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NOROVIRUS OUTBREAKS: USING AGENT-BASED MODELING TO EVALUATE SCHOOL POLICIES

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ABSTRACT

Norovirus is a highly contagious gastrointestinal illness that causes the rapid onset of vomiting, diarrhea and fever. The virus relies on fecal-oral transmission making children particularly susceptible because of their increased incidence of hand-to-mouth contact. Side effects from the virus' symptoms can be problematic for children, i.e. severe dehydration. This paper examines transmission of the virus among elementary school classrooms, evaluating policies to reduce the number of children who become infected. The model focuses on the daily activities that allow for students' exposure to the virus including classroom activities and lunch/recess. Two policies that limit the amount of student-student interaction and were derived from guidelines published by the Center for Disease Control were explored. The results demonstrated that implementation of either policy helps reduce the number of students who become ill and that the sooner the policy is implemented the shorter the duration of the outbreak.

1 INTRODUCTION

Norovirus, or "Norwalk-like viruses", are a highly contagious form of viral gastroenteritis (Teunis et al. 2008). The virus causes an onset of nausea, vomiting, diarrhea, and low-grade fever, often described as "flu-like" symptoms and spreads easily through food, water and surfaces contaminated with the virus (Center for Disease Control and Prevention (CDC) 2015). Illness can come from contact with as few as 18 particles of the virus (Teunis et al. 2008; Stals et al. 2015) and has rapid incubation period of 12 to 48 hours (Hall et al. 2011) making venues such as cruise ships, hospitals, retirement homes, schools, and daycares ideal for outbreaks to occur (Robilotti et al. 2015).

An estimated 21 million people a year contract the Norovirus in the United States (CDC 2015). The virus is most often not fatal, however can be more dangerous to younger children and the elderly because the virus' symptoms can lead to secondary effects such as dehydration (CDC 2015). This brings rise to concerns in environments where children may be exposed to the virus. For example, in the fall of 2015 Alice Springs elementary school in Reno, Nevada experienced a Norovirus outbreak that resulted in over 100 children experiencing nausea, vomiting and diarrhea, and more than 80 students being absent on a single day (Stockwell 2015). This equates to more than 10% of the students experiencing symptoms and just under 10% of the students in the school being absent. Decreasing the number of students who fall ill not only helps keep the individual student healthy but it also helps to keep the contacts, such as friends and family, of the student healthy as well. This paper develops a model that demonstrates how the spread of Norovirus in a classroom might look in order to experiment with policies that may decrease the spread of the virus and the duration of the outbreak in the school environment. The policies implemented in the model were derived from CDC guidelines on the virus.

2 BACKGROUND

Between 2009 and 2010, almost 1 million of the children who contracted the virus received some form of pediatric care with the combined cost of treatment costing an estimated $273 million (CDC 2013a). These costs included outpatient visits and hospitalization. Young children are more prone to having side effects from the symptoms of norovirus making them a more at risk group when the virus is contracted (CDC 2015; European Centre for Disease Prevention and Control (ECDC) 2013).

An infected individual sheds the virus in both their stool and vomit and passed to others through the fecal-oral route (Robilotti et al. 2015). In a study looking at the quantity of virus particles infected food handlers can spread to working surfaces, it was found that 18±7 virus particles were collected from the working surface where it was concluded that 18 viruses produced a 50% risk of infection (Stals et al. 2015). However, becoming infected with the virus does not always lead to illness, the illness rate from infection was about 10% when infected with a single dose (103 Norovirus genomes which is estimated as the 50% infection dose, i.e. 18 viruses) (Teunis et al. 2008).

While, this rate of infection is recognized as extremely high for viruses (Teunis et al. 2008) and worrisome for adults, children have an increased vulnerability because of their increased hand-to-mouth rate. One of the ways the virus, especially among youth, is spread by touching objects contaminated with the virus and then touching your mouth (CDC 2013a). In a study conducted looking at children's frequency of hand-to-mouth contact saw that children between the ages of three and 12 (mean age of seven) were observed to have hand-to-mouth contact 6.7 times per hour (Freeman et al. 2001, Xue et al. 2007), making children, especially young children, particularly vulnerable to the spread of the norovirus infection.

