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Article

Simulating Crime Prevention Strategies: A Look at the Possibilities

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Abstract While essential, the process of developing and testing crime prevention strategies is currently an expensive and time-consuming process. In addition, there are some potential crime prevention programs that are either too costly or unethical to test empirically. What if we could test these strategies in an artificial world first? In a world of increasingly uncertain resources, simulation offers a promising methodology for experimenting with potential strategies to identify the most promising ones before they are tested empirically. This paper introduces simulation and then explores the potential of and challenges to the use of simulation models to provide valuable information about the potential effectiveness of crime prevention strategies. One potential application of simulation is discussed in detail and several others are suggested.

Introduction

The purpose of this paper is to provide an overview of the potential applications of simulation modeling for testing crime prevention strategies. The traditional approach to developing crime prevention strategies involves collecting data about a specific crime problem, analyzing those data, developing and implementing appropriate strategies (which usually involves obtaining resources to change the physical environment or implement a program), and then evaluating the results (Clarke, 1997). Although effective, this traditional process is resource intensive, expensive, and time consuming. In a world of increasingly uncertain resources, simulation offers a promising methodology for experimenting with potential strategies *in silico* before investing in empirical research.

Most of us are familiar with computer simulation whether it is in the form of video games such as SimCity® or commercial training simulators to be used by trainee pilots or armed response units in the police or military. Such simulations create computer-generated models of real-world situations by combining complex behavioral programming with graphical representations that mimic reality. Their aim is to provide environments in which individuals play out scenarios that would otherwise be impossible for ethical, practical, or economic reasons, either as a training aid or, in the case of video games, for entertainment purposes.

Recently, simulation modeling has been applied within the social sciences to better understand how people make decisions in particular situations and how those decisions translate into observable

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phenomena. In the field of criminology, several theoretically based simulations create artificial worlds and populate them with virtual beings, referred to as agents. These agents are programmed with behaviors based on one or more theories from a number of disciplines, including environmental criminology, cognitive science, behavioral geography, and ecology, which dictate how they perceive, reason, and act within the simulation environment. While the model is running, agents interact with each other and their environment. Researchers then assess which factors might be important in offender decision making and how the results of those decisions produce specific crime patterns (Eck, 2005; Groff, 2007a; Liu *et al.*, 2005).

Once a model has been developed, it can be used to run simulation experiments, the results of which are analyzed to determine whether or not the mechanisms involved work the way theory would have predicted. After a model has been validated to ensure it is producing plausible results, candidate crime prevention strategies can be systematically implemented *in silico* and their effect on the individual agents and the outcome patterns can be explored. This paper introduces simulation as a methodology for developing and testing crime prevention strategies, and provides one illustrative example of its application and several additional examples of possible directions, ending with a discussion of some challenges that must be overcome for simulation to achieve its potential.

Using Simulation as a Research Method

Research using simulation begins with the representation of a theory in the form of a model. To do this, reality must be simplified and only the most important aspects represented in the model; all extraneous details are dropped (Epstein and Axtell, 1996; Gilbert and Troitzsch, 1999). In contrast to statistical models that are implemented as equations and solved within a software program, a simulation model is itself a software program. As mentioned above, one well-known commercially available example is the resource-management game SimCity®. In SimCity, the players are responsible for the development of a hypothetical city. They make decisions about where to build roads, provide services such as electricity and water, and whether to approve the construction of new commercial, industrial, and residential developments. Over time, the simulation evolves so that the players can observe the outcomes of their decisions as city-planners.

Similarly, researchers experimenting with simulation models are building theoretically based models in an effort to better understand how the components of dynamic systems within society are related. Several models that examine specific crimes have been developed, including commercial robbery (Liang *et al.*, 2002), street robbery (Groff, 2007a; Wang, 2005), heroin use (Perez and Dray, 2005), physical and cyber crime (Gunderson and Brown, 2000), and crime more generally (Birks, 2005; Brantingham *et al.*, 2005; Kongmuang, 2006). Another good example is the environmental criminology-based framework for agent-based modeling laid out by Brantingham and Brantingham (2004). These developments have stimulated even greater interest in simulation as a methodology and have led to this paper examining one of its most promising potential uses as a tool for exploring situational crime prevention strategies.

