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Modeling and Simulating Student Protests Through Agent-Based Framework

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ABSTRACT

This paper presents an agent-based model to study the effect of grievance, net risk, social, sympathy, and political influence on the likelihood of student protests emerging in South Africa universities. Studies of student protests in several fields have been conducted, but no ABM has been used to explore factors contributing to student protests. Student protests have proved to be disorderly, frequently leading to property damage, academic program cancellations, and injuries. Simulation experiments demonstrated that inequality level, number of activists, activist's influential size, number of friendship ties, suspend delay, and sympathy are elements that determine the model of social conflicts, since there are statistically significant in the logistic regression. For university administration to effectively handle disruptive student protest actions, risk management policies should focus on understanding network structures that integrate students' interactions to monitor the spread of opinions that initiate protest mobilization.

KEYWORDS

Agent-Based Model, Network Influence, Political Influence, Relative Deprivation, Social Conflicts, Social Influence, Student Protest, Sympathy

INTRODUCTION

Student protests at Public Higher Education Institutions (PHEI) in South Africa continue to be prevalent, even after more than two decades of democracy, for example, #FeesMustFall protest (Luescher, Loader, & Mugume, 2017). Students are becoming impatient when faced with current high tuition fees, decreased funding opportunities, inadequate student residence, and significant academic and financial exclusions, given the current political and socio-economical landscapes fueled by the promise presented by the National Plan for Higher Education (2001) document (Dominguez-Whitehead, 2011), hence we are currently witnessing high volume of state-directed protests in our

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institutions. Recent student protest actions have proven to be unruly and frequently leading to property damage, academic program cancellations, intimidation of non-protesting students, and injuries (Peté, 2015). Several studies of student protest have been conducted in a variety of fields, including social and political studies (Oxlund (2010); Dominguez-Whitehead (2011)), but no agent-based model (ABM) has been suggested to predict student protests at higher education institutions. The construction of such a model will aid in the forecasting of student protests.

Studying how social conflicts emerges from social context and how they lead into a protest remains a central important topic in political studies, history, social psychology, and sociology (Lemos, Lopes, & Coelho, 2014a). However, several studies that seek to evaluate communities through the framework of complex adaptive systems have increased in the last decade. The most adopted approach in modelling complex system is bottom-up technique, which represent a fundamental characteristic of ABM (Ormazábal, Borotto, & Astudillo, 2017). A number of studies based on conflict or violent collective behavior have shown how ABM through crowd simulation can support the development of a useful techniques to examine protests (Bhat & Maciejewski, 2006; Epstein, 2002; Lacko et al., 2013). In the early-2002, Epstein developed a widely adopted classical agent-based computational model of civil violence, and since then, crowd simulation has evolved. For example, the Epstein's model was adopted by among other, Lemos, Lopes, and Coelho (2014b), Kim and Hanneman (2011). Agent-Based Modeling Simulation (ABMS) approach is ideal when modeling a complex scenario, for example, studying the behavior of actual protest participants which involves the interaction of heterogeneous agents (Pires, 2014). This study aims to design, implement, and simulate a theoretically grounded Agent-Based Model (ABM) that predicts the emergence of student protests in order to gain insight understanding of macro-level behavioral dynamics of a complex student protest system at Public Higher Education Institutions (PHEI) in South Africa. The proposed model will assist in identifying micro-level behavioral patterns which may result into a protest action. The understanding of this emergent behavior will assist university management in several ways, such as identifying behavioral patterns that may result into a protest and subsequently prevent damage to property, intimidation of staff and non-protesting students and possible injuries (Peté, 2015).

The structure of this article is as follows: In the second section, an overview of the agent-based modeling method is provided. Then, the article presents an investigation of ABMs of social conflicts proposed by other scholars. Hypotheses and a conceptual model are then introduced with the description and implementation of the model. The article is concluded by the findings of the simulation experiment and followed by conclusion.

AGENT-BASED MODEL

ABM is an early majority modelling paradigm that is gaining its popularity in several fields that leads to modelling of complex dynamic systems such as student protests, artificial financial markets, pedestrian movement, and population dynamics (Macal & North, 2008). Agent based model is normally used as a bottom up individual-based approach to simulate heterogeneous and autonomous decision-making agents that uses behavioral rules to interact with their artificial world (Kiesling, Günther, Stummer, & Wakolbinger, 2012). ABM can be utilized as a methodology to simulate behavioral patterns which are challenging to be modelled using mathematical equations (Dada & Mendes, 2011). In addition, interactions of the agents within an ABM are represented by a set of behavioral rules and the emerged behavioral actions or patterns are observed at the macro level. Agents social interactions may have non-linear influence which can be a challenge to represent using analytical mathematical equations (Lu, 2017).

In ABM, social interactions can be categorized as micro-level, meso-level and macro-level. Micro-level represent agent to agent or agent to environment interactions at a local level (Démare, Bertelle, Dutot, & Lévêque, 2017). At micro-level, students can exchange their discrepancies in resources allocation (levels of inequalities) to formulate their dissatisfaction or grievances. Meso-level represents interactions between agents and their group of conformity (Kiesling et al., 2012). For instance, at meso-level, student activists can influence a group of students that are linked to their political group, or a student can influence friends that are linked to their social group as well as neighbors during protest recruitment. Macro-level represents the emergence of overall patterns of the system at a global level (Démare et al., 2017). For instance, macro-level represents the overall emerged behavioral pattern used to provide model users with insights about students' protest under conditions which are systematically represented within an environment. Co-evolution and emergence of social structures are the outcomes of agent-based model simulation (ABMS) which are mostly used in predicting human behaviour. System patterns accumulated from a series of changing behavioral rules by heterogeneous agents can lead to coevolving or emergent phenomena (Narasimhan, Roberts, Xenitidou, & Gilbert, 2017). Emergence represent the overall system behavioral patterns that are simulated, as well as resulting from the continuous interactions of agents at individual level over a set of time (Narasimhan et al., 2017). Co-evolving social structure are caused by peer-to-peer agent's behavioral influence. Agent Based Modelling approach represents a process that changes over a period of time (Dulac-Arnold et al., 2020). ABM contribute to the development of knowledge and understanding of significant processes and methods that enables complex adaptive systems to be solved. ABMs are used to formulate theories instead of regenerating the exact occurrence of events nor provide accurate predictive model (Dulac-Arnold et al., 2020). ABM aids in exploring the significance of several parameters under certain artificial world settings and various agents rule set (Dulac-Arnold et al., 2020).

