Management Tools for Public Safety: Behavioral Decision Making Considerations

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Abstract:

This paper focuses on security in public places and examines management decision making in high security contexts. Management decisions can include allocation of security staff and dissemination of public warnings. Based on prior theoretical developments, we develop a simulation model of security in public places. As an example, we apply the model to a case of safety in a northeastern university. Results indicate that by understanding behavioral decision making and feedback dynamics as applied to security systems, on-campus crime can be decreased in simulation runs by 14%. In addition, methodologically, we discuss how public management, in general, and security management, in particular, can benefit from a dynamic, simulation based approach to the problem.

Keyword: security, urban crime, public warning, optimization, feedback complexity
1. INTRODUCTION

Elise Chang, a seasoned business traveler, was checking her email and drinking a Starbucks latte when the Transportation Security Administration (TSA) security announcement came on. It was the usual “code orange” alert—she had heard this warning it seems a thousand times before. Slightly annoyed by the interruption, she turned back to her email. Sitting next to Elise in the waiting lounge was Elmer Wadsworth, making his first flight in over a decade to attend his father’s funeral. Elmer was somewhat alarmed by the TSA code orange announcement—“might another 9-11 event be brewing?”, he wondered to himself. Elmer looked around alertly and noticed that a deserted piece of carry-on luggage had been left under a counter in the waiting lounge. He reported this unattended luggage to the appropriate airline personnel.

Elise and Elmer are both part of a complex behavioral decision-making system. They both heard the same code orange alert, but Elmer’s threshold for action was lower than Elise’s. He took action, she did not. Elmer’s action, his decision to look up and be alert, was the kind of collective action that makes the airport safer. It is precisely the kind of action that the TSA seeks to promote by making the code orange alerts. But would Elmer react more like Elise if he had heard the same code orange alert over and over? Would he fall prey to the “crying wolf” syndrome if he repeatedly heard the alert but never experienced any real threat?

Other more sinister actors are at play in this system. Because code orange is a public warning, persons in the airport seeking to plan or to do mischief could hear it as well. If they hear the public warning and believe that the public is alert, they may be deterred from their mischief (many say that the safest day to fly in American airspace was right after the 9-11
attacks when everyone was on high alert). Deterrence is also part of TSA’s plan in making the alerts.

On the other hand, if the mischief makers come to believe that the public now reacts similarly to Elise, they will not be deterred. The complexity in this system arises because real threats and risks are determined by behavioral responses, and by shifts in passengers’ and mischief makers’ decision thresholds to act. And real threats and decision thresholds are entrained in complex interacting feedback loops of mutual causation.

A final actor in this system characterized by feedback complexity is the TSA itself. What if they made the warnings more frequent? What if they moved the warnings up or down to code red or green? This paper is about security managers such as the TSA managers who must make decisions about warning against threats in public places. How should such managers behave? Does it matter if such managers understand behavioral decision-making and feedback complexity? Would a more sophisticated understanding of these dynamic forces change their day-to-day management strategy? If so, how much difference might a more complete understanding of behavioral decision making and feedback complexity make to the safety of the public?

We view this paper as an example of a broader class of public management problems—how best to manage systems where the decision thresholds of key stakeholders can and will respond to management actions AND where real performance variables (such as measured threat) are caught up in feedback loops with behavioral decisions (such as a passenger’s decision to be alert).

Pinker (2007) first posed the problem that we are investigating in the form of an abstract mathematical model that formulated a theory of threat, deterrence, and costs associated with
safety in public places, proposing a kind of global cost-benefit approach to understanding public security. Ghaffarzadegan and Andersen (2010) elaborated on Pinker’s more abstract formulation by providing a specific instance of his theory that could be run in a computer simulation. This paper takes Ghaffarzadegan and Andersen’s model and reformulates it so that it represents risks, decision thresholds, and crime rates at a major university in the northeastern United States. The campus police, not the TSA are the system’s public safety managers. Students, not passengers, are reacting to public warnings and the mischief makers are mostly thieves perpetrating crimes against property on campus.

The paper proceeds as follows. First, we review the relevant literature and discuss the complex nature of warning issuance (Section 2). Then we introduce our research method, data, and simulation model (Section 3). In Section 4, we calibrate the model and examine the extent to which the model is able to replicate the data. Then using the calibrated model, we conduct optimizations under different scenarios and compare the results (Section 5).

