# Agent-based Simulation of the Classroom Environment to Gauge the Effect of Inattentive or Disruptive Students

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**Abstract.** The classroom environment is a major contributor to the learning process in schools. Young students are affected by different details in their academic progress, be it their own characteristics, their teacher's or their peers'. The combination of these factors is known to have an impact on the attainment of young students. However, what is less known are ways to accurately measure the impact of the individual variables. Moreover, in education, predicting an end-result is not enough, but *understanding the process* is vital. Thus, in this paper, we simulate the interactions between these factors to offer education stakeholders – administrators and teachers, in a first instance – the possibility of understanding how their activities and the way they manage the classroom can impact on students' academic achievement and result in different learning outcomes. The simulation is based on data from Performance Indicator in Primary Schools (PIPS) monitoring system, of 65,385 records that include 3,315 classes from 2,040 schools, with an average of 26 students per class collected in 2007. The results might serve teachers in solving issues that occur in classrooms and improve their strategies based on the predicted outcome.

## 1 Introduction

Young students form the bases of our societies. The way they interact with their environment and how it affects their achievement has been an interest of literature for years [4, 5, 29]. It is important to provide young students at such a young age with a respectful and suitable environment for learning, to eliminate the disturbances or minimise them when they occur. Creating this desired environment requires the full understanding of the interactions and their anticipated consequences in classrooms.

Interestingly, however, the literature on classroom simulation is limited. A relatively recent attempt by Ingram and Brooks [15] aimed to understand specifically the effect of seating and friendship groups on attainment. Their model calculates a weight for a number of influences, e.g. proximity to teacher, peers' state and student's own inclination to be either *productive* or *disruptive*. Their model takes into consideration the effect of teacher proximity to a student, as well as the student's friends' state. Specific types of disruptive behaviour was not addressed in this work, but, importantly, simulation of *attainment* was.

In this paper we aim to move further and understand the effect of having disruptive students in a classroom through simulating *Inattentiveness* and *Hyperactivity* behaviours. According to the World Health Organization [37], Inattentiveness indicates moving between tasks, leaving one unfinished before losing interest, while Hyperactivity implies excessive movements, particularly in a situation where calmness is expected, such as remaining in one's seat. The two types are symptoms of the Attention-deficit hyperactivity disorder (ADHD) that has a prevalence in 5.9% to 7.1% of the children and adolescents [24]. Our work considers a student's achievement and the influence of teachers' as well as peers' characteristics. We use a fixed positioning of students, as in a regular classroom setting [16], therefore a friend's state (assuming they are not proximal to the student in question) cannot be considered an influence, as in the case depicted by Ingram and Brooks [15]. However, due to our agent-based approach, this could be generalised to classrooms with more movement. Importantly, we take into consideration the level of *teacher quality* and *control* as an added influence on student state transitions. Specifically, we aim to answer the following research questions:

**R1**. *To what extent does the existence of (different types of) disruptive students affect other students?(specifically, inattentive or hyperactive students)*

**R2**. *How does teaching quality and teacher control along with peer characteristics contribute to the achievement of young students in a disruptive classroom?*

## 2 Related Work

### 2.1 Disruptive Behaviour in Classrooms

The issue of disruptive behaviour of students from different age groups has been addressed in several studies [13, 14, 30]. In classrooms, we usually find a number of students, up to a quarter of a class, who display some form of disruptive behaviour [10]. Such students regularly show lower academic performance than their peers in the same class [7]. Additionally, the presence of disruptive behaviour in a classroom can increase the general disruptive level in that class. Shin and Ryan [28] explored whether the provision of emotional support by teachers could ameliorate high levels of disruptiveness in classrooms. They found that classes low in teacher emotional support had higher level of disruptiveness by the end of the year compared to classes high in teacher emotional support. It was found that students in classes with low teacher emotional support were more likely to have similar disruptive behaviour as their friends, which shows the effect of a teacher against peers' influence. Therefore, emotional support by teachers showed to be effective in reducing disruptive behaviour. Taking measures to ensure stability in classrooms and reduce disruptive behaviour is vital, as such behaviour is linked to low achievement of the whole classroom [25]. Bourne [3] used 'economy tokens' as a measure of reducing unwanted behaviour in the classroom, which decreased some disruptive behaviours to over 50% by the 7th week of the experiment.

