

A Qualitative Approach to Modeling School Violence Using System Dynamics

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ABSTRACT

Violence is an increasing problem in schools across the United States, and the most extreme form of school violence, gun violence, is the leading cause of death among children and adolescents in the country. Previous studies have examined static relationships between school climate and aggression; however, few studies have examined the dynamic interaction of stress, support, and incidents over time. Therefore, in this study, we develop a system dynamics model of school climate that qualitatively examines the conditions under which a school climate might become stable or unstable. First, we examined the School Survey on Crime and Safety (SSOCS) data from the four completed survey years (2016, 2018, 2020, and 2022), and organized 23 items into three indices of stress, support, and incidents. These showed consistent positive correlations between stress and incidents ($r = 0.60 - 0.79$), which are used to confirm the sign of the modeled associations, not causal direction, and are not used to estimate the parameters. We then built a stock and flow diagram with five of those coefficients, the ones that correspond to the reinforcing loop between stress and incidents, and the balancing loop between support and incidents. We conducted targeted simulations and a one-at-a-time sensitivity analysis, which showed a dramatic threshold effect and that the modeled system can rapidly fall into crisis once it reaches a tipping point. Notably, the speed of administrative response emerged as a major stabilizing factor within the model, highlighting how it plays a crucial role in preventing collapse. The coefficients are illustrative and not necessarily calibrated; the results are thus hypotheses generated by the model, suggesting that institutional response capacity may play an important role.

1. INTRODUCTION

School violence remains a persistent threat to students across the United States, and its most severe manifestation, gun violence, has become one of the leading causes of death nationwide. In 2023 alone, 46,728 people died from gun violence [1], a number that has only been growing, establishing it as a major public health concern [2]. Studies highlight how children, in particular, are disproportionately impacted. In 2020, firearm deaths surpassed deaths caused by motor-vehicle crashes, making firearm violence the leading cause of deaths among children and adolescents [3]. The number of school gun violence incidents every year, too, continues to reach unprecedented levels, with “160 occurrences of gunfire on school

grounds in 2024” [4]. The effects of school violence on children are far-reaching. Schools that have experienced school shootings have shown decreases in standardized test scores [5]. These effects appear detrimental to students' long-term careers; school shootings are associated with a 3.4% decrease in graduation rates, 14.6% decrease in college completion, and a reduction of over \$100,000 in lifetime earnings among students [6]. The United Nations Educational, Scientific, and Cultural Organization notes that these findings highlight the importance of school intervention efforts; school violence prevention is paramount to achieving quality and equitable education for all students in the United States [7]. Yet gun violence is the most severe manifestation of a broader ecosystem of school violence, aggression, and climate dysfunction. In other words, it is a climate in which student stress, institutional support, and day-to-day disciplinary incidents interact with each other to either stabilize or destabilize a school environment. Understanding this ecosystem is essential for anticipating and ultimately preventing the escalation pathway to lethal violence in schools.

School climate, defined as “the quality and character of school life,” assesses a school's environment based on a variety of distinct yet interconnected pillars: safety, teaching and learning, interpersonal relationships, institutional environment, and leadership and efficacy [8]. Undoubtedly, school climate is essential for student success and learning. Findings from Aldridge and McChesney suggest that school climate is directly correlated with student mental health and well-being [9]. Specifically, Acoba notes that stress serves as a mediator between social support systems (i.e., from family, significant others, and friends) and mental health [10]. In other words, negative social support systems, or the lack thereof, result in an increase in stress, thereby decreasing mental health among students. Building on this, Cornell et al. find that having a school climate that places an emphasis on teacher-student relationships and fair discipline is linked with an increase in school engagement, academic grades, and educational aspirations [11].

Previous research investigating the relationship between school climate and aggression finds that the two are negatively correlated. A study conducted by Li et al. found that school climate had an indirect effect on aggression through self-control as a mediator, and a positive school climate significantly reduced the likelihood of school aggression [12]. Corroborating this notion, Waasdorp et al. affirm that a positive school environment is correlated with an increase in positive bystander responses during times of bullying and aggression in schools [13]. In sum, schools with less violence typically emphasize strong teacher-student relationships and an “environment that is orderly” [14]. However, little research has been conducted to investigate school climate's correlation to gun violence, not just aggression, in particular. While many studies have investigated static correlations between stress, peer support, and bullying in schools and violence, little has been done to investigate these dynamically on a holistic level, incorporating all three variables' interplay together. For this reason, developing a systems-based mathematical model of school climate and intervention feedback may help improve understanding of how targeted interventions can meaningfully reduce the prevalence of violent and disciplinary incidents in schools. While this framework is informed by general incident data rather than firearm-specific data, and its coefficients are illustrative rather than empirically calibrated, it may nonetheless inform thinking about the precursor conditions of more severe forms of school violence, such as firearm incidents.

Systems modeling analyzes the complex systems in which variables interact and evolve over time. Unlike static regression, it captures feedback loops and nonlinear behavior. For instance, a regression might show that homework correlates with stress, but a systems model would also capture how homework reduces sleep, which lowers grades, which feeds back into stress. By accounting for these recursive relationships, systems modeling offers a more complete picture of how complex phenomena emerge and persist. School climate and school violence operate as a similar system, with stress, disciplinary fairness, support, and incidents interacting through reinforcing and balancing loops over time.

School climate is well-suited for system dynamics analysis because student stress, disciplinary incidents, and institutional support can continuously affect each other over time through feedback loops. As a result, even small shifts in stress or support may produce much larger changes in overall school stability, making static models insufficient for capturing how those dynamics unfold.

Hence, the interplay between school climate and violence can be viewed under a systems modeling lens, where the state of the school climate is modeled and determined by a collection of fluctuating stock and flows. In this system, we assume that stress index, support index, and incident index are the interacting fundamental mechanisms that ultimately determine school climate.

2. METHODOLOGY

2.1: Dataset

The 2020 School Survey on Crime and Safety (SSOCS) Dataset, a national dataset gathered by the National Center for Education Statistics (NCES) on crime, violence, and safety practices in U.S. public schools, was first used in order to determine the relationship among the stress, support, and incident indices. The survey collects data from public school principals in the United States on the occurrence of school crime, discipline problems, and school safety policies. Because the dataset samples schools nationwide, it provides a valid and comprehensive data source for the analysis of relationships in school crime and safety practices.

