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Analyzing K-12 education as a complex system

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Abstract

Schools and school districts are complex, dynamic systems affected by numerous factors, from individuals' attributes to federal policies. In this paper, a modeling framework is presented for modeling a school as a complex system. An agent-based modeling strategy is developed such that users may better understand the attributes and relationships that may cause an intervention to succeed or fail. The system state change, including agents' attributes and their relationships, is modeled as a Discrete Time Markov Chain (DTMC). The modeling framework is demonstrated through a case study of a high school where an 'Engineers Without Borders' chapter is founded.

Keywords: Agent-based modeling; Simulation; Education; K-12; School Reform

1. Introduction

Educational interventions and reforms are commonplace, but only a limited number prove to be truly effective. From controversial federal policies such as 'No Child Left Behind'[1], to individual teachers adopting new pedagogical techniques, it can be difficult to measure the success of educational interventions and even more

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difficult to understand why some fail. The complexity of a school or school system is easily underestimated from the top-down view; curricula and interventions are often designed outside of the intended school settings or are copied from other schools, only to fail in context. There are many factors that can impact the outcome of an intervention, including the cognitive abilities of individual students, the grit of a teacher, the socioeconomic status of the community, the principal's pedagogical beliefs, the standardized testing regime, the school schedule, the level of parental involvement, and so on. In spite of the complexity of these systems, most educational policy makers and reformers have yet to rely on quantitative models to enable more informed intervention decisions. Our objective is to develop a modeling *framework* that will help policy makers identify and understand barriers and enablers for educational interventions in different school settings. No single model is applicable across a broad spectrum of school settings. However, a unified framework could be developed to create models for particular contexts. Ultimately, by applying the framework to diverse school settings, models will be built and analyzed to identify common attributes and relationships that are likely to help or hinder intervention implementation. The framework, models, and heuristics can inform policy makers about the risks of intervention implementation in a given school prior to resource allocation.

The educational system is a complex system because of the following properties: constant change, tightly coupled parts, feedback loops, nonlinearity, self-organization, adaptation, and emergence.[2] These properties represent characteristics of complex systems in general. As such, modeling such a system requires rigorous systems engineering and operations research techniques.[3] Recent advances in this area include the application of system dynamics (SD) and agent-based modeling (ABM) to simulate US student interest and selection in STEM (Science, Technology, Engineering and Mathematics).[4,5] These models are a good starting point, but they take a top-down view of the education system and do not adequately capture grass-roots mechanisms at the school level. While some system dynamics-based school-level models exist to investigate policy impacts on enrollment and academic performance of students, these models rely heavily on survey data to formulate causal relationships without a mechanism for distinguishing correlation from causation.[6,7] Beyond SD and ABM, social network analysis can be an important tool for understanding a particular school environment. Education researchers have begun to analyze the effects of teacher networks in implementing instructional reforms.[8,10] Thus far, however, social network analysis of school systems in the education literature is done in isolation of the modeling techniques in the engineering literature.

In order to better understand the effects of an intervention in a particular school system, systems engineering and education research approaches need to be combined, leveraging SD, ABM, and social network analysis where appropriate. This view is consistent with Maroulis & Guimerà, who call for the use of complex systems analysis, agent-based modeling, and social network analysis techniques in education policy.[11] These techniques are appropriate when dealing with social systems; people can be modeled as agents or as nodes of a social network connected through links representing their relationships. In this paper, a framework is presented for modeling a *particular* school system intervention and analyzing the critical factors that can cause the intervention to succeed or fail. This novel technique makes use of ABM and social network analysis, as well as several analysis tools from systems engineering to identify the aspects of the model that are most likely to impact the success or failure of a particular intervention. The remainder of the paper is organized as follows: In the next section, the modeling framework and a case study are presented in tandem such that each step of the framework is accompanied by an illustrative example. The framework includes the initial construction of a social network of agents, as well as detailed agent class definitions, attributes, relationships, and rules for state change. Simulation results and analyses are presented to enable deeper understanding of the drivers for intervention success, and model verification steps are provided. Finally, conclusions and future work are discussed.

2. Framework for Analyzing a School System

To begin development of the framework, a small case study is considered. The case study is an *Engineers Without Borders* [12] (EWB) chapter that was successfully implemented in a magnet school setting through a partnership with Georgia Tech as part of a National Science Foundation GK-12 grant. In its first year, the lead teacher and graduate student reformer were able to amass sufficient financial resources to send club members and chaperones to travel to Tanzania to implement a solar cooker project. While the EWB chapter continued for a second year, the lead teacher and principal of the school had changed. As a result, the enthusiasm of the teacher and other agents was not sufficient to raise the funds required to travel to Africa with the students. Because of these two known interventions and outcomes, this case study is ripe for testing a model under different conditions.