Our conclusions from all this modeling and empirical work (Section 6) are multiple. First, an understanding of decision thresholds embedded in complex behaviorally-driven feedback loops can lead to an improved (a form of optimal) level of performance as measured by minimizing the total thefts committed during a single semester. This approach can yield practical guidelines for defining best practice and can reduce theft on campus by about 14%\(^1\).

2. THE PROBLEM OF WARNINGS IN PUBLIC SECURITY SETTINGS

Security shortfalls are tightly connected to failures in public management (Sutcliffe, 2005; Bardach, 2005; Bazerman and Watkins, 2005; Greve, 2005). An effective governmental decision

\(^1\) 14% is not a figure that was directly measured in our study, rather it emerged from running a counter-factual set of scenarios of crime in a simulated environment.
is expected to increase security while minimizing related financial and social costs, such as costs of facing crimes, deploying guards, and social stress. Although there has been growing attention to the security problem, both from public management and policy perspectives, there are few empirical examinations.

Security warnings are issued to improve security in public places. Warnings are aimed at improving awareness, and it is expected that people become more defensive as results of warnings (Keohane and Zeckhauser 2003). Defensive behaviors among citizens and government employees give less opportunity to adversaries and criminals to attack or involve in crimes (Kivimaki and Kalimo 1993). However, there are both short term and long term costs for warning issuance. In the short run, warnings can induce social stress. Intuitively, people do not enjoy hearing continuous warning alerts.

There are several long term and complex cost components for warnings that make finding an optimal warning decision a complicated problem. One of the main sources of long term costs of warning issuance comes from false alarms. People’s perception of the level of threat plays an important role in the way that they behave (Bazerman and Watkins 2005, Mayntz 2006). False alarms are known to affect public perception of threat and decrease their sensitivity to future warnings (Roulston and Smith 2004). The effectiveness of warnings decline as sensitivity to warnings declines, also known as the crying wolf effect (Pate-Cornell 1986, Pate-Cornell and Benito-Claudio 1984, Roulston and Smith 2004).

Furthermore, in many public security problems, the source of a threat (e.g., adversaries, terrorists, criminals) reacts to warnings and people’s reactions, which makes the problem more complicated. On the one hand, public warnings can result in cancelation of an attack (the deterrent effect). On the hand, people may perceive those cancelations for which they did not
receive a feedback (what would happen if they did not respond to the warnings) as false alarms. Further, the way that the public responds to warnings can be observed by the sources of threat. A loss in public reaction can result in a decline in the deterrent effect (Ghaffarzadegan and Andersen 2010).

A long term analysis of security policies is proved to be important due to many side effects that intuitive security policies have (Sagan 2004, Bunn 2004, Ghaffarzadegan 2008). A cost-benefit analysis of warning decisions should consider the behavioral consequences of warnings which may happen under various scenarios (Ghaffarzadegan and Andersen 2009). This study is a step to a thorough cost-benefit analysis of security considering dynamic complexities of the system. Considering the wide range of studies on warning issuance, the literature lacks a dynamic approach to the problem of warning. Developing a dynamic model of security warning in public places that helps to find optimal decisions considering the long-term effects of our actions seems necessary.

3. METHOD

3.1. Data

We use data on security of a northeastern university. The university enrolls around 18,000 students and has three main campuses. The data include criminal incidents at all three campuses as well as dormitories, the status of criminal cases, the date and time that the incidents happened and were reported, in addition to some more details about the incidents. We use the data for four academic years (eight semesters) from September 1, 2006 to August 31, 2010. We focus on the theft like crimes (e.g., larcenies, thefts, fights, and burglaries). Figure (1) shows the trend of theft-related criminal incidents and its weekly moving average.
In addition, we gathered data on warning e-mails sent by the university police department and other centers in the university. The police department of the university sent warning e-mails to give information and notify the students, staffs, and faculty members. We coded e-mails sent by the police department of the university and other centers. In the time duration that we studied, a total of 118 warning e-mails were sent to the students, including 37 warning e-mails from the university police department. We control for the environmental factors such as the temperature in the town, raining, weekdays, exam days, and university off-days, including semester breaks.

