UNIVERSITY COLLEGE LONDON
MSc in Cognitive and Decision Sciences

The Use of Causal Bayesian Networks to Formalize Crime Scripts

With an Application to Cash-in-Transit Robbery

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Abstract

A crime script is a graphical representation of an offender's actions and decisions throughout the commission of a crime. It provides a more comprehensive understanding of a crime and thus facilitates the identification of intervention points. However, crime scripts lack formality in that they do not specify how the variables interact or any consistencies between them. Therefore, they serve primarily as a means to visually represent the factors involved in each stage of a crime, but do not serve as an interactive tool for analyzing how certain variables affect the crime as a whole. This project addresses this gap by proposing a method for formalizing crime scripts through the use of causal Bayesian networks. We demonstrate this formalization technique with the example of cash-in-transit robbery by first creating a crime script and then identifying various causal relations. By adding causal Bayesian relations between variables, such as identifying independencies or dependencies among variables, the formalized script could ultimately be used to model interventions and predict the ensuing effects to strengthen situational crime prevention strategies. We discuss the benefits and implications of this approach to crime analysis and possibilities for future research to make this tool more robust.

Key phrases: crime script, causal Bayesian network, cash-in-transit robbery, intervention, situational crime prevention

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1. Introduction

A security van rounds the corner and parks outside of a bank. As one of the security officers exits the van with a cash box for refilling the ATM inside, a man wearing a balaclava runs up wielding a knife and demands that the officer drop the box. After a moment's hesitation, the officer releases the box and the man flees, hopping into a car waiting nearby. The car speeds away with the offender and £20,000 inside. This is a typical scenario for an across the pavement cash-in-transit robbery and is one of the most common types of cash-in-transit robbery committed in the UK. In this project, we combined the properties of crime scripts and causal Bayesian networks to create a more formal graphical structure for representing the crime of cash-in-transit robbery. Crime scripts depict the various actions and decisions of an offender throughout the crime-commission process in sequential steps, which provides a broader understanding of the crime and helps identify possible intervention points. Causal Bayesian networks model the causal relationships between diverse kinds of variables and allow inferences about how changes to certain variables affect the system overall. Although these two techniques differ in the means by which they display the flow of information, combining them opens the possibility for a more formal and useful method of reasoning about the factors involved in a crime.

The aims of this project were both practical and theoretical: to summarize what is currently known about cash-in-transit robbery in an understandable and accessible format as well as to create the foundation of a formal tool for use in identifying opportunities for situational crime prevention. To accomplish this, we used a systematic approach of first creating a crime script for cash-in-transit robbery, and then applying properties of causal Bayesian networks in order to graphically represent the various factors, decisions, and actions involved and the causal relations between them. However, as this is a first attempt at synthesizing these two techniques, the formalized crime scripts are in their early stages. Nonetheless, long-term, this model could ultimately serve as a tool to simulate interventions and predict their effects. Also, the method could be expanded to capture quantitative data and employ other formal approaches, as well as be applied to other crimes, in order to more effectively analyze crime.

2. Literature Review

2.1 Crime Scripts

2.1.1 History of Scripts

A script is broadly defined as a sequence of actions comprising an event (Brayley, Cockbain, & Laycock, 2011). The concept originated in the field of artificial intelligence with a project by Schank and Abelson (1977) to create computer programs that simulate the human cognitive processes involved in understanding situations or stories. They determined that people create mental scripts, or predetermined sequences of actions, based on memories of their past experiences to help them comprehend situations they encounter frequently (Schank & Abelson, 1977). In this sense, scripts constitute a kind of schema, or knowledge structure that not only helps people interpret new situations based on previous knowledge of similar circumstances, but also reduces the cognitive load required to process that information by automatically filling in expected characteristics of the scene (Gureckis & Goldstone, 2010). In cognitive science, scripts more specifically typify an 'event schema,' which organizes knowledge about people's behaviors and actions (Cornish, 1994).

The classic example is the restaurant script, in which knowledge about eating out at a restaurant is organized into the stages of entering a restaurant, waiting to be seated, ordering, eating, asking for the check, paying, and leaving (Schank & Abelson, 1977). This main script can also contain various tracks (e.g. dining at a fancy restaurant, eating at a fast food place), shortcuts (e.g. waiter brings the check without the customer asking for it), and loops (e.g. the food was not to satisfaction so the customer orders again) to account for different experiences previously encountered. Organizing sequences of actions in this way guides human behavior by providing a set of expectations about how an event will unfold, thus enabling one to predict an outcome and act accordingly (Gavin & Hockey, 2010). If a script is violated and expectations of a situation fail to come to fruition, people must rewrite their scripts so they learn what to do the next time a similar situation occurs (Schank, 2010). Since a script captures an event from a specific actor's perspective and is based on that actor's experiences, scripts often differ between people, but nonetheless share similar characteristics that guide understanding.

The ability of scripts to schematically portray the routine performance of tasks made them popular in several applied domains, such as marketing and consumer research. For instance, the view that professional buyers and sellers possess scripts that guide their thinking and behavior during sales transactions has encouraged research into those scripts with the aims of revealing best practices and creating training strategies to improve performance (Cornish, 1994). However, using scripts in applied settings shifted their purpose from the original idea of programming a computer to correctly interpret stories as a human would through the use of standard scripts, to the goal of analyzing and improving the pre-existing scripts used by professionals in skilled tasks.

Their role changed once more when Cornish (1994) applied script theory to the domain of crime. He defined crime scripts as "step-by-step accounts of the procedures used by offenders to commit particular crimes" and asserted their usefulness in identifying the stages of a crime-commission process, the actions and decisions made at each stage, and the resources needed to effectively carry out each stage (Cornish & Clarke, 2011: 31). This approach differs from previous applications because the focus is not on improving the script for the benefit of the actor (e.g. training the professional to perform better), but instead lies in developing and advancing knowledge of the script used by the actor (i.e.

offender) to help the *researcher*. By arranging the stages of a crime-commission process in a schematic way, the researcher can dissect the individual steps of the crime into their various components and better understand the factors and resources required for each. The flip side does exist, though, in which offenders are believed to use scripts as a means of effectively and quickly carrying out routine crimes (e.g. burglary) and to add on to their scripts as they accumulate more experience (Wright & Decker, 1994). Just as professional marketers develop a selling script to follow when making sales transactions based on past successes, criminals create an offending script based on their objectives and past experience that enables them to efficiently and confidently commit an offense. However, for the purposes of this project, we employ the former use of a crime script—as a tool for the researcher to analyze the crime-commission process for better understanding.

2.1.2 Value of Script Theory

The script theory approach to crime offers many benefits. In general, creating a script containing the people, props, locations, and procedures needed to carry out a crime meticulously specifies all of the steps involved in the crime, even those that are sometimes tacitly assumed, and clarifies the aspects involved from start to finish without restricting attention to selected parts (Cornish & Clarke, 2002). This often results in the discovery of sometimes-neglected aspects of the crime and existing gaps in the information, as well as certain complexities, even in seemingly simple crimes (Cornish & Clarke, 2011). When scripts are applied to complex crimes, they often reveal links between related crimes and can even be used to illustrate webs of criminal activities within and across geographic areas (Cornish & Clarke, 2002). Furthermore, if developed over time, scripts could reveal an evolution of simpler crimes to more complex and organized crimes as well as an adaptation of certain crime-commission processes to changing opportunities and resources (Cornish & Clarke, 2002).

In regards to the behavioral side, since scripts portray offenders' current solutions to the risk, effort, and reward of a particular crime, they provide valuable insight into the offenders' mindset and rationale for exhibiting certain behaviors, even in apparently 'senseless' crimes (Cornish & Clarke, 2011). As a result, scripts serve to support the rational choice perspective, which maintains that criminals offend because it affords them the most efficient means of achieving their needs or desires (Tompson & Chainey, 2011). According to this perspective, offenders intuitively consider the perceived costs and benefits of actions as well as the strengths and weaknesses of targets when deciding to offend and seek to maximize their benefits, or the return on, their investments of time and energy (Hepenstal & Johnson, 2010; Cornish & Clarke, 2002). In this way, offenders act and make decisions in much the same way as other people—by trying to achieve their goals through the best available means under the circumstances. Crime scripts support the rational choice perspective because they portray criminals as (bounded) rational decision-makers who carry out a crime through instrumental and routinized actions dependent on the situational circumstances present (Cornish & Clarke, 2002). Therefore, the systematic distillation of information about a crime into a series of decision points and actions not only helps identify possible influencing factors contributing to an offender's choices and the logistical requirements for each step, but also elucidates how those components of the crime relate to each other (Tompson & Chainey, 2011). This is especially useful when trying to imagine how certain actions could have resulted in the crime occurring differently, which ties in to the ultimate goal of detecting intervention points for future crime prevention.

2.1.3 Future of Crime Scripts

Current research has applied crime scripts to sex offences (Leclerc, Wortley & Smallbone, 2011), child sex trafficking (Brayley et al., 2011), check forgery (Lacoste & Tremblay, 2003), cigarette smuggling (von Lampe, 2010), and suicide bombings in Israel (Clarke & Newman, 2006), amongst others. This research has primarily applied script theory to crimes as a means of mapping out the crime-commission process to facilitate identification of prevention strategies as discussed thus far. However, crime scripts hold great potential for use as a formal tool for analyzing crime by the addition of causal links between the variables. It is generally acknowledged that causal structure is inherent in scripts, as evidenced by the following claim by Nisbett and Ross (1980: 34):

> "Scripts generally are event sequences extended over time, and the relationships have a distinctly causal flavor, that is, early events in the sequence produce or at least 'enable' the occurrence of later events."

However, despite this assertion, to our knowledge no research has yet been published attempting to formalize the scripts either quantitatively or qualitatively. As a result, the introduction of causal Bayesian networks to the pre-existing framework of crime scripts serves to identify the specific causal links inherent to scripts and the restrictions that rule the interactions between the variables.