We then regrouped the variables in the dataset into three indices, namely the stress index, the support index, and the incident index. The stress index is a measure of institutional strain and disciplinary measures that place stress on school students, administrators, and staff. This encompasses suspensions, referral to alternative programs, required counseling, loss of privileges, and other disciplinary actions. The support index reflects institutional response capacity, more specifically the security personnel and emergency preparedness. In this paper, the term "support" is used in an institutional sense and not in an emotional or social sense (e.g., counseling, mentorship), which SSOCS does not consistently measure. Lastly, the incident index reflects the frequency of reported safety incidents such as theft, bullying, physical and verbal altercations, and/or weapon possession. A total of 23 variables were organized into the three indices as follows below:

Stress Index

The stress index was generated based on variables related to disciplinary burden, behavioral disruption, and institutional strain. These included total disciplinary actions, frequent disciplinary problems, violent and nonviolent offenses, suspensions, expulsions, and transfers to alternative schools. Combined, these variables were intended to reflect the general accumulation of institutional and behavioral stress within the school environment. Note that some of the factors in the stress index, such as suspensions and disciplinary actions, can be both stressors and part of the school's response to incidents. Because disciplinary consequences can add to the general tension in the school and thus contribute to a negative school atmosphere, they were included. The relationship observed between the stress and incident indices, however, might be strengthened by these factors, as they are related to incidents themselves, so the results should be interpreted with caution. Particularly, since these variables themselves happen to be institutional reactions to incidents, the stress-incident reinforcing loop might be definitional instead of strictly behavioral; for this reason, the threshold in coefficient a , the most influential parameter in the sensitivity analysis (Section 3.5), could be an exaggeration of the strictly behavioral pathway.

Support Index

The institutional support index was created by combining indicators of school preparedness and security capacity, such as the availability of full-time and part-time security personnel and the number of emergency response plans that the school has in place.

Incident Index

The incident index was created from variables measuring the frequency and severity of school incidents, including violent incidents, nonviolent incidents, incidents reported to law enforcement, and the number of students involved in recorded offenses. All SSOCS variable codes are defined in Appendix A.

Index	Variables Included	Conceptual Meaning
Stress Index	DISTOT, PROBWK, OUTSUS, REMOVL, DISCALC, DISATT, DISDRUG, DISFIRE, DISWEAP, OTHACT, TRANSF	Institutional strain and disciplinary burden
Support Index	CRISIS, SEC_FT, SEC_PT	Institutional preparedness and support capacity
Incident Index	INCID, NONVIOINC, STUOFF, SVINC, SVPOL, VIOINC, INCPOL, VIOPOL, NONVIOPOL	Frequency and severity of school incidents

Based on this, all values for each variable were normalized using the percentile value for the school in that variable. This was done in Excel using the PERCENTRANK function, which gives each

school a value ranging from 0–1 based on the percentage of schools in the dataset that are at or below it. A common scale is required because a school's "score" for each index would be the average of the variables in each index. If the values of one of the variables were larger than the other, then the average would be weighted toward that variable. Percentile ranks were employed instead of z-scores since the data were skewed to the right, and percentile-based scaling depends only on a school's rank rather than the size of its raw values, and hence is not adversely affected by outliers or skewed data. The average of these percentile values was then used to calculate the overall index score for each school. This was done for each of the three indices. Correlations were calculated between each of the indices after obtaining index values for each school, but these were used only to confirm the sign of each association, not causal direction, and not to estimate model parameters (Section 2.2). The following are the coefficients that were calculated:

Year	Stress × Support	Stress × Incidents	Support × Incidents	Excluded Variables
2016	0.362	0.790	0.364	NONVIOINC16, NONVIOPOL16
2018	0.182	0.600	0.352	DISTOT18, DISATT18, REMOVL18, TRANSF18
2020	0.246	0.673	0.338	None
2022	0.236	0.669	0.304	SVINC22, VIOINC22, NONVIOINC22

Table 1. Pearson correlation coefficients between the stress, support, and incident indices across four SSOCS survey years (2016, 2018, 2020, 2022). All three pairwise correlations were consistently positive across years, with the stress–incidents relationship being the strongest ($r = 0.60$ -- 0.79). Variables missing from a given survey year were excluded from that year's calculations, as noted in the rightmost column.

Limitations

Several limitations ought to be noted with regard to the credibility of our results, however. First, several values within the stress index variables were missing, denoted with a "-1" in the dataset. This represents a "legitimate skip," which SSOCS states occurs if the respondent indicated that their school did not possess any sworn law enforcement officers. In such cases, the institutional questions regarding disciplinary actions related to law enforcement would not apply. This holds for all variables in the stress index except PROBWK20. Additionally, due to the nature of items being dropped or reworded between administrations every few years, variables that were unavailable in a comparable form were excluded (see the rightmost column of Table 1 for the specifics). Data were also available for only a few years. Because of this limited, non-annual data, it is difficult to capture how variables influence each other over time. While it may capture correlational snapshots, these are insufficient for statistical modeling, which requires dense, longitudinal data. These correlations show that the stress index, support index, and incident index are consistently correlated across multiple years of national data, with the relationship between stress and

incidents being the strongest ($r = 0.60\text{--}0.79$). This empirical consistency is the motivation for the causal structure used in the remainder of this paper, in which these relationships are represented as directional flows. It should be noted, however, that correlations are symmetric and do not directly inform directional parameters; they were therefore used only to verify the sign of each association, not to estimate model parameters. The simulation parameters are instead selected to capture a wide range of system behaviors rather than to fit a particular school. Longitudinal school-level data could be used in future work to estimate parameters using regression methods. Having established that stress, support, and incidents are regularly and meaningfully linked, we now move from describing these static relationships to modeling how they change and influence each other over time. In the next section, these empirical relations are mapped into a dynamic systems framework, starting with a causal loop diagram and ending with a stock-and-flow model.

2.2: Systems Modeling

First, a causal loop diagram between the three indices of stress, support, and incidents was created. This offers an intuitive way of visualizing how the three indices interact with one another. In this diagram, each arrow represents a causal link between two variables. For instance, it is reasonable to assume that the stress index may contribute to the incidents index. Accordingly, an arrow would be drawn directly from the stress index to the incidents index.