As an initial investigation we run a set regression models to see how predictable the crime rate is. Table (1) reports the results from the best OLS regression model, and equation (1) reports the regression equation.

\[
\text{Crimes} = a_1 + a_2 \times \text{Temp} + a_3 \times \text{Rain} + a_4 \times \text{SchoolDay} + a_5 \times \text{ExamDay} + a_6 \times \text{Weekend} + a_7 \times \text{Weekend*open} + a_8 \times \text{Year}_i
\]

\text{equation (1)}
Table (1): Summary of the results from the best OLS regression model to predict crime rate in our case.

<table>
<thead>
<tr>
<th>Regression Statistics</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiple R</td>
<td>0.4</td>
</tr>
<tr>
<td>R Square</td>
<td>0.16</td>
</tr>
<tr>
<td>Adjusted R Square</td>
<td>0.15</td>
</tr>
<tr>
<td>Standard Error</td>
<td>1</td>
</tr>
<tr>
<td>Observations</td>
<td>1461</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Coefficients</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.100</td>
</tr>
<tr>
<td>Temp</td>
<td>0.003*</td>
</tr>
<tr>
<td>Rain</td>
<td>0.003</td>
</tr>
<tr>
<td>Uni-Open exam days (from reading day to the end of final exam)</td>
<td>0.789*</td>
</tr>
<tr>
<td>Weekend</td>
<td>-0.040</td>
</tr>
<tr>
<td>weekend*open</td>
<td>0.104</td>
</tr>
<tr>
<td>Y2007</td>
<td>0.051</td>
</tr>
<tr>
<td>Y2008</td>
<td>0.090</td>
</tr>
<tr>
<td>Y2009</td>
<td>-0.006</td>
</tr>
</tbody>
</table>

As stated, due to the complexity of the problem and the existence of several feedback loops in the system, a linear exogenous look at the problem can be misleading. Many security policies can have long term side effects and add to the cost components of the optimization procedure. Therefore, we are interested in developing a dynamic model that can endogenously predict the crime rate in order to conduct optimization. Next we explain the dynamic model structure.

3.2. Modeling: A Warning-Based, Dynamic Model of Security

Security is the outcome of interactions of many different players in the system. Manunta (1999) defines security as a function of protectors, assets, and the level of threat. Protectors can be both decision makers and guards who aim at ensuring an adequate level of security. Assets can be financial or can be the public being protected from adversaries. The level of threat means
the capacity of the adversaries to attack or commit crimes and their interest in doing so.

Following this logic, we develop the model in three major sectors to represent these three components. These three sectors are: the crime sector, the security system sector (decision makers and security staff), and the public sector (potential targets).

There are interactions within and across these sectors, and through these interactions the level of security is determined. In order to capture different interactions in the system, one should both think about how decision-making procedures that are followed in each of these sectors—e.g., how security managers, police officers, potential criminals, and the public make decisions, and how they behave in response to different stimuli—as well as how these sectors are influencing one another. Figure (2) depicts a holistic picture of our model. In the following, we explain the model.
As we see in Figure (2), there are two main environments around “crime”: the micro environment and the macro environment. The micro environment includes the factors that are endogenous to the system and are directly in interaction with the level of crime. For our purposes, the micro-environment contains all of the behavioral decision making and feedback complexity that are associated with public warning systems. The macro environment includes more exogenous factors, such as temperature, which can affect security but there is no impact from security to temperature. Macro environmental factors can influence crime level through affecting the micro environment. For example, as temperature (a macro-environment factor)
changes, it influences the way that the public sector and the criminals in the micro environment behave, and therefore it affects the level of crime. In general, the macro-environment contains exogenous factors that are not affected by behaviorally-driven decisions about risk (e.g., warnings have no impact on the weather) and are outside the boundary of feedback effects captured in the micro-environment.

We explore more on the micro environment links. First, from the left side, the security system can issue warnings, and this is one of the major ways through which the security system influences the public’s behavior. These warnings influence the behavior of the public, making people more aware of possible threats. On other hand, too many warnings, and especially too many false alarms, may result in less attention to further warnings. Second, crime opportunity in the university is the result of how the public and the security system behave. University students can decrease crime opportunities if they take more cautious actions, for example by taking care of their belongings or walking in groups late at night. On the other side, the security system can decrease crime opportunities by screening, controlling, and active presence. Third, crime opportunities and criminal actors determine the level of crime (in simple words, if there is no crime opportunity in the environment, or there is no criminal, we have no crime). Crimes in turn influence all of the three sectors.