Looking further at children's susceptibility of the Norovirus, the spread of the virus in the schools becomes an important focus area. Schools allow a large (and in some cases extremely large) number of children to be in a single location at a single time giving the virus opportunity to transmit to a large population, followed potentially by their families and the community. In recent history, outbreaks that occur in school settings have been handled by voluntary absenteeism (parents keeping children home to be safe), shutting the school down for a break (long weekend or early seasonal break) in conjunction with a disinfecting cleaning (Uren 2014, Wilson 2015). Nevertheless, there is no single policy put in place when a norovirus outbreak is identified at the school or classroom level. In order to explore how a classroom level policy may affect the spread of an outbreak, a model was created to simulate the spread of norovirus through a series of elementary school classrooms.

3 METHODOLOGY

3.1 Overview

Individual-based and transmission models have been used to evaluate influenza transmission and to assess policies implemented (in particular school closures) to help mitigate the spread of influenza among students and communities (Cauchemez 2008). Falling in line with previous models evaluating policies for reducing school contagion spread, an agent based model (ABM) was built to simulate the spread of the Norovirus among classrooms in a school. The model was built and run in Python using standard open-source packages, allowing different classes of agents to be built and evaluated. The main agent interaction takes place at the student level, however, the classrooms are able to implement different policies and the models metrics are collected at the school (entire grade) level.

The model focuses on the classrooms and students' interactions. The students' health status is based on the basic SEIR model, allowing students' health states to be susceptible, exposed, infectious, or recovered. This model focuses on three routes of exposure for students: seating arrangements (neighbors); daily group activities, which is the randomly pairing up students to work in groups of 2, 3 or 4; and the students' social interactions at lunch and recess. The students' social networks are represented using a small world network, which will be further described in Section 3.2.

Figure 1 shows a basic diagram of the daily routes of exposure for a student and the decision points used to model the exposure risks. Each route of exposure gives the student some level of risk to becoming infected. The students' infectious period is represented by a set number of days starting where the student is asymptomatic but infectious, followed by a set period where the student is symptomatic and removed from the classroom. Once the student enters the recovery stage, they return to the classroom and become healthy but susceptible since there is no immunity to norovirus. The simulation ends once all students have returned to a healthy status.

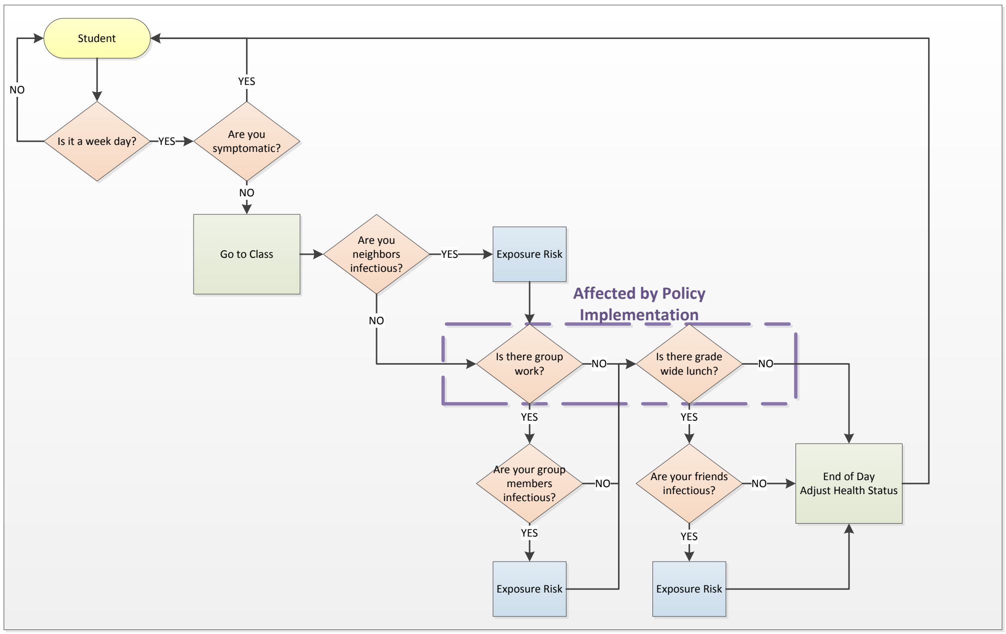

Figure 1: Daily decision points for each students' health.