Agent-based models of social conflicts, such as student protests, can help researchers get a better understanding of how social gatherings aimed at addressing social inequities mobilize a large number of people (Lemos 2018). Furthermore, the social conflict model may show how individuals choose to organize a collective group based on their perceived grievances (Kim & Hanneman, 2011; Lemos 2018). The social network aspect of ABM, in particular, may be utilized to better understand the function of newly emerging technologies like social media as a valuable protest mobilization tool (Filippov, Yureskul, & Petrov, 2020; Waldherr & Wijermans, 2017). Furthermore, protest simulation models may show how a network of social and political groups in deprived communities can be used to mobilize people in order to address accumulated grievance (Akhremenko, Yureskul, & Petrov, 2019).

SOCIAL CONFLICTS

Social conflict is an appropriate theory to investigate causes of protests within societies. Social conflict studies present how conflicts emerge, and their variations, as well as their societal effects. In the study of Lemos , Coelho, and Lopes (2017), social conflict is defined as confrontation or social dynamic of imposing will to produce desire end. For example, conflict can be in the form of a protest, disagreement between few individuals, or goes as far as an international conflict, such as World war (Pires, 2014).

Inequality in the distribution of resources and power have been identified as main sources of existence of conflicts between population groups (Pedersen, 2004). Furthermore, Social conflict generates beliefs, unity and sympathy among interacting individuals or groups within the society (Marx, 2020). Weber suggested two classifications of social actions, which are instrumental rationality, in which objectives are attained through rationally chosen actions, as well as value-oriented rationality whereby values are attained by conscious believe (such as religious, ethnicity, political, and so on) (Fukuda, 2018). Three social stratification dimensions—economic class, status group, and political party—were provided in other researchers (Protsch & Solga, 2016). These stratification dimensions show significant variations in how people behave or think. When it comes to protests, status groups offer chances for compassion and the mobilization of others who share the same grievance, while political parties offer forums that encourage the action of those who feel wronged (Bischof, 2012).

To conceptually study the interaction between class and race, as well as further examining the patterns of protest waves, Kim and Hanneman (2011) suggested an ABM to model crowd dynamics of workers' protests. According to Kim and Hanneman (2011), the motivation to protest is driven by a grievance, which is symbolized by relative deprivation brought on by wage disparities, a perception of an increased risk of being detained, and group affiliations, which is shown by ethnic and cultural identities. The simulation experiment results in Kim and Hanneman (2011) show that wage disparities (or grievances) have a significant impact on how frequently protests occur. However, Kim and Hanneman (2011) analysis only considers the neighborhood social contacts of agents without integration of influences from network structures and activists.

Similarly, the study of Ormazábal et al. (2017) developed an ABM to explore the dynamics of social conflicts on Epstein (2002)'s ABM of revolution when money distribution is incorporated to condition each individual's level of grievance. The study of Ormazábal et al. (2017) is aimed at evaluating the effect of inequalities in the distribution of resources on social mobilizations. Furthermore, Ormazábal et al. (2017) ascertained that protest outbursts and strength are significantly reduced when the level of dispersion of resources are even. However, unlike workers' protest model of Kim and Hanneman (2011), Ormazábal et al. (2017)'s ABM lacks factors that seeks to explore ethnic and cultural identities as well social and political network structures. Furthermore, the study of Fonoberova, Mezić, Mezić, Hogg, and Gravel (2019) presented an ABM of civil violence to explore the effect of non-neighbourhood links on protest dynamics when varying cop agents' density and network degree. The ABM proposed by Fonoberova et al. (2019) does not integrate the effect of friendship links, political ties and the influence of empathy towards aggrieved neighbors.

Pires and Crooks (2017) adopted a geosimulation approach by proposing an ABM that incorporate social interaction over a spatial environment. The model proposed by Pires and Crooks (2017) seeks to explore the effect of local interactions of heterogeneous individuals, their environmental characteristics, constructed from on empirical data of an actual geospatial landscape, population and daily activities of Kibera residence in to the emergence of riots. Rumor was utilized as an external factor to trigger the riots. The simulation results in Pires and Crooks (2017) indicate that youth are more attracted to rioting behaviour, which is evident that their model captures the right dynamics, and further provide support to existing empirical evidence and theories of riots. Although this model captures adequate social interactions of protesting civilians, and simulates more realistic dynamics of crowd patterns, it does not explore effect of risks as participation cost. In addition, their model does not incorporate network structures to explore the effect of social influence, political influence, and sympathy.

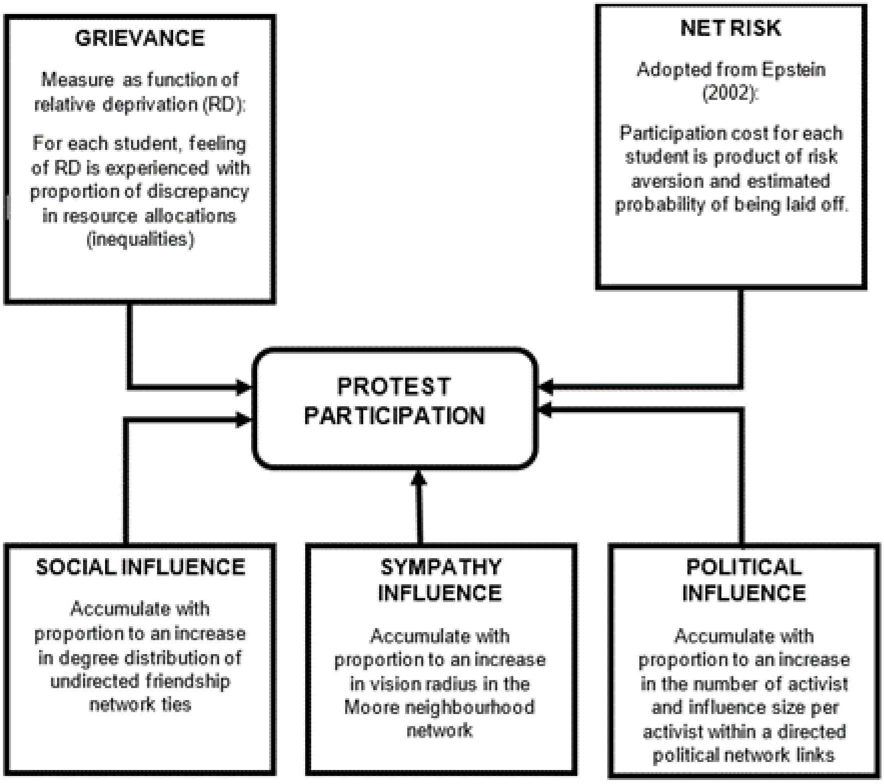
The goal of this research was to construct an ABM of student protests that builds on Epstein's ideas. The model incorporates the hardship resulting from resource distribution disparities which is computed as function of RD. Furthermore, the model investigates the impact of integrating sympathetic effect which arise from Moore's neighborhood network graph, political effect which was denoted by directed activist links, and social influence indicated by undirected friendship ties.