### 2.2 Agent Based Modelling in Education

*Agent based modelling* (ABM) is a tool for modelling systems through software agents and their interactions in an environment. Agents interact with other agents and with the environment based on a set of behaviours driven from their defined characteristics. An agent can represent an individual or a group and their relationships in a simulation are represent social relations [19].

Agent based modelling has been adopted in the field of education, to serve different purposes. Some utilised it as a support of the learning activity, by modelling games for younger students, such as the case with Ponticorvo et al [27], where they introduced a general ABM framework for designing digital games for young students by capturing the common features of educational materials and describing them in terms of interacting agents. A model of student behaviour [26] focused on cheating in assignments. Their model showed a strong connection between cheating and participating in extracurricular activities, as students who participated more in extracurricular activities had less time to finish their homework. Mauricio et al [22] used a multi-level model, as well as ABM, to explain the differences in effectiveness between schools using social ties. The model presents peers' effect in the form of friendships that affects a student's learning attitude and teacher's effect through feedback and attention given to each group based on their academic performance. It assumed that more attention is given by teachers to higher performance groups than lower performance ones. Not enough attention has been given to the simulation of factors of a learning environment, thus, we simulate the effect of disruptive behaviour of young students and peers in the classroom. We use a disruptive score range defined by scales with items that is almost identical to the diagnostic criteria for ADHD in the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (American Psychiatric Association, 1994) [23]. The model also takes into consideration different technical backgrounds of education practitioners, by providing a user-friendly front-end that allows them to easily use the model and observe its output during the simulation run. Validation process is complicated and requires sufficient real data to compare with [17]. We use the correlation coefficients comparison between input variables and output variables from real data and the model's simulated data.

## 3 Data

The main source of data was obtained from the Performance Indicators in Primary Schools (PIPS) monitoring system [33] [34][1], in which young students were assessed at the start of their first year in elementary school and again at the end of that year. Specifically, assessments were carried out at the start and end of the academic year 2007/8. PIPS was run by the Centre for Evaluation and Monitoring (CEM) (www.cem.org) at Durham University, UK [36] [12]. The assessment process also provided a score, given by the teacher, for symptoms of disruptive behaviour (i.e. Inattentiveness in a range from 0 to 9, Hyperactivity with a range of 0 to 6) for each student at the end of the

[1] RR344_-_Performance_Indicators_in_Primary_Schools.pdf (publishing.service.gov.uk)

school year. The data contains 3,315 classes from 2,040 schools with an average of 26 students per class. The dataset has 65,385 records of students that include the mentioned Inattentiveness and Hyperactivity scores, as well as gender, and scores with a mean of 19.7 and 39.3 for the initial and end of year assessments of Math, respectively.

## 4 Methodology

As noted, we used Agent Based Modelling (ABM) to create a simulation of the learning process interactions. This is because the target stakeholders for our research question are human stakeholders in education, such as educational researchers, teaching administrators, teachers and, ultimately, students. We need to not only predict a fixed-point outcome (e.g. end of year results), but also be able to simulate how changing variables (e.g. the way of teaching a class) influence the outcome at different points in time (e.g. during a class, at the end of a class, at the end of a given number of classes, etc.).

From a technical point of view, the model was built using Mesa, which is an ABM framework in Python licensed by Apache2 [21]. Mesa provides a browser-based interface to visualise the model, which allows the use of interactive tools while running the model. This is especially useful during this COVID-affected time, when most interaction has moved online. Moreover, as it is coded in Python, it also has access to Python's large analysis tool library, such as SciPy for scientific computing, Pandas for data analysis and Matplotlib for visualisation.

From a visualisation point of view, a classroom is presented in the simulation as a 5 x 6 grid to satisfy the limit of class size being 30 students per class in the UK [8]. Shown as coloured circles, students start the class session in a random state of either learning, passive, or disruptive. The state becomes a *learning state* (in green) when the student has a low disruptive behaviour score. It turns into a *disruptive state* (in red) if the student has a high disruptive behaviour score or the student's Disruptive Tendency score exceeds the threshold (Disruptive Tendency and Disruptive threshold are defined in Section 4.1), where 1 tick in the model represents 1 minute. When a student is being disruptive, he or she may affect the state of their neighbours, depending on the neighbours' disruptive score and the level of *Teacher Control* and *Teaching Quality*. As previously stated, every student has two disruptive behaviour scores: *Inattentiveness* and *Hyperactivity*, ranging from 0 to 9 and 0 to 6, respectively (as per PIPS). These values could in the future be set at the start of a class; for now, our model initialises each randomly. Students also have other attributes that will be explained in section 4.1.