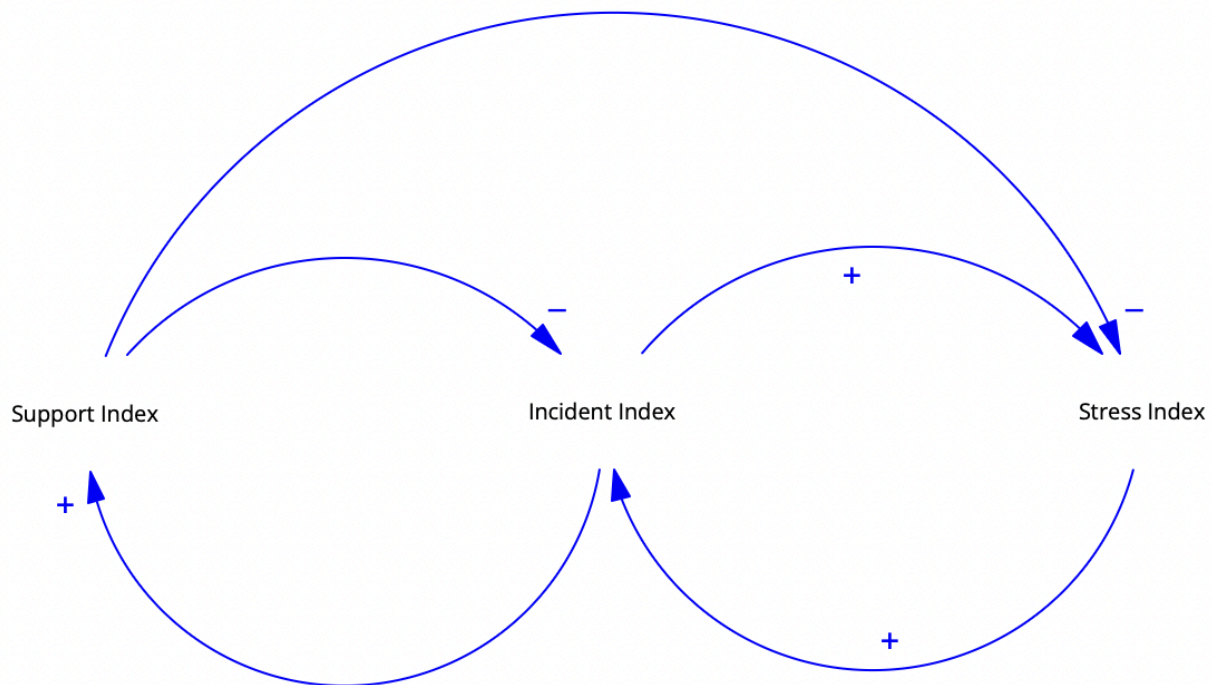


Figure 1: Causal loop diagram of the school climate system. The stress index and incident index form a reinforcing loop (R), where each amplifies the other, while the support index and incident index form a

balancing loop (B), where rising incidents trigger an increase in the support index, which in turn reduces the incident index. The support index also directly reduces the stress index. Polarity signs (+/-) indicate whether each link amplifies or dampens the target variable.

The interaction of these three indices, as shown in Figure 1, reveals their complex systems architecture. The link between the stress index and incident index serves as a reinforcing loop (R), where unchecked psychological strain would directly cause behavioral outbursts which would, in turn, exacerbate stressors among students due to the negative school climate. On the other hand, the link between the support index and incident index represents a balancing loop (B). Ideally, an increase in incidents would be accompanied by an increase in support mechanisms to mitigate those incidents, pulling the system back into equilibrium if the balancing loop is strong enough to counteract the opposing reinforcing loop. The support index is also modeled as directly reducing the stress index, which reflects the assumption that institutional response capacity lowers the perceived strain on students, administrators, and staff by signaling preparedness.

After establishing the fundamental relationships between the three indices, we transition into a Stock and Flow systems model, implemented in Vensim PLE. In this model, a Stock represents the accumulation of a system (e.g. how much water is present in a bathtub) while the Flow represents the rate of that accumulation or decumulation (e.g. the rate at which water enters or leaves the bathtub). Stocks represent the changing institutional states, while flows represent rates of change driven by feedback among stress, support, and incidents. In the context of a school climate, we represent the stocks to be stress index, support index, and incident index, modeled by the following flows (defined by the causal loop diagram):

Equation 1 – the Stress Equation (S): The stress index would accumulate based on the incident index and dissipate with the support index. The flow can be represented by the following differential equation:

$$\frac{dS}{dt} = a \times I - b \times U \quad (1)$$

Equation 2 – the Support Equation (U): The support index accumulates as a result of the incident index. We additionally assume that the support index naturally decreases by 10% per month. This decay is the loss of institutional support capacity that happens when there is no effort to renew it: security personnel move on to other jobs, grant and budget allocations expire, trained staff retire or move on to other opportunities, emergency-response plans go un-updated, and administrative attention is diverted to other priorities. Each month, a school loses some of this capacity unless it actively re-hires, re-funds, and re-trains to maintain the same level of preparedness. This 10% rate is an illustrative baseline rather than an empirically measured value; it was chosen to represent gradual but non-trivial erosion of support resources, such that institutional capacity would meaningfully deplete over a school year in the absence of active replenishment. We later vary this parameter directly in the sensitivity analysis (Section 3.5) to

confirm that the model's qualitative behavior is robust to this choice. This yields the following differential equation:

$$\frac{dU}{dt} = c \times I - f \times U \quad (2)$$

Equation 3 – the Incidents Equation (I): The incident index accumulates as a result of the stress index and lessens from support mechanisms. The corresponding differential equation is:

$$\frac{dI}{dt} = d \times S - e \times U \quad (3)$$

Where,

S = stress index; U = support index; I = incident index

a (aggravation) = stress generated per unit of incident index

b (stress relief efficacy) = how effectively support reduces the stress index

c (administrative response rate) = how quickly schools mobilize support after incidents

d (conflict sensitivity) = how readily stress translates into the incident index

e (incident reduction efficacy) = how effectively support reduces the incident index directly

f (support decay constant) = monthly rate at which the support index erodes from attrition

The governing Stock and Flow Diagram representing the Stocks and Flows of the system is depicted in the figure below.