Agent-based Modeling

While there are many types of simulation modeling, this paper focuses on agent-based modeling. Agent-based models represent the dynamic behavior of individuals. Agents are autonomous elements within the computer program that, while typically used to represent people, can also be neighborhoods, businesses, and organizations. What separates agent-based modeling from other types of simulation modeling is an emphasis on capturing how micro-level decisions of individuals that are interacting with one another translate into observable outcomes, in this case, patterns of crime. For this reason, they are ideal for examining situational crime prevention strategies as they provide an opportunity for researchers to explore how changes at the micro and meso levels play out at the macro level and establish which may have the greatest impact.

What Can We Hope to Learn from Simulation Modeling?

The potential value of simulation will be realized with the development of a model that both captures the essence of a particular theory and has been validated against empirical data, therefore allowing its use for prediction. The most straightforward use of such a model would be to change some aspect of the original model and observe the subsequent variance in results (see Appendix A for an overview of how to build a simulation model. More detailed descriptions can be found in Birks *et al.* (2008) and Groff (2007a,b)). For example, if we decrease the number of criminally motivated individuals by 10%, how much does that reduce the overall crime rate?

In this way, simulation provides a platform for experimentation (Dowling, 1999), allowing the manipulation of characteristics of people and the environment that would otherwise be impossible for ethical, economic, or logistic reasons (Axtell, 2000; Dibble, 2001; Dowling, 1999; Slavin, 1996). It also allows the exploration of phenomena for which data are not available. More specifically, it allows the modeling of individual-level data about human behavior and interactions. This advantage is particularly relevant to the subject of the current paper. For example, given a validated simulation model, specific crime prevention techniques, such as increased street lighting, could be evaluated and optimized before incurring the costs associated with implementation. While this type of experimentation is not a substitute for empirical research, it does provide a means for determining which possible interventions are most promising, thus allowing such interventions to be given priority. Conversely, small-scale interventions might first be tested empirically before using the results of their analysis to calibrate a model that can be used to examine the effectiveness and impact of larger scale and hence more expensive implementations.

Simulation modeling is particularly appropriate for exploring crime prevention strategies for the following reasons. Firstly, it does not require individual-level data as input, which means it is not subject to privacy issues (O'Sullivan, 2004b). Secondly, it can be combined with a geographic information system to capitalize on the wealth of environmental data now available (An *et al.*, 2005; Brantingham *et al.*, 2005; Groff, 2007b). By bringing together data *describing* the urban environment with artificial agents representing the people who are *using* the environment, we are able to test modifications to the built environment that would be prohibitively expensive to implement in the real world. Thirdly, simulation provides greater understanding of the underlying mechanisms involved in crime patterns and criminal events (for an overview of current efforts, see Eck and Liu, 2008). Finally, simulation enables the integration of these advantages in an experimental platform that is itself capable of producing policy relevant findings and informing subsequent empirical investigations.

However, addressing policy-related topics such as crime prevention is just one of the potential uses of simulation in research and practice that offers certain advantages over traditional approaches. Another plus of using simulation is that it promotes the *formalization of theory* (Gilbert and Troitzsch, 1999). In order to write a computer program to implement a theory in an artificial world, the theory must be as precise as possible. This requires greater specificity of the assumptions and mechanisms of the theory than are typically required for a written version (Birks *et al.*, 2008; Brantingham and Brantingham, 2004; Eck, 2005; Gilbert and Troitzsch, 1999; Groff, 2007a). Simulation as a means for greater formalization and specificity of theories is a major contribution in its own right (Gilbert and Troitzsch, 1999) and a necessary advancement to improving practice.

Simulation also enables *prediction*, although this is one of its most controversial and underdeveloped aspects. The main reasons for this are two fold. First, many simulations are not developed for prediction; rather, they are built to increase understanding of the mechanisms underlying a phenomenon. Second, when the goal is prediction, there are significant questions surrounding our ability to adequately validate model results (see section on challenges). Although such challenges exist, the authors do not believe them to be insurmountable and therefore, for the purposes of this paper, we assume that we will someday be able to develop a model capable of producing accurate crime patterns.

In order to further demonstrate the potential applicability of simulation models in crime prevention, the following section provides an illustrative example of how a simulation model might be used to inform crime prevention strategies in the future, in this case by investigating the effectiveness of different police deployment strategies.