2.2 Causal Bayesian Networks

2.2.1 Overview

A Bayesian network (BN) has two components: a qualitative graph structure and a set of quantitative underlying conditional probability tables. The graph is a directed acyclic graph comprised of nodes, which denote uncertain variables, and edges, which signify informational or causal dependencies between the variables (Pearl & Russell, 2003). These dependencies are quantified by conditional probability tables for each node given the possible states of its parents in the network (Pearl & Russell, 2003). In order for the model to be complete, all of these conditional probability tables must combine to form a joint probability distribution, or "the probability of every possible event as defined by the values of all the variables" (Pearl & Russell, 2003: 2). However, it is possible to have a BN without knowing the full conditional probability tables and still draw meaningful inferences from the graph structure. This is known as a qualitative Bayesian network because it simply "represents the presence or absence of dependencies between variables" (Lagnado, 2011: 197). A link connecting one node to another thus indicates that particular values of the first node will change the probability of obtaining certain values of the second node, but does not specify by how much. Although less precise, qualitative BNs still serve the purpose of demonstrating the interactions between variables. If the links between nodes represent causal relationships, the network is known as a causal Bayesian network. In causal BNs, the parents of each node indicate its direct causes. The absence of a direct link between two nodes signifies that there is no direct causal influence of the first variable on the second; instead, the influence is either mediated by another variable or no causal influence exists at all (Pearl & Russell, 2003). In this project, we utilized qualitative causal BNs since precise probabilities were not available and we wanted to focus on the causal influences of the variables.

The main properties of BNs involve identifying dependence or independence between variables and representing those relationships graphically. There are three main ways of doing this. To demonstrate with a simple example, for a set of three variables X, Y, and Z, there are three possible ways of connecting the pairs (X, Y) and (Y, Z) at the midpoint Y:

1. Serial connection: X → Y → Z
2. Diverging connection: X ← Y → Z
3. Converging connection: X → Y ← Z

In a serial connection, X propagates through Y to Z in a causal chain, and X and Z are conditionally independent given Y. In a diverging connection, Y is a common cause of both X and Z, making X and Z conditionally independent given Y. And in a converging connection, Y is a common effect of both X and Z and X and Z are independent, but conditionally *dependent* given Y because they compete as explanations for Y. If one of the variables (for instance, X) is found to be the cause of Y, then X 'explains away' Z as a cause for Y. The following two figures provide examples of these properties.

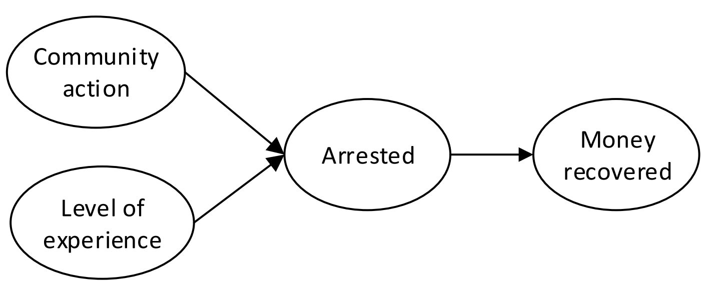

Figure 1: Serial connection (causal chain) and converging connection (common effect)

In Figure 1, each of the factors (X) on the left leads with some probability to the arrest of an offender (Y), which results in recovering the stolen money (Z). If one knows that the offender was arrested, it does not matter which factor led to the arrest because those factors are independent of the money being recovered, conditional on the fact that the offender was arrested. This example also illustrates a converging connection because "Community action" (X) and "Level of experience" (Z) are independent, but conditionally dependent given the offender was arrested (Y), and compete as explanations for the arrest. Furthermore, these two nodes (X and Z) exhibit a Noisy-OR combination function because they are independent of each other and combine independently to cause an arrest. Other possible combination functions include Noisy-ANDs, which we discuss later.

Figure 2 illustrates how after immobilizing a security van in a heist, forcing entry to the van (Y) acts as the common cause for both damage to the van (X) and obtaining the cash inside (Z). If one knows that an offender obtained the cash, it raises the probability that the van sustained damage. If one knows that an offender forced entry to the van, there is a certain probability the offender damaged the van and obtained the cash, but these are now conditionally independent given the forced entry to the van.

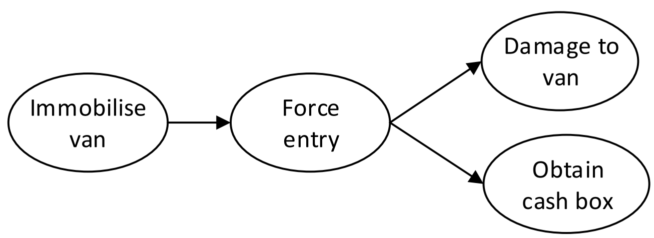

Figure 2: Diverging connection (common cause)

It is important to note that even though the variables in a BN can be binary, multi-valued, or continuous, the set of values for a variable must be mutually exclusive and exhaustive. Also, a key feature of BNs is the Markov condition, which states that a node is conditionally independent of its non-descendants given its parents (Neapolitan, 2009). In other words, BNs rely on the critical assumption that the parent nodes of a variable screen it off from all other variables in the network, except for those directly dependent on that variable. This condition is particularly helpful because it greatly reduces the number of variables included in computations for drawing inferences by allowing certain variables to be ignored that do not directly affect the node considered. As a result, BNs have gained popularity in a number of fields.

Due to their foundation in probability theory, quantitative BNs serve as an important formal approach to modeling uncertain relations between variables (Neil, Fenton, & Nielson, 2000). Although probability theory was first developed in the 1700s and probabilistic models based on directed acyclic graphs came into use in the 1920s with Wright's (1921) work in genetics (e.g. studying the factors influencing the weight of guinea pigs at birth), Bayesian networks were not employed until the 1970s (Pearl & Russell, 2003). Initially applied in the domain of artificial intelligence, their utility in representing and reasoning with uncertain knowledge has expanded to include applications in the fields of cognitive science (Tenenbaum, Kemp, Griffiths, & Goodman, 2011; for a review, see Margolin Rottman & Hastie, 2013), astrophysics (Loredo, 1990), medicine (Nikovski, 2000), and criminal profiling (Baumgartner, Ferrari, & Salfati, 2005). Qualitative BNs have also increased in prominence recently, especially in legal contexts. Evidential reasoning in particular benefits from utilizing qualitative BNs because numeric probabilities are often not available for certain evidence types, such as witness testimony, yet this information inevitably factors into an analysis of a suspect's guilt (Keppens, 2007; Lagnado, 2011). However, despite the increase in applications of both quantitative and qualitative BNs, some challenges persist that require resolution before BNs can extend their power further.

2.2.2 Advantages and Limitations

Causal Bayesian networks can be advantageous for a variety of reasons. First, since much of humans' knowledge about the world is based on causal relationships, it is both natural and logical to portray a group of variables with specified causal links between them (Pearl, 2000). Explicitly modeling causal factors also helps reason from causes to effects and vice versa (Fenton & Neil, 2011). Due to the constraint of satisfying the Markov condition, BNs require fewer parameter values than a full joint probability model because any node is only conditioned on its parents, which greatly simplifies the model and reduces the computational power needed to solve it (Fenton & Neil, 2012). Also, BNs have the capacity to combine diverse types of variables, such as subjective beliefs and objective data (Fenton & Neil, 2011). The property of 'explaining away' enables the revision of previous beliefs in light of new evidence yet still permits auditable reasoning because BNs do not have hidden variables and inference is made using Bayes' rule (Fenton & Neil, 2011). In addition, BNs can be created from partial or incomplete data but still allow predictions by revising probabilities for unknown variables (Fenton & Neil, 2012). Furthermore, causal BNs have the ability to represent a change in the state of the world and then reconfigure to portray the effects of that change (Pearl, 2000). This is particularly useful when introducing an intervention to the model, which fixes the value of a particular node and deletes the link from that node to its parent—since the other links remain unchanged, the effects of the intervention can be predicted (Pearl, 2000).

Despite these benefits, BNs are not without their drawbacks. One major concern is a lack of formalized principles for building the graph structure, which poses complications especially when dealing with large-scale BNs (Neil et al., 2000). Another challenge facing BNs is the asymmetry problem, in which all combinations of parents' states are considered, even if some are impossible, thereby adding unnecessary complexities to the analysis of the BN (Fenton & Neil, 2012). We present an example of this in a later section. Also, for quantitative BNs, determining and justifying the conditional probability values, especially in domains without relevant statistics, can be difficult. Nevertheless, researchers have devised solutions to a few of these issues. For instance, Neil et al. (2000) proposed a method for constructing the graph structure of a BN through the use of idioms, or basic causal structures that function as building blocks. Fenton, Neil, and Lagnado (2013) have recently expanded upon this notion and applied it to the domain of legal arguments thereby bolstering the potential of idioms as a solution for creating a BN structure. To solve the asymmetry problem, Fenton and Neil (2012) have suggested strategies such as adding a 'switch' node to the BN to resolve asymmetry caused by mutually exclusive paths or introducing a 'constraint' node to fix asymmetry resulting from distinct causal paths. As most of these solutions are recent, their true potential and ability to fully resolve the challenges facing BNs has yet to be determined. However, despite these unsolved issues, it is generally acknowledged that BNs are one of the most powerful tools for reasoning about uncertainty, especially due to their foundation in probability theory, and thus current research aims to further develop the capabilities of BNs and remedy their problems (Lucas, 2005).