HYPOTHESES

The conceptual framework of the model that predict student protest is demonstrated in Figure 1.

In the social conflict context, the first latent variable proposed is the grievance factor that can influence the willingness of students to participate in protest action (Epstein, 2002; Raphiri, Lall, & Chiyangwa, 2022). Klandermans, Roefs, and Olivier (2001) applied theory of relative deprivation to investigate grievance development in the South African context, where grievance was defined as the effect of objective conditions (such as perceived living conditions) and subjective conditions (in relation to others over time). Number of policies have been implemented to address inequalities caused by apartheid policies in South Africa, but these inequalities are still prevalent. Ortiz and Burke (2016) argued that, for government to be legitimized, they need to address the grievances of protesters, such as reducing inequalities within the society. Lemieux, Kearns, Asal, and Walsh (2017) theorized that high grievance will (a) increase the probability of any form of participation in political activities in

Figure 1.
Conceptual framework of student protest model



general (b) increase interest of participating in protest action (c) increase participation in conflicts activities. Thus, the first hypothesis considering the conceptual model in Figure 1 reads as follows:

H1: Grievances resulting from discrepancies in living conditions have positive influence on students' decision to participate in protest action.

At a personal-level, perceived risk of punishment has been identified to influence people's decision to engage in protest. Other scholars have identified operationalized risk as consequences rather than the probability that a potential punishment will be imposed on the individual (Lemieux et al., 2017). The study of Lemieux et al. (2017) further theorize that when risk is high: (a) it reduces the probability of any form of participation in political activities in general (b) it reduces interest of participating in protest (c) reduce participation in conflicts activities. Therefore,

H2: Perceived net risk resulting from risk aversion and probability of being suspend negatively influence students' decision to participate in protest activities.

When an individual is integrated into network structure, the likelihood that one will be targeted with messages during social movement mobilization process increases. For instance, van Stekelenburg and Klandermans (2013) emphasized that individuals with friendship links or acquaintances that are actively involved in a protest action are more likely to participate in social movement actions than others. Therefore, H3: Students with more social links develops high level of social influence which positively contributes to the emergence of protest.

Historically, activists heavily relied on mass media to stay connected to a larger public, but nowadays they have established their own platforms on Twitter and Facebook for protest mobilization and interactions with their (Poell & Van Dijck, 2015). For example, the Arab Spring revolutions, Occupation protests and #FeesMustFall protests managed to attract a larger number of people because activists' influential sizes were higher as a result of social media. Therefore,

H4: Student activists with larger influential size develops high level of political influence which positively contribute to protest occurrence.

van Stekelenburg and Klandermans (2013) argued that individual's first step in protest participation is guided by consensus mobilization, whereby the general society is distinguished into people who sympathize with the cause and others who do not. The more effective consensus mobilization has been, the bigger the number of sympathizers a protest can attract. Therefore,

H5: Sympathetic students who are exposed to other active students develops sympathy influence which positively contributes toward decision to participant in protest action.

DESCRIPTION OF STUDENT PROTEST MODEL

The "Overview, Design concepts, and Details" (ODD) (Grimm et al., 2010) protocol is used for the proposed simulating student protest model. The ODD protocol provides mechanisms to standardized model description, and to make it more understandable and repeatable.

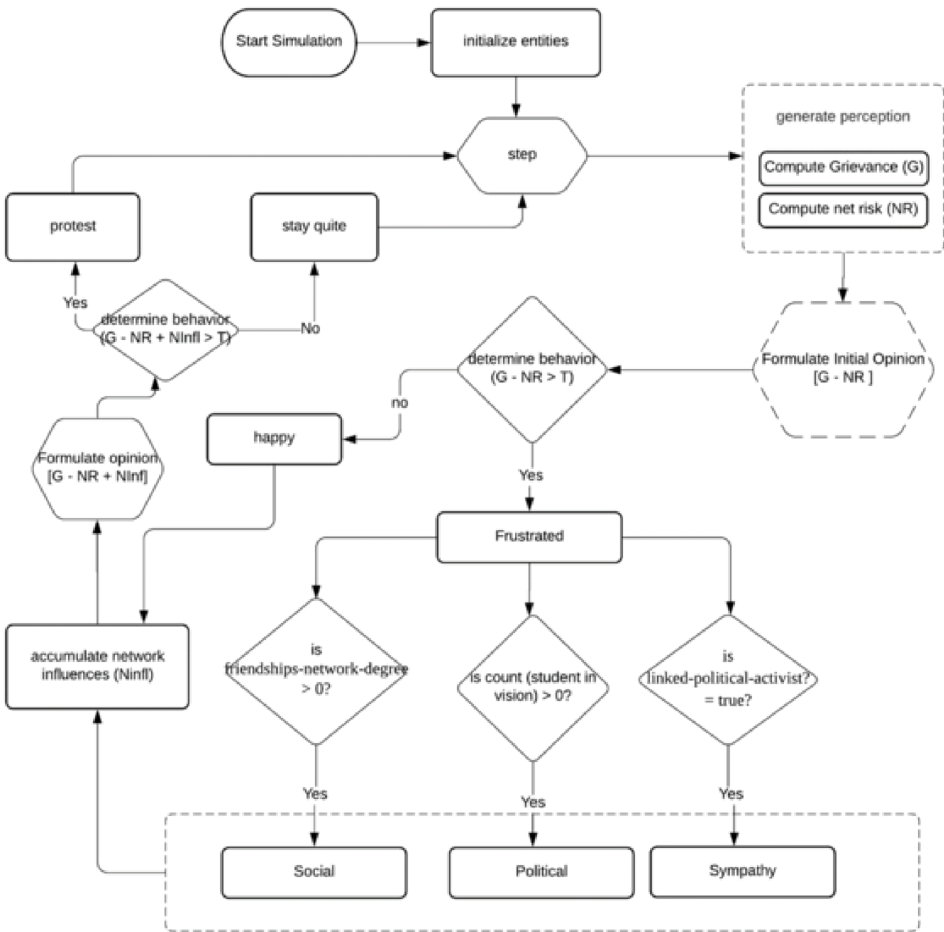
Purpose

The model presented in this study was to simulate the effects of grievance on the possibility of student protests. It used the factors of relative deprivation (RD), net risk, social influence, political influence, and sympathy influence on the likelihood of student to engage in protests action. To achieve this purpose, the classical model of civil violence proposed by Epstein (2002) was extended to incorporate the new decision parameters. For the proposed model to be simulated and analyzed, several equations are assumed to integrate state variables, behaviour and scale of model entities.