High-Visibility Policing: An Applied Example

High-visibility policing (HVP) is a policing deployment strategy implemented worldwide (Harocopos and Hough, 2005; Jones and Tilley, 2004). The goal of HVP is to deploy a highly visible police presence, usually through foot patrols, with the aim of providing a deterrent to potential offenders and increasing public reassurance. Scientifically speaking, HVP is based around two hypotheses: (1) increasing the number of visible police will increase deterrence of potential offenders and prevent more crimes; and (2) a visible police presence increases public reassurance. HVP is, for obvious reasons, inherently resource intensive; therefore, assessing its cost–benefit is essential. However, measurements of its effectiveness are not necessarily straightforward. Firstly, there is no metric for criminal deterrence or guardianship, whereby the presence of a visible police officer or other guardians prevents a potential offender from choosing to offend. Secondly, a number of factors dictate that public reassurance and, more generally, public perception of safety is difficult to capture at a sufficiently accurate level to assess the impact of individual operations. As such, the real impact of a visible police presence upon both the general public and any potential offenders within it will always remain, at least partially, obscured.

At present, practitioners and analysts tasked with assessing the impact on crime of HVP might use a geographic information system to delineate the area(s) and time frame(s) in which HV patrols took place and then record all the crimes that occurred while the HVP was in operation. These crimes can then be examined by making comparisons, either to a comparator area within the same time-period, or the same area at different times (e.g. the week before, etc.) to establish whether any significant impact on crime occurred within the program area.

In some cases, such analysis may provide consistent evidence that a HVP operation has caused a reduction in offending, but what does this tell us about the effectiveness of HVP in a different locality? HVP is inherently linked to the local environment, the actors within the area, and the interactions that occur between them. Therefore, assessing the overall effectiveness of HVP at reducing the incidence of crime is both a difficult and resource-intensive process. Ideally, it requires a number of programs in a variety of areas to be implemented and then evaluated if one is to draw any sound conclusions or make relevant recommendations.

Simulation, on the other hand, may provide a different type of analysis, allowing researchers to build a model based around the concepts of crime occurrence and HVP which can then be used as an interactive 'thought experiment' that investigates the relationship between HVP and criminal deterrence by allowing for exploration of the prevention metric absent in the real world. Thus, simulation allows researchers to examine the underlying hypotheses of the strategy prospectively.

In order to do so, researchers might conceive a hypothetical space that contains a finite number of individuals. Using a combination of local knowledge, received wisdom, and common sense, they might estimate that at any one time this population might contain *x* number of potential offenders. A simulation model of this space is then developed and populated with agents that represent potential victims, offenders, and law enforcement. A number of behaviours that define how the agents navigate around their environment and commit, become the victim of and, where applicable, prevent crime are established. This model is then validated against empirical data so that the crime patterns it produces can be considered sufficiently analogous to the real crime. The investigator then introduces differing levels of HV patrols and examines their effect on the number of offences committed, or, as we can measure it, the number of crimes prevented. By examining its findings, one can investigate the initial hypothesis that an increase in the numbers of visible police will lead to an increase in deterrence. Further, it may be possible to establish whether the relationship between the numbers of HVP and the numbers of crimes prevented is a linear one, resembling the graph in Figure 1 or a nonlinear relationship (Fig. 2) where the net gain in prevention decreases after a certain point, indicating that there may be a 'tipping point' beyond which additional police are not cost effective in preventing crime.

Depending upon the results of this initial experiment, investigators might design further experiments that examine the breadth of environmental conditions under which an observed relationship holds true. Importantly, all of this can be done before a single resource is diverted to performing an actual HVP operation. Although such a model is no replacement for empirical experimentation, it provides a potentially substantial contribution that should focus on empirical experimentation, doing so both quickly and cheaply. Once empirical experimentation has occurred the results may be used to further calibrate a simulation model. Such additional calibration should improve the deployment of subsequent interventions. Therefore, simulation provides a valuable contribution to crime prevention strategy development by facilitating *in silico* intervention prototyping.