2.2.3 Applied to Crime Scripts

The inherent nature of crime scripts to represent causal relationships between variables lends itself easily to formalization through an application of causal Bayesian networks. If sufficient quantitative data is available, precise probabilities could be added to the relationships to create a quantitative BN, but this is not essential. A qualitative BN still holds significant utility because it provides a framework for how to reason about a crime despite many unknown values. This is true when examining a crime as a whole as well as when analyzing a particular incident, especially if trying to link that offence to another related one. By using a causal BN, nodes representing the motivations of the offender, influencing factors for certain decisions, and the offenders' perceptions of different issues can all be modeled together for a more complete understanding. Formalizing crime scripts with BNs thus extends the primary use of the crime script as a means of visually displaying information about a crime in a coherent manner to include the ability to make inferences about that information. This new capability facilitates reasoning about the causes and effects of essential variables of the crime. Perhaps most importantly, though, the potential to introduce an intervention to the formalized script opens the opportunity of simulation to predict its effects and decide on the most efficient means of reducing the deleterious consequences of the crime. We demonstrate the value of formalizing crime scripts using a qualitative causal BN for the specific empirical example of cash-in-transit robbery.

2.3 Cash-in-Transit Robbery

2.3.1 CiT Robbery Types

Cash-in-transit (CiT) robbery[1] is the illegal appropriation of cash during its transportation from one location to another (Wainer & Summers, 2011). This transportation process can be broken down into five main stages (see Figure 3), corresponding to the five types of CiT robbery (Wainer & Summers, 2011)[2]. The dark blue boxes represent points at which the cash is stored or being held and the lighter blue arrows signify points of transfer.

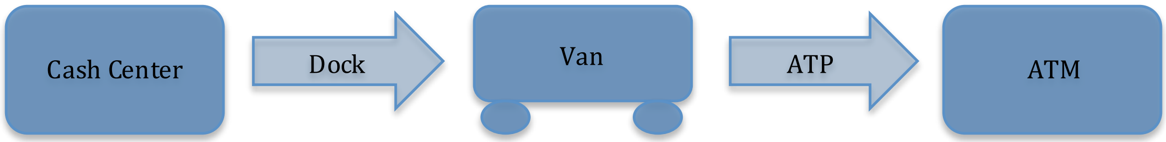

Figure 3: Five types of CiT Robbery

The first stage of CiT is the cash center, a secure location where cash awaits transfer to supply banks and other related businesses. Although cash centers hold the largest amounts of money and thus have the greatest potential reward for an offender, their powerful security measures mean they require the most effort to rob and often result in the most harm. These harms not only include significant financial losses but also damage to the premises since destructive force (e.g. knocking down a wall) is often required to gain entry; injury to the staff, either from damage to the premises or the use of violence by the offenders; and harms resulting from various crimes committed in preparation for the robbery (e.g. stealing vehicles, obtaining weapons). Due to the high level of obstacles and challenges involved, this type of CiT is usually committed by a group of offenders who carry out careful organization and planning prior to the offense.

Stage two of CiT is the transference of cash from the center to a security van at the cash center dock. This is typically done through a confined, secure area known as a vehicle trap, which hides the process from view and contains technologies that can withstand a variety of different attacks. This is the least likely type of CiT robbery to be committed and boasts the fewest successes.

Once the cash has been loaded into the security van, it begins its journey along a designated route for delivery to an ATM (automated teller machine). This is an attractive form of CiT robbery because vans vary in how much money they transport from up to £50,000 to £6 million for standard CiT vehicles. During transit, the van can be stopped and subsequently robbed by either a single offender or multiple offenders in what is known as a heist. In the former case, the solitary offender typically immobilizes the van and threatens one of the carriers, often with a weapon, while demanding the other to open the van and release the cash. This same duress modus operandi may also be used in the case of multiple

[1] Although also referred to as cash and valuables in transit (CViT) robbery, for the purposes of this project, cash-in-transit robbery will suffice.
[2] Unless otherwise stated, the subsequent information on CiT robbery is from the CViT report by Wainer and Summers (2011) on CiT robbery in the UK.

offenders; otherwise, the offenders access the van's secure area without the help of the security officers through the use of metal cutting equipment. This type of CiT robbery often requires planning (e.g. learning the van routes) and preparation (e.g. obtaining vehicles or equipment) and poses a very high risk to security personnel.

The second point of transfer, when the carrier walks the cash box across the pavement (ATP) to the ATM, constitutes the most vulnerable stage of CiT (Hepenstal & Johnson, 2010). Even though these are the least lucrative of all CiT robberies because the carrier only holds one cash box at a time (containing a maximum of £25,000), they are perhaps the easiest because they require minimal planning and thus are often opportunistic in nature. The two main ways this type is carried out are through the duress modus operandi, in which a weapon may be used to threaten the carrier to drop the box, or through the tactic of 'snatch and grab,' in which the offender grabs the box and flees. Although a single offender can commit this kind of robbery, often two offenders are involved—one to grab the cash box and one to drive the getaway vehicle waiting nearby. The risk of an ATP robbery is highest when the bank or ATM is located close to a busy intersection because the security van must park farther away, resulting in longer exposure of the carrier, and intersections provide multiple fast getaway routes for offenders in vehicles (Hepenstal & Johnson, 2010).

The last stage of the CiT process is the delivery of the cash to an ATM, which can be located either outside or inside a building or bank. This type of robbery can be further divided into whether the attack occurs during working hours or after hours. Attacks during working hours occur when the carrier is loading or collecting cash from an ATM and pose high risks to the security personnel, retail staff, and nearby pedestrians. Attacks after hours also pose risks to passersby if present, but additionally increase the possibility of criminal damage, as offenders must forcibly gain access to an ATM unit, especially if it is located inside a building. Since some ATMs contain locking bars that restrict access to one cassette at a time, offenders may also opt to remove the entire ATM.

2.3.2 CiT Robbery Overall

In addition to actions taken during the offence, several other issues also factor into the commission of CiT robbery as a whole. Prior to committing the crime, many offenders employ the expertise of acquaintances to obtain vehicles and weapons or get intelligence on the target through surveillance. Much of this preparation requires committing other offenses, such as stealing vehicles, buying illegal weapons, or obtaining cloned vehicle registration marks (VRMs) or plates. Furthermore, actions taken after the robbery also typically involve criminal activity, such as laundering the stolen cash or spending it on drugs or weapons. Therefore, CiT robbery is not an isolated crime and often serves to fuel a variety of other crimes. Also, the harms of CiT robbery are not limited to financial losses, but additionally include serious risks of physical and psychological harm to both security personnel and the public as well as damage to the premises or security vehicles.

However, not all offenders share the viewpoint that CiT robbery can have numerous negative effects. In interviews conducted by Wainer and Summers (2011), many offenders revealed that they view CiT robbery as a 'victimless' crime, in which only wealthy private companies, such as banks, are harmed financially. Also, even though many offenders had threatened to use violence during previous robberies, most admitted that they do not qualify a threat as violence, but only see gratuitous violence as real violence. This perception most likely contributes to the majority of offenders being unaware that CiT robbery yields high sentencing lengths. Another reason many criminals do not think of CiT robbery as such a 'bad' offense is because they believe that it is common ("everyone does it") and so easy that "even little kids" can commit one (Wainer & Summers, 2011: 81).

Due to these misguided impressions held by the offenders, the potential for creating effective interventions seems high, even if it is only through correcting the offenders' perceptions. Some research has been conducted in an attempt to understand offenders' motivations for committing CiT robbery and to improve prevention measures, but considering the various detrimental factors involved, there has not been as much as expected. In fact, most research only briefly mentions CiT robbery and instead, focuses on the broader context of commercial robbery. Exceptions include Martin Gill's (2001) paper relating his findings about the decision making of CiT robbers based on extensive interviews with previous offenders, research on the effectiveness of security systems and techniques (e.g. smart water, armor, vehicle tracking), research on the spatial concentration of CiT attacks (Hepenstal & Johnson, 2010), and an extensive report analyzing the harms of CiT robbery (Wainer & Summers, 2011). These four sources have devised some intuitive and feasible interventions that, if implemented, could successfully reduce the number of CiT robberies. This project seeks to expand upon those ideas and provide a means for testing their potential.

3. Methodology

3.1 Materials

The analysis was based on a pre-existing report including both quantitative and qualitative data by Wainer and Summers (2011), "Understanding the Harms of Cash and Valuables in Transit Robbery", commissioned by the CViT members of the British Security Industry Association (BSIA) and the Home Office. The quantitative data included information on offender criminal histories, sourced from the Police National Computer (PNC), and CiT attacks, which came from two sources: SaferCash (encompassing all of the UK) during the range of 1 January 2007 to 31 December 2009, and four major British police forces (Metropolitan Police Service, Greater Manchester Police, Merseyside Police, and West Midlands Police) during the year 1 January 2009 to 31 December 2009. SaferCash, a center for intelligence sharing on CiT robbery, is funded by the CViT members of the BSIA to maintain a database containing information on all CiT robberies that have occurred in the UK. The SaferCash data used for the CViT report contained 3,119 total offences with details of the timing and location of each attack, the type of attack, the level of violence and weapons used, the amount of cash stolen, the modus operandi, and a free-text field. The police force data contained almost all of this information, plus whether the location had been previously victimized, if any injuries were inflicted, the vehicles used and if they had been recovered, whether the cash was recovered, and the names of the offenders charged for the offence. The Metropolitan Police Service data contained 579 CiT robberies and 146 unique offenders, the Greater Manchester Police data included 101 CiT robberies and 14 unique offenders, the Merseyside Police data contained 52 CiT robberies and 10 unique offenders, and the West Midlands Police data included 48 CiT robberies and 15 unique offenders; all police data had also been checked against the PNC for validity.

The qualitative data were in the form of offender interview transcripts of ten offenders convicted of CiT robbery occurring in 2009 from one of the four police areas considered. The interview questions covered the following topics: offending history; the events leading up to, during, and after the attack for which the offender was incarcerated; the proceeds of the crime; knowledge of security and prevention measures and strategies for overcoming them; and the offenders' cost benefit analysis of the crime. All of the information provided by the offenders had been crosschecked using the PNC.

Although the CViT report served as the foundation of our analysis, research by Hepenstal and Johnson (2010) on the concentration of CiT robbery and research and interviews by Gill (2001) on the skills of CiT offenders supplemented the CViT report in providing background and further evidence for the crime-commission process.

