case
BUTTON	go	initiates the simulation through the GO procedure. The simulation will continue to iterate until it reaches the END-SIM tick or the simulation is stopped due to failure to egress.	procedure: go
BUTTON	profile scenario	runs the PROFILE-SCENARIO procedure to capture a code profile of procedure calls during a specific simulation run	procedure: profile-scenario
BUTTON	start-sim	sets the START-SIM input to the appropriate tick on which to start the simulation. This calculation is based on the MIN-PER-TICK slider and the number of days indicated in the DAYS input.	code: set start-sim days * (60 / min-per-tick) * 24

BUTTON	end-sim	sets the END-SIM input to the appropriate tick on which to end the simulation. This calculation is based on the MIN-PER-TICK slider and the number of days indicated in the DAYS input.	code: set end-sim days * (60 / min-per-tick) * 24
BUTTON	step	initiates one iteration of the simulation through the GO procedure.	procedure: go
BUTTON	heatmap-sites	runs the HEATMAP-SITES procedure in conjunction with the COLLECT-SITES switch (must be "on"). Visualizes aggregated event-sites as a heat-map.	procedure: heatmap-sites
BUTTON	clear-file	runs code to clear the current "simulation-sites.txt" file.	code: ifelse file-exists? "simulation-sites.txt" [file-delete "simulation-sites.txt" clear-output export-output "simulation-sites.txt"] [clear-output export-output "simulation-sites.txt"]
INPUTBOX	start-sim	indicates the tick on which the simulation will begin. This value can be set either manually or using the START-SIM button. If this value is greater than 0, the simulation run involves *burn-in*	type: Number
INPUTBOX	end-sim	indicates the tick on which the simulation will end (if the simulation is not stopped by failure/capture). This value can be set either manually or using the END-SIM button.	type: Number
INPUTBOX	days	used to designate the number of days into the simulation for either the START-SIM button or the END-SIM button.	type: Number
INPUTBOX	seed-number	indicates the seed number that will be used during the specific simulation run. This value can be manually entered or imported using the IMPORTED-SEED input and READ-SEEDS button.	type: Number

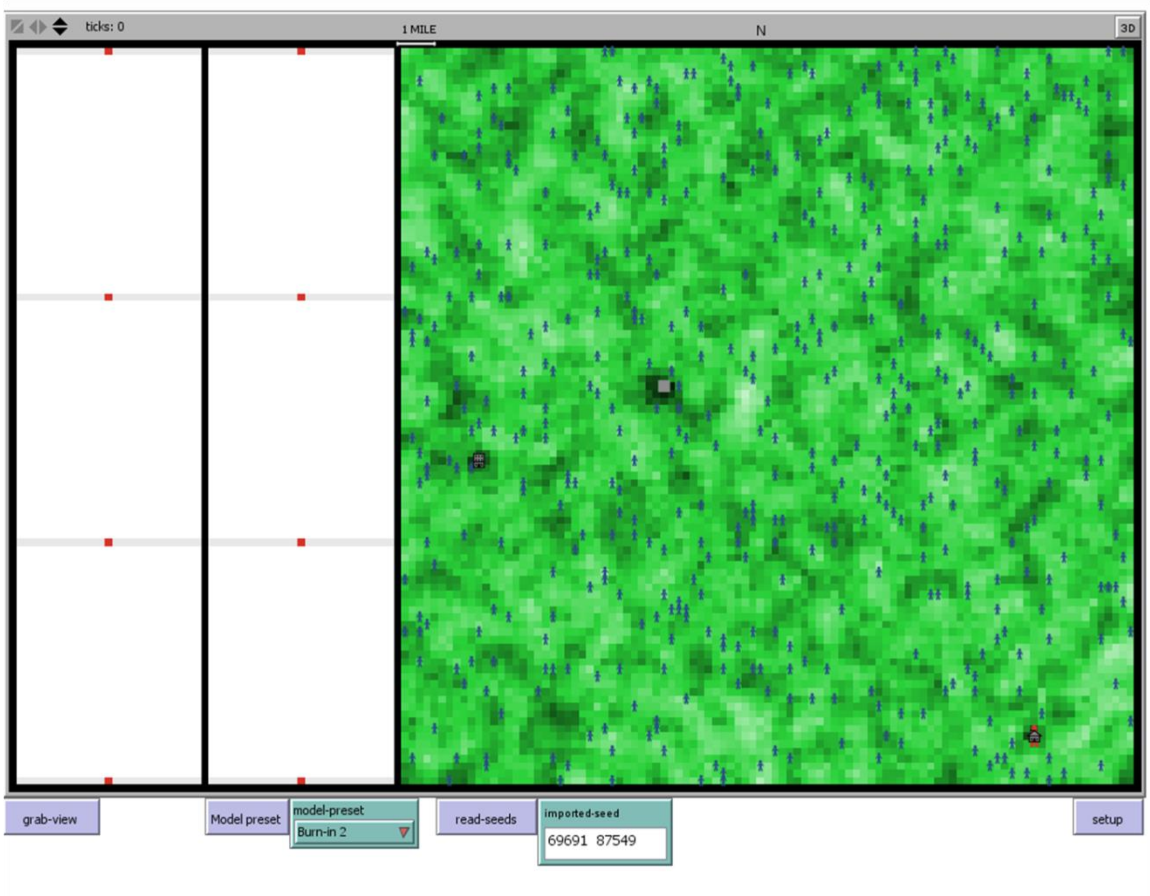
SWITCH	capture?	If switch is "on," failure to egress during dominant action is considered "capture" and the simulation will end. If switch is "off," failure to egress during dominant action is not considered "capture" and the simulation continues. This is used during *burn-in* to allow the subject to rapidly build tendencies without stopping the simulation.	value: ON/OFF
SWITCH	new-seed-num?	If switch is "on," the SEED-NUMBER input will change each time the model is run. Under these circumstances, each run of the same model will be unique. If switch is "off," the SEED-NUMBER input will not change. Under these circumstances, a specific run can be reproduced.	value: ON/OFF
SWITCH	grab?	if switch is "on," when output requirements are met, export a series of useful visualizations of event-sites when the simulation ends.	value: ON/OFF
SWITCH	narrative?	if switch is "on," record events during the simulation and, when output requirements are met, export the simulation events to a .txt file	value: ON/OFF
SWITCH	schedule?	if switch is "on," subject (and 90% of objects) follow a schedule as defined in Scheduling Procedures (SET-SCHED_TARGET and SET-SCHED_TARGET-OBJ)	value: ON/OFF
SWITCH	collect-sites?	If switch is "on," event-site locations and types are written to a file (simulation-sites.txt) that accumulates event-sites over multiple simulation runs. This allows the model to aggregate event-sites and visualize them as a heat-map using the HEATMAP-SITES button.	value: ON/OFF
MONITOR	->ticks	reports the number of time-steps represented by the DAYS input	source: days * (60 / min-per-tick) * 24

MONITOR	day(s)	reports the number of days into the simulation (from START-SIM input value). If time-steps have not yet reached START-SIM input value (during *burn-in*), reports a negative number representing number of days until simulation start.	source: floor ((ticks - start-sim) / ((60 / min-per-tick) * 24))
MONITOR	Active Goals	reports nominal active goal. A letter (A, B, C, D…) in any position indicates the goal incorporates a specific need, a "0" in any position indicates that need is absent. i.e. [A B C D E] or [A 0 0 D E]. Size of the goal (number of needs) is determined by the NEEDS slider under SUBJECT PARAMETERS.	source: [goals_active] of one-of subs
MONITOR	Target	reports the object the subject the subject is currently targeting for interaction (regardless of collaborative or dominant action)	source: [target] of one-of subs
MONITOR	time	Reports current (decimal) time represented in the simulation.	source: (((ticks - start-sim) / ((60 / min-per-tick) * 24)) - floor ((ticks - start-sim) / ((60 / min-per-tick) * 24))) * 24
MONITOR	Targeting	reports current targeting strategy (active or passive)	source: [targeting_method] of one-of subs
MONITOR	Tactical	reports current tactical strategy (cognitive resources: density, paths, depth, focus) as H/M/L	source: [tactical_method] of one-of subs
MONITOR	Extraction	reports current action strategy (dominant or collaborative)	source: [action_method] of one-of subs
MONITOR	loc score	reports the final comparison location score for the run	source: comp_location_score
MONITOR	com score	reports the final comparison completeness score for the run	source: comp_completeness
MONITOR	dpd	reports the mean days per dominant extraction for the run	source: day_per_extract
MONITOR	avg dbh	reports the mean number of days between dominant extractions for the run	source: avg_dbh
MONITOR	stdev dbh	reports the standard deviation of days between dominant extractions for the run	source: standard-deviation dbh

MONITOR	Breach	reports the running total of threshold breaches for the run	source: count sites with [site_type = "breach"]
MONITOR	TP	reports the running total of successfully conceptualized tactical plans for the run	source: count sites with [site_type = "tactical plan"]
MONITOR	Access	reports the number of successful accesses for the run	source: count sites with [site_type = "access"]
MONITOR	kills	reports the number of successful kills (dominant extractions) for the run	source: count sites with [site_type = "kill"]
MONITOR	dumps	reports the number of successful body dumps (post dominant extraction egresses) for the run	source: count sites with [site_type = "dump"]
MONITOR	Collab	reports the number of successful collaborations (collaborative extractions) for the run	source: count sites with [site_type = "collab"]
MONITOR	retreats	reports the number of successful retreats from attempted (but failed) dominant action	source: count sites with [site_type = "retreat"]
MONITOR	Fail	reports the number of unsuccessful retreats and/or unsuccessful egress after killing (dominant extraction). If CAPTURE? switch is "on," this reports the number of captures.	source: count sites with [site_type = "capture"]
MONITOR	runtime	reports current value of the runtime timer	source: time
MONITOR	agents	reports total number of agents currently active in the simulation. Includes subject, objects, locations, and other navigational and visualization agents.	source: count turtles
MONITOR	memories	reports the number of entries currently in the subject's METHOD_MEMORY	source: length [method_memory] of one-of subs
MONITOR	Thresholds	reports subject's current threshold values	source: [thresholds] of one-of subs
MONITOR	Needs	reports subject's current need values (needs-accumulator)	source: [needs_accumulator] of one-of subs
MONITOR	Goals	reports subject's current goal values (NEEDS - THRESHOLDS...> 0 indicates an active goal)	source: [goals] of one-of subs

MONITOR	hit day(s)	reports running list of kill (successful dominant extraction) days	source: hit_day
MONITOR	day(s) between hits	reports a running list of days between HIT DAY(S)	source: dbh
MONITOR	dbh cluster-score	reports the final dbh-score for the run	source: cluster-score
MONITOR	time(s) of day	reports running list of kill (successful dominant extraction) times	source: tod
OUTPUT	Model output	area in which the model writes various narrative, logging, and profiling outputs	not manually interactive

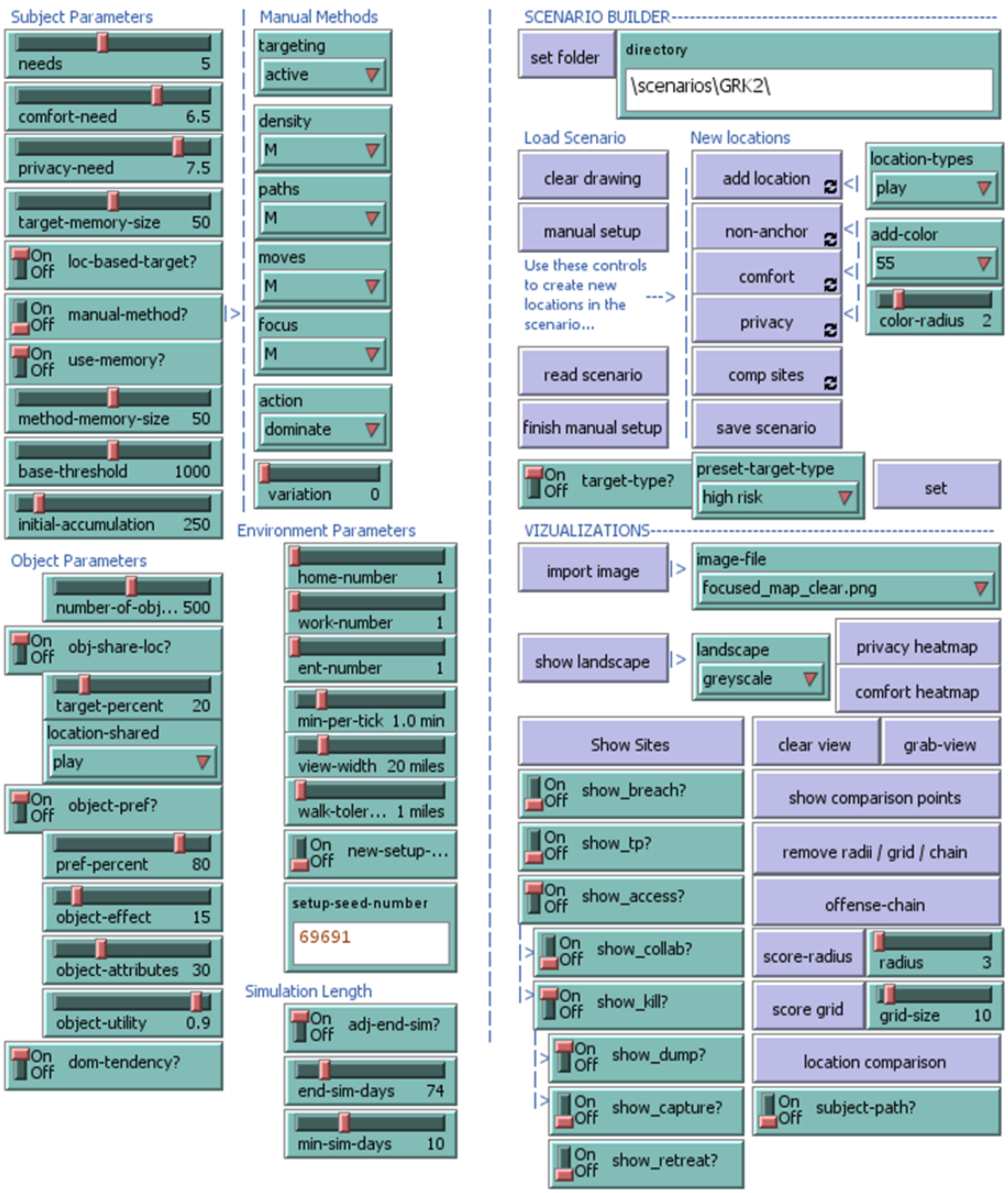
A2



ticks: 0
1 MILE
N
3D
grab-view
Model preset
model-preset
Burn-in 2
read-seeds
imported-seed
69691 87549
setup

A2			
Type	**Label**	**Explanation**	**Note…**
VIEW	Model View	space in which the model interactions are visualized. The space is divided into the *cognitive landscapes* and *environmental landscapes.*	for a more complete description see Chapter 2, Section 2.2.2
BUTTON	grab-view	runs the GRAB-VIEW procedure to export the current model view as a .png file	procedure: grab-view
BUTTON	Model preset	runs the PRE-SET-SETTINGS procedure to set interface parameters based on the MODEL-PRESET chooser	procedure: pre-set-settings
BUTTON	read-seeds	runs the READ-SEEDS procedure using the values listed in the IMPORTED-SEED input. The first value is used for the SETUP-SEED-NUMBER and the second value is used for the SEED-NUMBER	procedure: read-seeds
BUTTON	setup	runs the SETUP procedure to instantiate a stylized non-scenario-based simulation.	procedure: setup
CHOOSER	model-preset	used to designate which model preset will be activated using the MODEL PRESET button	values: "Model Baseline", "Series Baseline", "Manual Method", "Burn-in 1", "Burn-in 2"
INPUTBOX	imported-seed	used to list two values to be referenced by the READ-SEEDS button. The first value is used to set the SETUP-SEED-NUMBER and the second value is used to set the SEED-NUMBER	type: String

A3



Subject Parameters
needs 5
comfort-need 6.5
privacy-need 7.5
target-memory-size 50
On Off loc-based-target?
On Off manual-method?
On Off use-memory?
method-memory-size 50
base-threshold 1000
initial-accumulation 250
Object Parameters
number-of-obj... 500
On Off obj-share-loc?
target-percent 20
location-shared
play
On Off object-pref?
pref-percent 80
object-effect 15
object-attributes 30
object-utility 0.9
On Off dom-tendency?
Manual Methods
targeting
active
density
M
paths
M
moves
M
focus
M
action
dominate
variation 0
Environment Parameters
home-number 1
work-number 1
ent-number 1
min-per-tick 1.0 min
view-width 20 miles
walk-toler... 1 miles
On Off new-setup-...
setup-seed-number
69691
Simulation Length
On Off adj-end-sim?
end-sim-days 74
min-sim-days 10
SCENARIO BUILDER
set folder
directory
\scenarios\GRK2\
Load Scenario
clear drawing
manual setup
Use these controls to create new locations in the scenario...
read scenario
finish manual setup
New locations
add location
non-anchor
comfort
privacy
comp sites
save scenario
location-types
play
add-color
55
color-radius 2
On Off target-type?
preset-target-type
high risk
set
VIZUALIZATIONS
import image
image-file
focused_map_clear.png
show landscape
landscape
greyscale
privacy heatmap
comfort heatmap
Show Sites
clear view
grab-view
On Off show_breach?
show comparison points
On Off show_tp?
remove radii / grid / chain
On Off show_access?
offense-chain
On Off show_collab?
score-radius
radius 3
On Off show_kill?
score grid
grid-size 10
On Off show_dump?
location comparison
On Off show_capture?
On Off subject-path?
On Off show_retreat?