3.2 Creating Friendship Networks

In order to properly represent the social ties of children for this model a modified small world network structure was created at the start of each set of runs. Homophily theories suggest that children who share similar attitudinal and behavioral characteristics will be friends with each other, such that friendships are built on similarities (Espelage et al. 2007; Cairns et al. 1995; Kindermann 1993).

Studies looking at the nature of youth interactions have concluded that the small-world structure among students reflects the flow of various kinds of information and student contacts (Cotterell 2007). In another study on student's daily contacts as it relates to influenza immunizations strategies revealed a low variance small-world network with in the school (Salathé et al. 2010).

As found in small-world networks, the social structure of a school possesses clusters of reciprocal friendships and class ties that are distributed across all children to some degree (Espelage et al.2007; Cotterell 2007). In order to properly represent these clusters intra-classroom and cross-classroom connections, two variables were used to build the simulated friendship network. The basic network model is based on the Watts and Strogatz small-world network model (Watts and Strogatz 1998). First all nodes were connected in a lattice structure, pairing to their neighbor on either side. Then each node was given a 60% probability to rewire a connection. That connection would be chosen at random from the nodes classmates, with a 10% chance to rewiring to a node from another class, therefore allowing students to have more friends within their own classroom than cross classrooms (Vu and Locke 2014).

The rewiring probabilities were chosen based on experimentation with the resulting network parameters. The final probabilities gave degree distribution, average shortest path, and clustering coefficients that aligned with research that has been done on children's friendship networks. Table 1 shows the simulated and reference values for the social network. The reference values are based on studies from that examined social ties of students from K – 2^{nd} grade and 4^{th} – 6^{th} grade. Some of the variation in values was based on placement in the network, or the students status (i.e., popular or not), however, this is not being evaluated as part of the current model. Also, it was found that at younger ages, pre-school, kindergarten, early elementary school, peer groups of male and female children are of similar size (Vu and Locke 2014), therefore, sex of the agent was not a factor in this model.

Table 1: Parameters achieved with simulated small world network.

Parameter	**Simulated Network Value**	**Reference Value**	**Source**
Group sizes	range 3 - 8.5 *(stdv=0.8)*	range 3-9	*Witvliet et al. 2010*
Average Degree	4.5 *(stdv=0.5)*	3.9 to 4.5	*Vu and Locke 2014*
Average Path Length	5.0 *(stdv=0.4)*	--	
Clustering Coefficient	0.113	--	

As can be seen in Table 1, the simulated networks produced a network with acceptably similar features to that of the real world data. The small standard deviations of the simulated network provides that while the friendships between the students change with the random generation of each network the overall structure remains consistent across runs. An example of the randomly generated network is shown in Figure 2.

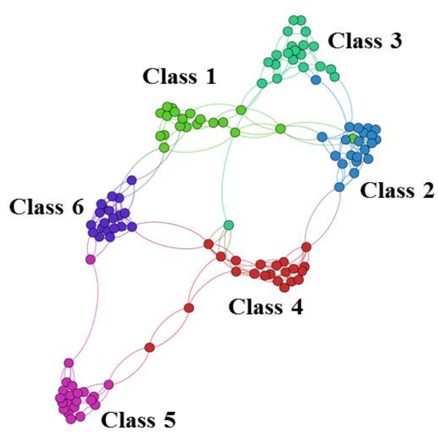

Figure 2: Example network structure.