3.2 Procedure

To accomplish the first aim of the project, we generated a basic crime script based on the information and data presented in the CViT report and the accompanying offender interview transcripts. For an initial overview of the crime, we broke CiT robbery down into three sections—plan and prepare, commit the robbery, and getaway and money use—and listed all of the relevant information from the report under each section. Next, we analyzed the information to determine the factors and actions necessary for the commission of a CiT robbery and organized these steps into six main stages spanning from the preliminary decision to commit a CiT robbery, through the planning, commission, and getaway, to the choice of whether to offend again (see Figure 4).

We once more identified the factors (or variables) involved at each step and then organized them graphically by representing each variable as a node in the shape of an ellipsis (in accordance with the conventions of Bayesian networks) and adding arrow links between them indicating their relationships to each other. Upon completing a preliminary version of the scripts, we sent them to the authors of the CViT report to be checked for

Figure 4: Main stages of committing a CiT robbery

completeness and accuracy. After making the necessary changes, we then had a fully functional crime script from which to begin establishing causal links.

In order to transform this crime script into a formal tool, we examined the data for any causal relations that could be added between variables in the CiT script. Specifically, we searched for dependent and independent relations among the variables in the form of connections (e.g. serial, diverging, converging) and any instances of screening off in which the Markov condition holds. Since formalizing crime scripts is a new procedure, we focused on incorporating the basic principles of qualitative causal BNs to provide a foundation for future work (e.g. adding quantitative probabilities). We also strove to find a balance between representing all of the variables involved in the crime and maintaining a simple but comprehensive model. After identifying various causal links, we used the offender interview transcripts to fill in any gaps and verify that our scripts correctly represented each CiT robbery discussed by the offenders.

4. Results

Based on the CViT report data and offender interview transcripts, we decided to create separate high-level scripts for the opportunistic offender, who is usually a novice CiT robber, and the experienced offender, who typically plans the offence (see Appendices A and B). In each high-level script, an ellipsis signifies an uncertain variable and a shaded ellipsis represents a decision made by the offender. We borrowed the notation of a rectangle from object-oriented BNs to indicate a node that can be further unpacked to reveal more detail (Fenton et al., 2013; Hepler, Dawid, & Leucari, 2007). For example, rectangular nodes are used to denote the commission of each type of CiT robbery because those variables can be broken down into multiple steps and factors (see Appendix C). This feature facilitates formalization because it not only allows different levels of analysis to fit together into a cohesive whole, but also permits the reuse of common sequences for a compact representation. Therefore, overall we have a high-level script, containing only the primary variables involved in the crime, as well as several unpacked low-level scripts, which include various tracks by which the crime can be committed and the variables that could factor into its commission. A novel feature that we incorporated into the scripts is a dotted line without an arrow linking two variables together. This represents a departure from standard BN graph structure because the two connected nodes are actually exclusive and thus would typically be combined into one node. However, since very diverse paths result depending on which variable is true, we adopted the notation of branching from event trees to represent how the script then splits into two separate directions. Event trees represent how processes might unfold and thus are more suited to capture how two possible scenarios might progress (Smith & Anderson, 2008). An example of this from our scripts is the dotted arrowless line linking the nodes “Arrested” and “Getaway” in the aftermath of committing the crime. Whether or not the offender is arrested directly determines the track of the rest of the script and using branching captures this asymmetry. Another important caveat is that even though the scripts portray the crime-commission process as by a single offender, almost all CiT robberies are committed by a group of offenders. However, due to the variability of the roles and actions of the co-offenders for each robbery, including them in the script would exponentially complicate the model without necessarily adding much value. The following paragraphs explain the rationale behind the structure of each formalized crime script we created and refer to Appendices A through D.

In regards to the two high-level scripts, an opportunistic offender differs from an experienced offender primarily in regards to the planning of the offence. Although some opportunistic offenders plan to the extent that they obtain a vehicle specifically to commit the robbery, they usually do not plan beyond this, such as through surveillance of the target or choosing a specific time and date. In fact, the offenders often already possess a vehicle (usually stolen) because many CiT offenders have a history of car-related offences (e.g. car theft, disqualified driving). Also, since several offenders additionally have a history of burglary or assault, they sometimes already have disguises (e.g. balaclavas) or tools (e.g. hammer that can be used to open the cash box) in the vehicle as well. They then decide to commit a CiT robbery if they happen to see the opportunity while driving around or doing their daily activities. Since they do not extensively plan, they typically commit ATP robberies. Our high-level opportunistic offender script portrays this through the thickness of arrows used leading from “Confirm type” to each type of CiT robbery. The thickest arrow goes to “ATP” because this is the most opportunistic type and requires the least amount of planning. The arrow of middle thickness leads to “ATM” because this can also be committed with minimal planning if the offender happens to see a security staff member loading or unloading an ATM and decides to take advantage of the opportunity. And the thinnest arrow leads to “Heist” because although this type can be spontaneous, at least a vehicle and a weapon, or cutting equipment, are needed in addition to a feasible location to stop the van.

In contrast to opportunistic offenders, the high-level script for experienced offenders is more complex. The primary difference is the node “Plan robbery,” which unpacks into a variety of different variables that could factor into the decision to commit a particular type of CiT robbery (see Appendix B). It is not necessary for an offender to carry out all of these actions as any combination of them could result in the commission of a CiT robbery depending on the type chosen and the resources available. Displaying the individual factors in this way, though, shows how they are related and how if one occurs, it might increase, or decrease, the probability of another occurring. For instance, if an offender successfully obtains a vehicle to commit the robbery, it is more likely that cloned plates will also be obtained for the vehicle. The other difference between opportunistic and experienced offenders is that experienced offenders commit cash center and dock robberies in addition to heists, ATP robberies, and ATM robberies. Therefore, there are thicker arrows leading from "Confirm plan" to the nodes representing the commission of those two types because given the offender is experienced, those types are more likely; however, dock robberies are not very common and those committed are rarely, if ever, successful. The next thickest arrow leads to "Heist" because, as previously mentioned, this type requires some planning and preparation. The next most likely type of robbery to be committed by an experienced offender is an ATM robbery, especially if committed after hours, because that sometimes involves breaking into the premises or knowledge of how to open an ATM. The least likely for experienced offenders is an ATP robbery, probably because it yields the least amount of money and experienced offenders typically have the skills to commit more complex crimes for larger rewards. In the high-level script, a "No disruptions" node leads into the "Cash center" node. This signifies that if no interferences arise, the offender will commit the planned type of crime. It is important to have a separate "No disruptions" node for each type of CiT robbery[3] because different disruptions might arise depending on the type committed. This could also serve as a possible place to introduce an intervention because if an unexpected deterrent is introduced that creates a disruption, it may prevent the robbery from occurring.

Unpacking each kind of CiT robbery reveals the necessary variables for successfully committing each type as well as the meaning and importance of adding causal links (see Appendix C). An example will help demonstrate this. In a dock robbery (see Figure 5), the offender must not only gain access to the dock, but also gain access to the inside of the vehicle trap in order to obtain the cash. The sequential links between these nodes thus signify the necessity of each previous node in order for the next node to be attempted. If the offender does not access the dock, damage to the vehicle trap cannot be inflicted or if damage to the vehicle trap is unsuccessful, the offender cannot access the contents inside. Another causal feature portrayed in the dock script is the possibility of having two routes by which a node can come about: the "Compliance" node can result from the "Threaten staff" node either directly, or indirectly via "Injury to staff." "Staff training" also factors into whether the security member complies because personnel are instructed to release the cash if threatened. Since "Staff training" alone does not lead to the security member's compliance in releasing the cash, but a threat is also required, this connection is an example of a Noisy-AND. Furthermore, this structure in which multiple variables influence

[3] Separate nodes are not portrayed in the high-level experienced offender script due to space so only one is shown leading into "Cash center" as an example.

"Compliance," which in turn directly leads to "Obtain cash" is an example of obeying the Markov condition. Knowing that an offender obtained the cash enables backward reasoning to infer that the security guard complied; but the exact reason for compliance is irrelevant because that information does not add any inferential benefit since it is already known the cash was obtained. Therefore, "Compliance" screens off "Obtain cash" from "Staff training," "Threaten staff," and "Injury to staff" and the latter three are conditionally independent of "Obtain cash" given the parent node "Compliance." This then simplifies reasoning about the model, especially if quantitative data is later added, because the three nodes can be ignored when considering the variable "Obtain cash" since they are conditionally independent.

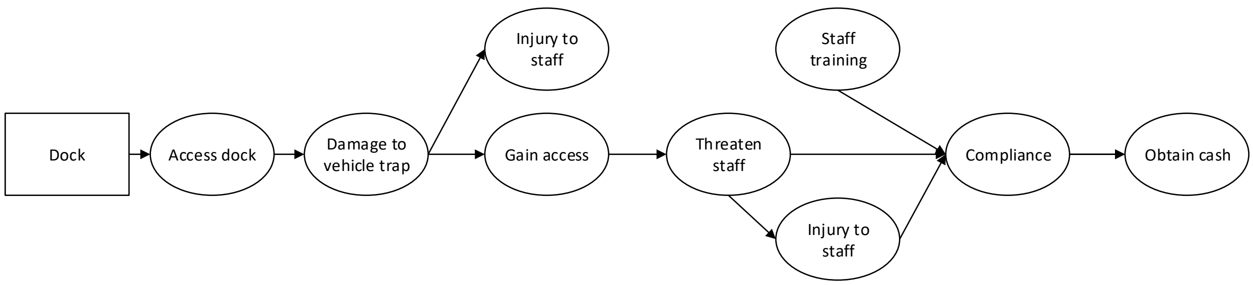

Figure 5: Dock robbery script unpacked

Another example of the importance of causal links is found in the unpacked Heist script. The node "Obtain cash box" is a common effect of either forcing entry to the van or having the van unlocked by security personnel. This converging connection implies that forcing entry and unlocking the van compete as explanations for how the cash box was obtained. They are independent if nothing is known about whether the cash was obtained, but become conditionally dependent given that the cash box was obtained; therefore, if one is known to be true, the probability of the other decreases. Representing this causal connection is especially useful in the situation in which there was damage to the van because the information propagates through the model to reveal that forced entry is the more likely modus operandi for the case rather than duress resulting in unlocking the van.