In turn, the existence of crimes in the recent past leads to higher perceptions of threat in both the public and the security system sectors. People talk about incidents and the word spreads. University administrators and police officers also receive information about the recent incidents, and their actions can be more influenced as the number of incidents increases. On the crime side, more crimes can result in more criminal behavior, exacerbating the situation through crime escalation. Such a reinforcing loop can be dangerous for the security of the university, where
people react to the crimes. Finally, the security system can influence the crime sector directly through arresting of criminals, or indirectly through deterrent effects. The latter effect can be the result of the active presence of police officers as well as public warnings. Police officers in turn may observe suspicious activities and get more information about the level of threat.

To formulate the conceptual model we consider a few simplifying assumptions. First, the time horizon of the analysis is a semester, and the time unit is a day. This helps us to assume a constant crime capacity in the environment, a constant technology level for security, and a steady crime capacity and socioeconomic status. The assumption helps to overcome many possible changes in the macro environment that can happen through the years, for which data might not exist.

The described conceptual model is mathematically formulated. The technical Appendix presents the formulation.

4. SIMULATION

The model is calibrated for the case. If the parameters are available, we set them directly using available data from the university. For example, the population of the university and the working days during the semester are available from the data. In addition, the simulation model reads the data about the macro environmental conditions including daily temperature, rain, school days, and exam days from an Excel file. For the cases in which parameters are not available, we calibrate the model to find the best values that result in the best fit of the simulation model with the data.
Figure (3) Comparison of simulation results with data for Fall 2008 criminal incidents.

Figure (3) shows an example of the results. It compares the simulation results and the historical data on a weekly moving average of crimes for the semester of Fall 2008. As we see, the model captures the dynamic trend of criminal incidents. Table (2) reports the statistics of replicating the historical data including R-squared, mean square error (MSE) and the Theil statistics. We compare the results with the OLS regression model that was reported in section 3-1. As we see, the simulation model can explain 20% of the variance in the data. In order to shed more light on the sources of the MSE, we also report the results of decomposition of MSE into three components (bias, covariance, and variation), as proposed by Theil (1966). The Theil statistics highlight that most of MSE comes from point-to-point covariation discrepancies, while MSE in the regression model was also attributed to difference between the mean of the data.
points and the simulation (bias) and the difference between the variance in the model and in the data.

Table (2): Statistics of Replicating Historical Data for Both the Simulation Model and a Regression Model.

<table>
<thead>
<tr>
<th></th>
<th>Simulation Model</th>
<th>Regression Model 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-squared</td>
<td>0.20</td>
<td>0.15</td>
</tr>
<tr>
<td>MSE</td>
<td>0.166</td>
<td>1.0</td>
</tr>
<tr>
<td>U-bias</td>
<td>0.02</td>
<td>0.23</td>
</tr>
<tr>
<td>U-variation</td>
<td>0.08</td>
<td>0.34</td>
</tr>
<tr>
<td>U-covariation</td>
<td>0.90</td>
<td>0.43</td>
</tr>
</tbody>
</table>

In sum, Table 2 indicates that the calibrated system simulation “fits” the data as well as or somewhat better than an OLS regression model, but also incorporates a dynamic theory of endogenous behavioral decision making.

5. OPTIMIZATION

Now we can use the calibrated model and conduct counter-factual analysis. We would like to find an optimal value for warning threshold(s) that maximizes our payoff function. In general, the payoff function can be defined as a function of total costs from crimes and from warning issuance. Other studies usually assume that the direct cost of warning issuance is negligible in comparison with the criminal incidents costs. Consistent with this common assumption, we focus on minimizing the total number of criminal incidents in a semester.
Further, it is not necessary to assume that the security system should have a single warning threshold during the semester, because in fact it can have different thresholds. To address this issue, we conduct static optimization to find a single threshold and then a dynamic optimization to find a series of thresholds for different time periods in the semester.

For static optimization, we count the total number of criminal incidents for different values of threshold to warning (30 values between 0.1 and 3). Due to the existence of the stochastic components in our model, for each threshold we conduct 1,000 simulation runs and average the results (total of 30,000 simulation runs). Figure (4) shows the results.