Entities, State Variables and Scales

The model consists of two instances of a turtle object, namely student and law enforcement officer agents. Student breed is further classified as activist or normal. Students and officers interact on an abstract model world represented by grid of 40×40 two-dimensional tori, referred to as patches in Netlogo. Other entities represented in the model are links which provide various network graphs for interactions of agents. Students and officers identify their next state by going through various processing steps. The main procedures implemented in this model are the setup (labelled as MODEL INITIALIZATION) and go (labelled as RUN MODEL CONTINUOUSLY). The setup submodel initializes global parameters, built the artificial world, and further create the agent population and network structures. The setup procedure further assigns initial states to all model entities. Meanwhile, the go submodel invokes other procedures that are implemented in the model, for example methods to updates, plot and store state variables of the model entities. Figure 2 presents an abstract flow diagram that outline the behavioural states of the student agents. The go submodel repeatedly executes: 1) the action rules for both student and officer breeds, 2) then run the move procedure, 3) decrement the suspend term of laid off students and suspend delay for rested officers, 4) increment the time step,

Figure 2.
Abstract flow diagram that outlines the behavioral states of student



and 5) display and update the macro or behavioural state of model entities using plots or interface controls provided by NetLogo.

Model Details

Initialization

The setup procedure initializes fixed parameters and properties of each entity used in the model. The development environment allows model observers to use sliders and switches to adjust global scales and categorical parameter input. The hypothetical environment simulated in this study does not denote any particular terrain, as there is no integration of spatial data to feature mountains, buildings, or forests that guide agents' movement. Lattice only portrays an abstract virtual environment focusing on the interaction of students. Table I provides the attributes of the student and officer breeds used in parameter sweeping when conducting simulation experiment.

Table 1.
Attributes of students and law enforcement officers

Parameter	Description	Value	Range
Student agent:			
risk-aversion (R)	Student's reluctant degree to take risks	$\sim U(0,1)$	0-1
Inequality-level	Inequality-levels (2 – low, 3 – median, 4 – high)	slider	
study-level	Undergraduate study level (diploma = 1, degree = 2, and honors degree = 3)	$\sim U(1,3)$	1 - 3
active?	Student's state (protesting or quite)	false	true or false
suspend-term	Student's suspension term	0	$\sim U(1, J_{max})$
Friendship-network-degree	Network degree of Student's friendship network structure	slider	
activist?	Student type (normal or political activist)	false	true or false
participate-politic?	Does student take part in politics?	$\sim U(true, false)$	true or false
Linked-political-activist?	Is student linked to any activist?	false	true or false
social-value	Accumulated social influence based on friendship network graph	0.0	Calculated based on Eq. 4.4
political-value	Accumulated political influence based on political network graph	0.0	Calculated based on Eq. 4.5
sympathy-value	Accumulated sympathy influence based on neighborhood network graph	0.0	Calculated based on Eq. 4.6
Officer agent:			
Waiting-to-suspend	Officer's resting duration before suspending next student	slider	

Submodels

In this study, five main submodels are implemented in the model to compute relative deprivation (grievance), net risk as well as network influences classified as social, political and sympathy. This fundamental submodels presented in this section forms decision variables in predicting the likelihood of protest occurrence.

a. Grievance

The ABM of student protest represent grievance as a function of a person's intuitive relative deprivation (RD). This model looked at consumable resources as a proxy for relative deprivation: consumable resources were viewed as a measure of a person's ability to access resources; whereby each unit of consumable resource reflected a distinct set of goods that were consumed. Each student's possible range of RD in relation to certain reference group (neighbors, social links, political groups) within the society is $[0, x^*]$, whereby x^* denote the maximum resource available in the society. For each student i, $[0, xi]$ represent range of resources accessible to i, whereas $[xi, x^*]$ denote range of resources for which i is deprived. The amount of RD ranging from [xi , x^*] or simply $\left(x, x + dx\right)$ can be computed by $1 - F\left(x\right)$, whereby $F\left(x\right) = \int_0^k f\left(y\right) dy$ is the cumulative resource distribution, and $1 - F\left(x\right)$ is the related frequency of students with resource accessibility above x. Grievance as a feeling of RD of student i at time t is defined in (1):

$$\mathrm{RD}\left(\mathrm{x}\right)_{\mathrm{i,t}} = \int_{\mathrm{x_i}}^{\mathrm{x^*}} \left[1 - \mathrm{F}\left(\mathrm{y}\right)\right] \mathrm{dy} \tag{1}$$

b. Perceived net risk

Students decide to participate in protest action if the grievance outweighs the cost or consequences. For student i at time t, cost of participation was quantified by perceived net risk ($NR_{i,t}$) of being suspended from academic activities. The $NR_{i,t}$ is denoted by a function of layoff probability estimate, risk aversion (RA), and maximum layoff term (J). The layoff probability estimate ($\mathrm{P}_{i,t}$) of student i at time t, is calculated based on (2):

$$P_{i,t} = 1 - exp^{\left(-k.\frac{V_{O,t}}{V_{AS,t}}\right)} \tag{2}$$

Where constant k = 2.3, $V_{AS,t}$ and $V_{O,t}$ represent the local ratio of the number of active students and law enforcement officers at time t in the vision radius, respectively. Vision radius is determined by the number of patches, based on Moore (or indirect) neighborhood network (Klancnik, Ficko, Balic, & Pahole, 2015), which each student can see, that can host other students and officers. Risk aversion (RA) represent a uniformly distributed value ranging from 0 to 1 which is heterogeneous and remained fixed for each student during simulation experiment. Whereas the maximum layoff term (J) was a fixed and homogenous value across all students. The net risk ($NR_{i,t}$) of student i at time t is represented by the (3):