2.1. *Agent-Based Model*

Agents

A first step in creating the ABM for a school system is to examine the network of people who play a role in the success of the intervention. In ABM, agents simply represent people or classes of people with different attributes. The network of agents for the EWB case study is shown in Figure 1. In this case, the principal, teacher, reformer, and school partner were key agents, as well as the community, which for simplicity is modeled as one agent rather than considering individual entities. However, within the class of students who participated, we do model individual students as having their own attributes and relationships. In the figure, certain students are shown to have larger or smaller spheres of influence—they may be popular or may be leaders, which would affect how many other students they influence.

It should be noted that this agent network is by no means exhaustive. For example, the federal, state and local governments that play a major role in the education system could have been included, or individual community entities could have been modeled. However, in order to keep this initial case study simple enough, these agents were omitted. This is a reasonable assumption in this case because the government did not directly impact the variables of interest. However, different cases may require larger and more detailed agent networks. Selecting appropriate system boundaries will be considered in more detail as the framework is further developed, but as with modeling any system, there will be a trade-off between model complexity and model accuracy.

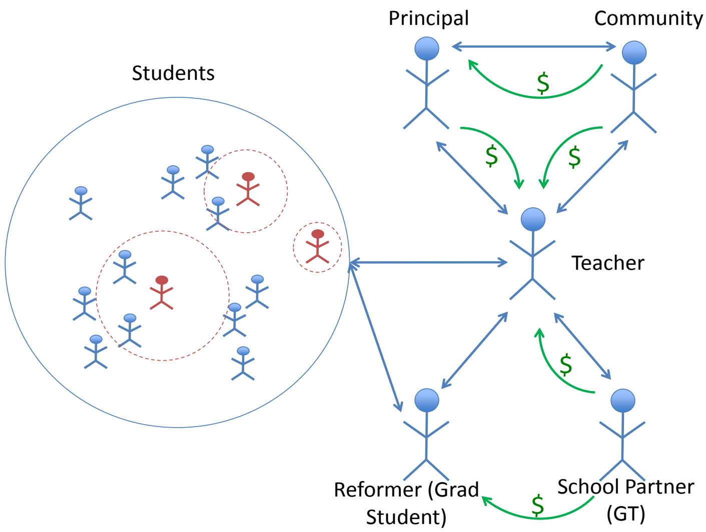

Figure 1: Agent Network for EWB Case Study

Attributes

Attributes are characteristics of the agents. In this case, the following attributes are modeled for each agent class:

- **Students:** Career aspirations, cognitive ability, self-efficacy, perseverance, socioeconomic status (SES)
- **Teacher:** Support for intervention, cognitive ability, self-efficacy, organizational citizenship
- **Reformer (Grad Student):** Leadership, cognitive ability, self-efficacy, perseverance
- **Principal:** Support for intervention, self-efficacy
- **Community:** Support for intervention, population, tax-base
- **School Partner (Georgia Tech):** Support for intervention

A detailed description of the above attributes and their measurement scales can be found in Llewellyn et al.[13] Research tools exist for measuring some of these attributes and many others that are germane to school studies [14]; however, for this case we used expert knowledge from the teacher to estimate these attributes on a Likert scale. Again, this list of attributes is by no means exhaustive. Defining the attributes that are relevant to a particular case study along with appropriate measurement instruments will be investigated in future studies.

Environment

In this ABM, the environment includes the relationships between the agents and the exchange of resources. Relationships enable agents to impact other agents' attributes, and each relationship is characterized by an attribute representing the relationship strength. In general, we refer to relationships between different agent classes as interrelationships, while we refer to the relationships among the same agent class, such as the student population, as intra-relationships. The blue arrows in Figure 1 denote the inter-relationships, and it is assumed that all of the students are connected via intra-relationships. While unlinked agents may interact with each other, it is assumed that limited interaction will not impact this case study. The resource flows are represented by the green arrows in Figure 1. In the EWB case study, there is a demand for money to send the agents to Tanzania to install a solar cooker. The sources of money in this case are the community and the school partner, and money flows from these agents to the principal and the teacher through the set of links that connect them. In general, the relationships modeled for this case study are limited to those that either facilitated resource flows or those which were directly affected by the intervention.

