Universidad Internacional de la Rioja (UNIR)

ESIT

Master in Artificial Intelligence

Breakfastclub - Agent-based model simulation of a virtual classroom

Master Thesis

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Abstract

Agent-based models have proven to be a useful tool to study complex social phenomena. In this work we have developed a simulation using an agent-based model of a virtual classroom, simulating the behavior of students and adolescents in an autonomous study group. The agent cognition is based on the widely used Big-Five personality trait model, and agent behavior has been aligned with empirical studies showing how specific personality traits correlate with academic success. The simulation software was used to compare how different classroom compositions with an increasing ratio of students with Attention-deficit hyperactivity disorder (ADHD) prototypical personality traits affect the classroom dynamics. We found a very strong effect of ADHD students on the mean classroom happiness and attention. Even a very small number of ADHD students can cause a shift in the behavior of None-ADHD students, decreasing their mean happiness and attention, in addition to more frequent classroom wide quarrels.

The simulation software in addition with the data analysis pipeline is available open source and under the MIT license.

Keywords: Agent-based model, Big Five, classroom, ADHD

Chapter 1

Introduction

This document is describing the Master Thesis developed by Manuel Pasieka as part of the Master in Artificial Intelligence at UNIVERSIDAD INTERNACIONAL DE LA RIOJA, S.A. 2018-2019.

As part of the Thesis we developed an Agent-based simulation named **Breakfastclub** (available at http://github.com/mapa17/breakfastclub) of a virtual classroom in order to study the effect of different Personality Traits on happiness and attention in a simulated class. This document is describing the development of the project and the results achieved.

The document is split into the following chapters.

- This first chapter introduces the reader into the motivation behind this work and its novelties.
- The second chapter will discuss the state of the art of the methods and technologies applied.
- The third chapter lays out the initials objectives as well as their adaption and final objectives of the Thesis.
- The fourth chapter describes in detail the implementation and technical solution to the proposed problem.
- The fifth chapter is focused on the Data Analysis of the results generated.
- The sixth chapter is providing a conclusion and summary of what has been presented, as well as an outlook on possible future projects and extensions.

1.1 Origin and Motivation

The social climate of modern classrooms have been studied extensively in the past [2], but common to many social studies, only the results of few empirical studies have been modeled successfully. This is changing, and in part because of the availability of computational methods and the availability of public data. Methods from statistical physics are applied more and more successfully in studying complex social systems (an extensive review on the topic can be found in [3]).

One method that has proven itself to be specially useful in studying social systems are **agent-based models**[4] that are a special type of multi-agent systems which model the behavior of individuals and can be used to study their interactions and emergent social behavior.

1.1.1 Simulations in the Social Sciences

In their work [5] the authors give a short history of simulations in the social sciences. They explain different reasons why simulations can be applied with different objectives,ranging from better understanding a social system, to prediction, to substitute human experts, as training tools, entertainment or as tools to for discovery and formalization of models.

Specially the later applications of simulations in the social sciences are interesting to us, as traditional approaches to understand complex phenomena in the social sciences have been focused on comparing the results of empirical studies to hypothesis generated with theoretical models.
One of the difficulty of this approach are increasing experimental costs in face of more and more complex models. The growing complexity and the degree of freedom of these models, demand an equally growing sample size increasing costs and the resources needed to generate results that can be used to verify and reject hypothesis in order to improve the models.

Figure 1.1 demonstrates how simulations can be used to support the discovery and improvements of new models and theories. Given a theoretical model one can produce hypothesis that are used to situate a simulation, providing the initial conditions and input parameters for the simulation. The simulation model is then run to produce concrete predictions, that can be compared to experimental studies. The overlap between the prediction and measured results is than used to form new hypothesis that can be used to improve theory and future models.