$$NR_{i,t} = RA_i.P_{i,t}.J \tag{3}$$

c. Social influence

Students' friendship network structure was constructed as undirected graph $G\left\{S,\ L\right\}c$, where S denote set of students and L is the set of communication links or social ties between friends. The social friendship graph integrated in the ABM of student protest is only able to represent basic properties such as vertex degree, distance between vertices, and the clustering of the network structure. For student i, node degree $deg\left(S_i\right)$ was described as a fixed heterogeneous number of friendship ties $L_i \in \left\{L_1, \ldots,\ L_{Random\left(1,\ Maxfriends\right)}\right\}$, whereby MAXFRIENDS was given as input parameter. At first, each student formulates friendship ties with other students whose distance between them is less than their vision radius and thereafter randomly select other students with similar study level if $deg\left(S_i\right) < L$. A random network graph was derived where friends of student i who are also neighbors are more likely to have social ties, whereas randomly chosen friends form strong ties with other students within their visibility. After constructing friendship network graph, (4) is used to compute the social influential ($SInf_{i,t}$) value to integrate the effect of social ties toward students' decision to participate in protest action:

$$SInf_{i,t} = \sum_{\in ASN_t} RD\left(x\right)_{i,t} - NR_{i,t}.\omega_1 \tag{4}$$

The propagated opinions among aggrieved individuals in the integrated social friendship network was quantified as the different between relative deprivation ($RD\left(x\right)_{i,t}$) and net risk ($NR_{i,t}$) at time t. Where $\in ASN_t$ represent the number of active students over time within the friendship network structure of student i and ω_1 denote global social influence weight which was constant.

d. Political Influence

The political network structure in the ABM of student protest is modelled in the form of a directed graph $G\left\{A \in \left[A_1, \ldots, \ A_{num\_activists}\right], E \in \left[E_1, \ldots, \ E_{\text{political\_influence\_size}}\right]\right\}$, whereby A and E represent set of activist nodes ranging from one to NUM_ACTIVISTS and set of directed edges ranging from one to POLITICAL_INFLUENCE_SIZE, respectively. Each edge represented an ordered pair node $\left(a, n\right)$ from $a \rightarrow n$ (whereby influential opinion is directed from activist (a) to normal student (n)). The constructed political network graph incorporated activists that have a positive out-degree denoted by $deg^{+}\left(a\right)$ which was defined by POLITICAL_INFLUENCE_SIZE in this model and zero in-degree ($deg^{-}\left(a\right)$). Each activist act as a source with directed links pointing to a proportion of randomly selected student population whose internal property of POLITICAL_PARTICIPATION? is equivalent to TRUE. Activists still maintain their individual undirected friendship ties. A student can be linked to multiple activists. Equation (5) was used to represent the form of political influence ($PInf_{i,t}$) in this model:

$$PInf_{i,t} = \sum_{\in NAP_i} RD\left(x\right)_{i,t} - NR_{i,t}.\omega_2 \tag{5}$$

Whereby, $\in NAP_i$ represent number of incoming opinions (quantified as $RD\left(x\right)_{i,t}$ minus $NR_{i,t}$) from political sources which are activist directional links for student i and ω_2 denote global political influence weight which was constant.

e. Sympathy Influence

In the constructed ABM of student protest, students can be sympathetic towards other active neighboring students located in their vision radius. For student i, Moore neighbourhood graph $G = \left\{\left[x, y\right] : \left|x - x_0\right| \leq r, \left|y - y_0\right| \leq r\right\}$, where $\left[x_0, y_0\right]$ represent the position of the patch occupied by i, $\left[x, y\right]$ are set of patches adjacent to $\left[x_0, y_0\right]$, including it, and r is the maximum vision radius defined as an input parameter. The number of square grids surrounding each student in the neighborhood graph of vision radius r can be summed up as the odd squares $\left(2r + 1\right)^2$. Sympathy influence ($SyInf_{i,t}$) of student i was calculated using (6):

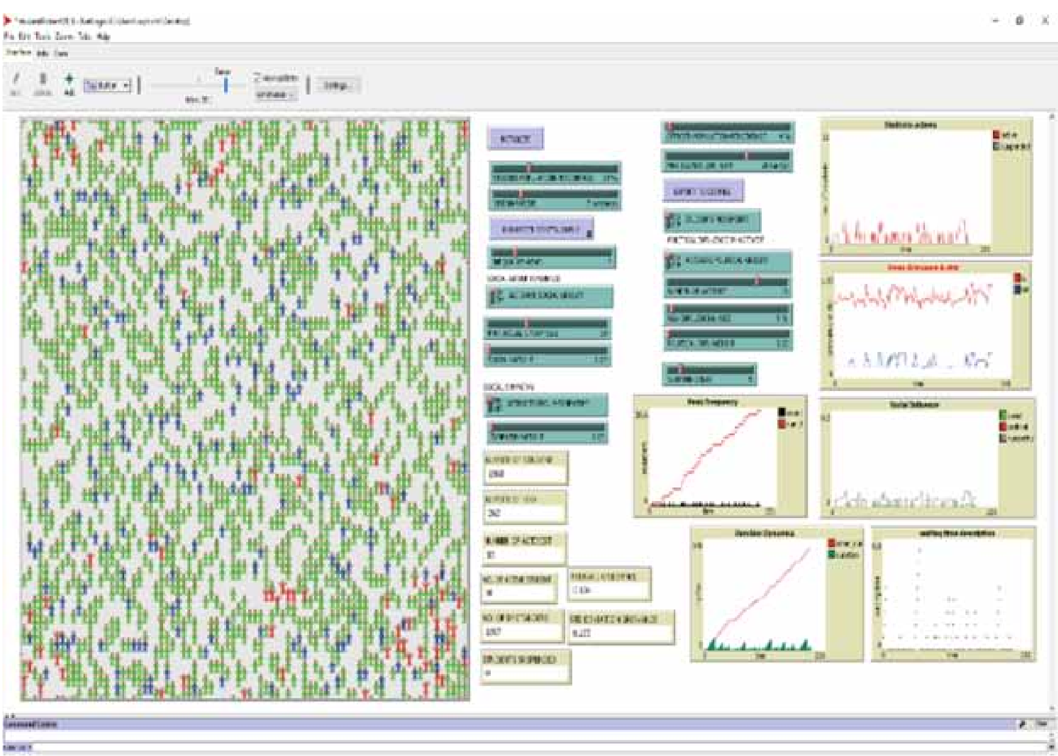
$$SyInf_{i,t} = \sum\nolimits_{\in AV_{i,t}} RD\left(x\right)_{i,t} - NR_{i,t}.\omega_3 \tag{6}$$

Similar to the other network structures, propagated opinions between protesting neighbors were calculated as the difference of relative deprivation ($RD\left(x\right)_{i,t}$) and net risk ($NR_{i,t}$) at time t. Where $\in AV_{i,t}$ denote set of active students in the neighbourhood graph of student i over time t, and ω_3 denote global sympathy influence weight which was constant.