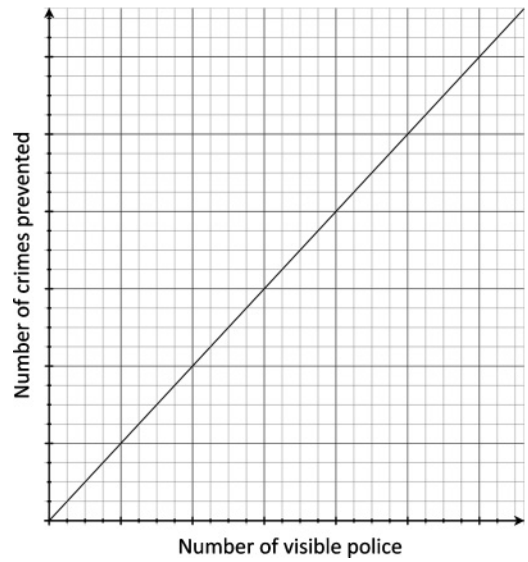

Figure 1: Linear relationship.

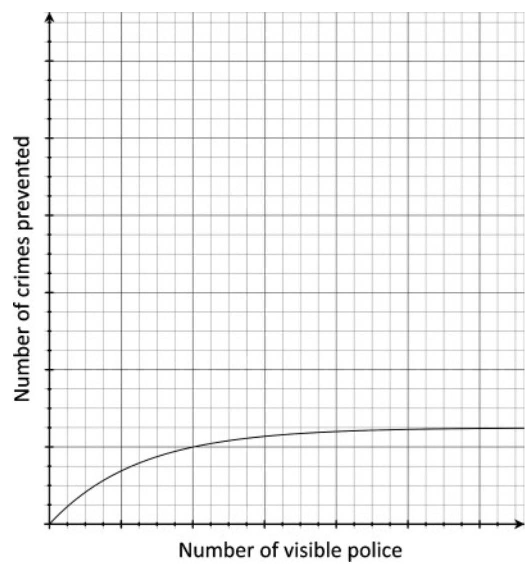

Figure 2: Nonlinear relationship.

Additional Ideas for Applying Simulation to Crime Prevention Efforts

This section offers additional ideas for how simulation modeling might be used in crime prevention. The potential applications discussed here assume that a model of crime producing 'realistic' crime patterns (i.e. sharing characteristics with 'real' distributions of crime) has been created and validated to some adequate degree. Our purpose in putting these ideas forward is to prime the research pump by illustrating how simulation modeling could be used to explore, for example:

1. the effect of street lighting on crime
2. drug markets
3. guardianship
4. risky places.

While there has been much empirical research done on the effect of street lighting on crime, the outcomes have been mixed (Painter and Farrington, 1997). By building on a basic agent-based model of crime, we could parse out the influence of street lighting on crime. Such a model would allow the systematic manipulation of the lighting level on every street so that it would be possible to establish the optimum amount and/or placement of lighting, given resource constraints. By examining several types of crime individually, the significance of lighting for preventing particular types of crime (robbery, theft from vehicle, theft of vehicle, burglary) could be established more conclusively.

Although drug markets have been well researched, simulation could provide the opportunity to test policy implications that are difficult to examine for monetary reasons. For example, previous research has demonstrated that drug markets tend to locate on side streets with easy access to major intersections (Rengert *et al.*, 2005). In addition, drug dealers prefer one-way rather than two-way streets. Crime prevention strategies with the goal of altering characteristics of the built environment that make a place more attractive as a drug market would be time-consuming and expensive to implement (e.g. altering street patterns). However, the same changes in an artificial environment are quick and inexpensive to implement.

The whole phenomenon of guardianship could also be explored in more depth. For example, one could design a simulation aimed at testing the effectiveness of place managers (Eck, 1995). Initially, this might involve creating a model of crime occurrence, examining this model's output without place managers to provide some baseline data. The researcher might then design and implement a class of place manager agents that is initially equally effective. Subsequently, through the introduction of incremental complexity, one could create a measure of place manager effectiveness, consequently running the model with a population of differentially effective place managers. At each stage model results are compared to both baseline simulation and empirical data. Further, one might attempt to build microsimulations of crime occurrence within specific facilities, for example, investigating how place managers 'work' as a crime prevention mechanism in bars.