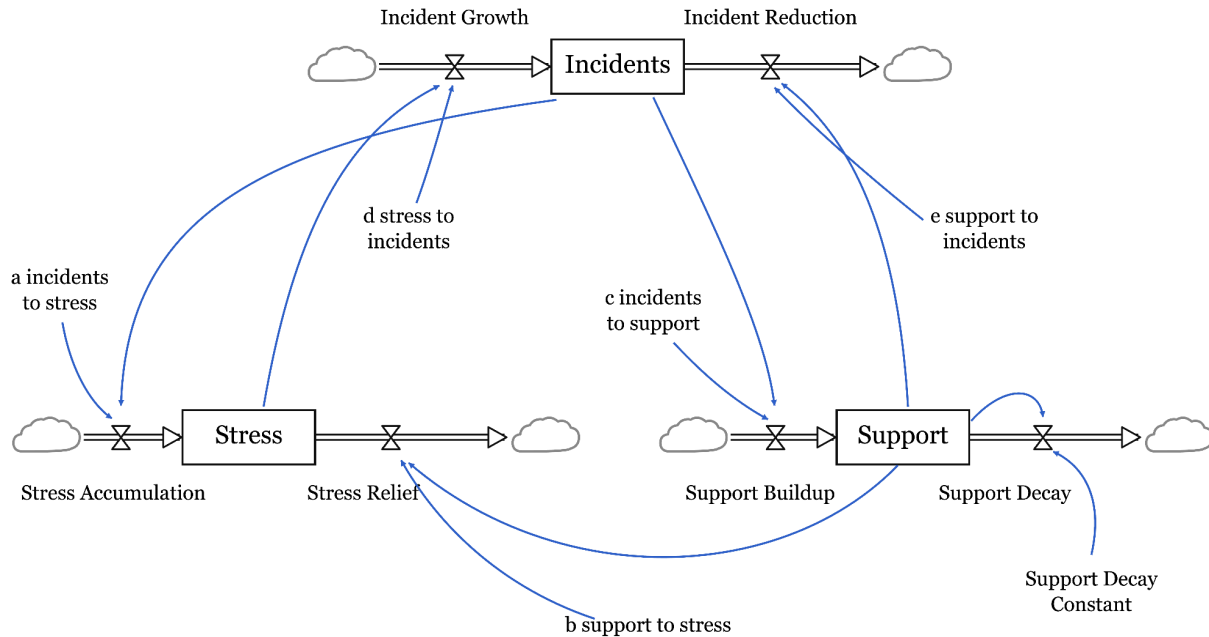


Figure 2: Stock and flow diagram of the school climate system. Three stocks - the stress index, support index, and incident index - accumulate and deplete according to the flows defined in Equations 1-3. Coefficients a, b, c, d, and e govern the rate at which each stock influences the flows, while the support index decays at a baseline rate of 0.1 per month due to institutional attrition.

We note, however, that the model coefficients were not directly derived from the SSOCS dataset. Instead, the parameter values were selected to represent various types of system behavior, including stability, slow escalation, and rapid collapse. This method enables the model to qualitatively investigate the breadth of dynamics that can occur across varying conditions of varying school profiles.

For reproducibility, the model was implemented in Vensim PLE using Euler integration with a time step of $dt = 0.03125$ months (1/32 month). To prevent stocks from going negative under extreme parameter settings, each outflow was capped at the minimum of its nominal rate and the available stock plus inflow within the timestep (i.e., $\text{outflow} = \text{MIN}(\text{rate} \times \text{source}, \text{stock} \times \text{max_rate} + \text{inflow})$ with $\text{max_rate} = 1.0$). All three stocks were initialized at 0.5 on the dimensionless 0-1 scale.

3. SIMULATION STRUCTURE

In the model above, what we want to ask is: under what conditions does a school reach a state of stability versus crisis? Put differently, what is the threshold for how much stress and support is needed to reduce the number of incidents in a school?

To study this, a single starting profile, at $t = 0$, is chosen for all simulations. The values of the stress, support, and incident indices are all initialized at 0.5 on the 0 to 1 range, with 0 representing the absence of the index and 1 representing the maximum. A value of 0.5 thus corresponds to a school at the middle of each index and a baseline condition of neither thriving nor crisis. We note that these normalized values represent the relative escalation or de-escalation of stress, support, and incident levels over time, and not absolute counts. Further, in some simulations, values higher than 1.0 mean that the index is greater than the maximum empirically observed, signaling crisis-level escalation rather than a specific number of events.

The balanced starting position allows for neither the reinforcing loop (between the stress and incident indices) nor the balancing loop (between the support and incident indices) to be pre-advantaged at time $t = 0$. Because of this, the simulations carried out in Sections 3.2-3.4 allow the study of the effect of the individual coefficients (a, b, c, d, and e) on the resulting trajectory of incidents. A lopsided profile would first lead to a preference for a particular trajectory, making analysis of the influence of individual coefficients on the dynamics challenging. The framework could be expanded to other starting school profiles to define profile-specific intervention thresholds.

Support decay is the same for all simulations (0.1). This is the 10% natural loss of school resources, as stated above. We assume that there is no intrinsic decay for the stress index and incident index, but there is for the support index, as support systems draw on external institutional resources which are by their nature limited in supply, while stress and incidents can be self-reinforcing phenomena that persist until acted upon by active institutional mediation. Stress and incidents do not disappear on their own over time - they must be mitigated by the institution's support. Unless otherwise modified, the institutional response to incidents (c) was set at 0.3 because it reflects a response-to-decay ratio of 3:1 that mimics a functional school administration.

Note: The simulation parameters used are illustrative and were selected to show the qualitative behavior of the system. They are not fitted to the SSOCS correlations reported in Section 2.1.

3.1: Model Stress Check

To confirm the validity of the model before performing our simulations, we test the edge cases. First, we turn off all support mechanisms and maximize the stress-incident reinforcing loop by setting b, c, and e equal to zero, and a and d equal to one. This, theoretically, should result in unbounded exponential growth, because there is no balancing mechanism in place to curb the compounding stress and incident

levels. This is corroborated by the model, as illustrated in Figure 3(a). Then, we remove the reinforcing loop of stress and incidents. In theory, this should quickly reduce the incident index, as there is no stress index that can drive the incident index up. We set b , c , and e to 1 and a and d to 0.

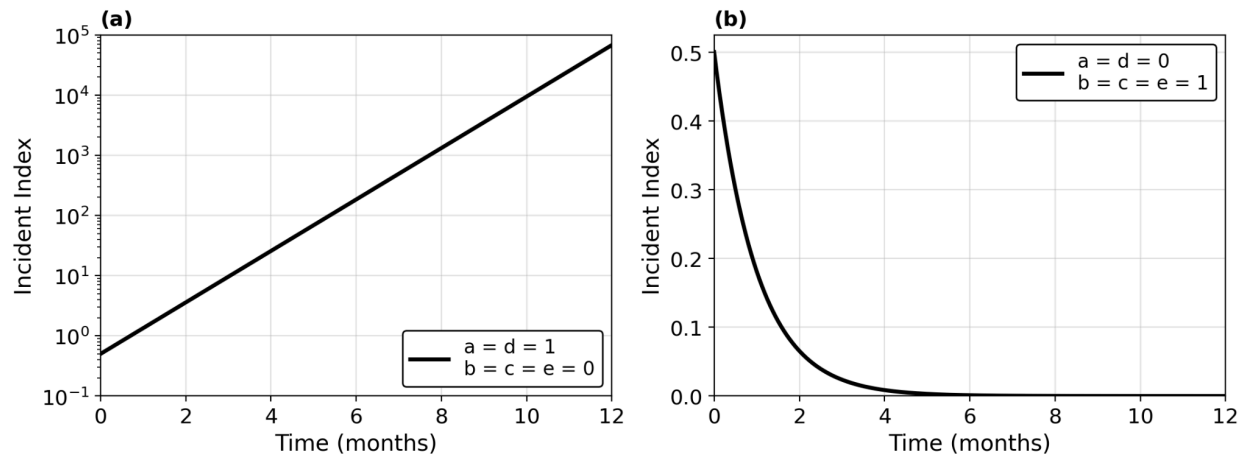


Figure 3: Model stress checks (12-month simulation). (a) Reinforcing loop only with all support removed ($b = c = e = 0$) and the stress–incident loop maximized ($a = d = 1$), the incident index grows without bound (log-scale y-axis), confirming the reinforcing loop dominates absent any balancing. (b) Balancing loop only, with the reinforcing loop disabled ($a = d = 0$) and all support maximized ($b = c = e = 1$), the index decays rapidly toward zero, confirming the structural validity of the balancing loop.