MODEL IMPLEMENTATION

The model constructed in this study was coded using Netlogo 6.1 which is an ABM integrated development environment (IDE) (Wilensky, 1999). Simulation experiments were carried out on Netlogo BehaviorSpace. In Netlogo, a model is implemented by simply drag-and-dropping components into the IDE's graphical user interface, and by writing source code through Netlogo programming language which represent a simplified English like syntax. Netlogo IDE further include a model documentation tab. The IDE allows developers to implement, simulate, and observe the model. In addition, the IDE provide helpful and easy to follow tutorials and documentation materials. BehaviorSpace aid in execution of the model in the background and provide model users with platform to run several scenarios, while conducting parameter sweeping and store simulated data into a comma separated values (.csv) file. Figure 3 shows the user interface of an agent-based model of student protest that was implemented in this study.

Figure 3.
Netlogo integrated development environment



Notes: Student population density = 70%, Law enforcement officers' density = 4%, Moore neighbourhood vision radius = 7 patches, Student's tolerance level = 0.1, Maximum suspend (layoff) term = 30, Students and Officers movement = TRUE, Weight of social friendship links and activist links = 0.05, Weight of sympathy to neighbours = 0.02, Grid size = 40X40, and Time ticks for each simulation experiments = 250 are used all model simulations.

EXPERIMENTS AND RESULTS

Experiments

The model presented in this study uses several combinations of parameters to simulate various conditions that led to the emergent of student protest behavior. The fixed global parameters values used in the model during simulation experiments that in this study, were adopted from social conflict research (Epstein, 2002; Kim & Hanneman, 2011; Moro, 2016; Ormazábal et al., 2017; Raphiri et al., 2022). Quick runs of the model were done using Netlogo's graphical user interface platform for debugging and testing the code, as well as instant visualization of simple system dynamics. Systematic simulation experiments were carried out using Netlogo BehaviorSpace, to enable parameter sweeping while storing model output into csv file for further in-depth analysis. This systematic simulation performed by BehaviorSpace also aided in improving model execution time. Each experimental scenarios of certain combined parameters were repeated 10 times for 250-time steps. Table 2 shows frequencies of variated parameters used during simulation experiments. The effect of grievance as a function of relative deprivation was computed through varying INEQUALITY_LEVEL parameter, while SUSPEND_DELAY was utilized to reduce the risk of active students being suspended by law enforcement officers. The variation of MAXFRIENDS was used to calculate the social influence, whereas political influence was based on the variation of NUM_OF_ACTIVISTS and POLITICAL_INFLUENCE_SIZE. Sympathy influence was activated using SYMPATHY_ACTIVATION? parameter.

Table 2 contains factors used in the experiment design. When other parameters were kept constant, the main focus was to evaluate how the degree of inequality level, number of activists, activist's influential size, number of friendship ties, suspend delay and sympathy affect the dynamics of student protests.

Running simulation experiments was challenging and time consuming due to resource constraints, such as high-performance computing desktop. A desktop computer with eight core processor was used to run the model. As illustrated by Netlogo' BehaviorSpace tool in Figure 4, simulation of ten experiments with similar combination of parameters took an average time ranging between 25 and 60 hours. Simulation experiments that took more time to complete were encountered when running scenarios with network structure that contains larger average degrees.

Model Calibration

Model calibration techniques were performed in verification, validation, and sensitivity analysis stages. Firstly, iterative programmatic testing is conducted throughout the model implementation phase to make sure that the code is free from syntax and logical errors, and that it behaves as expected (Anderson & Titler, 2014). Model-to-model validation is carried out to ensure that the dynamical patterns of the implemented model correspond to theories presented by Kim and Hanneman (2011)'s ABM of worker protest and other similar computational models when similar parameter values are used. Sensitivity analysis is carried out to explore the dependencies of model output to parameters variations and evaluate the influence degree of each input parameter toward the observed output (Iooss & Saltelli, 2017). Going through sensitivity analysis assisted in gaining insights understanding of various dynamics represented in the implemented model and the robustness of output towards parameter uncertainty.

Table 2.
Parameter sweeping for student and officer agents

Variables	*f*	Rel. *f*	cum. *f*	Percentile
Inequality level (INEQUALITY_LEVEL)				
Low	5184	0.33	5184	33.33
Medium	5184	0.33	10368	66.67
High	5184	0.33	1552	100.00
No. of activists (NUM_OF_ACTIVISTS)				
Minimum	5184	0.33	5184	33.33
Median	5184	0.33	10368	66.67
Maximum	5184	0.33	1552	100.00
Political infl. size (POLITICAL_INFLUENCE_SIZE)				
Minimum	5184	0.33	5184	33.33
Median	5184	0.33	10368	66.67
Maximum	5184	0.33	15552	100.00
Max. no. of social friends (MAXFRIENDS)				
Minimum	5184	0.33	5184	33.33
Median	5184	0.33	10368	66.67
Maximum	5184	0.33	15552	100.00
Max. suspend delay (SUSPEND_DELAY)				
Minimum	5184	0.33	5184	33.33
Median	5184	0.33	10368	66.67
Maximum	5184	0.33	15552	100.00
Activate Sympathy (SYMPATHY_ACTIVATION?)				
Sympathy (Yes)	7776	0.50	15552	50.00
Sympathy (No)	7776	0.50	7776	100.00

Results

As illustrated in Figure 5 and Figure 6, in each simulation run, a line graph indicating the average grievance (shown in red) and net risk (drawn in green) which were both calculated from inequality level, and suspend delay are plotted in each time interval. The dynamics of grievance and net risk over time in the social conflict scenario are recorded when system decision parameters are set to low, medium, and high. High inequalities rapidly increased grievances and reduced the risks of protesting because the grievance was always above the net risk in most time step.