A3: SUBJECT PARAMETERS			
Type	**Label**	**Explanation**	**Note…**
SWITCH	loc-based-target?	If switch is "on," the subject only records a location associated with object-attributes into TARGET-MEMORY.	value: ON/OFF
SWITCH	manual-method?	if switch is "on," the subject's preferred methods are manually set on the model interface using the MANUAL METHODS parameters. USE-MEMORY? Is automatically set to "off."	value: ON/OFF
SWITCH	use-memory?	if switch is "on," use the METHOD-MEMORY to define the subject's preferred methods.	value: ON/OFF
SLIDER	needs	defines the number of NEEDS	range: 1 --> 10 (default: 5)
SLIDER	comfort-need	defines the minimum comfort value of a cell for a subject to feel "comfortable."	range: 0 --> 9 (default: 6.5)
SLIDER	privacy-need	defines the minimum privacy value of a cell for a subject to feel "privacy."	range: 0 --> 9 (default: 7.5)
SLIDER	target-memory-size	defines the number of memory slots for the TARGET-MEMORY.	range: 0 --> 100 (default: 50)
SLIDER	method-memory-size	defines the number of memory slots for the METHOD-MEMORY.	range: 0 --> 100 (default: 50)
SLIDER	base-threshold	defines the base value for initial thresholds	range: 0 --> 2000 (default: 1000)
SLIDER	initial-accumulation	defines the base value for initial needs accumulation	range: 0 --> 2000 (default: 250)
A3: MANUAL METHODS			
Type	**Label**	**Explanation**	**Note…**
CHOOSER	targeting	manually defines the subject's targeting strategy. Requires that MANUAL-METHOD? Switch is "on."	values: "active", "passive"
CHOOSER	density	manually defines the tendency of the density (cognitive resource) of the subject's tactical planning strategy. Requires that MANUAL-METHOD? Switch is	values: "H", "M", "L"

		"on."	
CHOOSER	paths	manually defines the tendency of the paths (cognitive resource) of the subject's tactical planning strategy. Requires that MANUAL-METHOD? Switch is "on."	values: "H", "M", "L"
CHOOSER	moves	manually defines the tendency of the depth (cognitive resource) of the subject's tactical planning strategy. Requires that MANUAL-METHOD? Switch is "on."	values: "H", "M", "L"
CHOOSER	focus	manually defines the tendency of the focus (cognitive resource) of the subject's tactical planning strategy. Requires that MANUAL-METHOD? Switch is "on."	values: "H", "M", "L"
CHOOSER	action	manually defines the subject's action strategy. Requires that MANUAL-METHOD? Switch is "on."	values: "dominate", "collaborate"
SLIDER	variation	defines the percent of time that the subject will vary from each of the manually defined methods.	range: 0 --> 100
		A3: OBJECT PARAMETERS	
Type	**Label**	**Explanation**	**Note…**
CHOOSER	location-shared	defines what type of location will be shared between objects and the subject. Requires OBJ-SHARE-LOC? switch to be "on."	values: "work", "play" (default: “play”)
SWITCH	obj-share-loc?	if switch is "on," a percent (as defined by the TARGET-PERCENT slider) of objects will share a common location (anchor-point) with the subject. Requires SCHEDULE? Switch to be "on."	value: ON/OFF
SWITCH	object-pref?	if switch is "on," a percent (determined by the PREF-PERCENT slider) of objects with specific attributes congregate around the shared location	value: ON/OFF

SWITCH	dom-tendency?	if switch is "on," when there are no targeting strategies to select from in METHOD-MEMORY, the subject will have a 67% chance of selecting a dominant strategy. If switch is "off," under the same circumstances the subject will have a 50% chance of selecting a dominant strategy.	value: ON/OFF
SLIDER	number-of-objects	defines the initial population of objects in the run.	range: 1 --> 1000 (default: 500)
SLIDER	target-percent	defines the percent of objects that will share a common location (anchor-point) with the subject if the OBJ-SHARE-LOC? switch is "on."	range: 0 --> 100 (default: 20)
SLIDER	pref-percent	defines the percent of objects with specific attributes to congregate around a shared location if the OBJECT-PREF? switch is "on."	range: 0 --> 100 (default: 80)
SLIDER	object-effect	defines the mean of a random - normal distribution (with standard deviation of 15) that creates the list of object effect values for each object	range: 0 --> 100
SLIDER	object-attributes	defines the mean of a random - normal distribution (with standard deviation of 30) that creates the list of object attribute values for each object	range: 0 --> 100
SLIDER	object-utility	defines the mean of a random - normal distribution (with standard deviation of 0.15) that creates the list of object-utility values for each object	range: 0 --> 1
		A3: ENVIRONMENT PARAMETERS	
Type	**Label**	**Explanation**	**Note…**
INPUTBOX	setup-seed-number	indicates the seed number that will be used during model instantiation. This value can be manually entered or imported using the IMPORTED-SEED input and READ-SEEDS button.	type: Number

SWITCH	new-setup-seed?	If switch is "on," the SETUP-SEED-NUMBER input will change each time the model is instantiated. Under these circumstances, each new instantiation of the model (prior to being run) is unique. If switch is "off," the NEW-SEED-NUMBER input will not change. Under these circumstances, a specific model setup can be reproduced.	value: ON/OFF
SLIDER	home-number	defines the number of home locations (anchor-points) for the subject	range: 1 --> 10 (default: 1)
SLIDER	work-number	defines the number of work locations (anchor-points) for the subject	range: 1 --> 10 (default: 1)
SLIDER	ent-number	defines the number of play (entertainment) locations (anchor-points) for the subject	range: 1 --> 10 (default: 1)
SLIDER	min-per-tick	defines the number of minutes represented by a time-step of the model	range: 0.1 --> 5 (default: 1)
SLIDER	view-width	defines the width (in miles) represented by the view space	range: 1 --> 100 (default: 20)
SLIDER	walk-tolerance	defines the subject's tolerance for walking as opposed to using a vehicle. This parameter is used in the calculation of the subject's speed.	range: 0 --> 25 (default: 1)
A3: SIMULATION LENGTH			
Type	**Label**	**Explanation**	**Note…**
SWITCH	adj-end-sim?	if switch is "on," following the first kill (successful dominant extraction), the END-SIM input value will be adjusted to reflect the current time-step + the END-SIM-DAYS value (converted to time-steps). In calibration this ensures that recording the length of a series begins with the first kill (at the beginning of the series).	value: ON/OFF

SLIDER	end-sim-days	defines the number of days after the first kill (successful dominant extraction) the simulation will run. During comparison to a real series, this value should reflect the length (in days) of the series the model is being compared to.	range: 0 --> 365
SLIDER	min-sim-days	defines the number of days the simulation will run without a kill (successful dominant extraction) before ending the simulation.	range: 0 --> 30
A3: SCENARIO BUILDER			
Type	**Label**	**Explanation**	**Note…**
BUTTON	set folder	sets the user directory for the maps, cell lists, activity-space, comparison sites, and simulation sites utilized in a real-world series comparison (as defined by *directory* input).	procedure: set directory user-directory
BUTTON	clear drawing	clears all drawing elements from the view to start a new real-world series setup	code: cd
BUTTON	manual setup	clears all drawing elements and sets up the model for manual entry of view elements	code: reset-interface ca if new-seed-num? = true [set seed-number (120000 - random 60001)] random-seed seed-number CREATE-NEEDS-LIST SETUP-VIEW SETUP-LANDSCAPES
BUTTON	add location	allows a user to manually place a location (as defined by *location_types* chooser) in the view.	procedure: pick-location
BUTTON	non-anchor	allows a user to manually designate a cell as a non-usable location *(i.e.*, body of water) by changing the cell color value to 0 (black) as selected by the *add_color* chooser. Radius of cells effected is determined by the *color_radius* slider.	procedure: pick-non-geospatial-locations

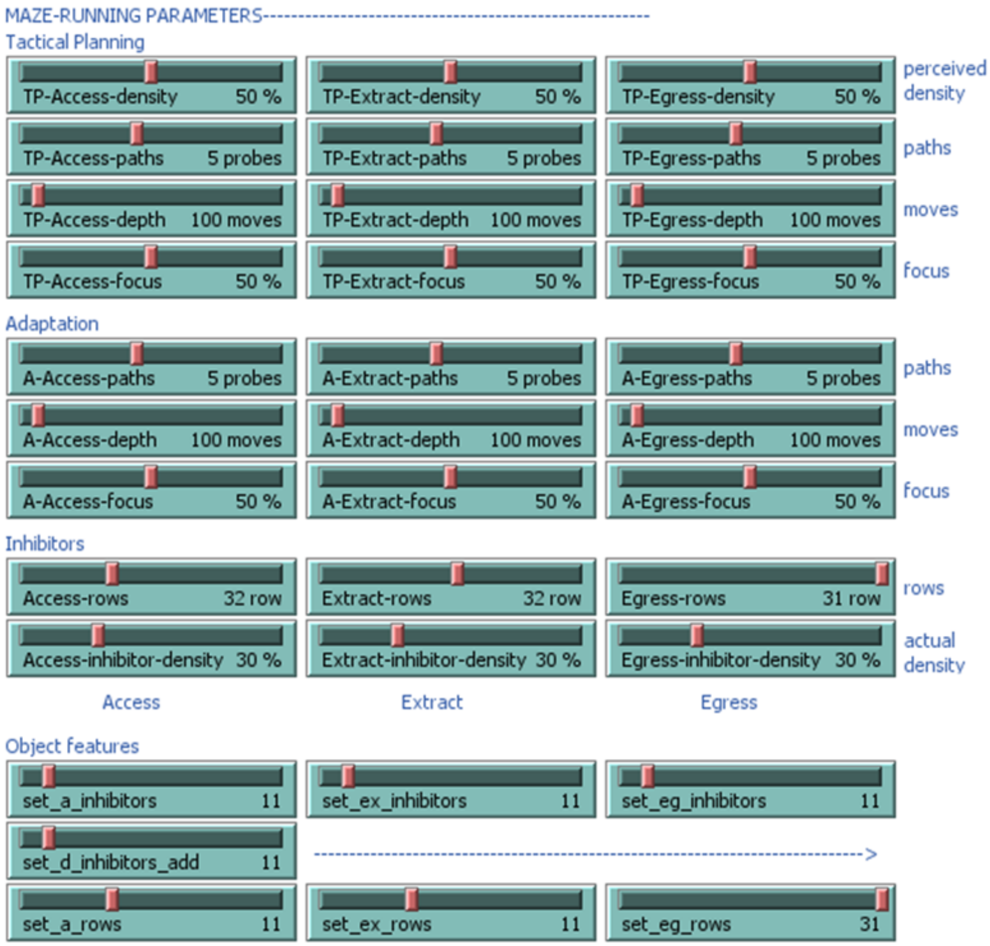
BUTTON	comfort	allows a user to manually designate a cell as an area of high comfort by changing the cell comfort value to between 6 and 10	procedure: pick-manual-comfort
BUTTON	privacy	allows a user to manually designate a cell as an area of high privacy by changing the cell privacy value to 10	procedure: pick-manual-privacy
BUTTON	comp sites	allows a user to manually place comparison sites from the real-world series into the view for comparison to simulation outputs.	procedure: pick-comp-sites
BUTTON	save scenario	allows the user to save the currently configured scenario to the root folder (as defined by *directory* input).	code: if "yes" = user-one-of "This will over-write any existing scenarios in the root folder...continue?" ["yes" "no"] [save-scenario-view]
BUTTON	read scenario	allows the user to load a previously saved scenario from the root directory (as defined by *directory* input).	procedure: read-scenario-view
BUTTON	set risk	allows the user to set target "risk" (as defined by the *preset-target-type* chooser) if the *target-type?* switch is "on."	procedure: set-preset-target-type
BUTTON	finish manual setup	allows the user to finalize the building of a real-world scenario by instantiating the model agents, cells, and scale.	code: SET-NEW-COMFORT SET-NEW-PRIVACY CREATE-PATCH-ATTRIBUTES CREATE-NEW-OBJECTS CREATE-NEW-SUBJECTS CREATE-SCALE reset-ticks
CHOOSER	location-types	defines the type of location manually placed in the view.	values: "home", "work", "play"
CHOOSER	add-color	defines the color of cells selected when identifying non-anchor locations, comfort, and privacy	values: 0, 55, 69.5
CHOOSER	preset-target-type	defines what target type will be created if the *target-type?* switch is ON. Use SET RISK button to set OBJECT FEATURE parameters.	values: "high risk", "low risk"

INPUTBOX	directory	defines the directory folder that contains scenario files	type: String (default: \scenarios\GRK2\)
SWITCH	target-type?	determine if the model will utilize target risk	value: ON/OFF
SLIDER	color-radius	defines the radius of effect when a cell is selected	range: 0 --> 10
A3: VISUALIZATIONS			
Type	**Label**	**Explanation**	**Note…**
BUTTON	import image	Runs the IMPORT-IMAGE procedure which imports the image file identified in the IMAGE-FILE chooser into the model view	procedure: import-image
BUTTON	show landscape	Runs the SHOW-LANDSCAPE procedure which visualizes the view landscape based on the LANDSCAPE chooser.	procedure: show-landscape
BUTTON	privacy heatmap	Runs the HEATMAP-PRIVACY procedure which visualizes the view landscape based on privacy values	procedure: heatmap-privacy
BUTTON	comfort heatmap	Runs the HEATMAP-COMFORT procedure which visualizes the view landscape based on comfort values	procedure: heatmap-comfort
BUTTON	Show Sites	Runs SHOW-SITES procedure which uses the SHOW-BREACH, SHOW-TP, SHOW-ACCESS, SHOW-COLLAB, SHOW-KILL, SHOW-DUMP, SHOW-CAPTURE, SHOW-RETREAT switches (if "on") to visualize event sites in the model view	procedure: show-sites
BUTTON	clear view	Runs the CLEAR-VIEW procedure to remove all objects on the model view drawing layer and reset locations and event sites.	procedure: clear-view
BUTTON	grab-view	Runs the GRAB-VIEW procedure to export the current model view as a .png file	procedure: grab-view
BUTTON	show comparison points	Runs the SHOW-COMP-SITES procedure to visualize the comparison event sites from a real world series.	procedure: show-comp-sites

BUTTON	remove radii/grid/chain	Runs code to remove Radii agents, offense chains, and score grid from the Model view	code: ask site-counts [die] ask offense_chains [die]
BUTTON	offense-chain	Runs the CREATE-OFFENSE-CHAIN procedure which visualizes the chain of sites (based on a specific victim) from access to body disposal during dominant action.	procedure: create-offense-chain
BUTTON	score-radius	Runs the SCORE-RADII procedure to create radii agents at each compsite and compare their locations to output disposal sites. The size of the radii is determined by the RADIUS slider.	procedure: score-radii
BUTTON	score grid	Runs the SCORE-GRID procedure to create a grid that will indicate areas in which there are model output disposal sites and real-world comparison sites. The size of the grid is determined by the GRID-SIZE slider.	procedure: score-grid
BUTTON	location comparison	Runs the COMPARE-LOCATIONS procedure to compare simulation output disposal sites to geospatial comparison sites by calculating comparison location and comparison completeness scores. This procedure runs automatically at the end of a simulation run.	procedure: compare-locations
CHOOSER	image-file	defines the image files that can be imported using the IMPORT-IMAGE button.	values: "focused_map.png", "compare focused_map.png", "focused_map_clear.png"
CHOOSER	landscape	defines the landscapes that can be visualized using the SHOW-LANDSCAPE button	values: "comfort", "privacy", "greyscale", "none"
SWITCH	show_breach?	if switch is "on," show threshold breach sites when SHOW-SITES button is activated.	value: ON/OFF
SWITCH	show_tp?	if switch is "on," show successful tactical planning sites when SHOW-SITES button is activated.	value: ON/OFF
SWITCH	show_access?	if switch is "on," show successful access sites when SHOW-SITES button is activated.	value: ON/OFF

SWITCH	show_collab?	if switch is "on," show successful collaboration (collaborative extraction) sites when SHOW-SITES button is activated.	value: ON/OFF
SWITCH	show_kill?	if switch is "on," show successful kill (dominant extraction) sites when SHOW-SITES button is activated.	value: ON/OFF
SWITCH	show_dump?	if switch is "on," show successful body dump (egress from dominant extraction) sites when SHOW-SITES button is activated.	value: ON/OFF
SWITCH	show_capture?	if switch is "on," show capture (unsuccessful egress from failed dominant access or action) sites when SHOW-SITES button is activated.	value: ON/OFF
SWITCH	show_retreat?	if switch is "on," show successful retreat (egress from failed dominant action) sites when SHOW-SITES button is activated.	value: ON/OFF
SWITCH	subject-path?	if switch is "on," retain the subject's path (as a red line) throughout the simulation in the model view, do not show maze running probe paths in the cognitive landscapes. If switch is "off," do not retain subject path, show maze-running paths probes in the cognitive landscapes.	value: ON/OFF
SLIDER	radius	defines the radius size for radii created with the SCORE-RADIUS button.	range: 1 --> 100
SLIDER	grid-size	defines the size of the grid created with the SCORE-GRID button.	range: 5 --> 50