The aftermath of the robbery remains fairly consistent for both opportunistic and experienced offenders. One exception, though, might be if an experienced offender held particular skill sets that could decrease the likelihood of certain factors, such as if the offender knew how to open the cash box, which would decrease the probability of hiring someone else to open it.[4] We broke the high-level representation of this section down into a more detailed low-level script, but it does not follow the object-oriented approach because certain variables do not unpack; instead, we simply included more variables in the low-level script than in the simplified high-level script (see Appendix D). We also divided

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[4] Currently, this possibility is not explicitly represented in the script because it would greatly complicate the model and our aim for this project is only to create a framework for formalized crime scripts.

this section into two separate scripts depending on whether the offender obtained straight cash from the robbery or the cash was enclosed in a box or cassette. The difference lies in the obstacle of opening the box or cassette without the dye detonating and how to clean the notes if it did. Nonetheless, both of these routes lead to the same ending points of the arrest of the offender and recovery of the money or the decision for the offender of whether to offend again. We did not link this final decision point back to the beginning of the script because this would create a feedback loop, which is not permitted in standard Bayesian networks. However, it is important to note that the decision to offend again may lead to the commission of another CiT robbery.

5. Discussion

5.1 Implications

The findings from this project have meaningful practical and theoretical implications for cash-in-transit robbery specifically as well as for crime in general. For CiT robbery, this tool provides a better understanding of the crime overall and helps guide police on how to allocate their resources in order to reduce the number of CiT robbery incidents and their seriousness. Policy makers and those working in the CiT security industry especially benefit from this research because they can focus their limited resources on the best intervention and disruption techniques as indicated by the formalized crime script. For instance, in a cash center robbery, the offender must break down the outside wall to gain access to the center and thus attempt to obtain the cash. However, if an intervention was implemented that fortified the walls surrounding the cash center, gaining access would become more difficult thereby reducing the appeal of this kind of robbery. This could be demonstrated in the crime script by adding a node called “Fortify wall” directly linked to “Break down wall” that when set to true might reduce the probability of an offender breaking down the wall and thus potentially lead to the abortion of the robbery. To accurately demonstrate this, more data is needed, but due to the flexibility of our formalized crime script, new information can be easily added and the script can be adjusted according to how the data portray CiT robbery.

For crime in general, thoroughly analyzing a crime for causal relations between variables contributes a better psychological understanding of criminal decision making and reasoning. As a result, intervention points for prevention measures can be more accurately detected (Jacques & Bernasco, in press). Ultimately, these interventions could be simulated using the tool and their effects compared, before choosing the best option for implementation in the real world. The possibility of expanding formalized crime scripts to capture effects such as interventions greatly enhances their potential, whereas regular crime scripts do not have this capability. This cost effective approach to strategic policing provides further benefits through its flexibility since crime scripts do not require complete data sets and can be amended in light of new information (Brayley et al., 2011). This adaptability also permits differences in the formalized crime script for various geographical regions. For instance, the commission of a crime might differ across cities depending on the landscape and layout of the city, the demographics, or the resources available. If weapons are more easily obtained in big cities and the crimes there are more violent as a result, formalized crime scripts can account for this by adding a stronger causal link between weapons and violence used during the crime, dependent on the size of the city. A formalized crime script can thus also help policy makers, legislators, and criminal justice officials anticipate and respond to evolving changes and complexities in crime (Cornish & Clarke 2002). This then guides intelligence-gathering, detection, and investigation by providing a fuller understanding of the instrumental behavior involved in crime and offering a wider range of possible intervention points (Cornish & Clarke 2002). Furthermore, with a better understanding of the crime and factors needed to effectively carry it out, those responsible for protecting the community can inform the general public about how crimes occur in the hopes of reducing fear, increasing awareness, and boosting confidence in the police (Smith, 2009 as cited in Leclerc, in press). Beyond these short-term benefits, this project ultimately opens the possibility for creating a robust and mathematical interactive decision tool from quantitative data that can permit effective analysis of specific crimes and the use of efficient prevention strategies.

5.2 Challenges and Considerations

Since no one has yet attempted this approach to formalizing crime scripts, our model serves primarily as a foundation for future research and remains a work in progress. Consequently, there are a few shortcomings of our CiT script that require attention. First, we do not have enough information to create a full model for CiT robbery. For instance, our model does not specify necessary versus sufficient causes. When an experienced offender plans a robbery, it might be valuable to know which nodes are necessary in order for the crime to be committed and which are simply sufficient; more data could provide guidelines for determining these. For the opportunistic offender, it might be interesting to examine how much the presence of a certain type of opportunity affects the type of CiT robbery committed. If an offender sees a security van, how does the probability of a heist compare to the probability of an ATP robbery or an ATM robbery? More data could reveal that opportunistic offenders are more likely to follow the van until the drop rather than commit a heist, but this may depend on the location of the van as well—more data would clarify these questions. Nevertheless, due to the flexibility added by incorporating BN properties, we can later add more information without disturbing the rest of the system. In domains such as crime, there will often be missing data so a method of formalizing crime scripts that does not require a complete data set adds to its appeal and utility.

Second, our aim was to create a general script that maintained simplicity while still capturing the various factors involved in a CiT robbery. Consequently, we did not incorporate co-offenders even though they might add more context to the commission of the crime. In addition, our script does not allow for interplay between variables, as this might create feedback loops. For example, in the unpacking of "Plan robbery," experienced offenders might first choose the type of CiT robbery they want to commit, then try to obtain the required resources and when successful, carry out the planned crime; alternatively, they might choose a type at first but fail to obtain the necessary resources or equipment and then return to selecting a different more feasible type of CiT robbery. Our model does not capture this latter possibility because it would result in a feedback loop that would require increased complexity in order to resolve. At this stage in the process of formalizing crime scripts, we felt it best to keep the graph structure relatively simple to serve as a framework instead of a robust finalized technique.

Third, our CiT scripts as they stand now are not perfectly formalized BNs. Because some variables are exclusive yet different paths ensue from each, we utilized properties of event trees to divide them into separate nodes, as indicated in the scripts by a dotted arrowless line. Making the scripts completely symmetric according to a pure BN would either result in a loss of important information (since they would not portray the different routes an offender could take in committing a crime), or involve many complicated features that may capture the information but at the cost of adding complexity. Therefore, we opted to maintain simplicity by using notation from event trees, but forfeit a strict Bayesian formalization and the ability to represent numerous causal connections. The issue of capturing asymmetry with BNs, however, is an ongoing problem. In order to convey real world dynamics, many variables must be added to a graph, yet this makes the BN extremely complicated, which can sometimes defeat the purpose of its use in the first place. Even in simple scripts, BNs alone cannot capture the asymmetries present so a richer means of building graphical structure is needed. Smith and Anderson (2008) attempted to resolve this issue through the use of chain event graphs, which combine the conditional independence structure of BNs with the topological description of how a process unfolds portrayed by event trees. While these provide a solution to the problem of asymmetry, their complexity makes them a less than ideal approach. Therefore, further work is needed to resolve this issue not only for formalizing crime scripts, but also for BNs in general.

5.3 Future Research and Additions

As this method of formalizing crime scripts is new, several opportunities exist for improving upon its design. One such possibility with more data is adding additional links and variables to the scripts. For instance, in the unpacked "Plan robbery" script, a link could be added from "Bribe security guards" to "Heist/van" implying that bribing security guards most likely results in obtaining knowledge of certain van routes which increases the probability that a heist will be the robbery type of choice. Also, lines of different thicknesses could join the "Obtain weapons" node to the "Injury to staff" node in each type of CiT robbery script to indicate if the ability to acquire weapons influences the amount of violence used in certain types of CiT robbery. The same technique could be used to link the “Obtain vehicles” node to certain types of CiT robbery depending on whether the ability to attain a vehicle alters the probability of the commission of a certain type of robbery. For example, since at least one vehicle is needed for cash center and dock robberies, the experienced offender’s ability to attain two vehicles might increase the likelihood of committing one of these types instead of an ATM robbery that does not necessarily even require a vehicle. Possible additions might include adding a node signifying various points at which an offender could abort the crime. Our data only encompassed fully carried out CiT robberies so a different data source of attempted CiT robberies would be needed, if such data exist. Such an addition might provide valuable insights into an offender’s decision-making process and risk analysis, especially if measured after the implementation of an intervention as a means of testing its effectiveness. A further change to the variables of our current scripts would be using more modules, or idioms, based on object-oriented BNs to represent repeatable sequences in the scripts. There is potential for this top-down approach in the links between “Threaten staff” and “Compliance” in the unpacked CiT types scripts. We did not use them here because we found minor differences among the types, but modeling the factors slightly differently might enable their use.

Another addition from which our scripts might benefit is incorporating other formalisms, such as influence diagrams. An influence diagram is a graphical representation of uncertain variables and decisions that explicitly depicts probabilistic dependencies and the flow of information (Shachter, 1986). It generally consists of three kinds of nodes: chance nodes (depicted as circles), representing the random variables or states of the world; decision nodes (depicted as squares), indicating choices made by the decision maker among a set of alternatives; and value nodes (depicted as rounded rectangles), signifying expected utilities (Shachter, 1986). As in Bayesian networks, each chance node is associated with a random variable for which there is an underlying joint probability distribution, but this is not true of decision or value nodes. The links, or arcs, connecting the nodes can be either conditional or informational. Conditional arcs lead into chance and value nodes and represent probabilistic dependence, but not necessarily causality; alternatively, informational arcs, lead into decision nodes and indicate that the information at the beginning of the arc was present at the time of the decision (Shachter, 1986). Classifying the specific types of nodes and arcs present in the model would enhance the robustness of the model and further clarify how the variables interact to create a more comprehensive view of the crime. Also, including utility nodes in the script would help represent the rational decisions made by the offender, such as weighing the amount of money that could be obtained and the risk of getting arrested. Links could also be added between the utility of the payouts of each type of CiT robbery and motivations for committing the robbery to depict any causal relations between wanting, or needing, money and which type of robbery the offender chooses to commit. However, these additions would require more specific data of individual cases and the profiles of the offenders involved.