Figure (4): Total crimes in a semester vs. the threshold to issue warnings.

Figure 4 summarizes the key findings of the calibration, simulation, and optimization work. It shows a clear policy-relevant story that is easy to interpret for a policy force interested in increasing public safety on campus. If the university police have a threshold of zero, this implies
that each day when any crime occurs, the police would issue a warning. The models predict that this zero threshold (or always alert for any crime) policy will yield on average about 126 simulated crimes per semester. This nearly daily warning touches off within the model an erosion of student alertness, a primary cause of the relatively high simulated crime rate.

As the university police become more prudent and restrained in issuing warnings, students become less callous and pay more attention to official warnings (and potential criminals also react differently to this pattern of warnings). For example, Figure 4 shows that if police issue a warning when there is an average of 1.5 crimes per day (that is 10.5 crimes per week), total crimes for the semester will drop to around 118 because of different behaviors touched off within the model. The lowest crime rate for the entire semester, about 109 crimes, occurs when warnings are issued only when the daily crime rate is 1.79 (or a weekly rate of 12.6 crimes per week). The model further predicts that if the university police issue warnings only when the daily crime rate reaches 3 crimes per day (21 crimes per week), total crime in the semester will rise to about 118 crimes. This rise is for reasons quite different from the lower threshold—students are deprived of information about high crime periods and are less vigilant due to ignorance, not “crying wolf” callousness and at the same time potential thieves are emboldened.

In sum, Figure 4 shows that a warning policy based on a formal and explicit model of behavioral decision making by students, thieves, and university police has the potential to drop simulated crime for a semester from 126 to 109 total crimes. That enlightened understanding of behavioral decision making dynamics and feedback complexity in public management of crime drops crime as simulated in the models by 14%.

The above analysis assumes that the university police department maintains a static decision-making threshold with a minimum rate of crime occurring when warnings are issued
when crimes rise above 1.79 crimes per day (12.6 crimes per week). As stated before, it is plausible that policymakers can change warning thresholds dynamically in different time periods. For example, the threshold could be higher at the opening or closing of the semester. Such a behavior may lead to higher utility. We conduct a Monte Carlo-based optimization of the model, in which we find optimal threshold values for 6 time intervals: 1–20, 21–40, 41–60, 61–80, 81–100, and 101–115 days. Optimization results are 1.97, 1.83, 1.77, 1.93, 1.66, and 1.0. For example, the dynamic optimization suggests a warning to be issued in the first 20 days if the moving weekly average of crimes passes 1.97 crimes per day. Interestingly, in the last weeks of the semester the model suggests a strategic behavior—that is, a lower threshold for warnings (more warnings to be issued)—due to the inherent assumption that during the between-semester breaks people will forget about the past warnings. Figure (5) compares total crimes in a semester under three different conditions: the current case of Fall 2008 (the real condition), static optimization of Fall 2008, and dynamic optimization of Fall 2008 (counter-factual conditions). Both optimizations, in comparison with the current case, decrease the number of crimes significantly. The static and dynamic optimization cases are not significantly different.
Figure (5): Total crimes in three conditions: base run, static optimization, and dynamic optimization.

Note: In the static optimization condition, a warning will be issued if the moving average of crimes passes 1.72 crimes, and in the dynamic optimization conditions, the threshold to warning takes the values of 1.97, 1.83, 1.77, 1.66, and 1.0 in each 20-day time period consequently. There is no significant difference between the static and the dynamic optimization results, while they are both better than the current case.

6. CONCLUSION

In this study, we developed a warning-based security model for public places. The model captures several feedback mechanisms that add to the complexities of security problems. We tailored and calibrated the model for a university. Then we conducted different simulation runs, including static and dynamic optimization, to find optimal warning decisions that lead to a better security level.
We fairly replicated the data and showed that the number of warnings has a U-shaped effect on security. Consequently, there is an optimal number of warnings that minimizes the number of incidents through raising the public attention and increasing deterrent effects. Furthermore, we conducted counter-factual analyses, and in our specific setting we proposed warning thresholds to be set around 1.79 thefts in a week in order to have the most effective warnings.

This study has several theoretical and practical implications. First, this research is the first empirical piece that uses a longitudinal data set and analyzes behavioral characteristics of a public place to develop decision tools to issue warnings. While previous attempts conduct myopic optimizations to find the best policies that decrease threat in the next time period, our model looks at a longer time interval, and therefore consider long term effects of warning issuance. Furthermore, this is the first attempt to use empirical data for the optimization of warning decisions.