A4


MAZE-RUNNING PARAMETERS--
Tactical Planning
TP-Access-density 50 %
TP-Extract-density 50 %
TP-Egress-density 50 %
perceived density
TP-Access-paths 5 probes
TP-Extract-paths 5 probes
TP-Egress-paths 5 probes
paths
TP-Access-depth 100 moves
TP-Extract-depth 100 moves
TP-Egress-depth 100 moves
moves
TP-Access-focus 50 %
TP-Extract-focus 50 %
TP-Egress-focus 50 %
focus
Adaptation
A-Access-paths 5 probes
A-Extract-paths 5 probes
A-Egress-paths 5 probes
paths
A-Access-depth 100 moves
A-Extract-depth 100 moves
A-Egress-depth 100 moves
moves
A-Access-focus 50 %
A-Extract-focus 50 %
A-Egress-focus 50 %
focus
Inhibitors
Access-rows 32 row
Extract-rows 32 row
Egress-rows 31 row
rows
Access-inhibitor-density 30 %
Extract-inhibitor-density 30 %
Egress-inhibitor-density 30 %
actual density
Access
Extract
Egress
Object features
set_a_inhibitors 11
set_ex_inhibitors 11
set_eg_inhibitors 11
set_d_inhibitors_add 11
set_a_rows 11
set_ex_rows 11
set_eg_rows 31

A4: MAZE-RUNNING PARAMETERS: TACTICAL PLANNING			
Type	**Label**	**Explanation**	**Note…**
SLIDER	TP-Access-density	This is not a manually set value. Defines the percent of inhibitors from the access panel in the perception landscape that will be generated in the access panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: density tendency (H/M/L)	range: 0 --> 100
SLIDER	TP-Access-paths	This is not a manually set value. Defines the number of paths that will be generated in the access panel of the simulation landscape to develop a tactical plan. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 1 --> 10
SLIDER	TP-Access-depth	This is not a manually set value. Defines the number of time-steps available to develop a tactical plan in the access panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: depth tendency (H/M/L)	range: Access-Rows --> 1000
SLIDER	TP-Access-focus	This is not a manually set value. Defines the tendency to move toward the end target in the access panel simulation landscape to develop a tactical plan. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 0 --> 100
SLIDER	TP-Extract-density	This is not a manually set value. Defines the percent of inhibitors from the extract panel in the perception landscape that will be generated in the extract panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: density tendency (H/M/L)	range: 0 --> 100

SLIDER	TP-Extract-paths	This is not a manually set value. Defines the number of paths that will be generated in the extract panel of the simulation landscape to develop a tactical plan. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 1 --> 10
SLIDER	TP-Extract-depth	This is not a manually set value. Defines the number of time-steps available to develop a tactical plan in the extract panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: depth tendency (H/M/L)	range: Extract-Rows --> 1000
SLIDER	TP-Extract-focus	This is not a manually set value. Defines the tendency to move toward the end target in the extract panel of the simulation landscape while developing a tactical plan. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 0 --> 100
SLIDER	TP-Egress-density	This is not a manually set value. Defines the percent of inhibitors from the egress panel in the perception landscape that will be generated in the egress panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: density tendency (H/M/L)	range: 0 --> 100
SLIDER	TP-Egress-paths	This is not a manually set value. Defines the number of paths that will be generated in the egress panel of the simulation landscape to develop a tactical plan. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 1 --> 10

SLIDER	TP-Egress-depth	This is not a manually set value. Defines the number of time-steps available to develop a tactical plan in the egress panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: depth tendency (H/M/L)	range: Egress-Rows --> 1000
SLIDER	TP-Egress-focus	This is not a manually set value. Defines the tendency to move toward the end target in the egress panel of the simulation landscape while developing a tactical plan. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 0 --> 100
A4: MAZE-RUNNING PARAMETERS: ADAPTATION			
Type	**Label**	**Explanation**	**Note…**
SLIDER	A-Access-paths	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of paths that will be generated in the access panel of the simulation landscape to adapt. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 1 --> 10
SLIDER	A-Access-depth	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of time-steps available to adapt in the access panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: depth tendency (H/M/L)	range: Access-rows --> 1000
SLIDER	A-Access-focus	THIS IS NOT A MANUALLY SET PARAMETER. Defines the tendency to move toward the end target in the access panel of the simulation landscape while adapting. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 0 --> 100

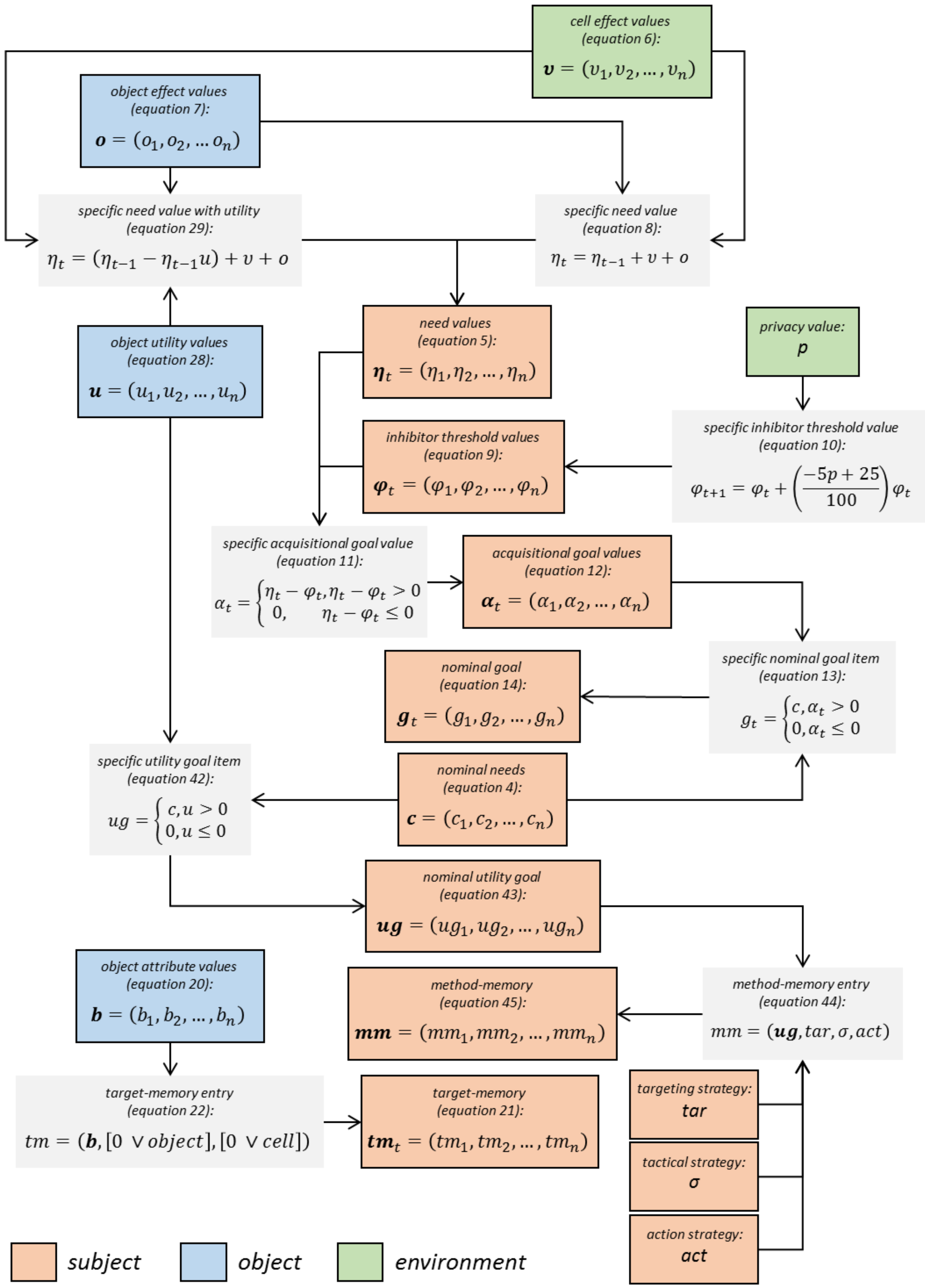
SLIDER	A-Extract-paths	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of paths that will be generated in the extract panel of the simulation landscape to adapt. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 1 --> 10
SLIDER	A-Extract-depth	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of time-steps available to adapt in the extract panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: depth tendency (H/M/L)	range: Extract-rows --> 1000
SLIDER	A-Extract-focus	THIS IS NOT A MANUALLY SET PARAMETER. Defines the tendency to move toward the end target in the extract panel of the simulation landscape while adapting. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 0 --> 100
SLIDER	A-Egress-paths	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of paths that will be generated in the egress panel of the simulation landscape to adapt. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 1 --> 10
SLIDER	A-Egress-depth	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of time-steps available to adapt in the egress panel of the simulation landscape. Automatically Generated based on the subject's tactical planning strategy: depth tendency (H/M/L)	range: Egress-rows --> 1000

SLIDER	A-Egress-focus	THIS IS NOT A MANUALLY SET PARAMETER. Defines the tendency to move toward the end target in the egress panel of the simulation landscape while adapting. Automatically Generated based on the subject's tactical planning strategy: paths tendency (H/M/L)	range: 0 --> 100
A4: MAZE-RUNNING PARAMETERS: INHIBITORS			
Type	**Label**	**Explanation**	**Note…**
SLIDER	Access-rows	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of rows in the access panel. Based on A_ROWS value from current target.	range: 1 --> (Max-pycor) - (Min-pycor + 1) - 10
SLIDER	Access-inhibitor-density	THIS IS NOT A MANUALLY SET PARAMETER. Defines inhibitor density of the current access panel in the perception landscape. Based on A_INHIBITORS value from the current target.	range: 0 --> 100
SLIDER	Extract-rows	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of rows in the extract panel. Based on EX_ROWS value from current target.	range: 1 --> (Max-pycor) - (Min-pycor + 1) - (Access-Rows + 2) - 5
SLIDER	Extract-inhibitor-density	THIS IS NOT A MANUALLY SET PARAMETER. Defines inhibitor density of the current extract panel in the perception landscape. Based on EX_INHIBITORS value from the current target.	range: 0 --> 100
SLIDER	Egress-rows	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of rows in the egress panel. Based on EG_ROWS value from current target.	range: 1 --> (Max-pycor) - (Min-pycor + 1) - (Access-Rows + 2) - (Extract-Rows + 2)
SLIDER	Egress-inhibitor-density	THIS IS NOT A MANUALLY SET PARAMETER. Defines inhibitor density of the current egress panel in the perception landscape. Based on EG_INHIBITORS value from the current target.	range: 0 --> 100

A4: MAZE-RUNNING PARAMETERS: OBJECT FEATURES			
Type	**Label**	**Explanation**	**Note…**
SLIDER	set_a_inhibitors	THIS IS NOT A MANUALLY SET PARAMETER. Defines access inhibitors as determined by PRESET-TARGET-TYPE chooser. TARGET-TYPE? switch must be "on"	range: 0 --> 100
SLIDER	set_ex_inhibitors	THIS IS NOT A MANUALLY SET PARAMETER. Defines extraction inhibitors as determined by PRESET-TARGET-TYPE chooser. TARGET-TYPE? switch must be "on"	range: 0 --> 100
SLIDER	set_eg_inhibitors	THIS IS NOT A MANUALLY SET PARAMETER. Defines egress inhibitors as determined by PRESET-TARGET-TYPE chooser. TARGET-TYPE? switch must be "on"	range: 0 --> 100
SLIDER	set_d_inhibitors_add	THIS IS NOT A MANUALLY SET PARAMETER. Defines defensive inhibitors (added to inhibitors if dominant action) as determined by PRESET-TARGET-TYPE chooser. TARGET-TYPE? switch must be "on"	range: 0 --> 100
SLIDER	set_a_rows	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of access rows as determined by PRESET-TARGET-TYPE chooser. TARGET-TYPE? switch must be "on"	range: 0 --> 31
SLIDER	set_ex_rows	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of extraction rows as determined by PRESET-TARGET-TYPE chooser. TARGET-TYPE? switch must be "on"	range: 0 --> 31
SLIDER	set_eg_rows	THIS IS NOT A MANUALLY SET PARAMETER. Defines the number of egress rows as determined by PRESET-TARGET-TYPE chooser. TARGET-TYPE? switch must be "on"	range: 0 --> 31

APPENDIX B

Diagram of the formalized variables involved in generating *needs* accumulation, and *acquisitional goal* development via threshold-driven behaviors. These variables are encapsulated in the integrated model within the *subject*, *objects*, environment, or interactions between these elements.


cell effect values (equation 6):
$\boldsymbol{v} = (v_1, v_2, \dots, v_n)$
object effect values (equation 7):
$\boldsymbol{o} = (o_1, o_2, \dots o_n)$
specific need value with utility (equation 29):
$\eta_t = (\eta_{t-1} - \eta_{t-1}u) + v + o$
specific need value (equation 8):
$\eta_t = \eta_{t-1} + v + o$
object utility values (equation 28):
$\boldsymbol{u} = (u_1, u_2, \dots, u_n)$
need values (equation 5):
$\boldsymbol{\eta}_t = (\eta_1, \eta_2, \dots, \eta_n)$
privacy value:
p
inhibitor threshold values (equation 9):
$\boldsymbol{\varphi}_t = (\varphi_1, \varphi_2, \dots, \varphi_n)$
specific inhibitor threshold value (equation 10):
$\varphi_{t+1} = \varphi_t + \left(\frac{-5p + 25}{100}\right)\varphi_t$
specific acquisitional goal value (equation 11):
$\alpha_t = \begin{cases} \eta_t - \varphi_t, \eta_t - \varphi_t > 0 \\ 0, \quad \eta_t - \varphi_t \leq 0 \end{cases}$
acquisitional goal values (equation 12):
$\boldsymbol{\alpha}_t = (\alpha_1, \alpha_2, \dots, \alpha_n)$
nominal goal (equation 14):
$\boldsymbol{g}_t = (g_1, g_2, \dots, g_n)$
specific nominal goal item (equation 13):
$g_t = \begin{cases} c, \alpha_t > 0 \\ 0, \alpha_t \leq 0 \end{cases}$
specific utility goal item (equation 42):
$ug = \begin{cases} c, u > 0 \\ 0, u \leq 0 \end{cases}$
nominal needs (equation 4):
$\boldsymbol{c} = (c_1, c_2, \dots, c_n)$
nominal utility goal (equation 43):
$\boldsymbol{ug} = (ug_1, ug_2, \dots, ug_n)$
object attribute values (equation 20):
$\boldsymbol{b} = (b_1, b_2, \dots, b_n)$
method-memory (equation 45):
$\boldsymbol{mm} = (mm_1, mm_2, \dots, mm_n)$
method-memory entry (equation 44):
$mm = (\boldsymbol{ug}, tar, \sigma, act)$
target-memory entry (equation 22):
$tm = (\boldsymbol{b}, [0 \vee object], [0 \vee cell])$
target-memory (equation 21):
$\boldsymbol{tm}_t = (tm_1, tm_2, \dots, tm_n)$
targeting strategy:
tar
tactical strategy:
σ
action strategy:
act
subject
object
environment

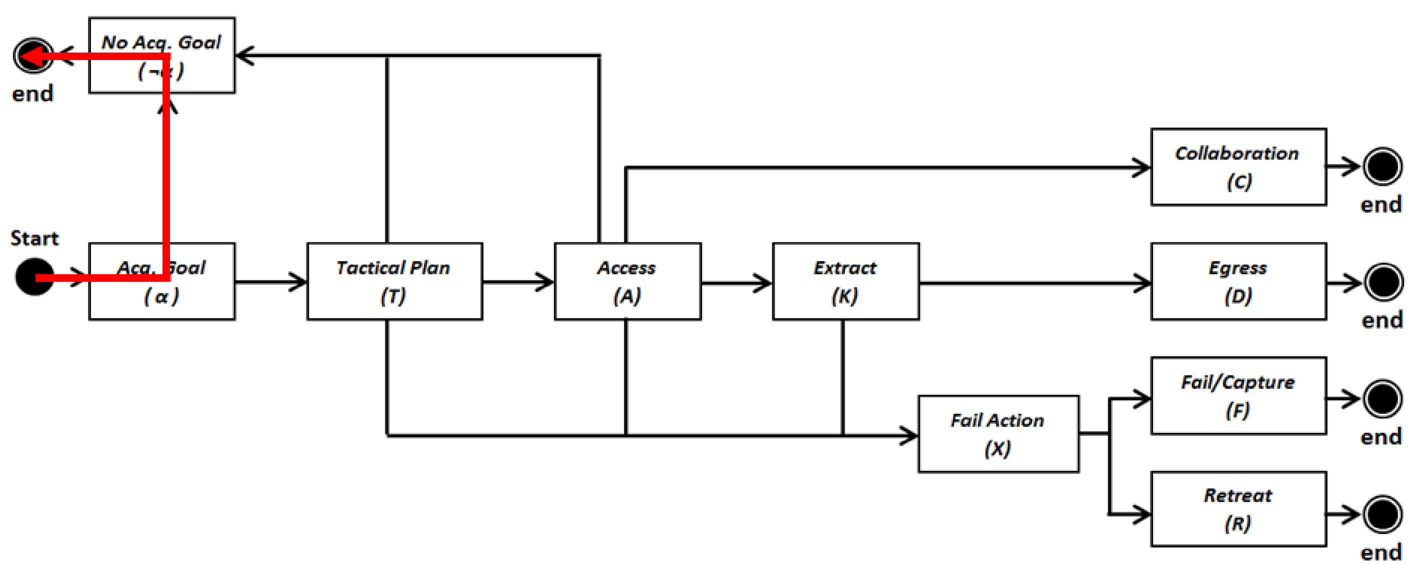
APPENDIX C

Diagrams of *subject event-chain* outcomes of the violent offending process, the causal-path of the *event-chain* expressed as a compound event, and constructed *event-chain* narratives as described in the discussion on model output narrative (see Chapter 2, Section 2.2.9).