A Math lesson lasts for 45 minutes (as recommended by the Department for Education and Skills, 2002), where a student will be moving between the three states: passive, learning and disruptive (as modelled using the PIPS data). Figure 1 shows a flow chart of the model we have created to illustrate the change of the student state.

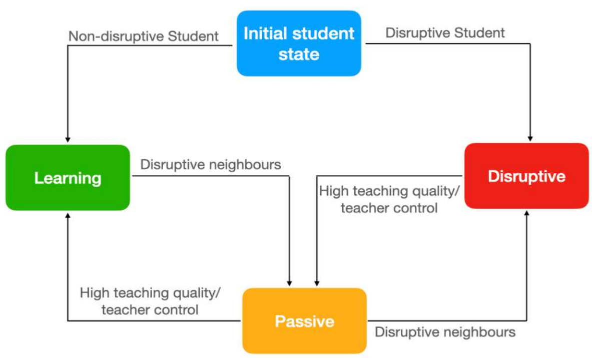


**Fig. 1.** SimClass model flow chart

### 4.1 Variable definition

The model offers first *switch variables* that can be manually altered for each run, as described below. These are partially informed by variables recommended by PIPS researchers, and partially self-derived. We discuss implications of choices in Section 7.

**Inattentiveness and Hyperactivity switch**: this variable switch can be tuned to indicate a high or low level of Inattentiveness/Hyperactivity behaviour in a class.

**Teaching Quality/Teacher Control switch**: This switch varies the quality/control of teaching, ranging from 1 (weak) to 5 (excellent) this scale is defined for this model and was not taken from PIPS, as it is not available; its purpose is understanding the effect of this variable as a part of the learning environment factors.

**Attention Span switch**: This variable represents the length of simulation time (ticks) the student maintains their learning state.

The model also computes a number of *derived variables* during the simulation runs, defined as follows below.

**Initial Disruptive Tendency**: students will be allocated this value based on their Inattentiveness. We propose to compute it using the following formula:

$$DT_{initial}(\mathrm{s},\mathrm{c}) = \frac{I(\mathrm{s})-\mu(s,c)}{\sigma(s,c)} \tag{1}$$

Where $I(s)$ is the Inattentiveness score of student $s$; $\mu$ and $\sigma$ are the mean and standard deviation values of Inattentiveness' scores for class *c* of student *s* that is taken from PIPS data for a realistic setting.

**Disruptive Tendency**: This variable will change over time - students who are disrupted frequently will be affected and their disruptive tendency will increase. The length of time a student will be in a disruptive or a learning state will be affected by a student's own characteristics, as well as that of the teacher's and peers':

$$DT(s,c,T_{current}) = \left(\frac{D\big(s,c,(T_{current}-1)-L(s,c,(T_{current}-1))\big)}{T_{current}-1}\right) + DT_{initial}(s,c) \tag{2}$$

Where $D(s,\ c, T_{current})$ represents the number of ticks (minutes) when the student *s* was in a disruptive state till $T_{current}$, while $L(s,c,T_{current})$ represents their learning state's ticks until $T_{current}$. The higher the disruptive tendency becomes, the higher the chance that the student will change to a disruptive state; $T_{current}$ represents the number of ticks that passed since the beginning of the school year.

**Math attainment level**: This variable accounts for individual differences between students; it is derived from their initial score in Math as follows [31]:

$$A(s,c) = \frac{Smath(s,c)-\mu_{smath(c)}}{\sigma_{smath(c)}} \tag{3}$$

Similar to disruptive tendency, we use the z-score of student *s*'s initial assessment in the Math subject, Start Math, $Smath(s)$, defined below, because we wish to obtain information on varying from an average value, as opposed to absolute values. $\mu$ and $\sigma$ are the mean and standard deviation values of Start Math scores for class *c* of student *s* that are computed before the simulation is initialised, either from PIPS data or model generated random data for the Start Math variable.