3.2: The Vulnerability Test (Varying a and d)

As shown in the causal loop diagram, stress and incidents form a reinforcing feedback loop, so we vary the associated coefficients a and d , which capture how much stress is generated per unit of incidents (a) and how readily that stress translates into new incidents (d). Varying a and d together is used to describe the strength of the reinforcing loop and to determine the conditions under which the reinforcing loop is stronger (when the incident index increases rapidly) and those under which the balancing loop is stronger (when sufficient support is mobilized to suppress the incident index). These individual contributions are then isolated in the sensitivity analysis (Section 3.5), and it is seen that the behavior of the loop is mainly due to one parameter, a .

We fix b (support to stress) as well as e (support to incidents) to 0.5 to represent a scenario where every unit of institutional support has a moderate efficacy of mitigating the stress and incident indices. Combined, these represent a theoretical “average” support staff, where they are neither overperforming nor underperforming in reducing stress and incidents. Finally, as mentioned in 3.1, the support decay constant and institutional response to incidents (c) are kept at a 3:1 ratio of 0.1 to 0.3 respectively to ensure that, under normal conditions, the school is capable of replacing diminished support when needed.

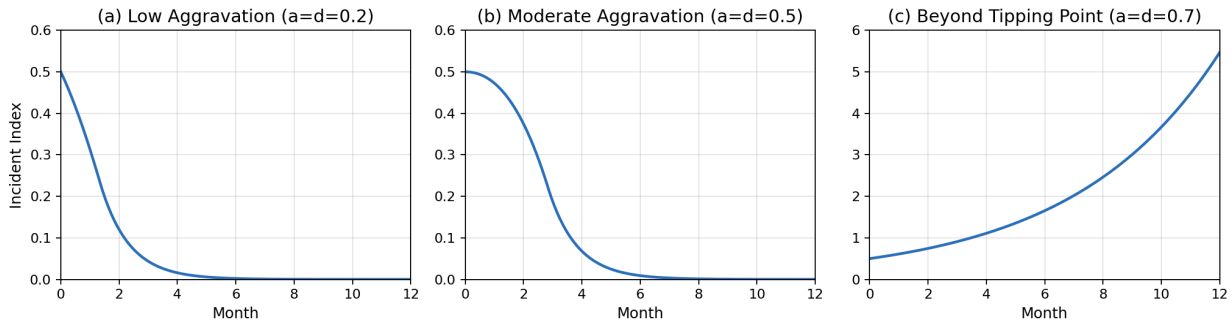


Figure 4: Vulnerability test. We vary the reinforcing-loop coefficients a and d jointly under a balanced support environment ($b = e = 0.5$, $c = 0.3$, decay = 0.1). (a) This is a low aggravation environment, ($a = d = 0.2$) where the balancing loop dominates and the index decays to zero within about six months. (b) This is a moderate aggravation environment ($a = d = 0.5$) where the index still decays, albeit more slowly. (c) This is an environment just beyond the reinforcing loop's tipping point ($a = d = 0.70$; tipping near $a = d \approx 0.69$), where the loop dominates and the index escalates steadily without recovering, reaching about 5.5 by month 12.

3.3: The Inaction Penalty (Varying c)

Figure 5 shows the administrative response rate, c , in isolation. In this scenario, where $c = 0.08$ (panel a), less than the support decay rate of 0.1, the school loses support faster than it can be replenished, and the incident index increases even when the other factors remain moderate. If $c = 0.2$ (panel b) - just above the decay rate - the system stabilizes and the index tends to zero, which demonstrates that even if a relatively small amount is put into response capacity, there is enough to prevent collapse. At $c = 0.7$ (panel c), a high response capacity brings incidents to an end quickly, which corresponds to the maximum level of crisis prevention that can be realized through response.

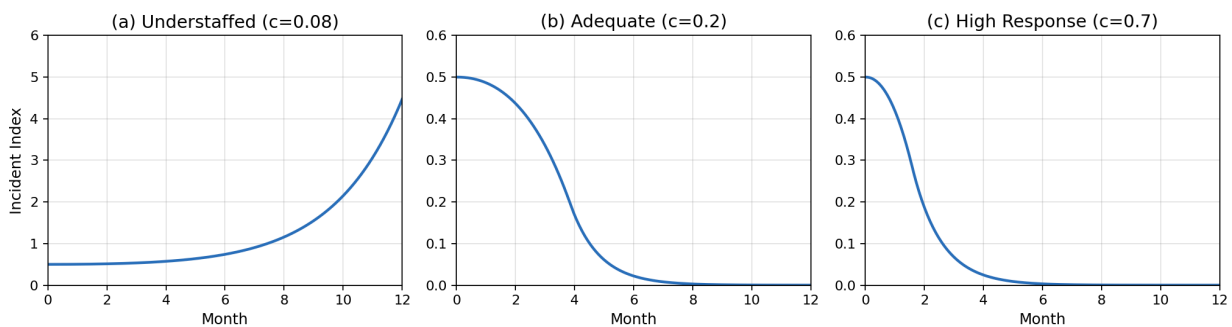


Figure 5: Inaction penalty. We vary the administrative response rate c ($a = b = d = e = 0.5$, decay = 0.1). (a) Exemplifies a school that is severely understaffed ($c = 0.08$, below the 0.1 decay rate), and support erodes faster than it is replaced and the index escalates. (b) A school that is marginally adequate ($c = 0.2$, just above decay), and the system stabilizes and the index decays to zero. (c) A school with High-standard response ($c = 0.7$), and the index decays rapidly, illustrating the upper bound of crisis prevention through response capacity.

3.4: Evaluating the Efficacy Buffer (b and e)

Finally, we now investigate the quality of intervention. Whereas section 3.3 showed that the amount of response (c) is crucial for institutional survival, this test will examine whether the quality of institutional support programs can offer a structural buffer in high-risk environments. In system dynamics terms, we are measuring the strength of the balancing loop (B). If b and e are sufficiently large, the balancing loop (B) should be able to overpower the reinforcing loop (R) of stress and incidents, even if administrative hiring is low.