In order to completely formalize the crime script and test it for full functionality, quantitative data should be added to the model. Then, the full joint probability distributions can be utilized and the model truly tested. This would perhaps be the most helpful addition to the model because then analysts could compare the numeric probabilities of certain events occurring to better evaluate particular situations. In particular, quantifying the thickness of the arrows leading to the various types of CiT robbery would provide a better idea of exactly how likely each type is and thus which requires the most attention. Also, quantification would further clarify how the variables interact by enabling the identification of other causal relations, such as combination functions (e.g. noisy-OR, noisy-AND, linear addition), and by testing the model's capacity to represent the effects of external interventions, such as via the 'do' operator, in order to reason counterfactually and make predictions of a later action in the script based on the offender's precious decisions (Pearl, 2000). Lastly, quantification would allow validation of the graph for a more complete and valuable model. However, adding numeric data brings problems of accurately quantifying the prior probabilities and conditional probabilities. Therefore, more research is needed to first attempt to quantify the model and then test it for accuracy.

Another method that could help develop the explanatory power of a casual Bayesian crime script is integrating other forms of data into the creation of the model. For instance, instead of relying solely on police records and interviews, spatial and temporal analysis of the crime could help identify other factors that motivated or influenced the offender. This is especially useful when examining specific crimes for which the time and location are known because then analysts can compare the temporal and spatial information for each crime and look for patterns. Hepenstal and Johnson (2010) conducted research on this exact idea and found that the spatial distribution of CiT robberies does not depend on the spatial distribution of targets, but instead, CiT robberies cluster around intersections. This finding can then factor into the crime script and further help policy makers devise effective intervention strategies. A similar advancement could be adding known psychological models to the script in order to help predict behavior. Crime scripts are already believed to support the rational choice perspective, so predictions made from introducing an intervention should be based on the assumption that the criminal is trying to achieve a goal. By incorporating psychological models, the formalized script could more accurately capture factors affecting the offender's behavior to help predict the consequences of certain actions. This could be particularly important in answering questions such as how certain motivations for committing a crime affect how the offender carries out the crime. For instance, our CiT scripts currently show that the motivations of an offender for committing a CiT robbery differ depending on whether the offender is opportunistic or experienced. However, more data could further determine if a certain motivation directly influences the type of CiT robbery an offender will commit. This would then provide a clearer idea of why the crime is committed and how to prevent it.

Lastly, further work could build on the foundation presented in this project by applying formalized crime scripts to other crimes and perhaps even expanding the methods to integrate other actors into the script, such as a victim and guardian. Using our example of cash-in-transit robbery, future research could apply the same strategies and techniques to a range of different kinds of crimes (e.g. human trafficking, rioting) to test the model's generalizability. This would add support to the value and abilities of formalized crime scripts. In addition, Leclerc, Smallbone, and Wortley (in press) have recently incorporated the role of the victim into crime scripts of child sexual abuse and Leclerc (in press) has proposed the added benefit of also including a guardian, if present, into the script. These ideas could hold particular importance if applied to a formalized crime script by revealing whether the actions of the victim or guardian truly influence the offender's next move. If certain actions were shown to either aggravate or moderate an offender, policy makers could educate the public about this in the hopes of at least reducing the severity of the crime, if not preventing it. This would be particularly useful in intrusive crimes, such as rape and murder, but nonetheless helpful overall in better understanding the motives and decision making of offenders.

5.4 Concluding Remarks

Despite the current challenges and need for further research, our approach of combining crime scripts and causal Bayesian networks to create a formal tool for analyzing crime holds vast potential. With more data alone, several improvements could be made, such as adding more variables and links and quantifying those links, which would increase the utility of a formalized crime script. It is clear though that crime scripts alone cannot capture dependencies between variables or serve as an interactive tool for modeling crime. The addition of causal Bayesian relations as well as other graphical models, such as event trees and influence diagrams, extends the power of crime scripts to more effectively serve the role of identifying opportunities for situational crime prevention. Ultimately, such a formal tool could provide not only a more comprehensive understanding of crime, incorporating various kinds of data and psychological models, but also the ability to modify, adapt, and intervene on certain components to predict the effects of those changes. The possibilities of more research in this area abound and would greatly impact the future of analyzing crime.

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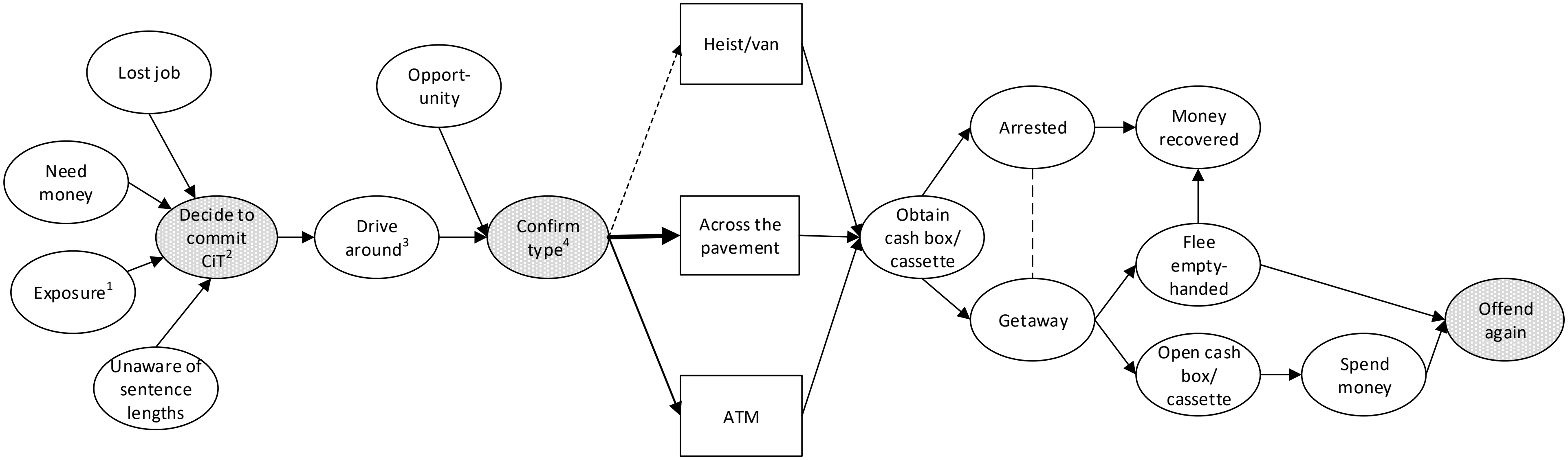
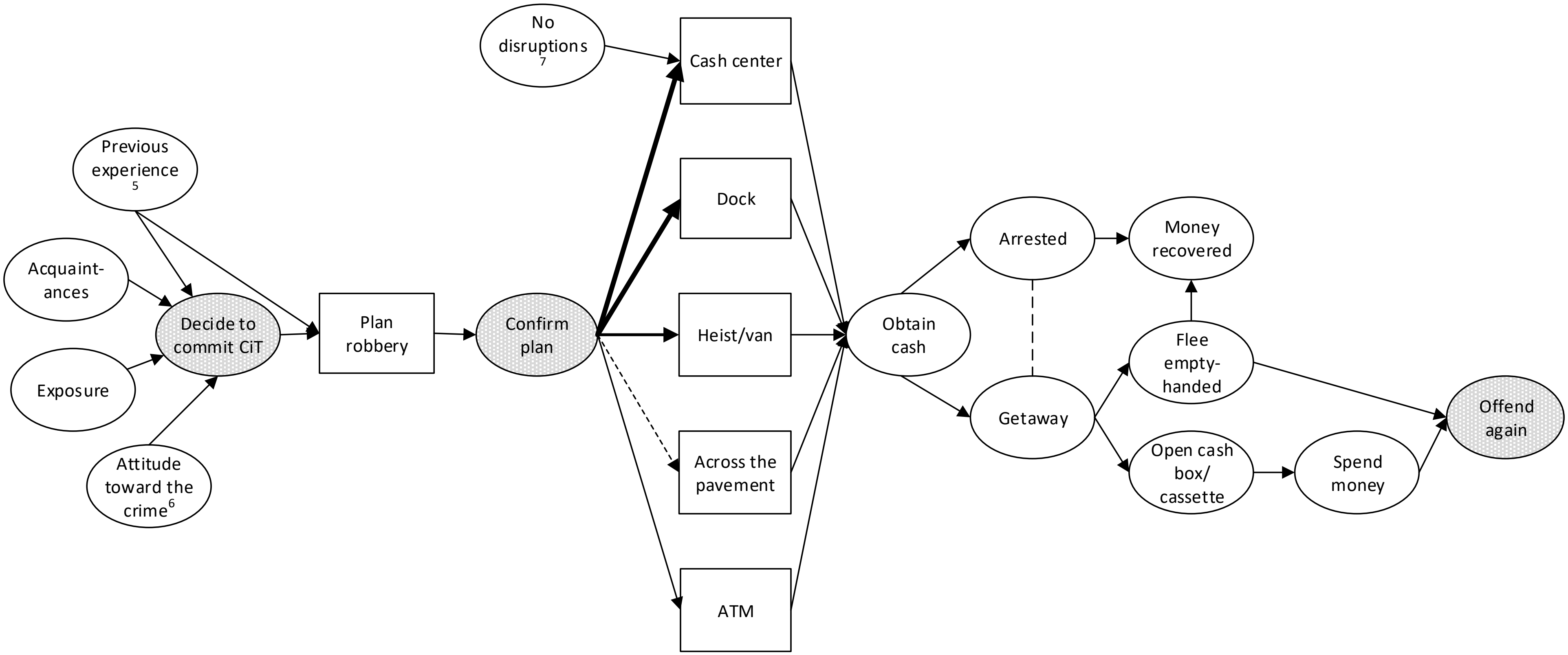
Appendix A: Opportunistic Offender Script



Footnotes:

1. Exposure: The offender witnessed a CiT robbery in the process of being committed and thereby had the idea to commit one.
2. Decide to commit CiT: Arrows leading into this node represent reasons an offender might decide to commit a cash-in-transit robbery instead of a different kind of crime.
3. Drive around: Opportunistic offenders often drive around looking for an opportunity (e.g. a security van) or are simply going about their daily activities when they see an opportunity.
4. Confirm type: The offender decides which type of CiT robbery to commit depending on the opportunity available.