**Start Math**: This variable can be taken from PIPS or produced randomly by the model for each student. Its range (0-69) corresponds to the PIPS data range. Here, we took the values from PIPS, to simulate a realistic environment.

**Start Math scaled**: As number of ticks the students learn indicate here their final score in Math, we have rescaled the Start Math score to represent *minutes of learning*:

$$Smath_{scaled}(\mathrm{s},\mathrm{c}) = \left(e^{Smath(s,c)}\right)^{\frac{1}{n}} \quad (4)$$

We use *n* in the exponent to fit the logarithmic function to map the 'learning Minutes' into 'Score' in a similar manner as the work of [22], who used the logarithmic function to map 'Teacher feedback' into 'Score'. To fit the logarithmic function, we use the total number of minutes the students would possibly have in a school year, which equals to *end-time =8550*. Since $log\ 8550^n = 69$, we calculate *n* to be ≈ *7.621204857*.

**End Math**: The simulated End Math score is shown in Equation 5, where $L(s, c, T_{end-time})$ represents the total learning time student *s* had throughout the simulated year:

$$Emath(s, c) = \log(L(s, c, T_{end-time}) + Smath_{scaled}(s, c))^n + A(s, c) \quad (5)$$

**Disruptive threshold**: represents one standard deviation above the mean disruptive tendency of the class [2, 11].

### 4.2 Functionality

As per Figure 1, students would be in a **learning state** if one of the following occurs:

- Disruptive Tendency is lower than the Disruptive Threshold of class.
- Disruptive Behaviour is low, and Teaching Quality or Teacher Control is high [35].
- Current state is passive, and more than half of the neighbours are in a learning state.

Students will be in a **passive state** if one of the following situations occurs:

- Disruptive Tendency is higher than the Disruptive Threshold, but Teacher Control or Teaching Quality is high.
- Current state is disruptive, but Teacher Control is high.
- Disruptive Behaviour is low, and Teaching Quality is low.
- Two neighbours are disruptive.
- Ticks of learning state exceed the attention span value.

Students will be in a **disruptive state** if one of the following situations occurs:

- Disruptive Tendency is higher than the Disruptive Threshold, and Teacher Control or Teaching Quality is low.
- Disruptive Behaviour is high, and previous state is passive.

- Previous state is disruptive, and Teacher Control is low (regardless of disruptive score)[35].
- Four or more neighbours are disruptive. The threshold of four is arbitrary defined for our current model, but can be further set by simulation requirements.

An ABM agent is a self-directed independent entity with attributes and protocols of interaction with other agents and their environment [20]. Our agent representing a student will remember its previous state and choose the next state based on earlier states. For example, if a student is *disruptive* for long, they can change to either *passive* or *learning*, based on characteristics or statuses of the teacher and neighbours. The model's simulation visualisation (Figure 2) will display the changes in student states during a minute (tick) in a lesson, with a line graph (below) that updates as the model runs. The graph follows the total number of disruptive students and learning students in every tick of the model. The black line represents the average End Math score of the class computed on every tick, while the red and green line represents the total number of disruptive and learning students.