C1: No acquisitional goal outcome (α – ⌐α).

$$\neg\alpha \Leftarrow \langle(\neg\alpha|\alpha)\rangle$$

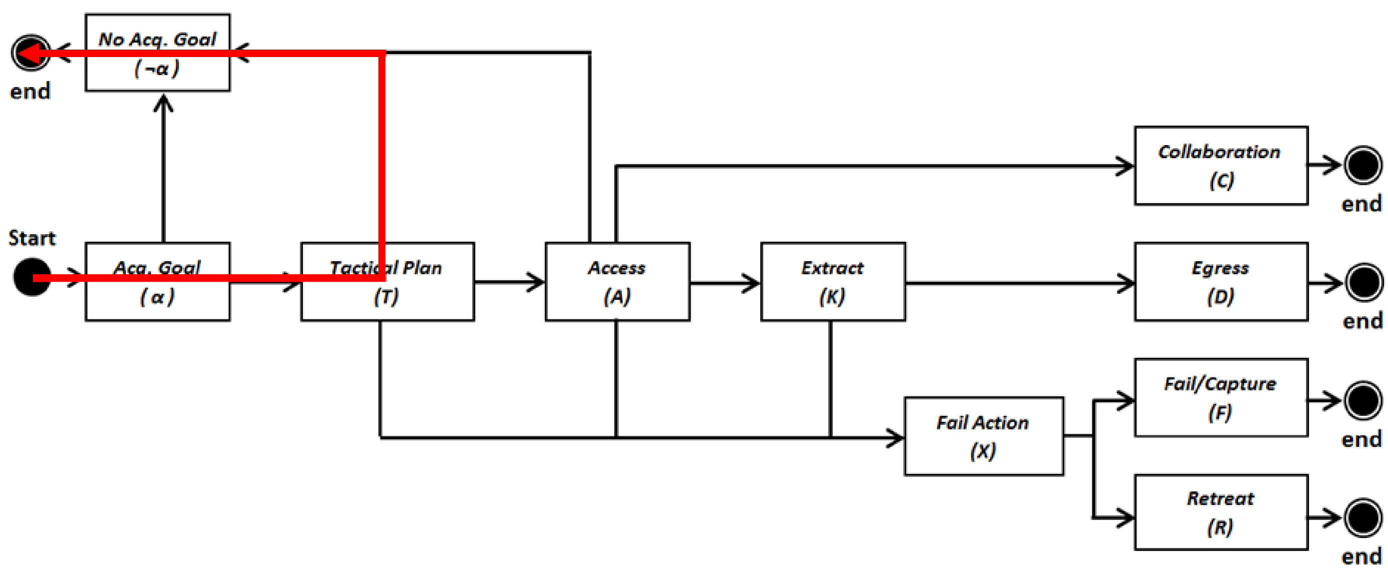
	α	⌐α	
event-chain 1	The subject has developed an interest in exerting control and having a sexual experience.	The subject has lost interest in exerting control and having a sexual experience.	**end**



C2: No acquisitional goal outcome ($\alpha - T - \neg\alpha$).

$$\neg\alpha \Leftarrow \langle (T|\alpha) \wedge (\neg\alpha|T) \rangle$$

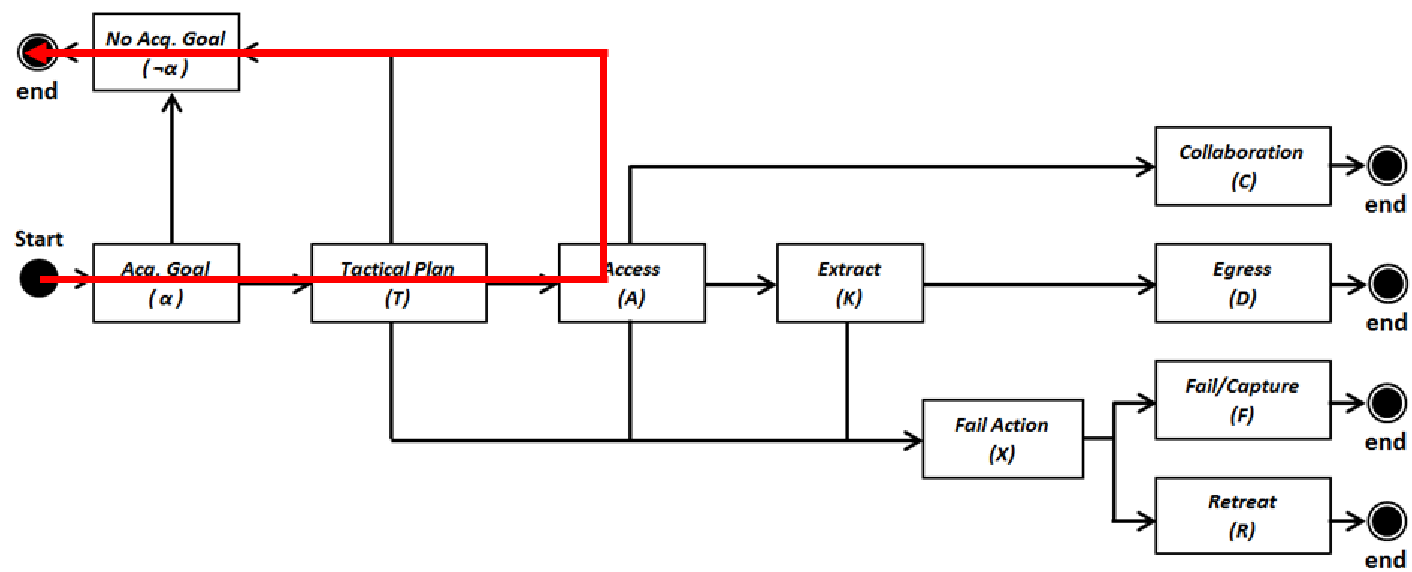
	α	T	⌐α	
event-chain 2	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate) or engage the services of a prostitute (collaborate).	The subject has lost interest in exerting control and having a sexual experience.	**end**



C3: No acquisitional goal outcome (α – T – A[collaborate] – ⌐α).

$$\neg\alpha \Leftarrow \langle (T|\alpha) \wedge (A|T) \wedge (\neg\alpha|A) \rangle$$

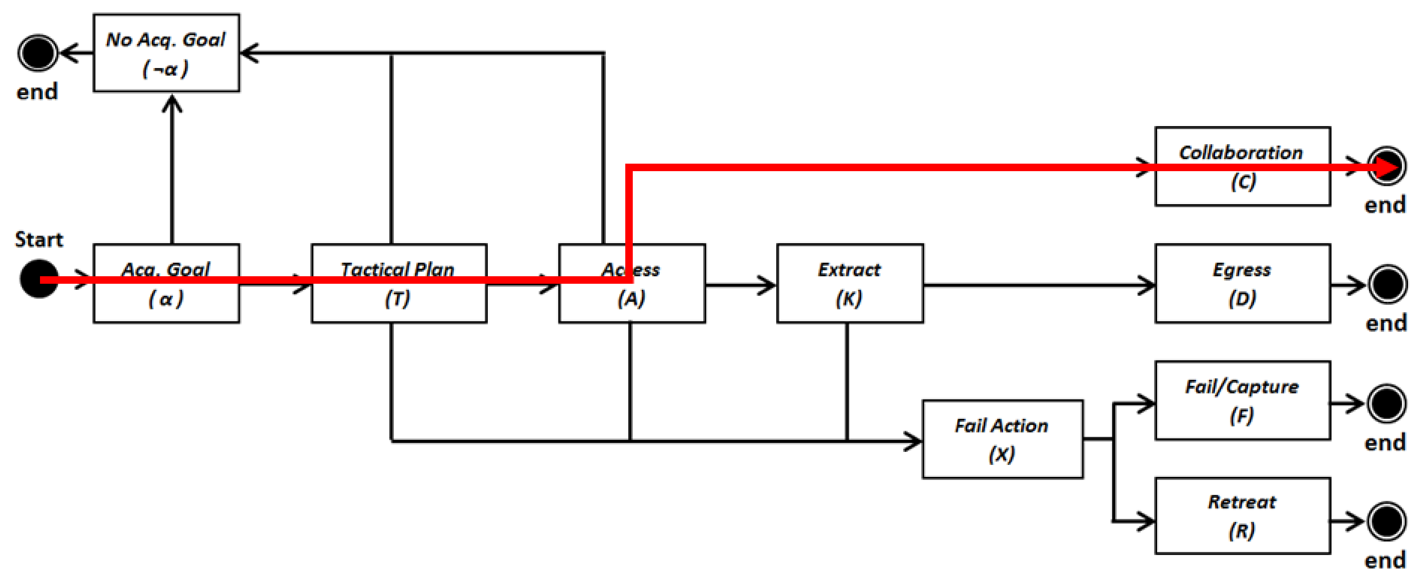
	α	T	A	⌐α	
event-chain 3	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has successfully secured the services of a prostitute (collaborate).	The subject has lost interest in exerting control and having a sexual experience.	end



C4: Collaboration outcome (α – T – A[collaborate] – C).

$$C \Longleftarrow \langle (T|\alpha) \wedge (A|T) \wedge (C|A) \rangle$$

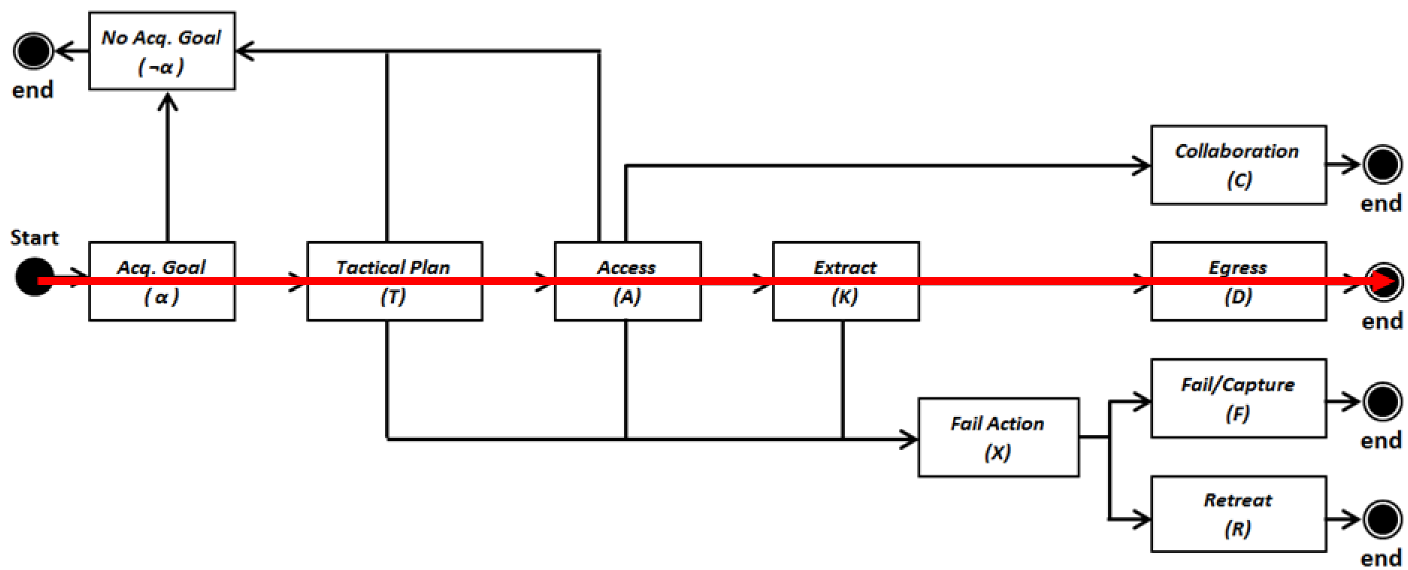
	α	T	A	C	
event-chain 4	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to engage the services of a prostitute (collaborate)	The subject has successfully secured the services of a prostitute (collaborate).	The subject has successfully engaged in sexual interaction with a prostitute.	end



C5: Successful Offending outcome (α – T – A[dominate] – K[dominate] – D).

$$D \Leftarrow \langle (T|\alpha) \wedge (A|T) \wedge (K|A) \wedge (D|K) \rangle$$

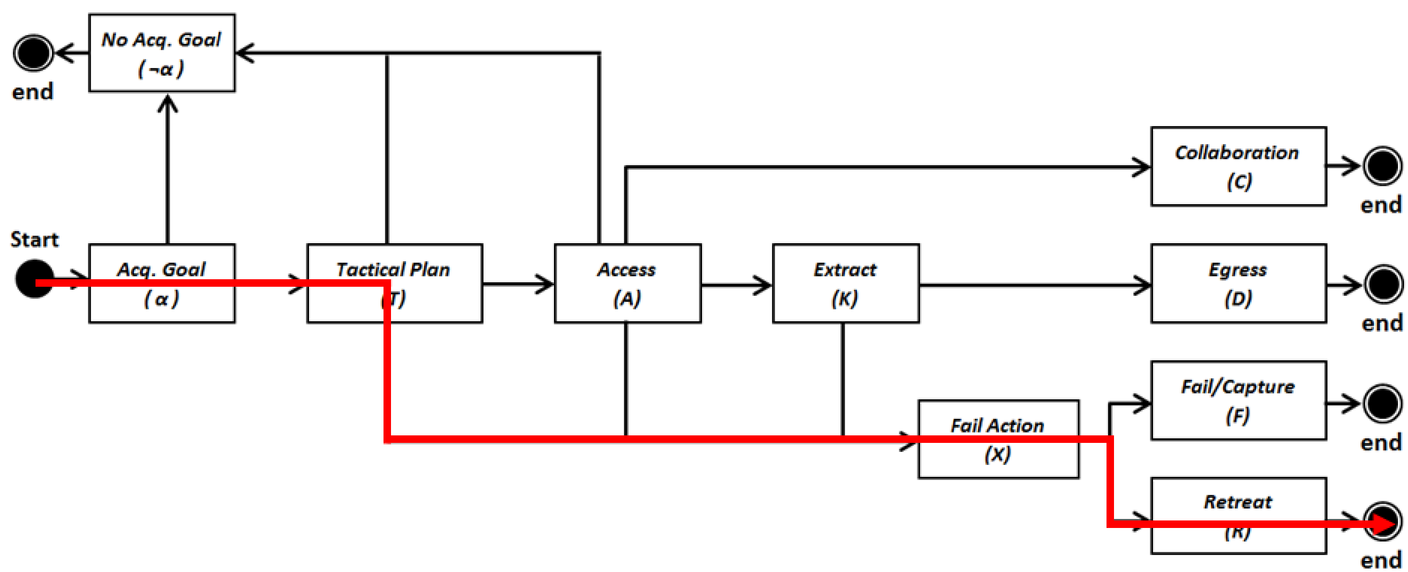
	α	T	A	K	D	
event-chain 5	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has successfully abducted a female (dominate).	The subject has successfully raped and killed the female victim.	The subject has successfully dumped the female victim's body.	**end**



C6: Successful retreat from failed offending outcome (α – T – X[dominate] – R).