Appendix B: Experienced Offender Script



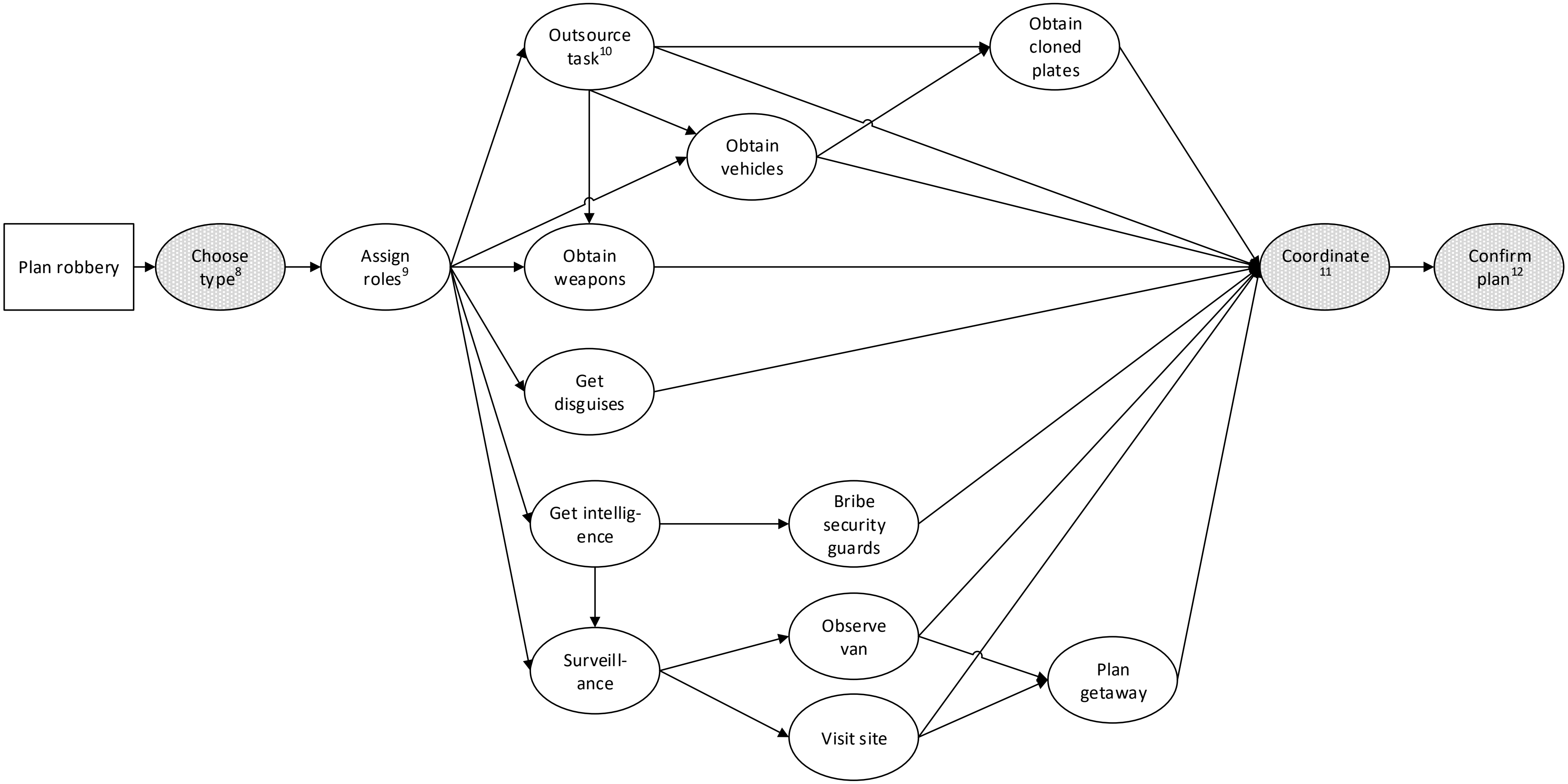
Footnotes:

5. Previous experience: This node influences both the decision to commit a CiT robbery (e.g. due to an offending history of burglary/car theft/robbery or an escalation in offending) and how the offender might plan the robbery (e.g. depending on previous offences and/or connections that might make obtaining certain tools more feasible).

6. Attitude toward the crime: Many offenders indicated in interviews (from the CViT report) that they viewed CiT robbery as a victimless crime, saw the violence used as non-gratuitous, and thought of it as a common crime (e.g. "where I live, everyone does it").

7. No disruptions: If no unexpected situations arise that would disrupt the commission of the crime, the planned type of CiT robbery will be committed. This node is only shown to influence a cash center robbery in this high-level script due to space, but a separate "No disruptions" node is necessary for each type of CiT robbery in order for it to be committed (see Results section for more details).

Plan Robbery Unpacked:



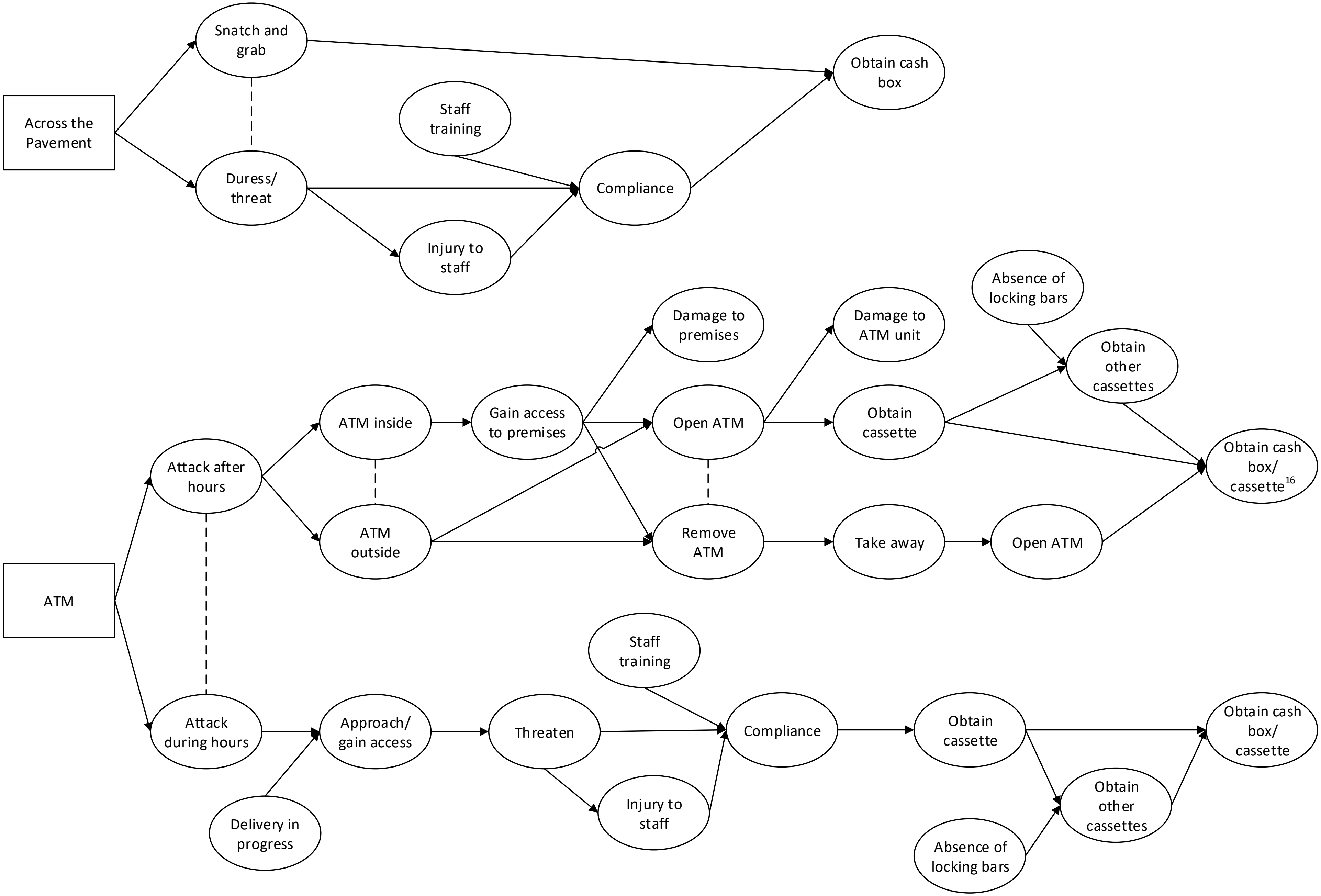
Footnotes:

8. Choose type: Offenders initially choose which type of CiT robbery they wish to commit so they know which resources they need to obtain before commission (see Discussion for more details).

9. Assign roles: The nodes following this one are not restricted in the sense that all of them could be true or only some of them could be true, depending on each specific CiT robbery. For instance, weapons and vehicles could be obtained as well as surveillance used, but no disguises may be used. Thus, any combination of these factors could lead to coordinating and ultimately committing the robbery.