To isolate quality as the primary variable, the school is placed in a high-aggravation environment with a statistical likelihood of collapse. We set the values of the control environment variables as follows: aggravation (a) = 0.7, sensitivity (d) = 0.5, and administrative response rate (c) = 0.2, which was deemed to be somewhat satisfactory in section 3.3. The model has a rather steep quality threshold around $b = e \approx 0.51$, and Figure 6 contrasts programs on either side of this value. Just below the threshold ($b = e = 0.5$; panel a), the efficacy is not sufficiently high to break the reinforcing loop, and the index rises. Just above it ($b = e = 0.55$; panel b), the index is contained and eventually falls to close to zero around month 8. The balancing loop is dominant at high quality ($b = e = 0.8$; panel c) as the index tends to zero at around month 5, suggesting that the index could be stabilized in a high-aggravation school when the quality is high enough.

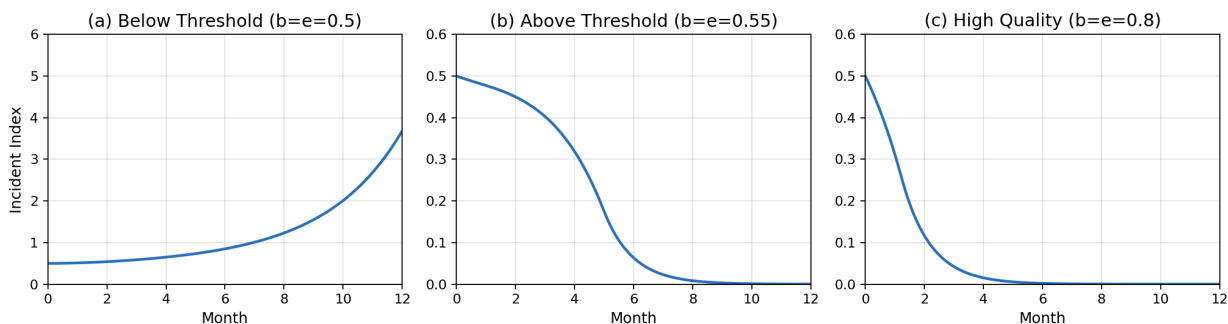


Figure 6: Efficacy Buffer. We tune the program parameters b and e together in a high aggravation setting ($a = 0.7$, $d = 0.5$, $c = 0.2$, $\text{decay} = 0.1$) and find the quality threshold to be around $b = e \approx 0.51$. (a) Just below the threshold ($b = e = 0.5$), the index escalates. (b) Just above it ($b = e = 0.55$), the index drops to almost zero after about month 8. (c) In a high quality ($b = e = 0.8$) environment, by month 5, the index has dropped to almost zero, indicating that, in theory, a high-aggravation school environment could be stabilized by providing sufficient quality support.

3.5: Sensitivity Analysis

As mentioned in sections 3.2-3.4, we used representative scenarios for each of the parameters, but used a sensitivity analysis to assess the robustness of the model's findings, which is a common approach in system dynamics [15]. In particular, a one-at-a-time (OAT) sensitivity analysis was done. On the conceptual level, this analysis points to the identification of structural parameters which actually drive a school to either stabilize or deteriorate and those which have little effect. Leverage points that have an

important effect on the trajectory are the ones that have the greatest meaning for intervening, while those that have a minimal effect on the outcome are less relevant to intervention. In the analysis, each of the six model parameters was changed over a realistic range, while the values of the other parameters were kept at the at-risk baseline ($a = b = d = e = 0.5$, $c = 0.3$, $\text{decay} = 0.1$). We took the maximum value of the incident index during the 12-month simulation for each of the parameter sweeps. These parameters, a , b , c , d , and e , were changed over 11 evenly spaced values between 0 and 1.0, increasing by 0.1. The 0-1 sweep range was not selected with a behavioral basis, but rather to facilitate comparisons of the coefficients, such that each coefficient has a natural range of 0-1. The support decay constant was varied between 0 and 0.5 due to the fact that the range of plausible support decay constants is much more limited (100% of support is unlikely to be naturally removed within a one-month time period). All 66 simulations were conducted in Excel, and the peak incident index values for each simulation were recorded. Stable trajectories often resulted in a peak value equal to the initial value of the incident index, since all simulations were initialized with an incident index of 0.5. The peak metric therefore primarily distinguishes whether the system escalated beyond baseline, rather than measuring the speed of recovery. We therefore also measured the incident index at month 12, as a second measure. This separates transient escalation with recovery ($d = 1.0$ peaked at 1.18 and $a = 0.8$ at 0.54 with both moving back towards zero), from sustained escalation (month-12 values close to peak values, e.g. $a \geq 0.9$, $b \leq 0.2$, $c = 0$), and marginal equilibrium ($c = 0.1$ and $\text{decay} = 0.3$, where the index held at its initial value of 0.5); the ranking remains the same as in Section 3.5.3. The OAT analysis led to three main conclusions.

3.5.1: Threshold Behavior in Reinforcing Loop Parameters

The threshold of parameter a (incidents to stress) was steep, while that of d (stress to incidents) was not. The peak incident index was steady at 0.5 (rising only to 0.54 at $a = 0.8$) until $a = 0.9$, when it suddenly rose to 8.99 and increased to 39.23 at $a = 1.0$. Parameter d , however, only showed a slight increase from 0.50 to 1.18 at $d = 1.0$ and did not become a crisis. This means that the rate of conversion of stress into incidents (d) has less destabilizing effect than the amount of stress created by each incident (a); in other words, it is a that determines when the loop becomes destabilizing. The support decay constant (which is not a direct reinforcing loop parameter) was found to follow a similar pattern; the peak incident index remained at 0.5 up to $\text{decay} = 0.3$ and increased dramatically above this value, reaching 10.92 at $\text{decay} = 0.5$. This indicates that at low to moderate values these parameters have little effect, but they show a threshold effect: once they are above a certain value, the reinforcing loop takes over the balancing loop and the system falls apart.

3.5.2: Saturation in Balancing Loop Parameters

Low values of the balancing loop parameters b (support to stress), c (incidents to support), and e (support to incidents) resulted in crises, which were avoided once these parameters exceeded a low threshold. Parameter b in particular produced a peak incident index value of 22.68 at $b = 0$, 10.92 at $b = 0.1$, and 2.62 at $b = 0.2$, and the peak incident index was maintained at 0.5 for all values $b \geq 0.3$ (that is, the incident index never surpassed its initial value of 0.5 and instead decayed towards zero). Unlike the former, the threshold for parameter c was even lower, with only $c = 0$ triggering a crisis (with a peak of 32.22), and all higher values converging to 0.5. Likewise, parameter e did not cause any crises for $e \geq$

0.2. This suggests that the balancing loop parameters act as a switch for stabilization: once they exceed a low threshold, the system stabilizes, and increasing them further has little additional effect.