$$R \Leftarrow \langle (T|\alpha) \wedge (X|T) \wedge (R|X) \rangle$$

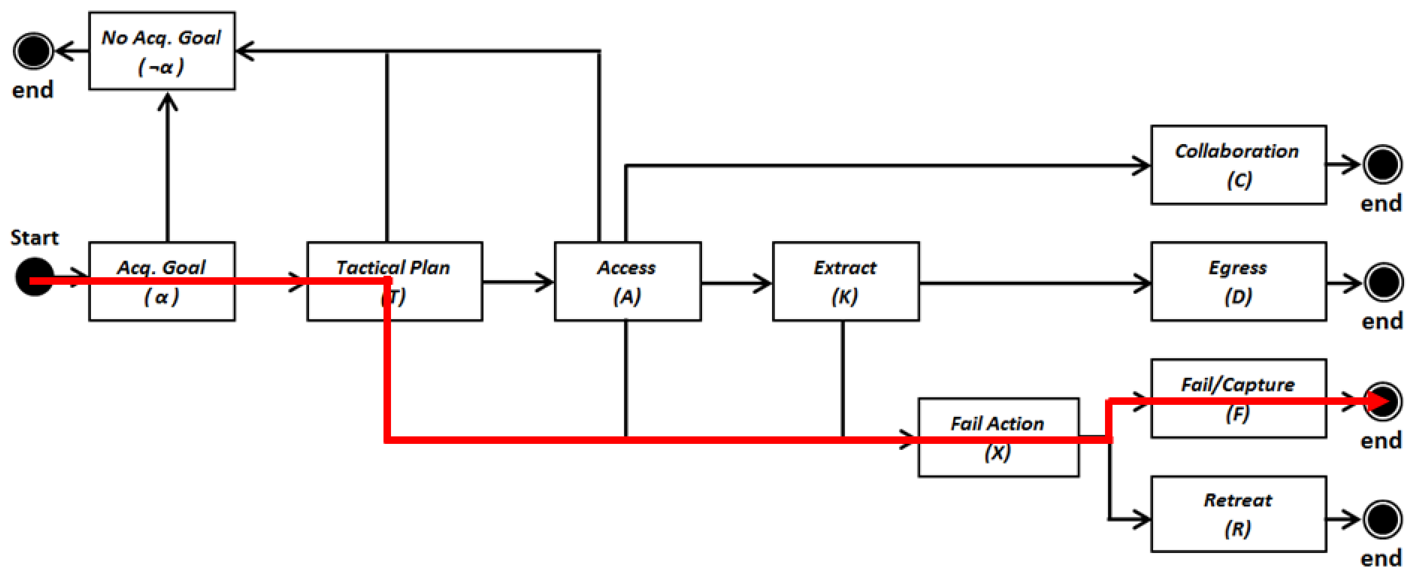
	α	T	X	R	
event-chain 6	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has failed in his attempt to abduct a female victim and must now retreat without being detected or captured.	The subject has successfully avoided detection and arrest.	**end**



C7: Failed retreat from failed offending outcome (α – T– X[dominate] – F).

$$F \Leftarrow \langle (T|\alpha) \wedge (X|T) \wedge (F|X) \rangle$$

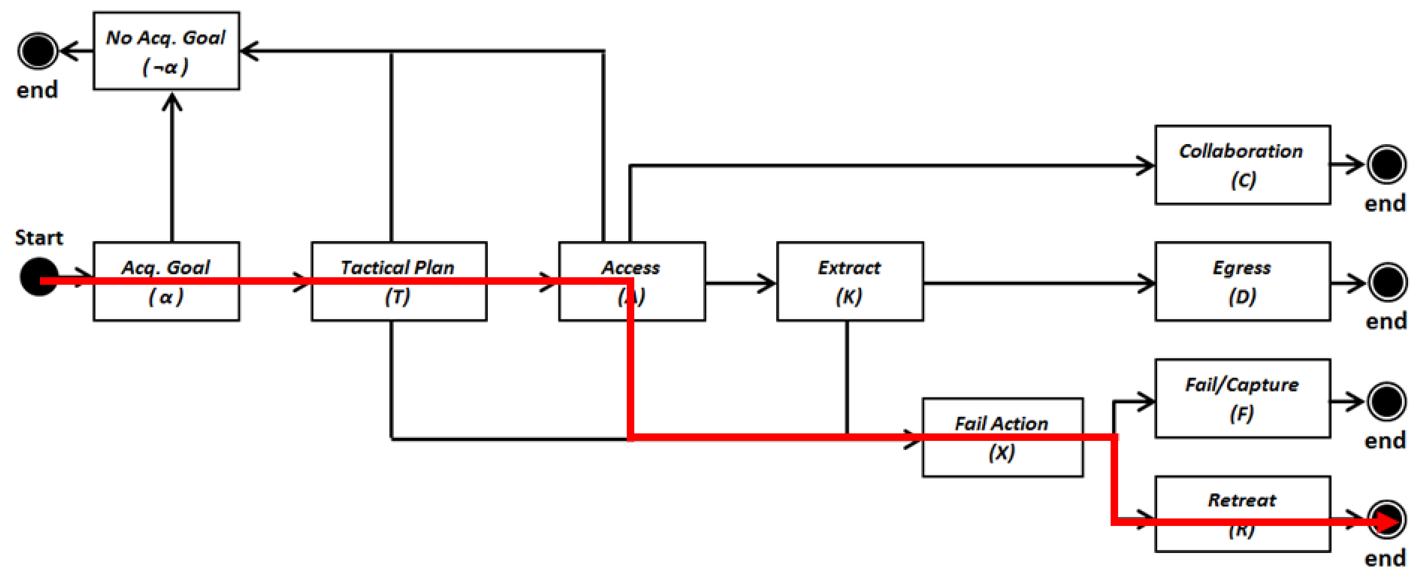
	α	T	X	F	
event-chain 7	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has failed in his attempt to abduct a female victim and must now retreat without being detected or captured.	The subject has failed to retreat and is arrested.	**end**



C8: Successful retreat from failed offending outcome (α – T – A[dominate] – X[dominate] – R).

$$R \Longleftarrow \langle (T|\alpha) \wedge (A|T) \wedge (X|A) \wedge (R|X) \rangle$$

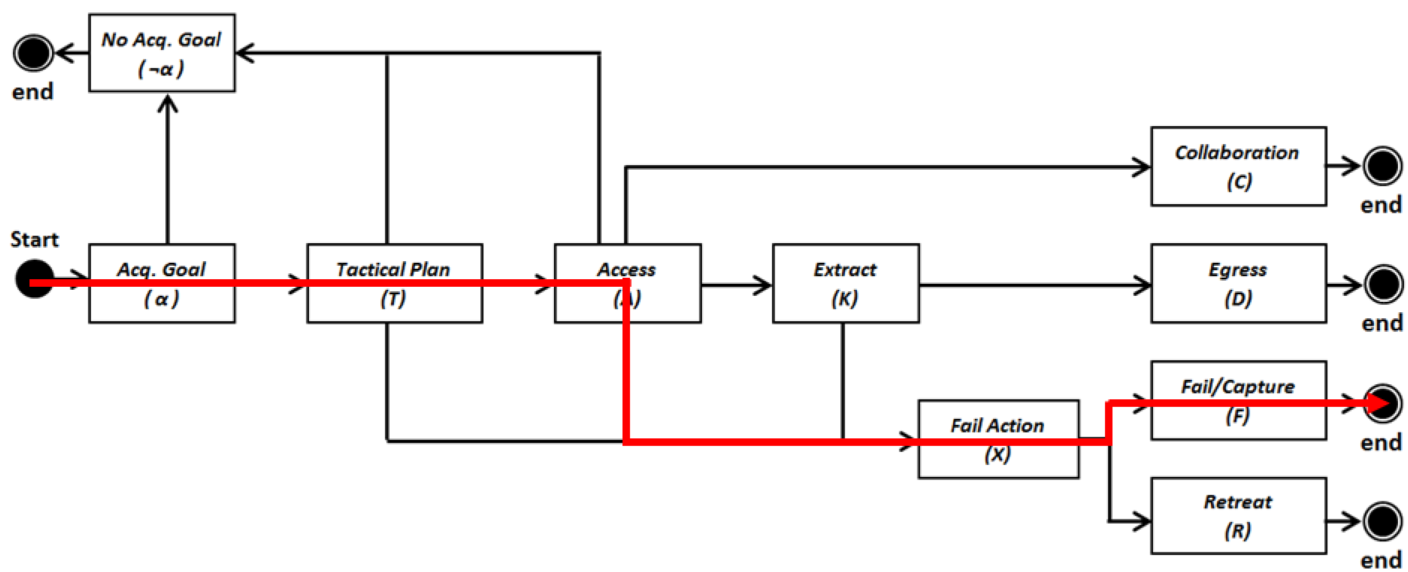
	α	T	A	X	R	
event-chain 8	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has successfully abducted a female victim (dominate).	The subject has failed in his attempt rape and kill the female victim and must now retreat without being detected or captured.	The subject has successfully avoided detection and arrest.	end



C9: Failed retreat from failed offending outcome (α – T – A[dominate] – X[dominate] – F).

$$F \Longleftarrow \langle (T|\alpha) \wedge (A|T) \wedge (X|A) \wedge (F|X) \rangle$$

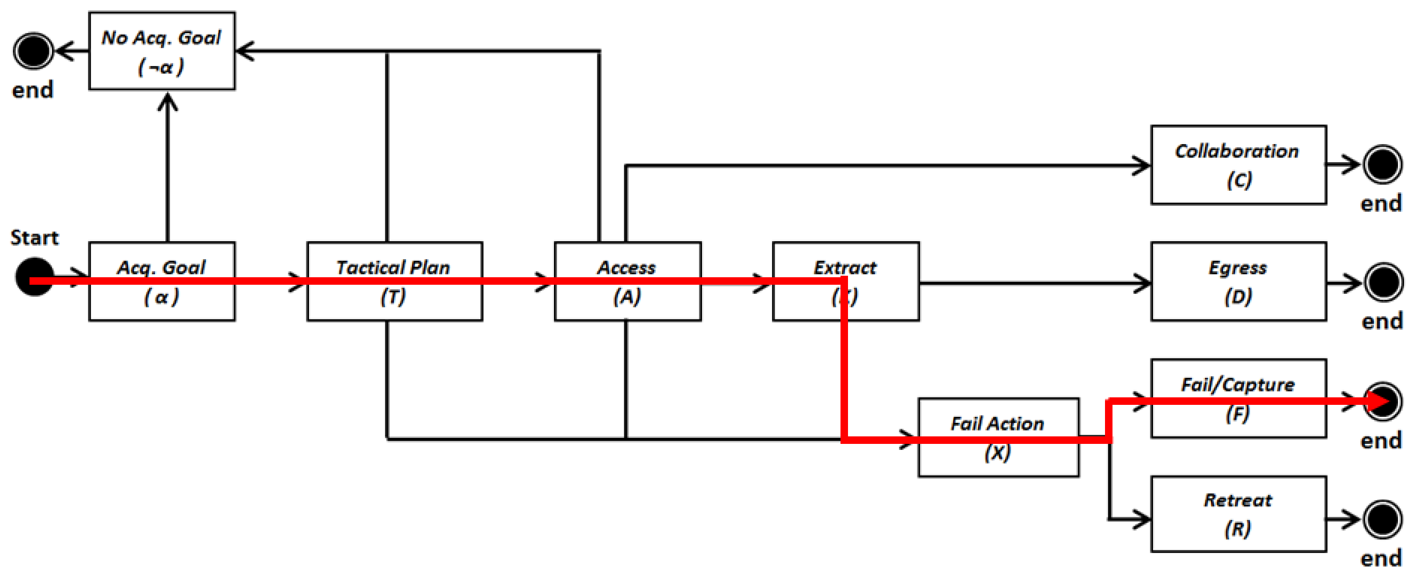
	α	T	A	X	F	
event-chain 9	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has successfully abducted a female victim (dominate).	The subject has failed in his attempt rape and kill the female victim and must now retreat without being detected or captured.	The subject has failed to retreat and is arrested.	**end**



C10: Failed retreat from failed offending outcome (α – T – A[dominate] – K[dominate] – X[dominate] – F).

$$F \Leftarrow \langle (T|\alpha) \wedge (A|T) \wedge (K|A) \wedge (X|K) \wedge (F|X) \rangle$$

	α	T	A	K	X	F	
event-chain 10	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has successfully abducted a female victim (dominate).	The subject has successfully raped and killed the female victim.	The subject has failed in his attempt to dump the victim's body	The subject has failed to successfully egress and is arrested.	**end**



APPENDIX D

Aggregated code profiles used during verification of the integrated model to monitor procedure calls.

		Stage 1		
Process Name	baseline	scheduling	location-based	cluster
ACTION-ACCESS	14401	14401	14401	14401
ACTION-EGRESS	14401	14401	14401	14401
ACTION-EXTRACT	14401	14401	14401	14401
CHECK-NEEDS	14401	14401	14401	14401
CHECK-PATH	2856	4010	1362	7824
CHECK-PATH-START	2856	4010	1362	7824
CHECK-PRIVACY	14401	14401	14401	14401
CLEAR-COGNITIVE-SPACE	21633	13867	24724	7669
CLUSTER	2	2	2	2
COMPARE-LOCATIONS	2	2	2	2
CONTROL-TARGET	14401	14401	14401	14401
CREATE-NEW-INHIBITORS	205	148	190	250
CREATE-NEW-OBJECTS	--	--	--	--
CREATE-NEW-PROBES	205	148	190	250
CREATE-NEW-SUBJECTS	--	--	--	--
CREATE-NEW-TP-PROBES	520	384	486	712
CREATE-SCALE	--	--	--	--
DEVELOP-GOALS	14401	14401	14401	14401
DISTANCE-NAV_TARGET	1216317	882416	1224841	849672
GENERATE-ACTION-PATH	2856	4010	1362	7824
GENERATE-A-INHIBITORS	615	443	571	751
GENERATE-C-INHIBITORS	615	443	571	751
GENERATE-PROBES	615	443	571	751
GO	14401	14401	14401	14401
IDENTIFY-TARGET	14401	14401	14401	14401
INSERT-METHOD-MEMORY	14401	14401	14401	14401
INTERACT	14401	14401	14401	14401
MOVE-AGENTS	14401	14401	14401	14401
MOVE-PROBES	989	807	638	1364
OUTCOME-EXTRACTION	14401	14401	14401	14401
PRESERVE-AGENTS	--	--	--	--
REFINE-PROBE-PATHS	173	128	162	237
RESET-GOAL	21249	13686	24339	7418
RESET-LANDSCAPES	205	148	190	250
RESET-THRESHOLDS	14402	14402	14402	14402
RESET-TP-ACTION-SWITCHES	21249	13686	24439	7418
RUN-PROBES	205	148	190	250
RUN-REFINE-ADAPTATION	492	480	200	835
SET-METHODS	268	136	259	222
SET-NEW-PARAMETERS	205	148	190	250
SET-PATCH-COMFORT	14401	14401	14401	14401
SET-PAUSES	--	4650	--	2925
SET-PAUSES-OBJ	--	13310	--	13311
SET-REGIONS	205	148	190	250
SET-SCHED_TARGET	14401	14401	14401	14401
SET-SCHED_TARGET-OBJ	7168806	7168295	7178152	7156928
SET-TARGET-LANDSCAPE	205	148	190	250
SETUP-LANDSCAPES	205	148	190	250
SHOW-SITES	--	--	--	--
TACTICAL-PLANNING	14401	14401	14401	14401
TRANSFER-INHIBITOR-ADAPT	492	480	200	835
WRITE-TO-EVENT-LOG	6	4	3	7

		Stage 2				
Process Name	baseline	low-risk	high-risk	Variation=0	Variation=25	Variation=50
ACTION-ACCESS	14401	14401	14401	14401	14401	14401
ACTION-EGRESS	14401	14401	14401	14401	14401	14401
ACTION-EXTRACT	14401	14401	14401	14401	14401	14401
CHECK-NEEDS	14401	14401	14401	14401	14401	14401
CHECK-PATH	2856	7712	4265	3046	3277	4499
CHECK-PATH-START	2856	7712	4265	3046	3277	4499
CHECK-PRIVACY	14401	14401	14401	14401	14401	14401
CLEAR-COGNITIVE-SPACE	21633	8275	12744	21218	20119	17797
CLUSTER	2	2	2	2	2	2
COMPARE-LOCATIONS	2	2	2	2	2	2
CONTROL-TARGET	14401	14401	14401	14401	14401	14401
CREATE-NEW-INHIBITORS	205	274	334	625	338	220
CREATE-NEW-OBJECTS	--	--	--	--	--	--
CREATE-NEW-PROBES	205	274	334	625	338	220
CREATE-NEW-SUBJECTS	--	--	--	--	--	--
CREATE-NEW-TP-PROBES	520	695	922	1866	974	599
CREATE-SCALE	--	--	--	--	--	--
DEVELOP-GOALS	14401	14401	14401	14401	14401	14401
DISTANCE-NAV_TARGET	1216317	846070	849278	1200783	1212596	1205245
GENERATE-ACTION-PATH	2856	7712	4265	3046	3277	4499
GENERATE-A-INHIBITORS	615	823	1003	1876	1014	659
GENERATE-C-INHIBITORS	615	823	1003	1876	1014	659
GENERATE-PROBES	615	823	1003	1876	1014	659
GO	14401	14401	14401	14401	14401	14401
IDENTIFY-TARGET	14401	14401	14401	14401	14401	14401
INSERT-METHOD-MEMORY	14401	14401	14401	14401	14401	14401
INTERACT	14401	14401	14401	14401	14401	14401
MOVE-AGENTS	14401	14401	14401	14401	14401	14401
MOVE-PROBES	989	1482	1110	2477	1462	1193
OUTCOME-EXTRACTION	14401	14401	14401	14401	14401	14401
PRESERVE-AGENTS	--	--	--	--	--	--
REFINE-PROBE-PATHS	173	232	307	622	325	200
RESET-GOAL	21249	8024	12303	20038	19485	17420
RESET-LANDSCAPES	205	274	334	625	338	220
RESET-THRESHOLDS	14402	14402	14402	14402	14402	14402
RESET-TP-ACTION-SWITCHES	21249	8024	12303	20038	19485	17420
RUN-PROBES	205	274	334	625	338	220
RUN-REFINE-ADAPTATION	492	906	374	605	562	670
SET-METHODS	268	208	351	623	391	266
SET-NEW-PARAMETERS	205	274	334	625	338	220
SET-PATCH-COMFORT	14401	14401	14401	14401	14401	14401
SET-PAUSES	--	2413	4452	--	--	--
SET-PAUSES-OBJ	--	13226	13082	--	--	--
SET-REGIONS	205	274	334	625	338	220
SET-SCHED_TARGET	14401	14401	14401	14401	14401	14401
SET-SCHED_TARGET-OBJ	7168806	7156496	7049906	7093557	7139080	7133270
SET-TARGET-LANDSCAPE	205	274	334	625	338	220
SETUP-LANDSCAPES	205	274	334	625	338	220
SHOW-SITES	--	--	--	--	--	--
TACTICAL-PLANNING	14401	14401	14401	14401	14401	14401
TRANSFER-INHIBITOR-ADAPT	492	906	374	605	562	670
WRITE-TO-EVENT-LOG	6	8	21	13	8	9