Rules

Rules govern the change in attributes of the agents and the environment. We model the change in the states as a Discrete-Time Markov Chain (DTMC), meaning that future states depend only on the current state of the system and not on its past states. There are two main assumptions that must be made to model system changes as a DTMC. First, it is assumed that change can be modeled as taking place in discrete time steps. Second, it is assumed that changes in the agents' attributes depend only on the current attribute level and current relationships and does not depend on past system states. To model this, the time horizon for the intervention is divided into discrete time periods, during which the attributes of the agents and their relationships have some probability of change. There are three possible movements in the states: improving, no change, or worsening. The state change probability equation is made up of two components: one is for the phenomena captured in the model, that is a *non-random* component, and a *random* component accounts for parameters outside the scope of the model which may affect the state change. The following equation represents the general structure of the changes taking place in the model:

$$p_{change} = w_{non-random} \cdot p_{non-random} \cdot f_s + w_{random} \cdot p_{random} \tag{1}$$

where p_{change} is the overall probability of change, $p_{non-random}$ captures the 'modeled' aspects of change, and p_{random} captures chance occurrences. These probabilities are vector quantities representing the three possible state changes, $[p_{improve}, p_{stay}, p_{worsen}]$, which add up to 1. In addition, there are weights, $w_{non-random}$ and w_{random}, which quantify the percentage of change probability associated with each of the non-random and random probability vectors. The sum of these weights is always 1, but individual weights can be tuned for each model and their impacts can be investigated using sensitivity analysis, which will be discussed in subsequent sections. Finally, the non-random portion of the equation includes a multiplicative factor f_s which captures an 'S' curve pattern in learning. This curve represents cumulative adoption of innovation or change in a complex adaptive system.[15]

Rules: Change in Attributes

The non-random change probability, $p_{non-random}$, for a particular agent is a function of three qualities: the current attributes of the agent, the agent's current relationships with other agents, and the attributes of the agents with whom the agent has relationships. Different agents' attributes change over time. As an illustration, consider the non-random change probability for the attribute 'support for intervention' of the agent 'community,' shown below:

$$p_{nr-comm}(t+1) = w_p \cdot inter_{p-c}(t) \cdot support_p(t) + w_t \cdot inter_{t-c}(t) \cdot support_t(t) \tag{2}$$

where $p_{nr-comm}(t+1)$ is the non-random probability of change in the community support for intervention in time period $t+1$ and is dependent only on the system state at time t. As seen in Figure 1, the community has relationship ties with the principal and the teacher. As such, the first term is for the relationship with the principal, where w_p is the weight for this term, $inter_{p-c}$ is the interrelationship between the principal and the community at time t, and $support_p$ is the principal's support for intervention at time t. Similarly, w_t is the weight for the teacher term, $inter_{t-c}c$ is the interrelationship between the teacher and the community at time t, and $support_t$ is the teacher support for intervention at time t. Again, $w_p + w_t = 1$ and weights may be tuned for the particular case. This equation is representative of attribute change probability equations for different agents in the model.

Rules: Change in Relationships

In addition to attributes, relationships also change over the course of the intervention: relationships can become more positive, stay the same, or may sour. Two concepts from social network theory aid in modeling this change in relationships: homophily and structural balance.[16,17] Homophily assumes that individuals are more likely to form ties with other individuals similar to them, including demographics, hobbies, and interests. Structural balance assumes that individuals are more likely to form positive ties with friends of friends, negative ties with friends of enemies, and positive ties with enemies of enemies. We use these two concepts to model the change in relationships. The following equation models the non-random intra-relationship change probability for two students i and j as a function of their structural balance and homophily.

$$p_{nr-ij}(t+1) = \underbrace{w_{sb} \cdot \underset{k \in S \backslash \{i,j\}}{\text{avg}} \left\{ \text{sign}\big(intra_{ik}(t) \cdot intra_{kj}(t)\big) \cdot \min\{|intra_{ik}(t)|, |intra_{kj}(t)|\} \right\}}_{\text{structural balance}} + \underbrace{w_h \cdot h_{ij}(t)}_{\text{homophily}} \quad (3)$$

where $p_{nr-ij}(t+1))$ is the non-random change probability between student i and j in time period $t+1$, and S is the set of all agents belonging to the student population. To model structural balance, the weight for this term, w_{sb}, is multiplied by the average relationship strength for all the students in S with whom i and j interact. The sign function captures the structural balance tenets described previously, while the minimum function depicts that the magnitude of the effect is constrained by the *weaker* of the two relationships that students i and j have with another student, k. Therefore, $intra_{ik}$ is the intra-relationship between students i and k and $intra_{kj}$ is the intra-relationship between students k and j in time period t. For the homophily component, w_h is the weight and h_{ij} is the measured level of homophily between student i and j. Again, $w_{sb} + w_h = 1$ and these weights may be adjusted appropriately. The change in the relationships between the other agents is modeled similarly; however, relationships between different agent classes are bi-directional, meaning that feelings do not have to be mutual.