Finally, Clarke and Eck (2007) have proposed the idea of risky places (i.e. places that account for more than their fair share of crime) to understand why some places have more crimes than others. Simulation allows us to explore which characteristics of risky places are the biggest contributors to increased risk and how they interact with the users of the environment to mitigate or increase that risk. Each of the following characteristics of risky facilities could be explored in detail:

- Size of the facility
- Existence of desirable targets
- Location convenient to motivated offenders
- Frequency of repeat victimizations
- Extent to which it is a crime attractor
- Design and layout
- Management.

For example, once these characteristics have been identified within a simulation, they can be manipulated one-by-one to identify the key strategies for reducing crime.

Given sufficiently accurate models, the list of possibilities seems endless: optimizing the location of CCTV and automatic number plate recognition (ANPR) to maximize detection, examining the effect of selective target hardening, predicting the magnitude and types of displacement (Barr and Pease, 1990), and/or diffusion of benefits (Clarke and Weisburd, 1994) after a particular intervention, to name but a few.

Challenges to the Use of ABM

While the potential for simulation models to assist with strengthening criminological theory and understanding the mechanisms underlying crime patterns is indeed significant, important hurdles remain and will need to be addressed before their potential can be translated into advances in situational crime prevention. This is because convincing policy implications derived from simulation models require model validation. Unfortunately, this is the area in which simulation is the weakest.

Challenges to model validation come from a variety of sources. Some are intrinsic to simulation modeling, such as the lack of standardized techniques for both building and analyzing simulation models, the relative paucity of model replication between researchers, the dangers of overfitting models to calibration data, and the fact that multiple models can produce similar results given vastly different mechanisms (Batty and Torrens, 2005; Manson, 2001; O'Sullivan, 2004a).

Additionally, and perhaps most importantly within the criminological arena, there are problems associated with validation of simulation models with respect to empirical data. The inherent problems with official crime data are well known (Maguire, 2002) and will not be reiterated here; rather, the effect of data inadequacy is discussed. In a nutshell, the dilemma is that we cannot reliably validate the results of a model that aims to simulate all crimes with official data that only represent an unknown subset of all crimes (i.e. recorded crime). Another complicating factor is that, despite increases in micro-level data about places, data describing individual behavior in space and time are still not available and probably will not be in the near future (O'Sullivan, 2004b). Thus, it is very difficult to verify input data on individual space–time behavior. This may have an especially great effect when comparing crime generated by simulated offenders in a model of a real-world location to that perpetrated by the real offenders in that area.

Discussing the problems with the accuracy of recorded crime data, Eck and Liu (Eck, 2005; Eck and Liu, 2008) have suggested that agent-based models be built with a filter that models crime reporting and crime recording, so that model results are more directly comparable with official crime data. These filters would incorporate all the decisions in the reporting process as a model component (i.e. decisions by the victim whether or not to report a crime and those by officers whether to take a report would be included). This would allow the simulation to produce crime patterns that are subject to many of the same reporting biases as real crime patterns. In addition to making more accurate models, the ability to explore and perhaps quantify the 'dark figure' of crime that has been a mystery for so long is an appealing research endeavor.

Thankfully, better recognition of data issues may lead to advances in both the type of and ways in which data about offences are collected. Improvement in empirical data could take the form of (1) more complete reporting by the public; (2) additional data sharing by the police; or (3) additional data collection by the police. The need for better data may spur improvement of police/community relations and encourage more complete reporting and recording of crime data. It may also encourage sharing of more data that are collected about the most prolific offenders, and therefore, about those who contribute most significantly to an area's crime problem. These data are rarely systematically imparted beyond the operational level. Finally, it may inspire the collection of supplementary data about known crime in a way that will further our ability to both think about and attempt to tackle crime.

Conclusion

As we have discussed, there is potentially much promise for simulation techniques within the field of crime prevention research and practice. Given the wealth of both spatial and temporal data about places that are now collected by numerous agencies, agent-based models seem the obvious next step in examining what is inherently a dynamic process: crime.