3.3 Initializing the Model

Model runs use a standard United States (US) school week, where students go to school for five days and are home for two. The model does not simulate exposure over the weekend in the home or public venues. The Maryland State Department of Education 2013 Class Size Report assessed the average elementary classroom size in the state of Maryland to be 20.1 (The Maryland State Department of Education 2013). Furthermore, Maryland elementary schools were found to have approximately were found to have approximately 120 students per grade (US Department of Education 2001). Based on this information, the model was initialized with a classroom size of 21 students and a total of six classrooms for the grade. Each classroom was set with assigned seats arranged in rows, giving each child two neighbors whose desk touches their own, with the exception of students with end seats who only have a single neighbor.

In addition, the assumption is made that the majority of daily teaching is done within the same classroom setting, unlike classroom systems where students move around throughout the day (e.g. high school). This model focuses on classrooms taught by a self-contained teacher, or teachers who teach multiple subjects, keeping the class together throughout the day (Perie et al. 1997). This helps alleviate effects that could arise from students cross-contaminating classrooms. A study looking at the amount of time teachers spend teaching during a normal school day saw an average of six hours twenty-four minuets spent in the classroom per day, most of which is spent with a core class of student (Perie et al. 1997). This model aims to recreate the classroom exposure and the lunch/recess exposure. The current version of the model does not evaluate potential exposure risks that come with elective periods when classes move classrooms.

For the five school days, the students have the opportunity to become infected with the virus by their assigned neighbors (based on assigned seats), students they connect with for group work, and their lunch and recess friends. Each one of these networks holds a certain probability of exposure. The neighbors of a sick student and group members of a sick student are given a 10% chance of becoming sick themselves. This is based on the assumption that virus shed by the sick neighbor to the shared desktops, which are hard surfaces, contains at least the single dose of the virus (18 virus particles) needed for infection (Teunis et al. 2008; Stals et al. 2015). An 18 virus dose was studied to have a 50% probability of infection (Teunis et al. 2008), however, since the exact measure of virus particles exist on hard surfaces in schools experiencing outbreaks, it is assumed that the 18 virus particles is a minimal exposure and all students who are exposed become infected, but have only 10% chance of becoming sick (Teunis et al. 2008; Stals et al. 2015). Students in the infected students' friendship network are given a very slightly increased probability of being infected (12% versus 10%). This increase is assumed because of the increased hand-to-mouth contact that would take place during lunch time interactions.

Once a student becomes sick, they are treated as asymptomatic for two days' time (incubation period) during which time they can spread the illness to others (CDC 2015; CDC 2013b; Gemmetto et al. 2014) while not showing symptoms themselves. After the two day incubation period the sick student is sent home for an isolation period of three days. Following the three day isolation, the student is assumed to have resumed a healthy status and returns to school (CDC 2015; ECDC 2013). The students 'sick'/ 'healthy' status is updated at the end of each day, as well as, there absentee status. If the student has completed 2 days with 'sick' status, they are temporarily removed from the school. At the start of the simulation attendance is taken at the classroom and school level to identify the number of students that are absent and to assign policies (if implemented) as needed. Table 2 shows all the initial model parameters selected for the model, excluding those shown in Table 1 for the creation of friendship networks.

Table 2: Initial model parameters.

Parameter	Value	Source
Classroom Size	21 Students	*The Maryland State Department of Education 2013*
Number of Classrooms	6	*US Department of Education 2001*
Risk of Infection	50%	*Teunis et al. 2008*
Illness Rate (Post Infection)	10%	*Teunis et al. 2008, Stals et al. 2015*
Incubation Period	2 days	*CDC 2015, CDC 2013b Gemmetto et al. 2014*
Symptomatic Period	3 days	*CDC 2015; ECDC 2013*
School Days per Week	5 days	--
Weekend Days per Week	2 days	--

3.4 Policy 1

Policy 1 follows the same procedures as the baseline except the classrooms keep count of the number of students absent and change their social interactions accordingly. The classrooms make a daily decision based on the absenteeism rate (AR) on whether to implement the policy or not. If the class reaches an AR higher than the defined limit, Policy 1 is implemented. For example, an AR of 10% for a classroom of 21 students would be 2 students absent when the policy is implemented; where as an AR of 40% would require 8 students to be absent before implementing the policy.