Rules: Resource Flows

Resource flows are the final component modeled in the ABM framework. Resources could be time, money or any other precious entity depending upon the case being modeled. In the EWB case, the resource is money to send a group to Tanzania, and this demand drives the school partner and the community to provide funding. Each agent has a budget which cannot be exceeded. For this model, it is assumed that the school partner had a specific budget from a grant and that the community budget depends on its tax base and the number of people in the community. However, the full budget amount is not always supplied; money flows are dependent on the strength of the relationship between the agents through which the money must move. The equation below represents the flow of money at time $t+1$ from the school partner to the teacher:

$$m_{sp\to t}(t+1) = inter_{sp,t}(t) \cdot support_{sp}(t) \cdot b_{sp} \quad (4)$$

where $m_{sp\to t}(t+1)$ is flow of money from the school partner to the teacher in time period $t+1$, $inter_{sp,t}$ is the interrelationship between the school partner and the teacher in time period t, $support_{sp}$ is the school partner's support for intervention at time t and b_{sp} is the available budget for the school partner. Other money flows are modeled similarly. This completes the set of rules which govern the state changes in the ABM. In the next section the simulation and analysis portion of the framework is presented for the EWB case.

2.2. Simulation Results

To simulate the case study, the initial state of the system must be defined. For the EWB case, data was collected regarding the initial and end states of the system after the intervention with the help of the teacher involved in the EWB reform—this is the same teacher agent shown in Figure 1. Because this is a first trial of the framework, using expert knowledge is considered to be a viable option. In future studies, more robust data collection instruments will be used. After the initial state is provided, the user must then define the criteria for a successful end state. This acceptable end state may be quite different from case to case, but in this case we defined the following success criteria: 4 students to install the solar cooker with positive relationships amongst themselves, the teacher and the reformer, adequate student test scores, and enough money to send at least 4 students, the teacher, and the reformer to Tanzania with a solar cooker, which translates to ~\$20,000 raised.

Once the initial state and the criteria for success are defined, the agent-based simulation is run to determine the final state of the model. For this case, the model was coded using *C#* in Microsoft Visual Studio 2010. The system configuration was Windows 2007, 64 bits, 8GB Ram and 1.73 GHz Processor. An average over 1000 simulations was used to determine the simulation outcomes for years 1 and 2, the runtime for this was about 55 seconds each.

Year 1 Results: The final state at the end of the simulation for the first year met all the criteria for the trip to Tanzania to be feasible. Specifically, the community support for intervention reached was 1.8 on a scale of (-2, 2), the total money generated to meet the demand was about \$44,100, and the relationship criteria were satisfied. Hence, the end state reached by the model was consistent with reality, where 7 students, the teacher, and reformer successfully installed a solar cooker in Tanzania.

Year 2 Results: In the second year of the intervention the social network changed drastically. The new principal and teacher involved did not have strong community ties. In this case, the final simulation state did not meet all the criteria for the trip to be feasible. Even though there were qualified students with positive relationships, the community support for intervention was not very high, and so the estimated total money generated was only about \$10,400, which is significantly less than the required \$20,000. This end state is also consistent with reality in year 2 when the trip did not happen due to the shortage of funds.

2.3. Analysis

While simulating outcomes that are consistent with reality is helpful in this initial framework development stage, the real contribution of this framework is two-fold: the sensitivity analysis of the model and the determination of factors that greatly affect the outcome. To assess the model dependency on uncertain parameters such as weights and the S-curve parameter, we conduct a sensitivity analysis of the results with respect to the model parameters that are not inputs. In order to then discern the most important attributes and relationships in the initial state, we use a factorial sampling method called the Method of Morris (MoM) to analyze the effect of inputs on the output.[18] This method is useful to determine a subset of input variables from amongst a larger set that most likely have a significant impact on a particular outcome.