10. Outsource task: Often offenders use acquaintances with influential connections to obtain weapons for them or pay teenagers to steal high performance vehicles for them.
11. Coordinate: Once everything has been obtained and organized, offenders plan the opportunity by picking a date, time, and location for the robbery. Sometimes, this choice directly depends on what resources they were able to obtain (see Discussion for more details).
12. Confirm plan: Depending on the circumstances on the day of the planned robbery, offenders may decide to continue with the robbery as planned (i.e. keep with the same time and location) or they may choose to slightly change their plans (e.g. if the target van did not arrive at the planned time and location, they may choose to rob a different van for which they know the schedule).

Appendix C: CiT Robbery Types Unpacked


Across the Pavement
Snatch and grab
Duress/ threat
Staff training
Injury to staff
Compliance
Obtain cash box
ATM
Attack after hours
Attack during hours
ATM inside
ATM outside
Gain access to premises
Damage to premises
Open ATM
Remove ATM
Damage to ATM unit
Obtain cassette
Absence of locking bars
Obtain other cassettes
Obtain cash box/ cassette[16]
Take away
Open ATM
Delivery in progress
Approach/ gain access
Threaten
Staff training
Injury to staff
Compliance
Obtain cassette
Obtain other cassettes
Absence of locking bars
Obtain cash box/ cassette

Footnotes:

13. Threaten staff (true for all subsequent “Threaten staff” nodes): Threatening the staff (physically or verbally) could directly result in compliance or, alternatively, could result in injury to the staff which then leads to compliance.

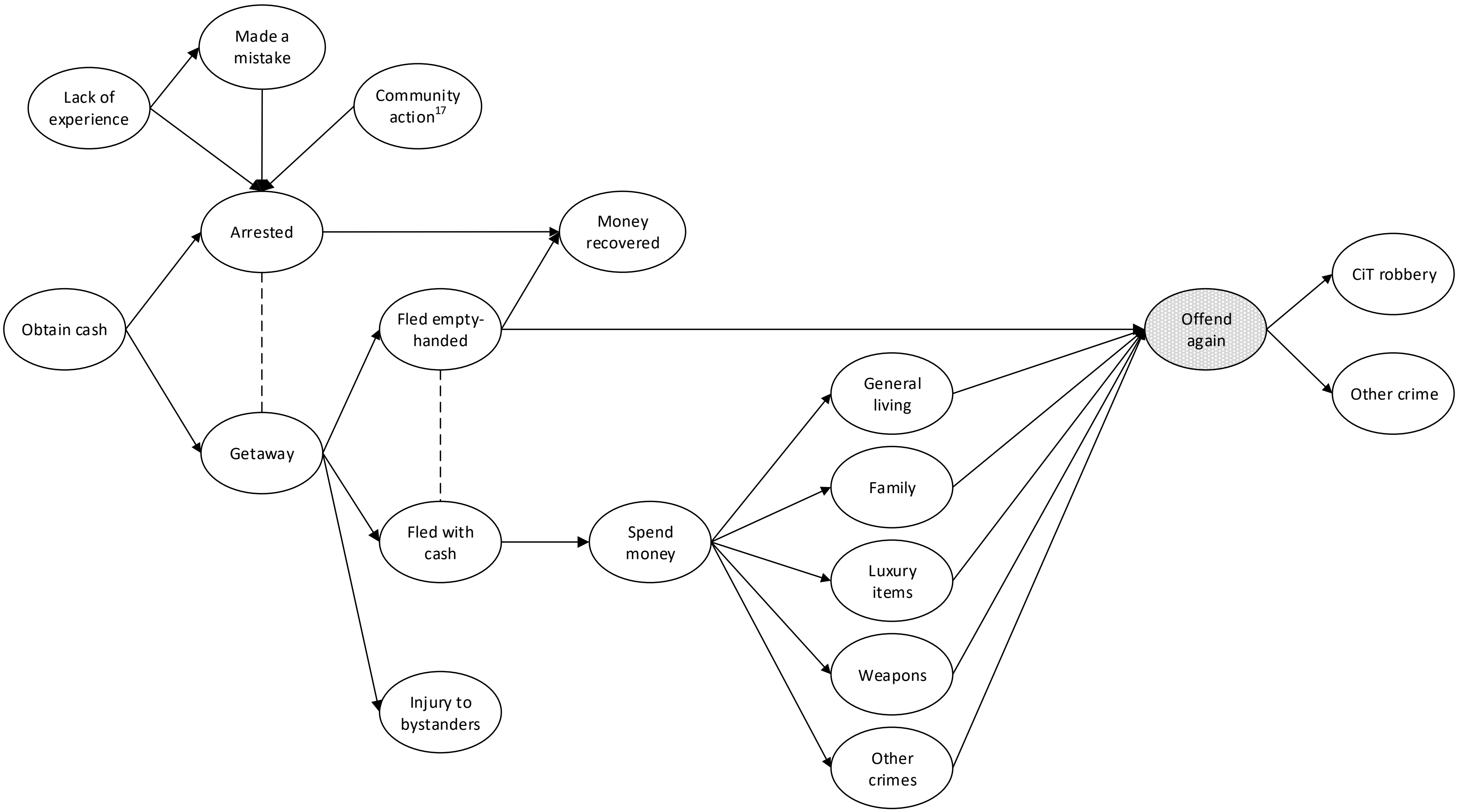
14. Staff training (true for all subsequent “Staff training” nodes): The staff employees and security personnel have been instructed to give up the money if threatened, which factors into the likelihood of compliance. Also, the combination of the “Threaten staff” and “Staff training” nodes exemplify a Noisy-AND (see Results for more details).

15. Force entry: The dotted arrowless line between this node and “Duress/threat” (true for all other dotted arrowless lines in the scripts) signifies the use of branching instead of standard Bayesian formalisms (see Results for more details).

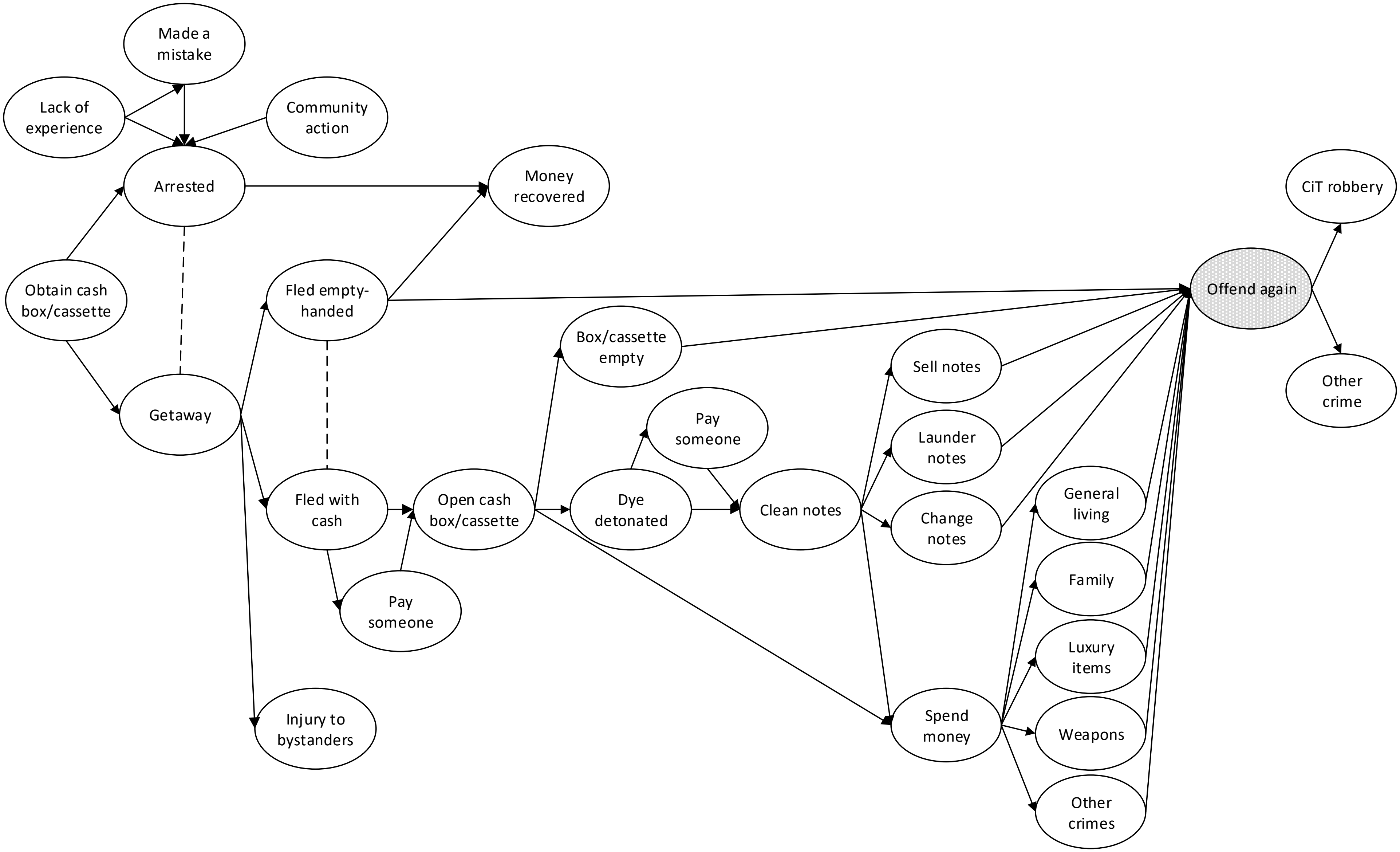
16. Obtain cash box/cassette: This node was added as a means of tying the ATM unpacked script into the aftermath script and encompassing the possibility of obtaining additional cassettes.

Appendix D: Aftermath

Straight Cash Obtained:



Cash Box/Cassette Obtained:



Footnote:

17. Community action: This node describes the role members of the community play in bringing about an arrest by phoning in descriptions, locations, and suspicious behaviors to the police, helping them catch the offender.