An increase of decision factors (i.e., number of activists, maximum activist's influential size, and number of social friendships links) result in rapid increase of network influential values (which are political, social, and sympathy values) as shown Figure 7. An increase in the number of activists as well as maximizing their influential size, which may be regarded as optimizing mobilization resources, resulted in an increased in the political influence value, more especially when students are sympathetic towards one another.

As mentioned earlier, the focus in this research was to evaluate how various factors presented in the proposed conceptual model significantly assist in the prediction of student protest emerging.

Figure 4.
Netlogo' BehaviorSpace tool

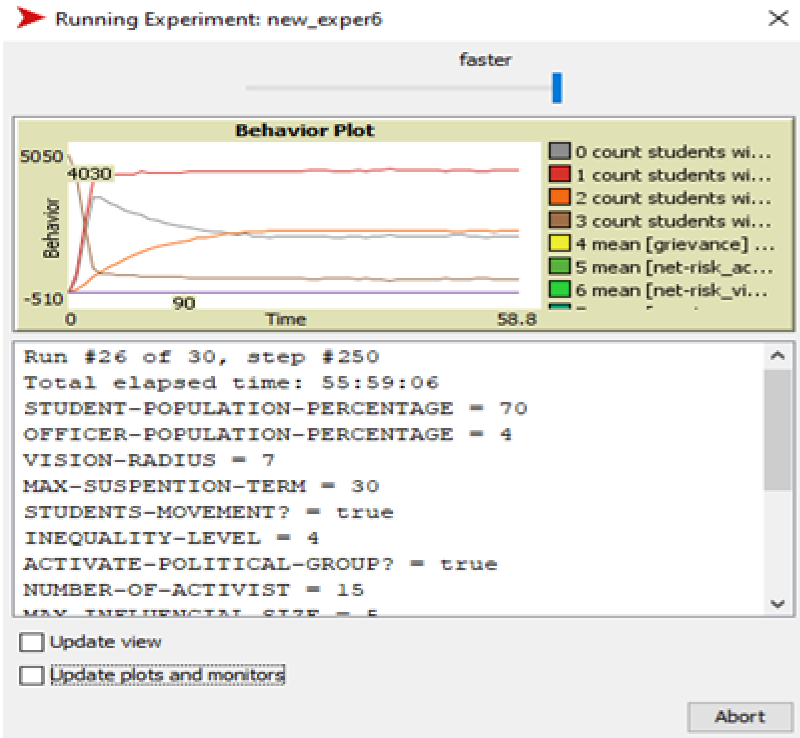
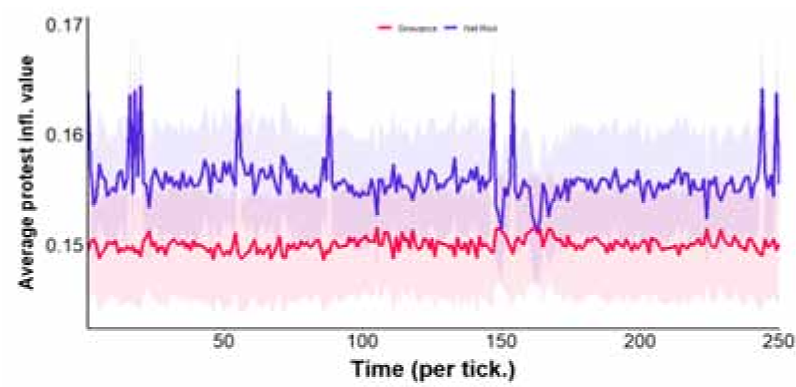


Figure 5.
Grievance and net risk based on median inequality level and median suspend delay



Therefore, the logistic regression model to evaluate the effect of each parameter on the probability of protest emerging was conducted using Python. As demonstrated in Table 3, all predictor variables in the model were statistically significant with p-value less than 0.01.

The accuracy of logistic regression classifier on test set is 0.949. The precision of 0.96 for false positive prediction and 0.95 for true positive predictions and the recall of 0.98 for false positive prediction and 0.89 for true positive predictions can be observed from Figure 8.

Figure 6.
Grievance and net risk over time based on high inequality level and median suspend delay

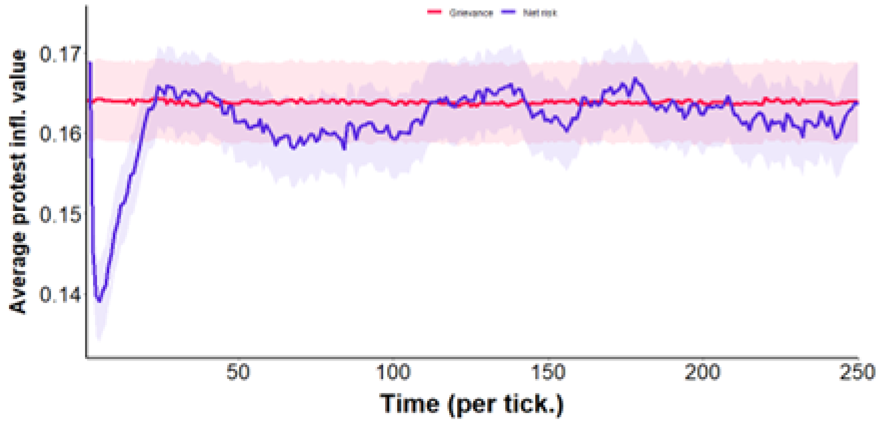
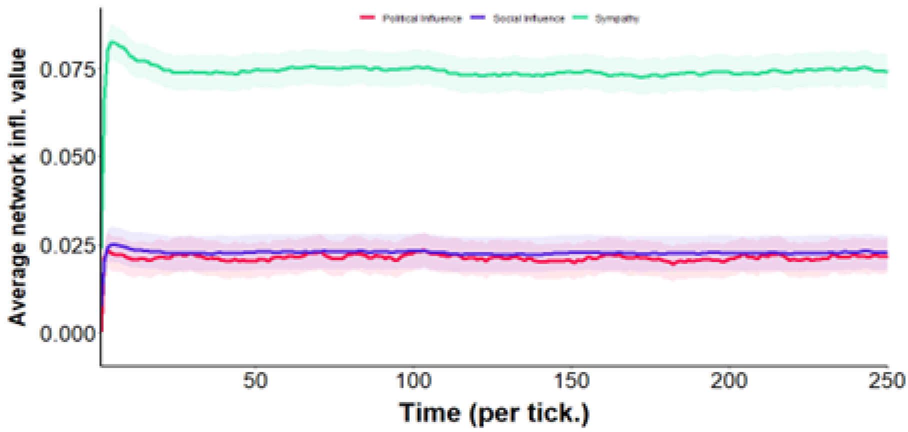


Figure 7.
Trends of political, social and sympathy influences based on high decision variables



DISCUSSION OF RESULTS

Grievance from Inequality Level

The findings of this study show that growing levels of inequality have an impact on students' grievances; as was shown in the statistically significant in predicting the likelihood that students would take part in a protest action (Coef. =3.4779; p value < 0.05). This is consistent with the research of Lemieux et al. (2017) who claimed that a certain degree of resentment tends to enhance the likelihood of an individual participating in political activities like protest actions. This result thus supports hypothesis (H1) from section IV.