On the practical side, our paper specifically suggests decision tools for the studied setting with several implications for other similar settings. Basically the model offers a decision model that gets the maximum possible effect from warning issuance. The lessons from this modeling practice can be applied to many other similar contexts for which data might be more restricted.

We believe that the major contribution of this paper is that it demonstrates that the dynamic complexity of crime warning systems as it pertains to behavioral decision making can and should be understood more completely. Our study suggests that theory-based understandings of decision-making behaviors, when embedded in complex feedback systems, can decrease crime in settings such as the university setting studied here by up to 14%.
Many other public policy systems also contain combinations of behavioral decision-making embedded within a micro environment of feedback interactions. For example, when police screen and stop members of the public for searches, when case workers screen clients to receive expensive public supported services, or when physicians make clinical judgments about treatments (that are being paid for by public funds), similar patterns of behavioral decision-making dynamics touched off by feedback complexity will come into play. Hence, delivering and managing public service systems such as policing, social services delivery, or sky-rocketing medical care costs requires that public managers and policy analysts drill down to obtain deeper theory-based understandings of behavioral decision making and feedback complexity.
REFERENCES


Appendix: Model Formulation

Accumulated past warnings = smoothi(warnings, time to forget, 0)
a = 0.7
b = 0.7
Crime = crime opportunity * crime capacity + noise
CrimeData := GET XLS DATA('BySemester.xls', 'F08', 'A', 'b2')
Crime capacity max = 0.95
Crime opportunity = Opportunity max * (1 - public reaction)^a * (1 - Guards reaction)^b
Crime capacity = max (crime capacity max/deterrent effect, 0)
Deterrent effect = smooth(warnings * A + Guards reaction * B + C, 7)
Public deviation = public perception of threat - tolerable threat for public
Guard deviation = security systems perception of threat - tolerable threat for Guards
effect of warnings on public perception of threat = smooth3((K*sensitivity to warnings*warnings) + 1, time to hear warnings)

exam days := GET XLS DATA('BySemester.xls', 'F08 (daily)', 'A', 'F2')
f([(0, 0)-(4, 1)], (0, 0), (1, 0.25), (2, 0.66), (3, 0.85), (4, 0.9))
g([(0, 0)-(4, 1)], (0, 0), (1, 0.25), (2, 0.66), (3, 0.85), (4, 0.9))
h([(0, 0)-(1, 4)], (0, 1), (0.244648, 1.24561), (0.5, 2), (0.8, 3.5), (0.908257, 3.85965), (1, 4))
h1([(0, 0)-(2, 1)], (0, 0), (1, 0.5), (1.10703, 0.824561), (1.52294, 0.947368), (2, 1))
initial public perception = 0.59
initial Guards perception = 1.23
K = 17.929
Opportunity max = (B0 + B1 * Temp + B2 * Rain + B3 * "Uni-Open" + B4 * exam + B5 * WeekOpen)
public perception of threat = SMOOTH3i(Crime, time to perceive, initial public perception) * effect of warnings on public perception of threat
public reaction = smooth3(f(Public deviation), time to act public)
Rain := GET XLS DATA('BySemester.xls', 'F08 (daily)', 'A', 'D2')
security systems perception of threat = SMOOTH3i(Crime, Guards time to perceive, initial Guards perception)
X = -0.188
sensitivity to warnings = max(1 + X*accumulated past warnings*time to forget, 0)
Guards reaction = smooth3(g(Guard deviation), time to act for Guards)
Guards time to perceive = 7.46
Temperature := GET XLS DATA('BySemester.xls', 'F08 (daily)', 'A', 'C2')
time to act public = 3
time to act for Guards = 2
time to forget = 60
time to hear warnings = 1.48
time to perceive = 7
tolerable threat for public = 0
tolerable threat for Guards = 0
"Uni-Open" := GET XLS DATA('BySemester.xls', 'F08 (daily)', 'A', 'E2')
warnings := GET XLS DATA('BySemester.xls', 'F08 (daily)', 'A', 'h2')
weekOpen := GET XLS DATA('BySemester.xls', 'F08 (daily)', 'A', 'G2')