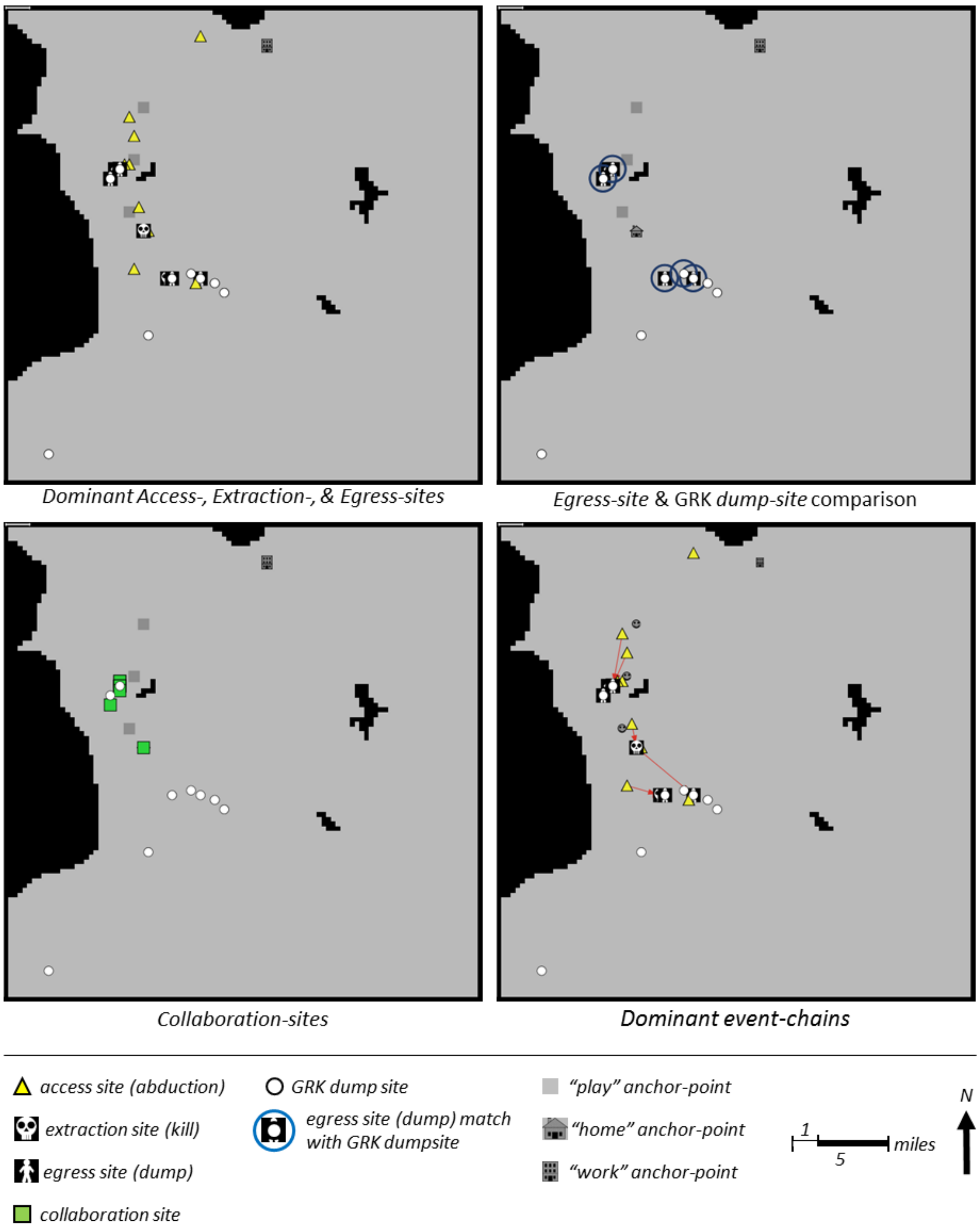
		Stage 3	
Process Name	baseline	Method-memory	Burn-in
ACTION-ACCESS	14401	14401	28801
ACTION-EGRESS	14401	14401	28801
ACTION-EXTRACT	14401	14401	28801
CHECK-NEEDS	14401	14401	28801
CHECK-PATH	2856	2414	12916
CHECK-PATH-START	2856	2414	12916
CHECK-PRIVACY	14401	14401	28801
CLEAR-COGNITIVE-SPACE	21633	22541	25494
CLUSTER	2	2	2
COMPARE-LOCATIONS	2	2	2
CONTROL-TARGET	14401	14401	28801
CREATE-NEW-INHIBITORS	205	264	1010
CREATE-NEW-OBJECTS	--	--	1
CREATE-NEW-PROBES	205	264	1010
CREATE-NEW-SUBJECTS	--	--	1
CREATE-NEW-TP-PROBES	520	644	2700
CREATE-SCALE	--	--	1
DEVELOP-GOALS	14401	14401	28801
DISTANCE-NAV_TARGET	1216317	1222996	2432067
GENERATE-ACTION-PATH	2856	2414	12916
GENERATE-A-INHIBITORS	615	793	3030
GENERATE-C-INHIBITORS	615	793	3030
GENERATE-PROBES	615	793	3030
GO	14401	14401	28801
IDENTIFY-TARGET	14401	14401	28801
INSERT-METHOD-MEMORY	14401	14401	28801
INTERACT	14401	14401	28801
MOVE-AGENTS	14401	14401	28801
MOVE-PROBES	989	778	2916
OUTCOME-EXTRACTION	14401	14401	28801
PRESERVE-AGENTS	--	--	1
REFINE-PROBE-PATHS	173	215	900
RESET-GOAL	21249	22121	24202
RESET-LANDSCAPES	205	264	1010
RESET-THRESHOLDS	14402	14402	28802
RESET-TP-ACTION-SWITCHES	21249	22121	24203
RUN-PROBES	205	264	1010
RUN-REFINE-ADAPTATION	492	240	941
SET-METHODS	268	262	738
SET-NEW-PARAMETERS	205	264	1010
SET-PATCH-COMFORT	14401	14401	28801
SET-PAUSES	--	--	--
SET-PAUSES-OBJ	--	--	--
SET-REGIONS	205	264	1010
SET-SCHED_TARGET	14401	14401	28801
SET-SCHED_TARGET-OBJ	7168806	7174772	14373970
SET-TARGET-LANDSCAPE	205	264	1010
SETUP-LANDSCAPES	205	264	1010
SHOW-SITES	--	--	1
TACTICAL-PLANNING	14401	14401	28801
TRANSFER-INHIBITOR-ADAPT	492	240	941
WRITE-TO-EVENT-LOG	6	3	3

APPENDIX E

Examples of event-sites captured during a run from each configuration.

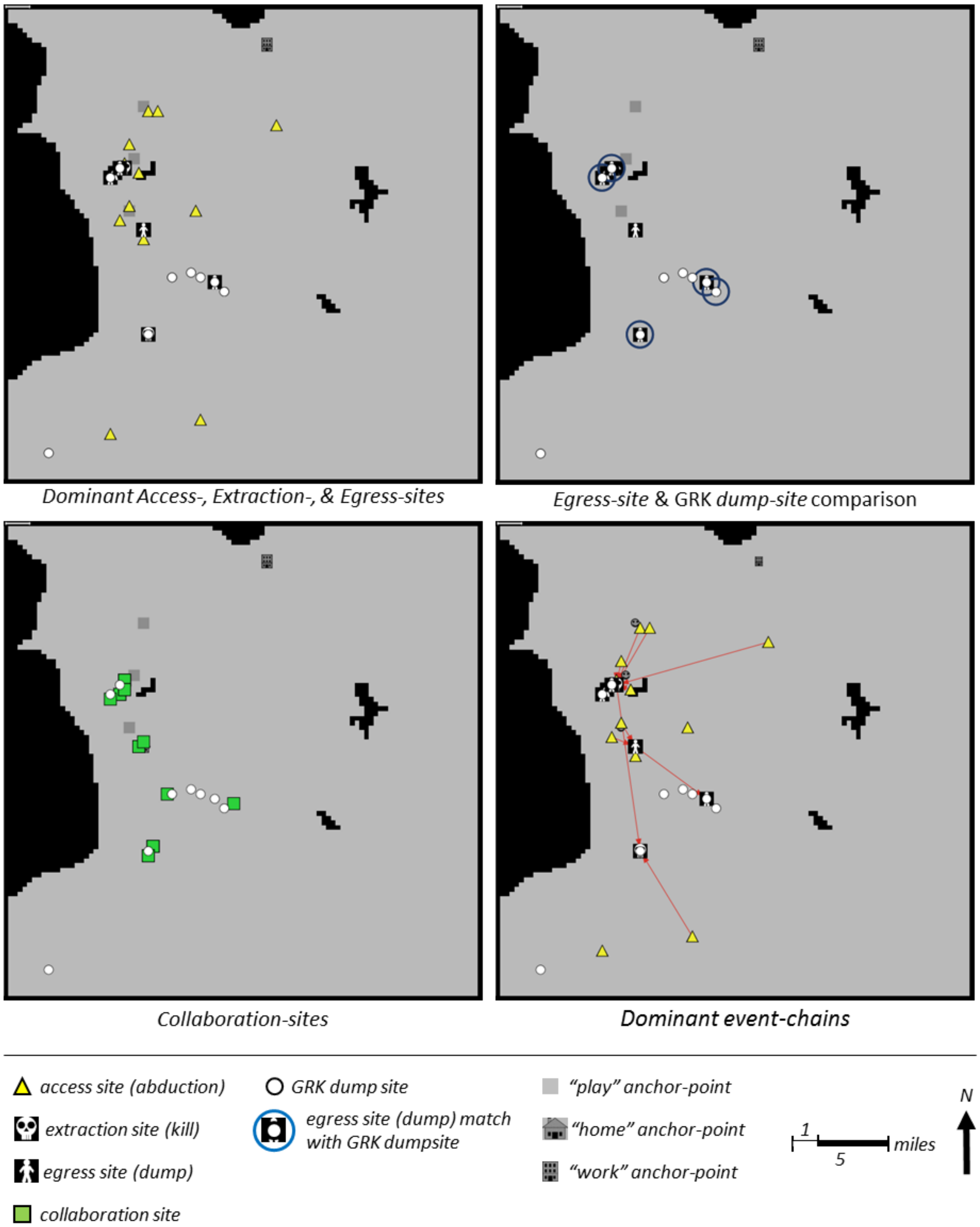
MB-1

(74072-79946)



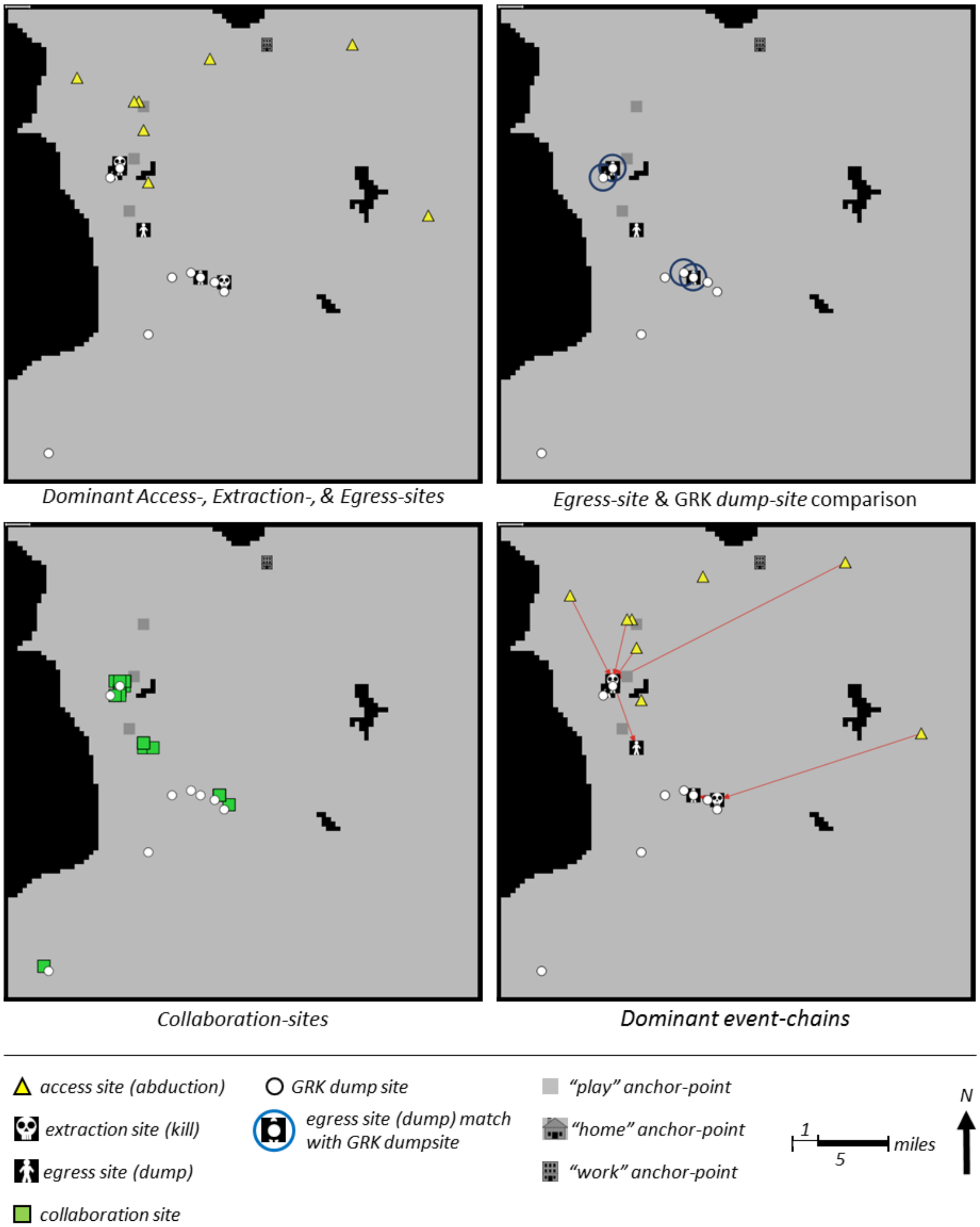
SB-3

(82794-71909)



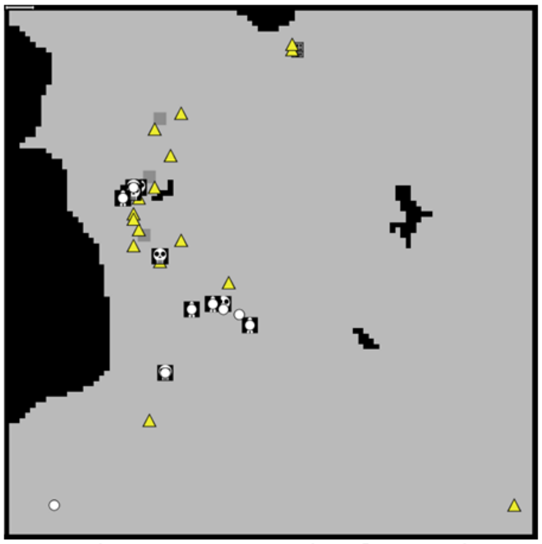
MM-1

(70009-63457)

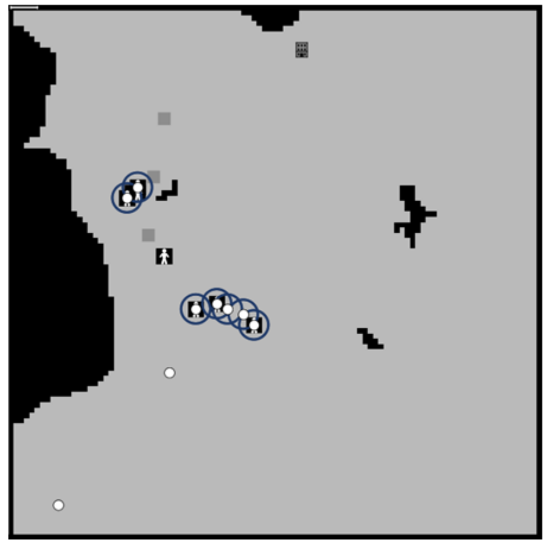


B1-3

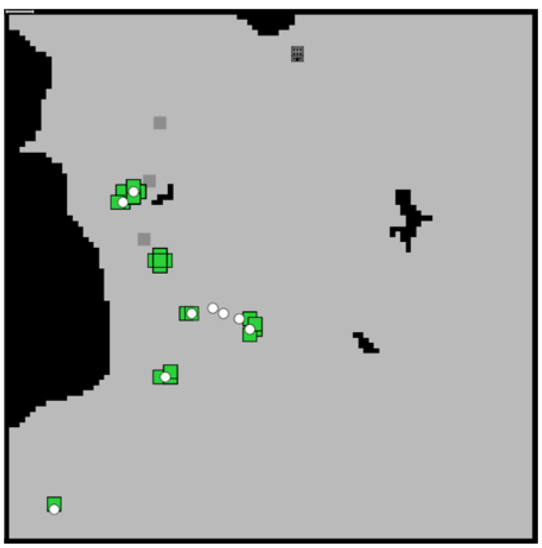
(114705-88707)