Policy 1 instructs classrooms to stop conducting group work, thereby removing one of the routes of exposure as based on recommendations by the CDC for policies to use in Norovirus outbreaks in healthcare settings (CDC 2013b; CDC 2011). For simulations running Policy 1, students can still become infected by seat neighbors and by friends at lunch/recess.

3.5 Policy 2

Policy 2 is implemented in the same manner as Policy 1. The classrooms take daily attendance and once the AR value has been reached the policy is implemented. Policy 2 builds on the CDC recommendation used for Policy 1, discontinue all forms of group activities (CDC 2011). In the first policy, group activities alone were restricted whereas Policy 2 suspends both group activities within the class and grade-wide lunches. For a policy such as this to be implemented, the children would be required to eat in their classrooms to minimize contamination from outside their classroom. When Policy 2 is implemented the only method of spread is through assigned seat neighbors because the students no longer interact with their group work or friendship networks.

3.6 Implementation

At the start of each simulation the following parameters were randomly assigned: the initial ‘sick’ student, the network connections of each student, the teacher assigned group (size and group members). Based on the initial randomized parameter assignment, a single simulation should be run multiple times to explore the variable space of that particular configuration. Therefore each simulation of the model is run 4,000 times in order for the average across the runs to stabilize. Run increments were tested from 1,000 to 10,000, however, 4,000 was the point where the averages reached a steady state. Table 3 shows the average outbreak duration, standard deviation and variance at four different run increments to demonstrate how increasing the number of runs beyond 4,000 did not provide a significant change to the output of the model. This was additionally tested with a traditional T-test to verify there was no significant difference in results between the 4,000 runs and 10,000 runs. Similar tables were created for the other variables to identify the minimum number of runs that appropriately capture the behavior of the model, all which resolved to 4,000 runs. This conclusion was also verified graphically as the point at which additional runs do not affect the models output and the averages reach a near steady state.

Table 3: Stabilizing results across runs.

Outbreak Duration (Days)			
Number of Runs	**Average**	**Standard Deviation**	**Variance**
4,000	22.32	2.56	6.57
6,000	22.27	2.55	6.51
8,000	22.31	2.67	7.17
10,000	22.32	2.66	7.11

Additionally, it should be noted that because the start of the virus is a randomly selected student and then transmission is based on probabilities relating to contact, approximately 3% of the runs resulted in no outbreak. However, this percentage remained consistent regardless of the number of runs, i.e. an average of 30 runs per 1,000 saw no outbreak. Therefore the effect of the ‘no outbreak’ runs is proportional across the baseline or policy implementation results.

The baseline, Policy 1 and Policy 2, with varying ARs, were each run for 100 simulations at 4,000 runs per simulation. The baseline simulations have no policy implementations and the virus is allowed to run its course through the school.

4 RESULTS AND DISCUSSION

4.1 Baseline

The baseline simulation was run in an effort to verify that the model matched closely with reality, such that the influence of policies could be tested. From the baseline simulations the results (Table 4) showed the average outbreak duration was 22.1 days, average maximum absentee rate was 11 students (9%), and average total number of affected student population at the end of the outbreak was 31.8 students (25%). Since the baseline runs include 100 randomly simulated networks, the range of total affected students is also shown. This rate ranged from 17% to 34% (21 to 43 students of the 126 total).

A study that reviewed 47 Norovirus outbreaks across different venues provided information on the virus’ duration within a population. The average duration across healthcare facilities (average 25 days), hospitals (average 22 days) and nursing homes (average 14 days) is reported at 20 days (combining all facility types) with a range of 9 – 92 days (Harris et al.2010). The average seen in the school simulation was 22.1 with a range of 5 – 100 days.

Table 4: Baseline simulation results.