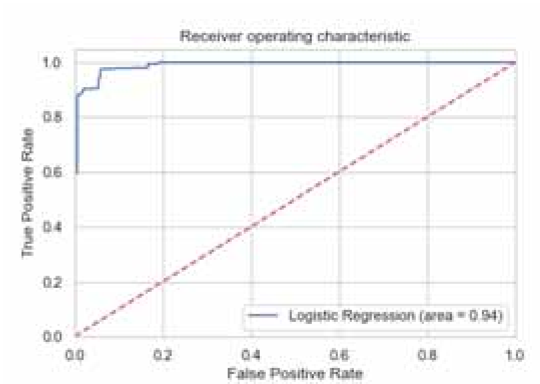
Perceived Net Risk Based on Suspend Delay

The research's findings also highlighted the significant of the contribution of perceived suspension delay, which is used to compute net risk (Coef. =-0.8446; $p < 0.05$), that indicates the likelihood of students engaging in protest behavior. This is in line with the findings of a study by Lemieux et al.

Table 3.
Logistic regression

```
Results: Logit
=====================================================================
Model: Logit Pseudo R-squared: 0.458
Dependent Variable: Protest AIC: 42001.9391
BIC: 42074.4722
No. Observations: 64000 Log-Likelihood: -20993.
Df Model: 7 LL-Null: -38710.
Df Residuals: 63992 LLR p-value: 0.0000
Converged: 1.0000 Scale: 1.0000
No. Iterations: 7.0000
------------------------------------------------------------------
Coef. Std.Err. z P>|z| [0.025 0.975]
------------------------------------------------------------------
Political Active 0.3707 0.0247 15.0351 0.0000 0.3224 0.4190
Social Active -0.4284 0.0247 -17.3427 0.0000 -0.4769 -0.3800
Inequality Level 3.4779 0.0313 111.0566 0.0000 3.4166 3.5393
Suspend Delay -0.8446 0.0116 -72.9114 0.0000 -0.8673 -0.8219
No. of activists -0.2121 0.0048 -44.4070 0.0000 -0.2215 -0.2028
Activist's Infl. size -0.1953 0.0047 -41.1816 0.0000 -0.2046 -0.1860
Max. Social Size -0.2933 0.0050 -58.7068 0.0000 -0.3031 -0.2835
Sympathy 3.3129 0.0320 103.5826 0.0000 3.2502 3.3756
=====================================================================
```

Figure 8.
ROC graph (Precision and Recall)



(2017), who claimed that when risk reaches a certain level, (1) it reduces the likelihood of engaging in any political activity, (2) it decreases interest in taking part in protest, and (3) it reduces engagement in conflict-related activities. Therefore, this finding supports (H2).

Social Influence as Function of Friendship Ties:

According to the study's findings, bidirectional friendship networks are a statistically significant factor in the likelihood that a student will engage in protest behavior (Coef. =-0.2933; $p < 0.05$). This finding is further supported by a research by van Stekelenburg and Klandermans (2013), which found that people (participants) are more likely to take part in social movement activities if they have friends or acquaintances who are actively engaging in a demonstration. As a consequence, the outcome supports the hypothesis (H3)

Political Influence Based on Number of Activists and Activist's Influential Size

The simulation findings show that both of the political impact calculation components were statistically significant determinants of the likelihood that a student would engage in protest behavior (=-0.2121; p 0.05) and (=-0.1953; p 0.05). These results are consistent with earlier work. Political discourses like protest, according to Singh , Kahlon, and Chandel (2019), are largely articulated via several levels of concerns including the spread of political influence and political mobilization. According to Poell and Van Dijck (2015), the widespread use of social media platforms has made it possible for activists to mobilize huge numbers of people for protests, which has increased protest participation. Consequently, this outcome supports (H4).

Sympathy Influence

The findings of this study imply that sympathetic impact contributes statistically significantly to the likelihood that students would engage in protest behavior (=3.3129; p 0.05). According to a research by van Stekelenburg and Klandermans (2013), the initial stage in a person's protest involvement is determined by consensus mobilization, in which the general public is divided into those who support the cause and those who do not. The more supporters a demonstration may gather, the more successful consensus mobilization has been. As a result, the conclusion supported by this finding (H5).

CONCLUSION

The literature review showed that recent student protests have been disruptive, leading in property destruction, academic program cancellations, intimidation of non-protesting students, and injuries, to name a few outcomes. In this study, we adapted Epstein's (2002) AB of civil violence in the context of students' protests. Simulation experiments demonstrate that inequality level, number of activists, activist's influential size, number of friendship ties, suspend delay and sympathy are elements that determines the model of civil violence proofed by the statistically significant in the logistic regression model. We discovered that when these independent variables have increased in various scenario's studied, both the volume of outbursts and strength of protests increases. The results of this research imply that university administration or policy-makers should design their risk management strategies and policies to concentrate on understanding the network structures that integrate student interactions that seek to support the spread of students' grievances. The interception of such channels by policy-makers will aid in reduction of the disparities in resource distribution, and subsequently lessen grievances that causes frustrations among students.

FUTURE RESEARCH DIRECTIONS

The model created in this study offers a general tool to explore some processes that influence the genesis of protest activities, although it is yet unclear if the model can be applied to actual events. Future research may thus use actual empirical data to confirm the model assumptions to build more plausible models that can also be used to forecast student protest events. Additionally, the model developed included endogenous decision-making factors that influence students whether to protest or not. As was shown during the #FeesMustFall and #RhodesMustFall social movements, using exogenous mechanisms to launch messaging, such as tweets about active protest activities, would have a huge influence on student participation in protests.

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