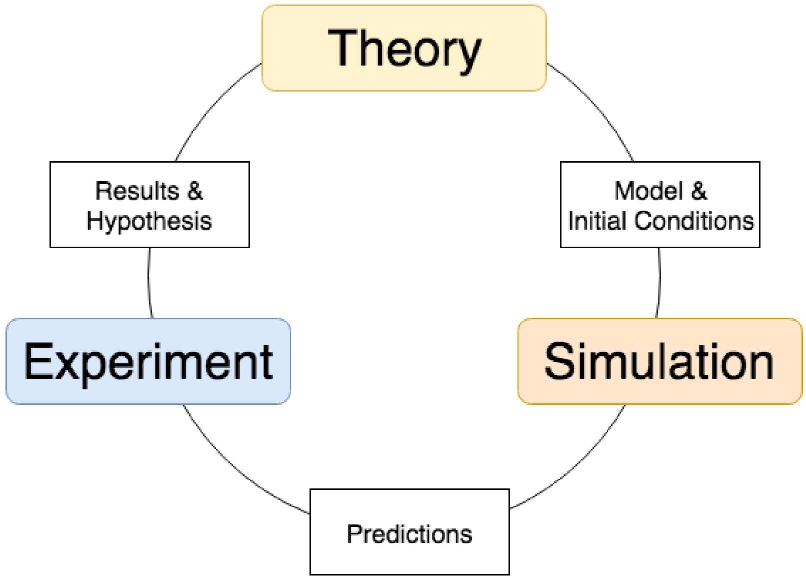


Figure 1.1: Cycle of Theory, Simulation and Experiment

As will be described in more detail later, our work is focused on studying the group dynamics of children in a classroom, in particular that of a autonomous study group.
In order to achieve this, we split the task in two goals

1. Develop a flexible and extendable agent-based model of a virtual classroom

2. Study how different personality traits effect attention and happiness of individuals and the group as a whole

Chapter 2

State of the art

In this chapter we will provide introduction into what agent-based models are and how they are used in the context of social studies. We will provide an overview of existing simulations platforms, and software particularly developed to simulate a virtual classroom. We discuss the deficiencies of those systems, and why we decided to develop our own.

2.1 Social Simulations and Agent-based models

Agent-based models (**ABM**)[4] have been used in various fields to study complex systems that result from the interaction of many individual agents.

Examples of such systems are the stock market, crowds, beehives, social networks and many more. Social Simulations are a type of ABM that focus on modeling social dynamics of humans or animals [6].

Early examples of such social simulations is Shellings work [7] studying the dynamics of social segregation or more recently on the spread of contagious diseases[8] within a city.

The intention of many of those simulations is to find emerging social phenomena present and empirically observed in the complete system (i.e. the group), but which are absent in the individual agents[4]. Hence it is the search for emerging properties, often observed but not understood, that can be explained by the interaction of simple mechanisms of the individual agents.

With simulating such multi-agent systems one has the possibility to construct, monitor and manipulate the system with perfect granularity and with very little cost, making such simulations an excellent tool to study complex dynamic systems.

2.2 Agent-based model Software

A series of open source as well as commercial distributed Agent Software[9] exists. Some of the more popular ones are NetLogo[10], Swarm[11], or Mesa[12], that provide frameworks to develop multi-agent simulations, often including visualization and a GUI.

We decided against using those existing frameworks, and instead develop our own solution based on the Unity3d[1] Game and Simulation Engine.
In particular Unity3d provides us with the following features that are absent or underdeveloped in other frameworks.

- **State of the Art Visualization:** Unity3D is used to develop triple A computer games and provides the possibility to build simulations with realistic appearing visuals and even virtual reality environments.

- **User Interaction:** User interaction if present at all is implemented very poorly in the most simulation frameworks. As User Interaction is an essential part in every computer game, Unity3d provides an excellent support for that.

- **Integration with other Machine Learning tools:** In the last year Unity3d has been extending its capabilities as a Agent based modeling framework by including a Machine Learning Agent toolkit that provides an easy interface between State of the Art machine Learning Tools like Tensorflow or Pytorch and the Unity simulation.

- **Actively Maintained:** Many simulation frameworks have been academic endeavors with a short lifespan, and on multiple occasions stopped to be maintained and to be available after a short period of time. Relying on a commercial sustained framework like Unity3d ensures availability and eases future development of the project.

Although the current version of the simulation is not making full use of all those features at the moment, Unity3d has been chosen to serve as a platform for future development based on the results achieved during the thesis.

[1]Developed by Unity Technologies and available from https://unity.com

2.3 Simulations of virtual Classrooms

Of particular interest to us are Simulation Systems that focus on a virtual classroom. Several academic and commercial systems have been developed with different objectives.

Some of those solutions (e.g. TLE TeachLivE[13][14] or simSchool [15]) focus on teacher education, providing a virtual classroom that can be used for new teachers to learn how to interact with a class and resolve issues. Others (e.g. Katana Sim:Classroom [16]) are used as a simulation environment for academic research, focusing on psychological studies.