3.5.3: Ranking of Parameter Sensitivity

The peak incident index range was measured for each parameter throughout its sweep to compare how each parameter affects the model output. The results indicate that parameter a has the largest range effect (38.73), followed by c (31.72), b (22.18), the support decay constant (10.42), e (7.96), and d (0.68). These results can be visualized in the figure below.

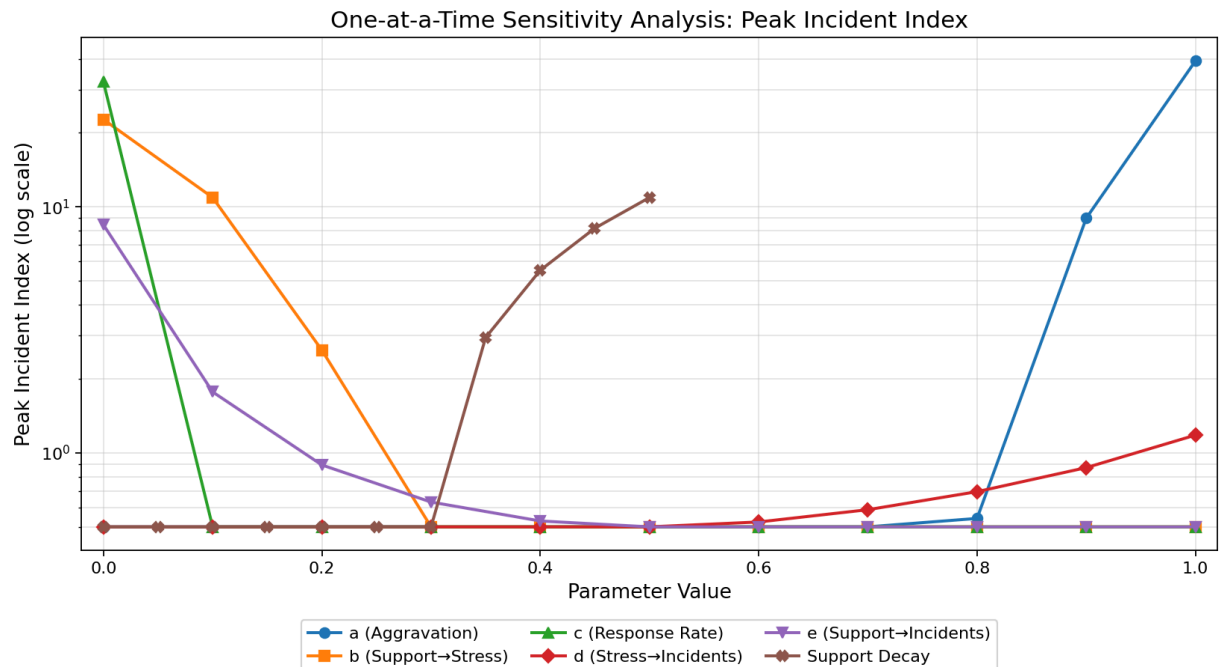


Figure 7. Combined one-at-a-time (OAT) sensitivity sweep showing the peak incident index across the 12-month simulation as each parameter is varied independently across its plausible range, with all other parameters held at the at-risk baseline; the vertical axis is logarithmic so that curves of very different magnitudes remain readable. There are three sets of parameters. The aggravation parameter a and the support decay constant are destabilizers with steep thresholds and relatively large regions of neutrality (inertia) before they suddenly escalate to a crisis. The parameters for the administrative response rate (c), and the efficacy parameters (b and e), are stabilizing switches which prevent the crisis if they reach a low threshold, with c switching more sharply than b and e. The stress-to-incident conversion rate (d) has a very slight and continuous impact with no particular threshold.

3.5.4: Implications for the Model

The sensitivity analysis confirms the threshold structure seen in Sections 3.2 - 3.4 and explains what each parameter means in a school. The most important destabilizers are the stress generated per incident (a) and the support decay rate. The parameter a represents the extent to which the disturbance of an incident spreads into pressure on students, staff, and administrators: the model shows that a school with a below the critical value can absorb incidents indefinitely, while a school with a above it suddenly tips from stability to escalation. Similarly, a school that loses support capacity faster than it can rebuild it will destabilize. The conversion of stress into incidents (d), while part of the same reinforcing process, has only a weak independent effect, so the system's trajectory is determined far more by how much stress incidents generate (and whether support keeps pace) than by how responsive incidents are to stress. In contrast, the stabilizing factors - administrative response speed (c) and program efficacy (b and e) - act as switches: raising them a few points above a low threshold is enough to prevent collapse, but increasing them beyond a moderate level yields diminishing returns. Taken together, the analysis suggests that schools are best served by keeping the destabilizers (stress accumulation from incidents and the erosion of support) below their tipping points and by securing a baseline capacity to replenish support, rather than by maximizing programs that are already adequate.

4. RESULTS

Three principal findings emerge from the targeted simulations (Sections 3.2-3.4) and the sensitivity analysis (Section 3.5). Crucially, we note that the coefficients are illustrative, and that these findings are model-generated hypotheses rather than empirically supported conclusions.

First, the school climate system is characterized by non-linear dynamics, referred to as threshold dynamics, meaning that it does not change smoothly or proportionately. When a reinforcing stress-incident loop is weak, the system tends to return to a stable, low-incident state. However, as soon as the strength of the loop exceeds a certain point, the system spirals rapidly out of control. Indeed, the incident index will drop to zero at $a = d = 0.2$ and 0.5 , but then rise rapidly beyond a tipping point, found at $a = d \approx 0.69$ (Section 3.2). This transition is localized in the aggravation parameter a that is roughly inert over most of its range, but triggers between $a = 0.8$ and $a = 0.9$ (the peak changing from 0.54 to 8.99). Overall, the bottom-line effect is that there may be a period of apparent normality in a school for a long time; however, it is important to recognize that even an incremental change in the amount of stress each incident generates can tip the climate over from recovery to crisis. Conversely, the impact of stress becoming new incidents (d) has little independent effect, suggesting that the danger is not in the incidents that emerge from stress, but in the amount of stress that the incidents generate.

Second, and perhaps the finding most relevant to policy hypotheses, is that the extent to which a school is able to replace support is an independent factor of stability. However, if the administrative response rate is

less than the rate of support decay ($c = 0.08$ vs. decay = 0.1), then even with otherwise moderate conditions ($b = e = 0.5$), the system becomes unstable, and support will cease to be sustained; if the rate of administration exceeds that of support decay, even slightly ($c = 0.2$), on the other hand, the system is stable and incidents are rapidly suppressed by a high rate of response. This is confirmed by the sensitivity analysis which shows the response rate to be the second most influential variable overall. Capacity to deploy and continuously renew support - not just its presence - is what determines whether a simulated school holds.