Because this is a stochastic model, the same set of inputs can give different outputs. However, if we run a sufficiently large number of iterations, the variance in the results is small and we can take an average of the results over these iterations to simulate a 'deterministic' output. This is necessary in order to perform accurate sensitivity analyses so that results are not skewed by the model's natural variance. To accomplish this, we run 1000 iterations for the same inputs and use an average result. In this way, the change in the output can be attributed to the change in the inputs with a sufficient level of confidence.

<u>Sensitivity Analysis</u>

Sensitivity analysis is conducted with respect to the weights used in the change equations, parameters of the S-curve, and the granularity of time periods. Table 1 shows the effect of change in the principal and teacher weights from equation (2) on the community support for intervention and total money generated. A few extreme values are shown on either end of the spectrum, and the weights are incremented in step sizes of 2% in the range of interest for this particular case study. These weights represent the relative influence of the teacher and principal on the community's attributes; for example, a weight of 0% for teacher implies that the community is only affected by the principal, and the total weight must add up to 100%. The range of interest was determined using expert judgment from the teacher involved in the intervention. The support for intervention attribute is quantified using a scale from -2 to 2. The negative scores on this scale represent negative traits of the attribute, with zero being neutral and positive numbers indicating positive traits. The actual numbers on this scale are unimportant—it is the relative change in the attribute levels across time periods that defines the success or failure of the intervention. The principal and teacher initial support for intervention are taken as 1 and 2, respectively. This is different from the starting conditions in year 1 when both the teacher and principal support for intervention were 2. This change is made to better conduct the sensitivity analysis—the starting conditions in year 1 would have masked the effect of change in these weights on the final state. The community support for intervention and the total money shown is the level reached by the end of the time horizon for this case study and is based on the average of 1000 simulation runs.

Table 1: Sensitivity analysis with respect to weights

Number of iterations	**Principal Support_t_0**	**Teacher Support_t_0**	**w_principal**	**w_teacher**	**Community Support_t_n**	**Total Money_t_n**
1000	1	2	0%	100%	1.83	44100
1000	1	2	30%	70%	1.59	36406
1000	1	2	50%	50%	1.41	30315
1000	**1**	**2**	**60%**	**40%**	**1.32**	**27373**
1000	**1**	**2**	**62%**	**38%**	**1.3**	**26652**
1000	**1**	**2**	**64%**	**36%**	**1.29**	**26251**
1000	**1**	**2**	**66%**	**34%**	**1.27**	**25667**
1000	**1**	**2**	**68%**	**32%**	**1.24**	**24834**
1000	**1**	**2**	**70%**	**30%**	**1.24**	**24453**
1000	1	2	80%	20%	1.14	21627
1000	1	2	90%	10%	1.05	19003
1000	1	2	100%	0%	0.93	16184

There are two key observations that can be made from this analysis. One is that the community support for intervention and the total money generated are indeed responsive to the change in weights; specifically, the final state of these attributes decrease as the weight for the principal increases because the principal support for intervention is less than the teacher support for intervention. Another observation is that for the highlighted region, where the weights are assumed to lie for this case study, the weights do not have a significant impact on the outcomes. This is appropriate, as we are interested in determining whether or not the final state is likely to fall under an umbrella of acceptable states without knowing this weight precisely. In this case, all the final moneys exceed the required \$20,000. In addition to this analysis, sensitivity analysis was carried out for other weights, parameters of the S-curve, and the number of time periods. The model is again sensitive to these parameters, but not to an extent that the final state would become unacceptable due to slight changes in these parameters. This is useful in establishing the reliability of the model results.

Method of Morris

In this second phase of analysis, the most significant attributes, or model inputs, are identified for this case study. The analysis is done using the Method of Morris (MoM). For a more detailed discussion about the methodology please see Morris, 1991.[18] The MoM experiment is conducted with 24 different input variables, including attributes of the teacher, principal, and students, and the relationships between them at the start of the intervention. The response variable used to analyze the effect of the inputs is the total money generated by the end of the intervention.