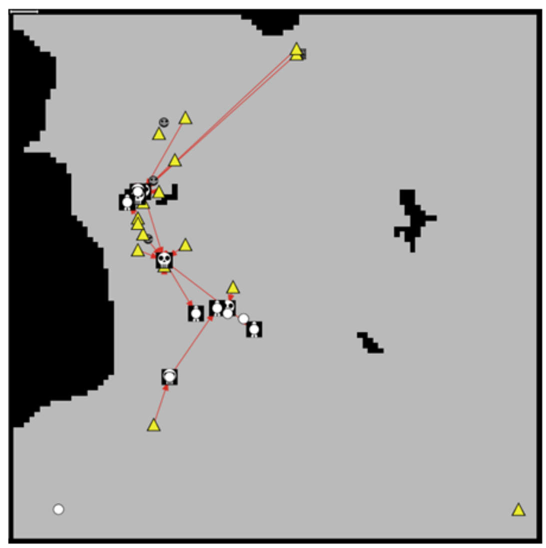
Dominant Access-, Extraction-, & Egress-sites



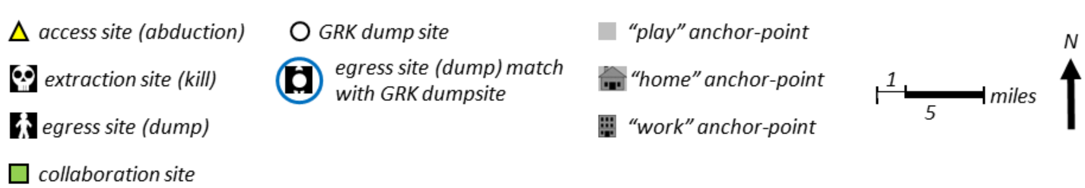
Egress-site & GRK *dump-site* comparison



Collaboration-sites

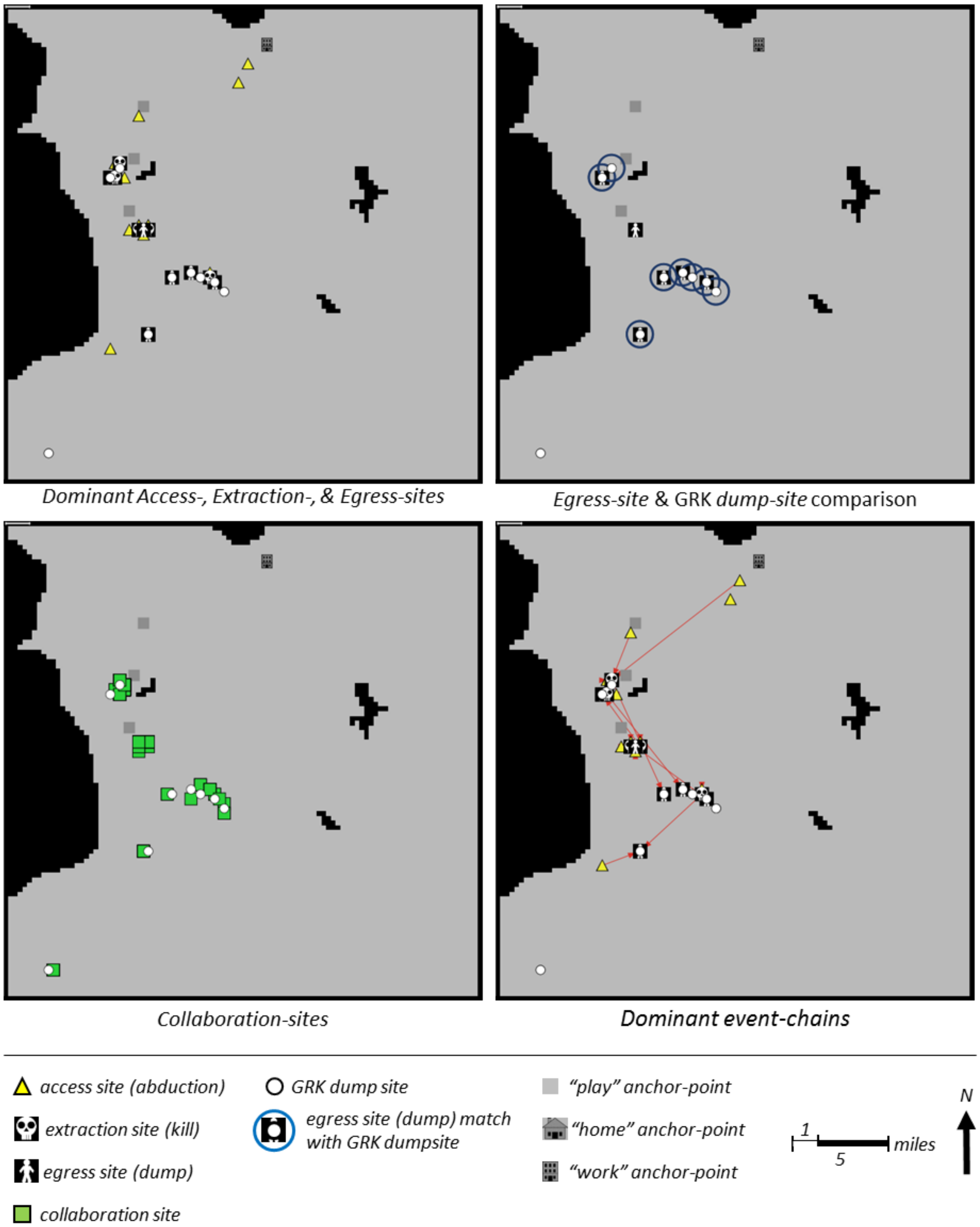


Dominant event-chains



B2-3

(69685-61636)



APPENDIX F

Dissertation defense presentation slides.

Slide 1

UNCLASSIFIED

Toward Implementing a Complex Social Simulation of the Violent Offending Process:
The promise of a synthetic offender

Thomas J. Dover
Ph.D. Candidate
Computational Social Science Program,
George Mason University

Dissertation Defense
April 12, 2016

Slide 2

UNCLASSIFIED

Motivation…

- *Can violent "offenders" be identified prior to attack?*
- *Is it possible to discover and/or predict violent offending trajectories?*
- *How does violent offending depend on micro-level features of the offender?*
- *Can hidden attributes/features of a violent offender be effectively examined?*

4/12/2016 2

Slide 3

UNCLASSIFIED

Motivation…

Limitations to current violent offender research

- *Outcome-driven approach*
- *Limited generalizability /offender population size*
- *Inaccessible populations…*

Adding complexity to violent offender research

- *Process-driven approach*
- *Generate offender populations in silico*
- *Watch violent behavior emerge…*

4/12/2016 3

Slide 4

UNCLASSIFIED

Computational Criminology…

State-of-the-art:

- *Test criminological theory*
- *Explore complexities of geospatial patterns & visualize event clustering and hotspots*
- *Data-mining*
- *Discover criminal social networks*
- *Series tempo*
- *Insider threat*

4/12/2016 4

Slide 5

UNCLASSIFIED

Computational Criminology…

Primarily focus on…

- ✓ *Macro-level interactions*
- ✓ *Micro-level rule-sets that "imitate" behavior (non-generative).*

4/12/2016 5

Slide 6

UNCLASSIFIED

Research Question…

Does implementation of the violent offending process as a complex social simulation provide meaningful insights into the internal and external drivers of violent offending behaviors?

4/12/2016 6

Slide 7

UNCLASSIFIED

Research Objectives…

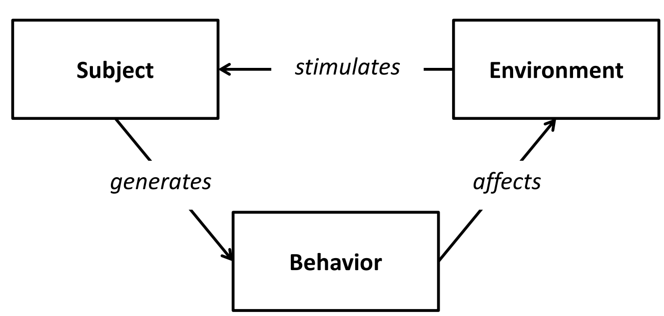
1. *Create a prototype integrated model of the violent offending process,*
2. *Establish internal validation of the model,*
3. *Apply the model to a real-world series of violent offenses,*
4. *Develop methods to evaluate efficacy of the integrated model.*

4/12/2016 7

Slide 8

UNCLASSIFIED

Design…*the big picture*



4/12/2016 8

Slide 9a

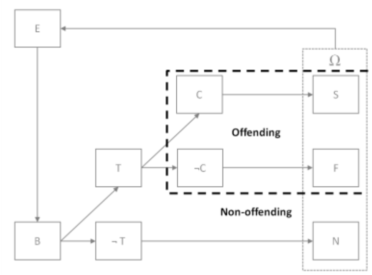
Design…

Behavior emerges from Problem-solving

- *Canonical Theory (fast process)*
- *Offender Interaction Process Model (OIPM)*

B = Strategic
T = Tactical
C = Execution
E = Evaluation

Ω ---------------------------
S = Successful Offending
F = Failed Offending
N =No Offending



$$S \Longleftarrow \langle (B) \wedge (T|B) \wedge (C|T) \rangle$$

Slide 9b

Design…

Behavior emerges from Problem-solving

- *Canonical Theory (fast process)*
- *Offender Interaction Process Model (OIPM)*

B = Strategic
T = Tactical
C = Execution
E = Evaluation

Ω ---------------------------
S = Successful Offending
F = Failed Offending
N =No Offending

$$S \Longleftarrow \langle (B) \wedge (T|B) \wedge (C|T) \rangle$$

Slide 10

Implementation…*hybrid*

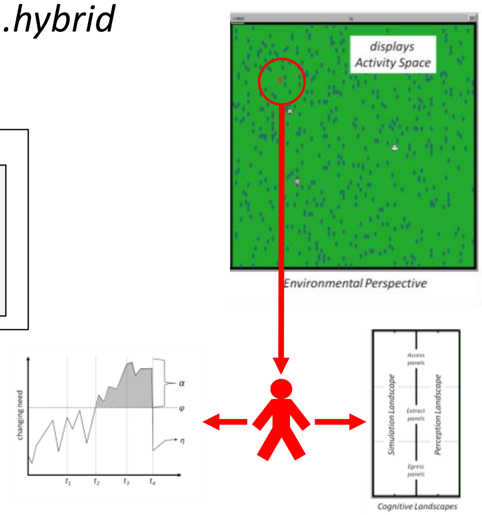
NetLogo 5.2.0

Subject-Environment

Subject

Needs accumulation

Tactical Planning & Adaptation



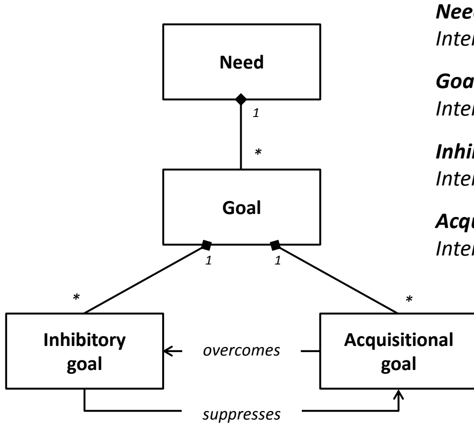
Slide 11

Unique Features…

1. *Goals are generated with a driven threshold system,*
2. *Associative memory enables learning from experience,*
3. *Tactical planning and adaptation are internally represented and simulated,*
4. *Outputs can be explicitly defined and represented as a forward-branching model with accompanying transition probabilities.*

Slide 12

Implementation…*needs & goals*



Need
Internal drivers that motivate

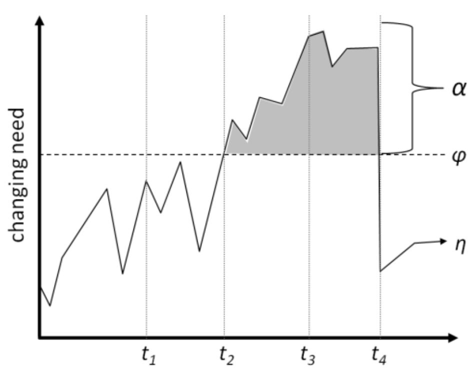
Goal
Intended state of the world

Inhibitory goal
Intention to keep from satisfying a need

Acquisitional goal
Intention to satisfy need

Slide 13

Implementation…*needs accumulation*



Acquisitional goal (α)
$\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_{n-1}, \alpha_n)$,
$$\alpha = \begin{cases} \eta - \varphi, & \eta - \varphi > 0 \\ 0, & \eta - \varphi \leq 0 \end{cases}$$

Inhibitory goal (φ)
$\boldsymbol{\varphi} = (\varphi_1, \varphi_2, \ldots, \varphi_{n-1}, \varphi_n)$
affected by external stimuli (i.e., privacy)

Need (η)
$\boldsymbol{\eta} = (\eta_1, \eta_2, \ldots, \eta_{n-1}, \eta_n)$
accumulates via external stimuli

Slide 14

UNCLASSIFIED

Implementation…*learning*

Target memory *– associative*

- *object attributes (index),*
- *object and/or*
- *location*

Method memory *– associative & episodic*

- *utility goals (index),*
- *targeting ("active" v. "passive"),*
- *tactical (cognitive resources), and*
- *action ("dominate" v. "collaborate")*

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Slide 15

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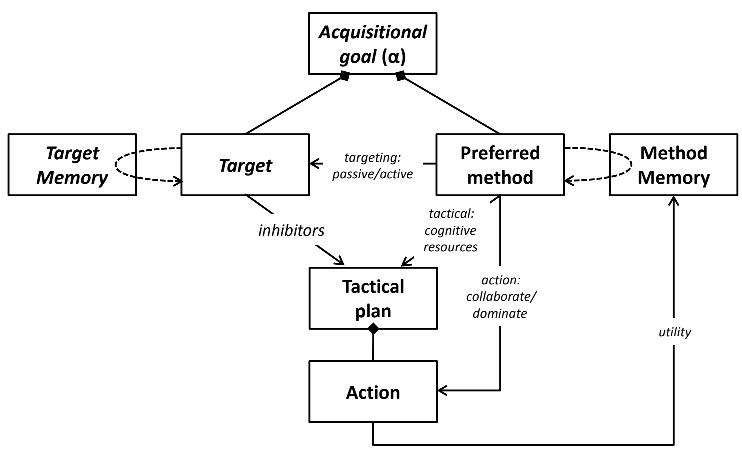
Design…*learning to achieve a goal*