Third, the quality of a program needed to help stabilize a school is not predetermined, but increases dramatically as the school environment becomes more difficult. Efficacy parameters are used to stabilize the system when they are above low thresholds ($b \approx 0.3$, $e \approx 0.2$), so that even mediocre programs will work at the mild sensitivity baseline ($a = 0.5$, $c = 0.3$). The required quality, however, rises greatly in the Section 3.4 environment ($a = 0.7$ and $c = 0.2$), where programs below about $b = e = 0.51$ do not contain the reinforcing loop, and higher-quality support ($b = e = 0.8$) results in complete recovery (Figure 6c). The level of program quality required will therefore increase as a function of underlying strain; quality will not be a free substitute for a low level of aggravation and adequate capacity to respond, since under high strain the quality required may be beyond the reach of a strained school.

5. DISCUSSION

The findings of this paper suggest model-generated hypotheses relevant to future school climate policy and systems modeling efforts. As the threshold behavior of the reinforcing loop governed by a and d shows, schools can stay at what look like stable conditions for a long time before suddenly falling into a state of rapid decline. The system dynamics model illustrates how these two combine in a nonlinear fashion, with the capacity to create tipping points, where small and minute changes to schools can make the difference between a school being in recovery and in crisis. This highlights the importance of early warning signals for school climate which do not just rely on incident levels, but also on factors contributing to these levels, which can amplify. This is not usually captured in the existing measures. Additionally, the finding that administrative response rate is a key aspect of achieving climate stability even when other parameters are favorable suggests, as a hypothesis, a new way of thinking about school violence prevention – that response capacity is as important as program quality. In fact, much of the literature has been devoted to the need for program quality (e.g., evidence-based curricula, trained counselors, restorative-justice models) to help maintain system stability; our model suggests that there are other paths to stability. The administrative response rate is the most significant of these stabilizers in the sensitivity analysis. It also proposes, however, that if program quality is very high, it can compensate even when response capacity is only marginally adequate, indicating that program quality and response capacity are not strictly hierarchical but partially substitutable. One implication is that the program quality required to make up for limited response capacity is high. Therefore, in high-stress contexts, interventions that improve program quality without also expanding response capacity are unlikely to stabilize a school unless they raise quality to a very high level. Finally, the OAT sensitivity analysis adds another layer of

nuance: the concept of stabilizers and destabilizers. If these dynamics hold in real schools, policy interventions should emphasize the need to maintain the destabilizers below their thresholds rather than actively work to maximize the stabilizing parameters, since destabilizers produce escalating damage above their thresholds while stabilizers provide only binary protection. If stabilizers are above their thresholds, further investments in them will have little impact on school climate.

Another interpretive note is that the literature cited in the Introduction (Acoba, Cornell et al., Aldridge and McChesney) focuses on emotional and relational support, while the support index models a more limited institutional-security based capacity. The stabilizing effects of the balancing loop in Sections 3.3-3.5 thus refer to institutional response capacity, not to counselling or relational support, and may not be applicable to these two kinds of support, which probably act in different ways.

Several limitations of the study should nonetheless be reported. The model is not an empirically calibrated one, and it does not express quantitative behavior, only qualitative. We recognize that it does not fit any one school completely. Likewise, the model assumes that all schools follow the same structural dynamics, while in reality, schools vary substantially in terms of their demographics, resources, administrative structures, and community context. As a result, the parameters that govern the interaction between stress, support, and incidents can differ between these circumstances, and this variation is not reflected in the present model. The model also treats incidents as an undifferentiated stock, but in reality they may differ in nature, with nonviolent incidents having different dynamics and underlying causes than violent incidents. The OAT sensitivity analysis also accounts only for individual parameter sensitivities, and does not consider the interactions between parameters that may also influence the system's behavior. The 12-month time horizon was selected because it was considered a reasonable period given the natural time cycle of a school year. Other considerations, such as leadership change, demographic shifts, and adaptive responses, would need to be added to the model and would be difficult to capture in a multi-year extension. A final limitation concerns our support index, which reflects institutional support (e.g., security staff, emergency-response planning) rather than emotional or relational support (e.g., counseling, mentorship, teacher–student relationships), the latter being most frequently associated with student stress in the school-climate literature. The assumption of the model, however, that there is a direct impact of support on stress (b) is less well founded: it is an institutional-signaling effect, not a measured psychological effect. We were unable to include emotional support, since it was not consistently measured by SSOCS; future research incorporating the SSOCS and climate survey data would enable us to model emotional and institutional support as separate stocks.

These limitations can be overcome in future work by directly estimating the parameters using longitudinal school-level data. Along with this, one might explore whether the threshold behaviors described here can be detected empirically in actual schools using observational data. Another key element would be extending the framework to firearm-specific incident modeling, using a data source such as the Everytown School Gunfire database, so that it speaks more directly to the most severe forms of school violence.

6. CONCLUSION

This study proposed a system dynamics model of school climate, which modeled stress, support, and incidents as a coupled stock-flow system. Three main conclusions were drawn from the simulations and one-at-a-time sensitivity analysis: (1) schools show strong threshold characteristics, (2) the most critical single stabilizing factor is the speed of administrative response, and (3) if it is possible to achieve high enough levels of program quality, it can be a stabilizing factor on its own, but is a fragile one. Future research should calibrate the model using longitudinal school-level data and extend it to firearm-specific incidents.

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APPENDIX A: SSOCS VARIABLE DEFINITIONS

Definitions follow the SSOCS codebooks; year suffixes in Table 1 (e.g., DISTOT16) denote the survey year. Stress index: DISTOT - total disciplinary actions recorded; PROBWK - discipline problems occurring at least weekly; OUTSUS - out-of-school suspensions; REMOVL - removals with no continuing services; DISCALC - disciplinary actions for alcohol; DISATT - for physical attacks or fights;

DISDRUG - for illegal drugs; DISFIRE - for a firearm or explosive device; DISWEAP - for a weapon other than a firearm; OTHACT - other disciplinary actions; TRANSF - transfers to specialized schools.

Support index: CRISIS - written plans for crisis scenarios; SEC_FT - full-time security staff or sworn law enforcement officers; SEC_PT - part-time security staff.

Incident index: INCID - total incidents recorded; INCPOL - incidents reported to police; VIOINC / VIOPOL - violent incidents recorded / reported to police; SVINC / SVPOL - serious violent incidents recorded / reported to police; NONVIOINC / NONVIOPOL - nonviolent incidents recorded / reported to police; STUOFF - students involved in recorded offenses.

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