	Simulated Values	Reference Values	Source
Duration (Days)	22.1	20	*Harris et al. 2010*
Duration Range (Days)	5 – 100	9 – 92	*Harris et al. 2010*
Max Absentee Rate	11 (9%)	Not available	
Total Number of Students Affected	32 (25%)	28%[1], 25%[2-7]	[1] *Matthews et al. 2012* [2] *CBS News 2014* [3] *ABC News 2015* [4] *Lopez 2012* [5] *Stockwell 2015* [6] *Uren 2014* [7] *Wilson 2015*
Range of Students Affected Across Runs	21 - 43 (17 -34%)	13% - 43%1 , 17% - 34%[2-7]	

Two methods were used to evaluate the attack rate, the overall number percent of the population affected by the virus. A study that reviewed attack rates across 44 school outbreaks found an average of 28%, with a range of 13% to 43% (Matthews et al. 2012). This was complemented by a cursory look at recent (2012 – 2015) US school based Norovirus outbreaks. Five news reports were pulled to see how the reporting matched to the references. The data pulled from the news reports is provided in Table 5. The average attack rate was calculated at 25% with a range of 17% to 34%. It is noted that these calculations are based on the total number of students infected at the time of the news report.

Table 5: Statistics pulled for schools experiencing Norovirus outbreaks.

Report Date	School	Approximate School Population*	Reported Number Students Ill[ł]	Calculated Attack Rate[ł]	Source
2015	Alice Smith Elementary School (Nevada)	746	100	13%	*ABC News 2015* *Stockwell 2015*
2015	Conger Elementary School (Oregon)[3]	401	75	19%	*Uren 2014*
2014	Garfield Elementary School (Minnesota) [4]	385	80	21%	*Willson 2015*
2014	Condon Elementary School (Massachusetts)[5]	800	150	19%	*CBS News 2014*
2012	Medea Creek Middle School (California)[6]	1127	320	28%	*Lopez 2012*

** Based on 2015 data search for number of students (School Digger 2015)*
[ł]At the time of the news report

4.2 Policy Implementation

Following the establishment of a baseline, the two policies were then modeled to test how the classroom policies affect the spread of the virus. The selected starting AR was 10%, meaning that classrooms would implement Policy 1 or 2 when more than 2 students were absent with norovirus symptoms. The results implementing the policies in the simulation are shown in Table 6. All the metrics for the simulation showed a significant drop, based on a 95% confidence, over the baseline. Policy 2 showed a significant difference from Policy 1 at 95% confidence. These results suggest that implementing either policy with a

10% AR would help reduce the duration of the outbreak, minimize absenteeism rates and decrease the total number of students affected by the illness.

To examine how sensitive these results are to the AR, the AR was varied from 10% to 40% (2 student – 8 students) before policy implementation. The results are shown in Table 6, all values are show significant reduction, with 95% confidence, except the maximum student absentee rate for Policy 1 at AR 40%. The value here was not statistically different from the baseline.

The results from policy implementation demonstrate either policy at any point in the outbreak can help to reduce the number of students who fall ill and become absent, reducing the overall duration of the outbreak, AR and total number of students affected. Other mitigation models which look at minimizing school closures cite one reason to reduce the socio-economic impact of closure for parents and the community (Gemmetto et al. 2014). The policies suggested in this paper, do not require school closure only classroom and school day modification. In addition the policies are limited to the classroom, when that classroom reaches its critical point, therefore not requiring entire school or entire grade participation.

As one would expect, the longer delay between the start of the outbreak and the implementation of policy leads to diminishing returns for both Policy 1 and Policy 2. An AR will be reached where it will too late to implement policies for any large benefit. The point where the policy was fully ineffectual was not reached in the simulations, AR 40% indicates that point being approached. For Policy 1 at an AR 40%, the maximum absentee rate seen does not differ with significance from the baseline. While statistically not greatly different, the values for duration and attack rate for Policy 1 at 40% are approaching those of the baseline. As could be imagined, 40% of a single class being absent is extremely high and not likely to occur unprovoked by illness; more favorable results would come implementing policy prior to this point.