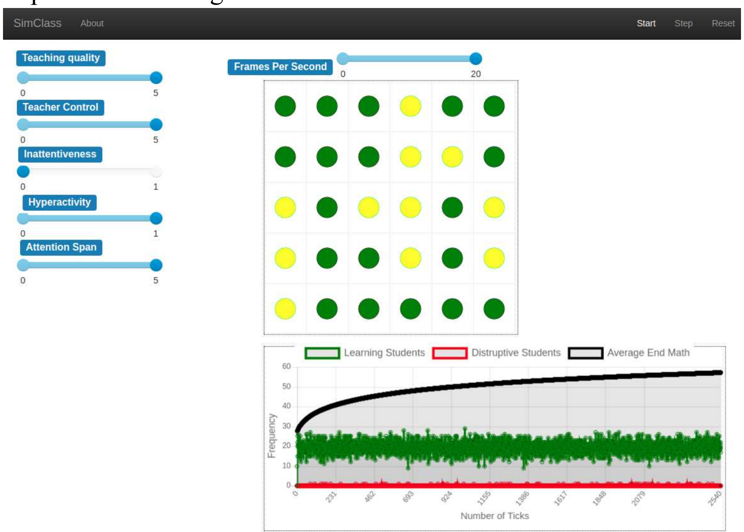


**Fig. 2.** Running the SimClass model with Inatentiveness=0

## 5 Data Analysis

To answer the first research question, R1, and understand the effect of *disruptive* students on other students (here, the whole class), we explore the relationship between **disruptive behaviour** and **End Math scores** (here, representing general attainment – see Section 1). Specifically, we compute this End Math average score in classes with high number of disruptive students and then compare it with classes with lower number of *disruptive* students. We define the (set of) *disruptive* students as DS⊆S:

$$DS = \{s \in S, where\ ds(s) \geq M\} \qquad (6)$$

$$M = \{median(ds(s)) | \, s \in S\} \qquad (7)$$

Where *S* is the set of all students, *s* is an individual student, *ds(x)* is the disruptive score function, and *M* is the median. The median, rather than mean, was chosen to define the threshold, because the data, according to Shapiro's test, is not normally distributed [1]. According to the data from PIPS, Inattentiveness has a median of 5, while Hyperactivity has a median of 3.

Out of 3,315 classes in the data set there were 2,337 classes with students categorised as *disruptive*. To have a deeper look into the data, we calculated the percentage of disruptive students per class and the average of the End Math score for that class and compared the two. Table 1 shows the correlation test results, where we can see that the percentage of disruptive students has a higher negative correlation (of -0.16) with the average of End Math. This suggests an effect of the number of disruptive students in a class over the general attainment - represented by End Math scores - in that class.

**Table 1.** Correlation test between disruptive behaviour and Math scores

| | Start Math | End Math | Average End Math |
|---|---|---|---|
| Inattentiveness | -0.27 | -0.33 | -0.07 |
| Hyperactivity | -0.14 | -0.18 | -0.06 |
| Percentage of disruptive students | -0.04 | -0.06 | -0.16 |

## 6 Results

Running the simulation model for 8,553 *ticks* represents a 45 minutes Math lesson a day for 190 days in a year [18]. We here present 3 *runs* with different parameter inputs, to observe their effect on student End Math scores. Results are shown in Table 2.

**Run 1**: In the first simulation run, we set all parameters with the maximum value for each (Teaching Quality and Teacher Control = 5, Inattentiveness/Hyperactivity = 1 and Attention span = 5). We chose this setting to be the baseline, to allow us to explore the different impact of each parameter in other runs.

**Run 2**: In this run of the model, we switched off Inattentiveness and kept the rest of the parameters at maximum value, in order to understand the effect of Inattentiveness variable over the results when compared with the baseline.

**Run 3**: Here, we aimed to observe the impact of Teaching Quality; therefore, all parameters had the maximum possible values of their ranges, except Teaching Quality, which was given the lowest possible value from its range, i.e., 1 out of 5.

**Table 2.** Results of End Math and Disruptive Tendency variables of three runs

| | Math | | Disruptive Tendency | |
|---|---|---|---|---|
| | First tick (Start Math) | Last tick (End Math) | First tick | Last tick |
| Run 1 | 27.43 | 43.08 | 1.16 | 0.12 |
| Run 2 | 27.43 | 66.16 | 0.73 | -0.53 |
| Run 3 | 27.43 | 36.45 | 1.05 | -0.07 |

## 7 Discussion

Three different parameter inputs into the simulation model provided different results. Therefore, we computed Cohen's *d* to present the effect size between the three runs (see Table 3). An effect size of *.2* is considered small, *.5* medium and *.8* large [6]. We can see that the effect size is large between the runs. We used t-test and found the differences between End Math scores of the three runs to be statistically significant.