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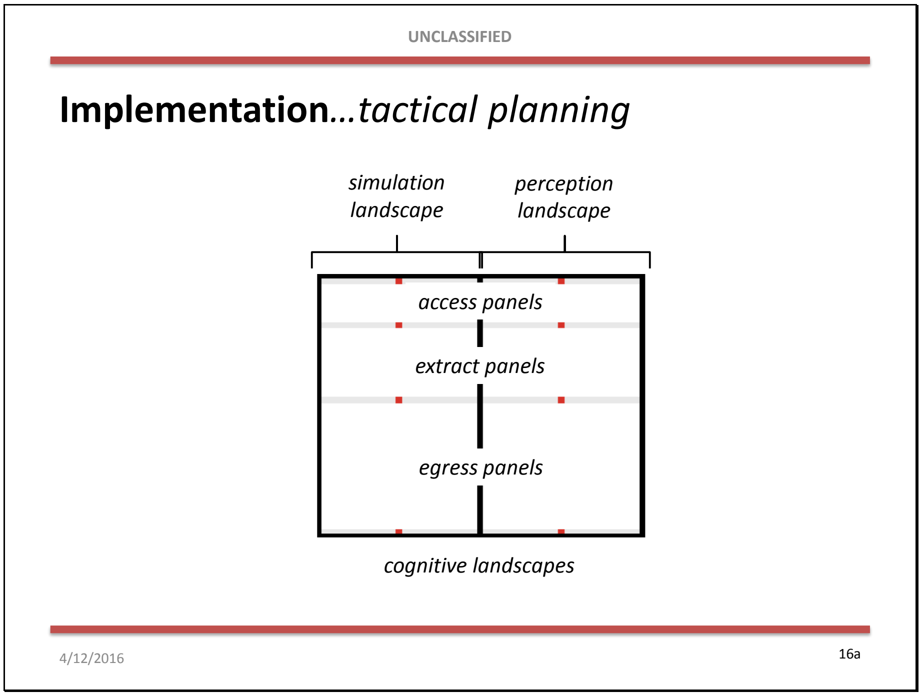
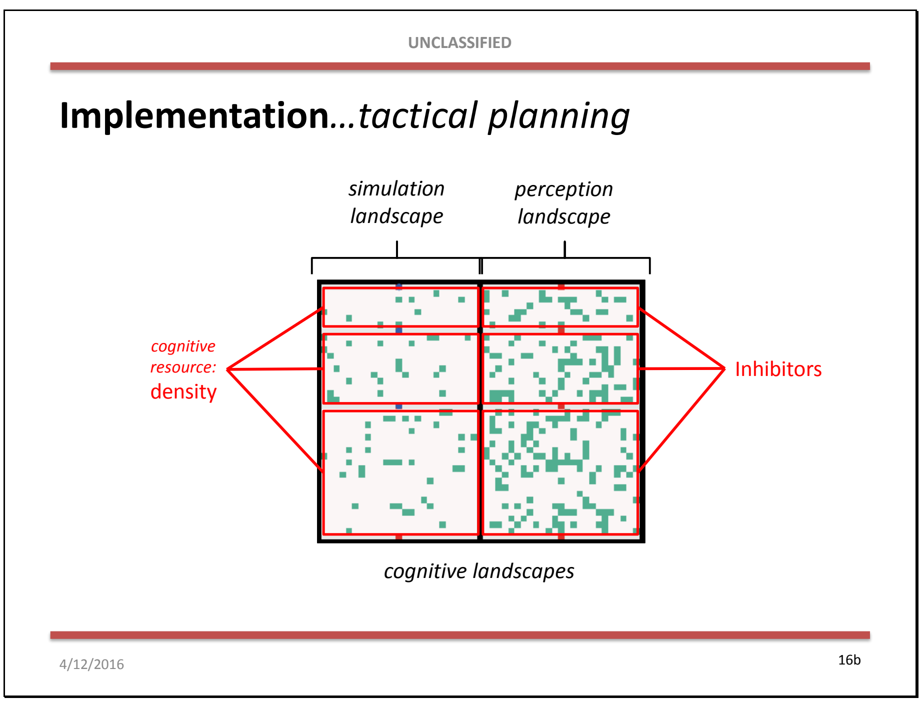
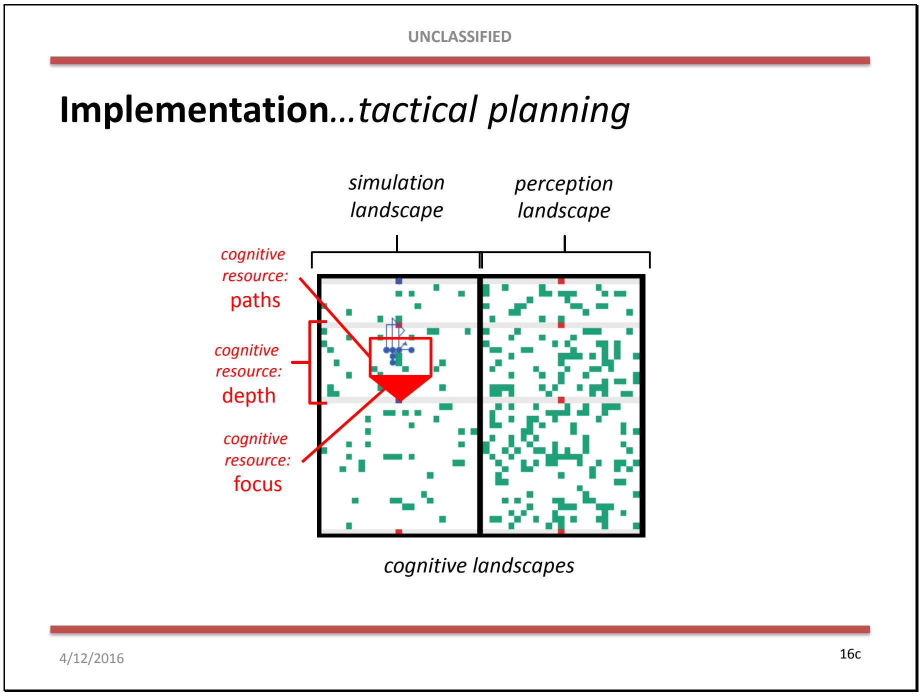
Slide 16a



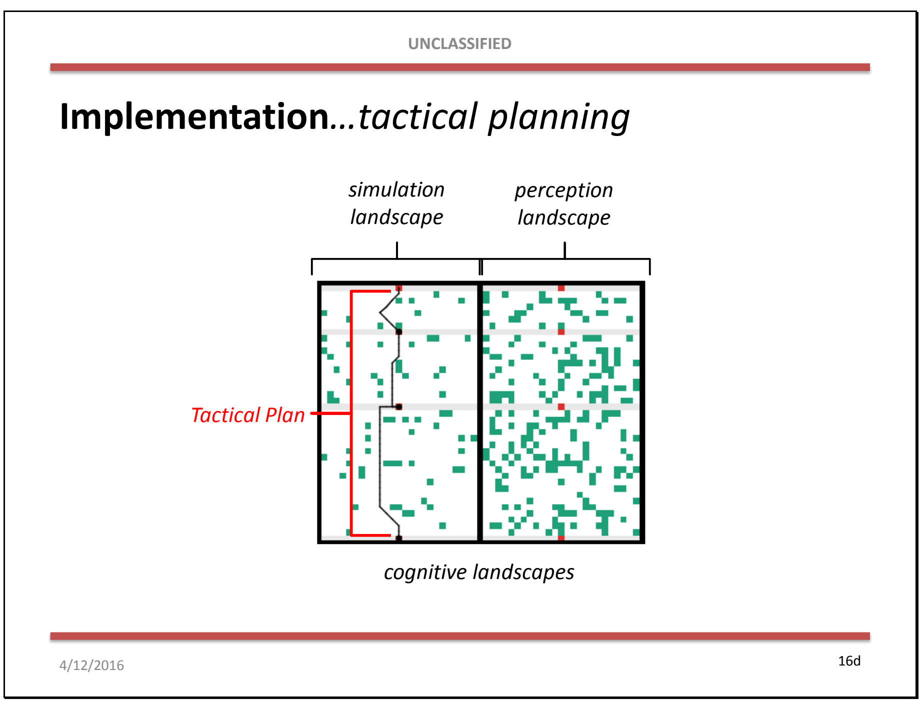
Slide 16b



Slide 16c



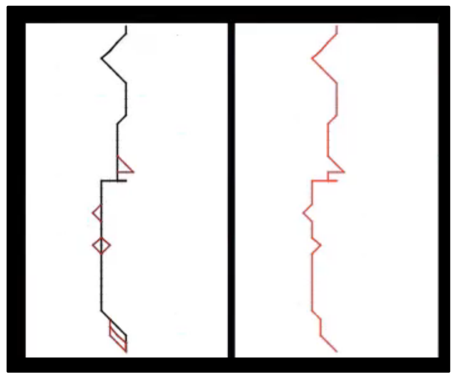
Slide 16d



Slide 17

UNCLASSIFIED

Implementation...*tactical planning & adaptation*



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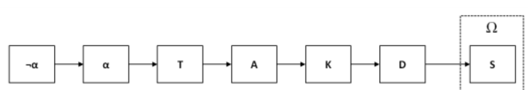
Slide 18a

UNCLASSIFIED

Design...*outcomes*



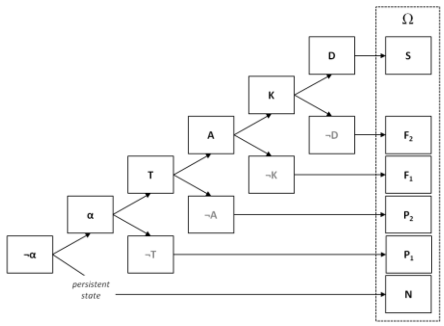
¬α = no acquisitional goal
α = acquisitional goal
T = tactical plan
A = access
K = extraction
D = egress

Ω ----------------------------
S = Successful Offending

4/12/2016 18a

Slide 18b

Design...*outcomes*



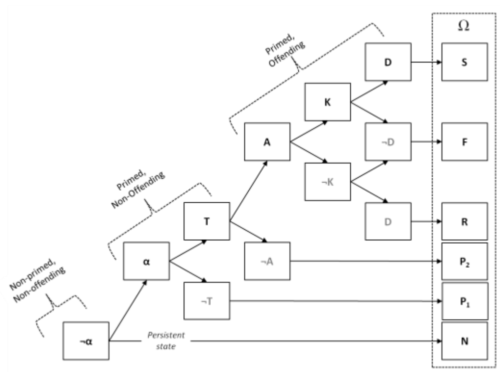
¬α = no acquisitional goal
α = acquisitional goal
T = tactical plan
A = access
K = extraction
D = egress

Ω ---------------------------
S = Successful Offending
F = Failed Offending
P = Primed
N =No Offending (¬α)

- *Forward-branching process, similar to fast process of the Canonical Theory*
- *Extends the Offender Interaction Process Model (OIPM)*

Slide 18c

Design...*outcomes*



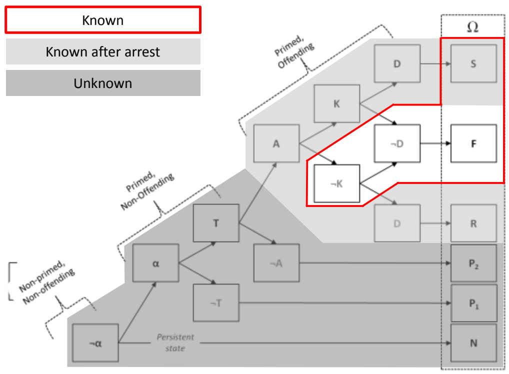
¬α = no acquisitional goal
α = acquisitional goal
T = tactical plan
A = access
K = extraction
D = egress

Ω ---------------------------
S = Successful Offending
F = Failed Offending
P = Primed
N =No Offending (¬α)
R =Retreat

- *Forward-branching process, similar to fast process of the Canonical Theory*
- *Extends the Offender Interaction Process Model (OIPM)*

Slide 18d

Design...*outcomes*



¬α = no acquisitional goal
α = acquisitional goal
T = tactical plan
A = access
K = extraction
D = egress

Ω ---------------------------
S = Successful Offending
F = Failed Offending
P = Primed
N =No Offending (¬α)
R =Retreat

- *Forward-branching process, similar to fast process of the Canonical Theory*
- *Extends the Offender Interaction Process Model (OIPM)*

Slide 19a

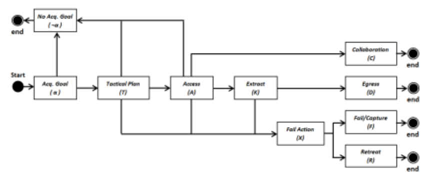
Implementation...*event-chains*

State		Example Interpretation...(i.e. Sexual Murder)
Acq. Goal	α	The subject has developed an interest in exerting control and/or having a sexual experience.
Tactical Plan	T	The subject has developed a tactical plan to either engage the services of a prostitute (collaborate) or abduct a female victim (dominate).
Access	A	The subject has successfully secured the services of a prostitute (collaborate) or abducted a female (dominate).
Collaboration	C	The subject has successfully engaged in sexual interaction with a prostitute (target).
Extract	K	The subject has successfully raped and/or killed the female victim.
Egress	D	The subject has successfully dumped the female victim's body.
Fail Action	X	The subject has failed in his attempt to abduct and/or rape/kill the female victim and must now retreat without being detected or captured.
Fail/Capture	F	The subject has failed to retreat and is either arrested or killed.
Retreat	R	Although the subject has failed in his attempt to abduct and/or rape/kill the female victim, he has successfully avoided detection or capture.
No Acq. Goal	¬α	The subject's interest in exerting control and/or having a sexual experience did not persist.

Slide 19b

Implementation…*event-chains*

	α	T	A	K	D	
event-chain 1	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has successfully abducted a female (dominate).	The subject has successfully raped and killed the female victim.	The subject has successfully dumped the female victim's body.	**end**
	α	T	A	C		
event-chain 2	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to engage the services of a prostitute (collaborate)	The subject has successfully secured the services of a prostitute (collaborate).	The subject has successfully engaged in sexual interaction with a prostitute (target).	**end**	
	α	T	X	R		
event-chain 3	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has failed in his attempt to abduct the female victim and must now retreat without being detected or captured.	The subject has successfully avoided detection or capture.	**end**	
	α	T	A	X	F	
event-chain 4	The subject has developed an interest in exerting control and having a sexual experience.	The subject has developed a tactical plan to abduct a female victim (dominate).	The subject has successfully abducted a female victim (dominate).	The subject has failed in his attempt rape and kill the female victim and must now retreat without being detected or captured.	The subject has failed to retreat and is arrested.	**end**



Slide 20

Validation…*why a murder series?*

- ✓ *"Serial murder" accounts for a small fraction of ~15,000 murders a year in the U.S.*
- ✓ *Estimates of the occurrence of serial murder unknown…*
  - *20-50 active serial murders at any time…?*
- ✓ *Involves hidden population of "primed, non-offender" subjects who often "hide in plain site"*
- ✓ *General structural questions about serial vs. single offending*
  - *Why does an offender repeat events?*
  - *How many "serial" offenders are arrested after only one event (even though they intended to continue)?*
  - *What underlying features have an impact on series longevity and tempo?*

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Calibration…*Green River Killings (GRK)*

Scenario*

- *49 sexual murders*
- *Young women (prostitutes and runaways)*
- *1982 – 1998: Seattle-Tacoma Metro Area, WA*
- *Victims abducted/taken from prostitute "stroll" **(abduction-site)***
- *Bodies dumped in secluded areas **(dump-sites)***

Gary Ridgway

- *Lived and worked in area*
- *Hyper-sexual, frequented prostitutes*
- *Solicited victims for sex, then killed victims at his home and secluded areas near dumpsites **(kill-sites)***
- *Known to return to dump-sites with prostitutes or to have sex with victim corpses **(collaboration-sites)***

* *open source*

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GRK…*configuration*

Configuration

✓ *First 9 murders…*

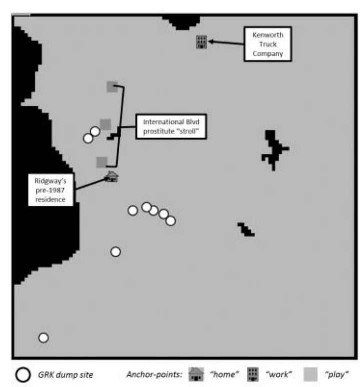
✓ *Geospatial elements*
- *anchor-points & comfort*
- *dump-sites & privacy*

✓ *Location-based targeting*
- *prostitute "stroll"*

✓ *Targets "high risk"*

✓ *5 configurations, 100 runs per*

✓ *Outputs*
- *"Dominate" vs. "Collaborate"*
- *abduction-, kill-, & dump-sites*
- *days-between-hits (DBH)*



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Analysis & Results...*overall findings*

Spatial

- *Subject tendency to favor certain areas to abduct, kill and dump*
- *Centroids paths do not have same dynamic spatial features as GRK*
- *Additional factors need to be considered (i.e., investigation, target situational awareness)*

Temporal

- *Increased variation in preferred methods – structurally similar to GRK*
- *Increased adaptability – longevity similar to GRK*
- *Nuanced spatial and temporal (behavioral) consistency*

Criteria-based

- *Individual criteria useful, but as a whole this method did not perform as well as expected.*

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Discussion...

- *First to explore efficacy of computationally implementing the violent offending process.*
- *Narrative event-chains provide invaluable way to contextualize outputs.*
    - *Future work should differentiate between needs to develop more robust representation*
- *Internal cognitive features offer a new and useful way to represent a problem space and derive tactical planning and adaptation solutions.*
- *Significant representation of "primed-" offending and non-offending behaviors.*

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Further…*Research*

1. *Calibrate to other series and types of violent behavior (i.e., murder, rape, robbery, insider threat, terrorism, etc.)*
2. *Role of adaptability in series longevity and tempo*
3. *Causal-path analysis and transition probabilities of outcomes*
4. *Co-morbidity of "collaborative" and "dominate" event-sites*
5. *Factors in reduction of the "killing inhibition"*
6. *Risk-terrain modeling as a feature of offender decision-making*
7. *Explore structural similarities of events at different scale*
8. *Guiding principles of primed behavior…*

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Conclusion…*enduring questions*

Can offenders be identified prior to attack?

- *Examination of "primed, non-offending" behavior…*
- *Outputs that include not only observable states, but also hidden states…*

Is it possible to discover and/or predict offending trajectories?

- *Outputs as states,…significant opportunities for analysis.*
- *Causal-path analysis of first-order transition probabilities*
- *Terrorism analysis*
- *Role of opportunity-based targeting*

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Conclusion…*enduring questions*

How does offending depend on the micro-level features of offenders?

- *Representation of endogenous aspects of the subject through an accumulator model and an internal simulation of a problem space.*

How can hidden attributes and features of violent offenders be effectively examined?

- *Explicit representation of implicit theoretical foundations.*
- *Observable outputs of internal features and their traceable effects on external interactions…*

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Questions?

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Thank You.

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