Table 6: Results for Policy 1 and Policy 2 with varying AR.

		Duration (Days)	**Max Absentee Rate**	**Total Number of Students Affected**	**Range of Students Affected Across Runs**
Baseline		22	11 (9%)	32 (25%)	21 - 43 (17 -34%)
Policy 1	***AR 10%***	17	8 (6%)	18 (14%)	13 - 24 (11 -19%)
	AR 20%	19	9 (7%)	24 (19%)	17 - 35 (14 -28%)
	AR 30%	21	10 (8%)	27 (22%)	19 - 37 (15 - 29%)
	AR 40%	21	11** (8%)	30 (24%)	19 - 41 (15 - 33%)
Policy 2	***AR 10%***	9	5 (4%)	6 (5%)	6 - 7 (5%)
	AR 20%	13	7 (6%)	12 (10%)	10 - 15 (8 - 12%)
	AR 30%	16	9 (7%)	18 (15%)	14 - 24 (11 - 19%)
	AR 40%	19	10 (8%)	24 (19%)	17 - 32 (13 - 26%)

***Not significant from baseline at $p < 0.05$*

Additionally, it should be pointed out that Policy 1 is far easier to implement than Policy 2. Policy 2 would require more logistics and be more costly for school administration to accommodate students who purchase or receive lunch through the school. Food would have to be delivered to the classroom or picked up and brought back by students in order for lunchtime to be contained to the classroom. Also classrooms would likely need support for teachers during the lunch period since it is often contractual that unionized teachers in public schools receive a lunch break (most often in the same timeframe as when students eat). This likely does not include all logistic challenges that implementation of Policy 2 would encounter, it demonstrates that policy implementation does not come without challenges.

4.3 Assumptions, Limitations and Future Work

This model provided very positive results for the implementation of school policies to help reduce the duration of a norovirus outbreak, however, like much of the work done in the field of policy modeling there are assumptions and limitations that were required to build an experimental model. First and foremost, it is assumed that information is readily available for decision making, i.e. the teacher knows the number of children who are out and why they are out at the beginning of the day in order to implement one of the policies. Second, the model assumes that parents keep the student home for the full 3 days while the child is symptomatic. Additionally, the model is limited by the modes of transmission included. As stated previously, this model does not look at cross grade transmission or environment-to-student transmission from rotating classrooms throughout the day or week or the use of restrooms in the school environment.

Future iterations of this model, or models of this type, would benefit from including the environment-to-student modes of transmission. This would allow for experimentation of sanitation/disinfecting policies that could be put into place during an outbreak.

5 CONCLUSIONS

The Norovirus model detailed in this paper provides a reasonable representation of how the virus spreads between students in for a single grade of an elementary school. The policies selected were simple requiring minimal change to the constructed school day and not requiring entire school commitment since they can be implemented per classroom. Both policies were evaluated with an AR which varied from 5 – 40% and showed the improved duration and total number of students infected, when implemented with lower ARs. This is a very logical conclusion because the sooner the policy is implemented the fewer contacts each student has reducing the spread of the illness.

Diseases that are spread through schools are not restricted to staff and students. When the school day is over, children go home and can expose their parents, siblings, neighbors, and community to the virus as well. Outbreaks of viruses, such as Norovirus, can cause social and economic stress on a community. A study was conducted to look at the economic costs of Norovirus outbreaks in Spain. The study shows how the virus accumulates cost when incorporated the cost of medical visits (hospital/doctor's office), medications, lab diagnostics, etc., as well as costs for lost work days (either from sickness or caring for others who are sick) (Navas et al. 2015). These costs are mostly unexpected costs (not routine), since they are based on the contraction of a virus. This can create strain on individual families and potentially the community. While the policies put forward in this paper are idealized; they help put forward ideas on how to minimize the number of children exposed to the virus through schools which could reduce the socio-economic impact of an outbreak on the community.

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