The prospect of building models to sidestep the cost and ethical concerns of empirical research seems an extremely enticing one. However, we have also highlighted a number of issues associated with model construction and validation, which must be addressed if we are to provide practitioners and policy makers with tools to aid their decision-making process. Firstly, current technology requiring programming knowledge is a substantial barrier to developing simulation models for practitioners. Therefore, a bridge between the domain experts with most to gain and those with the technical know-how to design and develop models must be built. Secondly, work must be done to address the issues associated with validating simulation output against recorded crime data. These are serious but not insurmountable hurdles that must be addressed.[1]

While skeptics might lament the fact that simulations will always rely on assumption (much like all modeling, we might add), as long as interventions continue to be implemented around similar assumptions, there is a place for simulation to aid those who must prioritize budgets and resources. Especially as part of a progression from *in silico* to empirical research, simulation provides a method in which strategies for crime reduction can be examined prior to their implementation.

Appendix A: How Is a Simulation Model Constructed?

The following section describes how a simulation model is constructed that provides the foundation for understanding how the model can be systematically manipulated to test crime prevention strategies. The construction of a simulation is typically divided into a number of steps. The first step is defining what exactly is to be modeled. Similar to the process used in situational crime prevention, the examination of specific behaviors is emphasized. This typically involves focusing on specific types of crime (e.g. street robbery with a gun rather than robbery).

The next step is to create a conceptual model that defines the important components of the model and how they are related to one another. The conceptual model is almost always based on theory and is usually best expressed as a diagram. This is the second parallel with situational crime prevention, both rely on diagrams rather than equation-based models to describe a process (Clarke, 1983, 1997).

Finally, once a model has been specified, it is implemented by formalizing its theoretical and conceptual components as a series of rules and/or behaviors that are given to the agents. The agents are then situated within an adequate representation of their environment. Practically speaking, this formalization involves the implementation of a model within a software development environment. There are many different development environments that can be used for this purpose; some are designed specifically for the development of agent-based models, whilst others provide more general purpose programming tools in which an agent-based model may be developed from the ground up. Most offer comparable basic features, but each package has its own strengths and weaknesses. Given the rapid iteration of many of these products, an assessment of each is beyond the scope of this paper; rather, a brief description of two popular programs popular

[1] Space constraints prohibited a full discussion of model validation issues (see Eck and Liu, 2008, for an overview as they relate to criminological models).

within in the social science community, NetLogo® and Repast®, is provided next.

NetLogo makes use of a graphical user interface and allows for rapid application development through a 'what-you-see-is-what-you-get' designer that allows the developer to draw much of the required visualization elements of a simulation and simply add scripted events to the inbuilt agent classes. NetLogo's strength is getting simple models up and running quickly. For more advanced models, Repast® is an agent-based modeling development environment that offers implementations in several programming languages, including Java, .NET, and Python. Because of this, Repast® offers a more open-ended environment for development. However, it requires researchers to have substantial programming skills or to partner with programmers who do.

An important part of designing and developing a simulation model is selecting the types of agents that will be incorporated within it. For example, if the theory represented puts forward that all people behave similarly, regardless of readiness to commit a crime, than the modeler will have to represent only one class of individuals, all of whom are potential offenders. Alternatively, if the theory suggests that criminals react differently than the rest of the populace, then it makes sense to have two different types of agents, one representing offenders and the other nonoffenders.

In addition to the types of agents being represented, another part of the modeling process is deciding on the rules or behaviors that allow agents to evaluate situations and make decisions. Once again, such rules are derived from the represented theories. If the theory suggests that an offender will attempt to minimize the risk of detection by not committing offences while others are around, a behavior perceiving the offender's local environment and returning a value relating to the perceived risk of detection at a given point in time and space will be created. A further behavior might then evaluate this value with respect to some threshold in order to determine whether or not the offender chooses to offend.

Finally, for simulations dealing with the spatial distribution of events, behaviors that dictate how agents move through space will have to be developed. Historically, these types of simulations have allowed agents to move on some form of grid, most typically, as part of a random network on an artificial landscape. More recently, agents have been developed that undertake movement along streets as represented by a vector network, i.e. intersections represented by points that are connected by a series of roads represented as lines (Groff, 2007b; Birks *et al.*, 2007). This representation most closely resembles realistic movement, since the street network structures the subsequent behavior of agents. However, an even more realistic pattern of activity spaces can be achieved by also including the opportunities for housing, jobs, and other activities that are distributed. The level of realism chosen is dependent on the goals of the model. In addition, there is a constant tension between the simplicity and complexity. The results of simpler models are easier to interpret but limited in what they can explain.

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