**Table 3.** Cohen's d and t test between End Math scores of all runs

| | End math (Run 1) | End math (Run 2) | End math (Run 3) |
|---|---|---|---|
| End math (Run 1) | - | 1.43 (p = 4.13e-42) | 7.81 (p= 6.41e-07) |
| End math (Run 2) | - | - | 9.12 (p = 3.09e-37) |
| End math (Run 3) | - | - | - |

In the case of the third simulation, when Teaching Quality was reduced, the End Math results produced by the model were the lowest, with an average of *36.45*, indicating that students made the least progress in Maths of all runs. This means that Teaching Quality as a characteristic of the teacher influenced the attainment of the class by the end of the year. Additionally, we can see that students had also the highest disruptive tendency in this run. In contrast, the highest average of End Math scores was seen in the second run, when the Inattentiveness switch was off, resulting in *66.16* for the average End Math score, which presents an answer to Run 2 showing a negative effect of disruptive students in a class over their attainment. An average of *43.08* falls in between the previous two in the baseline run, when all variables used in the model had the maximum value allocated for each range. To compare with the real-world PIPS data[2], we ran a Pearson correlation test for the three different simulation runs.

**Table 4.** Correlation test between simulation runs results and model variables (8,553 ticks)

| | End Math (Run 1) | End Math (Run 2) | End Math (Run 3) | End Math (PIPS) |
|---|---|---|---|---|
| Start Math | 0.71 | 0.74 | 0.66 | 0.70 |
| Inattentiveness | -0.31 | -0.09 | -0.38 | -0.34 |
| Hyperactivity | -0.13 | -0.11 | -0.12 | -0.18 |

Table 4 shows that the correlation results of the three runs are close to End and Start Math of PIPS data, which was (computed separately to be) *0.70*. The nearest correlation score to PIPS data can be seen in the first run, with 0.71, where all parameters had the maximum values possible. Therefore, we computed the correlation between this run's simulated End Math and PIPS End Math and found the correlation to reach 0.68. These results can be used for finding adjustment of the model such as adding elements of learning, changing ticks representation and adjusting neighbours' affect.

[2] Please note however that PIPS data is only available for Start Math and End Math, thus only the start and end of the simulation process.

Next, we consider our various parameters in more details. We have used here inattentiveness as disruptive, but this may not be the case. It can be passive, such a daydreaming. But impulsivity can be disruptive. As we do not have a direct measure of disruption, anything in the model is a proxy. Follow-up work can look into the relation between Disruptive Tendency and its impact on personality. We have here simulated, analysed and compared results at classroom level, and compared averages. We showed the link between pupil disruption and Math attainment for pupils and for classes, i.e. at *two levels*. This naturally leads to *multi-level models* for future simulations. Beside the 3 runs presented here, we have run simulations with various parameters. More structured experiments are planned with models with slight variations, gradually moving toward each of the extremes represented here as Run 1, Run 2, Run 3, and graph the results. A related issue, to be addressed by multiple runs, is the stability of the models – how much variation there is when parameters hardly change. Start Math scaled, introduced here, is currently rather deterministic – if we know how much time has been devoted to Maths we will know the score in Maths. But children's Maths scores rise and flatten and rise again and stagnate in unexpected ways. Future work could contain an element of randomness, to note if results change significantly. The model can then be applied by teachers to understand the effect of the disruptive students in each classroom depending on their numbers, positions and work towards minimising this effect through management styles or rearrangements. Teachers can use the model by uploading their own dataset for initial scores or have the model generate these scores randomly. They can then set the range of available parameters to the setting they would like to explore and run the model. The simulation will display in real-time output showing the changing variables over time.

Limitations include addressing only *Inattentiveness* and *Hyperactivity* as factors influencing disruptive behaviour in class, while other student characteristics, such as gender or social economic status, might impact on disruptive behaviour. Also, data are from only one country (UK), and are from 2007. Society's evolution means young students are more digital natives than ever, social interactions have evolved. Finally, more student characteristics could be modelled and simulated to further fine-tune the results.

## 8 Conclusion

This paper has presented an ABM model design to understand the *effect of disruptive young students in a classroom environment using the PIPS data*. The model simulates the interactions for one school year. The results show an increase in average End Math scores when the *Inattentiveness* variable is reduced, which confirms the effect of disruptiveness in a class over *attainment*, conforming to the PIPS data. In contrast, a decrease in the average End Math scores was seen when the *Teaching Quality* was reduced, showing the effect of teacher characteristics over students' attainment. The model was created using a user-friendly front, which allows users to make adjustments to the model easily to find how to apply pedagogical strategies. Future work includes exploring and validating further additions to this model, such as teacher intervention using rewards or adding a teacher assistant to observe the impact over attainment.

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