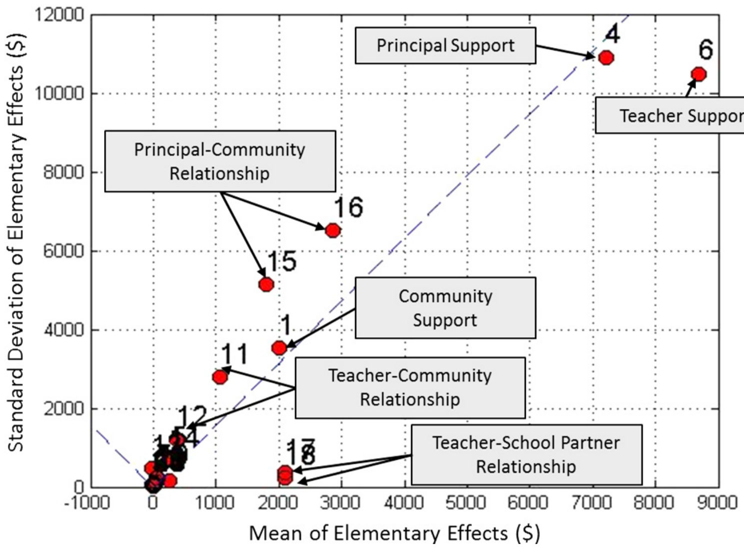

Figure 2: Method of Morris, Total money generated

Figure 2 shows a graph of the mean and standard deviation of the money generated due to each input variable. The mean of the effects is the x-axis and the standard deviation of the effects is the y-axis. The dotted lines correspond to the equation: Mean = ±2·SEM, where SEM is the standard error of the mean and is equal to the standard deviation divided by the square root of number of random orientations for each input, which for this analysis is equal to 10. The circles represent the different inputs. Inputs laying outside of the 'v' or far from zero have an impact on the response variable that is statistically different than zero. From the figure, the teacher, the principal and the community support for intervention, the bi-directional relationships between the teacher and the community, the bi-directional relationships between the principal and the community, and the bi-directional relationships between the school partner and the teacher have a significant impact on the money generated for the Tanzania trip. Clearly, if the success criteria were different, however, different attributes may dominate the response. MoM is versatile enough to accommodate these changes and isolate the main effects in a large collection of variables, though it requires the user to define the success criteria correctly.

2.4. Model Validation

The following steps were completed to validate the model results for the EWB case. For larger case studies a more comprehensive validation process would be use. The steps undertaken here are discussed in more detail in.[19]

Face validity: We asked subject matter experts (SMEs) including education researchers and school teachers whether the model and its behavior were conceptually logical and whether the model's input-output relationships were reasonable. A total of 8 SMEs were used. This was conducted in parallel to the conceptual model development and resulted in a number of iterations to improve model accuracy.

Internal validity: Several evaluations of the model were used to determine the stochastic variability in the model. The standard deviation in the results was two orders of magnitudes less than the mean implies model consistency.

Data validation: For this case, the data validation required comparing predicted money generated using the model to actual money generated in reality. In addition, attribute levels were verified for accuracy using a SME. For larger and more comprehensive cases, more comprehensive data validation will need to be performed.

Event validity: The occurrence of events, which in this case was only the 'trip to Africa', was compared to reality. For both years the occurrence or non-occurrence of this event was consistent with the reality.

Extreme condition tests: The model was subjected to extreme conditions of the inputs to catch any errors in the coding or the logic flow of the model. This aided in debugging the model and enabled understanding the inner mechanisms of the model.

Parameter variability- Sensitivity analysis: The model was run under different sets of parameter and input conditions and the output was analyzed. This is discussed above in the analysis section.

3. **Conclusions**

We have developed an initial framework for modeling a school as a complex system and identifying the key attributes affecting intervention success. The framework includes agent-based modeling and social network analysis techniques, coupled with sensitivity analysis and factorial sampling using MoM. We illustrate this using the EWB case study over two years, one in which the intervention was successful and the other in which it was not. The attributes that were identified to be most critical were the support for intervention of the principal and teacher, while the most important relationships were found to be between the principal and community, the teacher and community, and the teacher and school partner. Sensitivity analysis shows that the parameters used in the model apart from the input variables are fairly robust. This is important because the data can have inherent variability, and this noise should not cause significant changes in outcomes.

This case study was ideal for initial framework development because it had two different outcomes over two different years, which helped in developing insights about the success of this intervention. In future work, the framework will be expanded to accommodate larger and more comprehensive case studies. For example, school-based reforms often involve network of teachers that could affect the success or failure of the intervention. Modeling the teacher network and examining its impacts on a different case study is a likely next step. Ultimately, the modeling framework must be validated using several different case studies.

A systems perspective of a school setting while implementing an intervention can be helpful in determining the factors which are likely to affect its success or failure. The framework presented in this paper is a starting point for applying industrial and systems engineering techniques to the educational domain.

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