Evaluating the different simulations we found that all of them lacked one or more of the following features, and therefore decided to develop our own solution.

- **OpenSource:** The Simulation should be open source and freely available for academic and commercial purposes, in order to support its adoption and support the sustainability of the project.
- **Agent Model:** The agent behavior should depend on an flexible agent logic that is based on empirical psychological studies.
- **Flexibility:** It should be possible to configure the simulation in class size, student profiles and classroom environment.
- **Reproducibility:** The simulation outcome (except of user interaction) should be reproducible, in order to provide a framework to study particular group dynamics. If multiple runs of the same simulation produce different results, it is unclear how alterations of the simulation configuration affect the outcome.
- **Data Analysis:** The simulation should include methods and tools to study the results generated. In particular it should be possible to execute multiple instances of the simulation with slightly changed conditions in order to perform a statistical analysis of the outcome.

Chapter 3

Objectives

As it is typical for projects beyond certain size, the objectives and scope had to be adapted according to the progression of the project after the initial planning phase. This chapter describes the initial envisioned objectives as well as the objectives reached with the final version of the thesis.
One of the initial objectives of the thesis was to develop a simulation environment that could be used interactively as well as a closed loop simulation (i.e. once defined and setup would run without any user interaction until a defined state is reached).
In addition as the simulation is based on Unity3d, the Machine Learning Package was intended to be used to implement agents trained using a Reinforcement Learning approach. Because of time constrains the interaction and ML-Agent features have not been included in the final version developed during the Thesis, but are included in the last chapter on the outlook of the project.

The objectives for the final version based on the resources and time available have been the following:

- **Closed Loop Simulation:** Implementation of Unity3d based virtual classroom simulation, including a 2D top down visualization.
- **Psychological agent model:** Development of a psychological model governing the behavior of agents that is based on empirical and theoretical grounds.
- **Deterministic Simulation:** The closed loop simulation should be deterministic and the random components should be seedable, making it possible to reproduce results of previous simulations if the same seed is provided.

- **Simulation and Classroom configuration:** The simulation as well as well as the psychological profile of the classroom should be easily configurable and alterable without the need to modify the simulation software.
- **Agent and Classroom based analysis:** As part of the data analysis it should be possible to analyze the behavior of individual agents (i.e students) as well as the average of the complete classroom (i.e. group).
- **Comparison of pre-defined psychological classroom profiles:** Based on empirical pedagogical studies a defined set of psychological interesting classroom profiles are compared to each other.

Chapter 4

Development

This chapter describes in detail the main components of the simulation and how they where implemented. How and why certain decisions have been taken and alternative solutions. The project was developed in an iterative fashion, starting out with a prototype and a reduced model, that has been redesigned and improved in small steps.
Presented here is the final solution developed during the thesis.

4.0.1 Unity3d

As mentioned before, Unity3d[1] is the game engine that has been chosen to implement the simulation. Unity3d is one of the most popular game engines, and has been used to develop not only triple A computer games but as well is applied more and more to build simulations for commercial and academic purposes. Unity3d is distributed under various licencees, including a free of costs license, which enables its use for Indie Game Developers as well to be applied in Academia.

For our purposes Unity3d is a generic simulation framework that provides the tools to create virtual 3d environments, a physics engine, a user interface and autonomous agents. The simulation is implemented as a Unity3 application with a single scene that is dynamically generated based on the simulation and classroom configuration.
All objects (Agents and Tables) in the classroom are Unity GameObjects that are updated in a defined sequence with a constant rate of 1 Hz. The agent logic is therefor running in discrete steps, although the underlying Unity3d engine is executed continuously (as much as this is possible on a discrete computer system).

[1] Developed by Unity Technologies and available from https://unity.com

During development it was taken care to as much as possible separated, simulation logic from Unity specific elements like visualization, or digital content management, in order to reduce dependence and reusability of the system. The simulation logic is implemented as C# scripts that interface the Unity3d Framework.

4.1 Agent-based model

As described briefly in the chapter on the State of the Art (1.1.1) an agent-based model is a multi agent simulation with a special focus on the interaction of agents and resulting group dynamics. The main components of an Agent-based model are the following:

- **the environment:** The environment is a strictly defined space in which the agents can move and interact with each other as well as with other objects that are part of the environment.
- **the agents:** The agents are autonomous dynamic systems with certain properties, sensors and actors that interact with each other and with the environment.
- **the simulation mechanics and agent logic:** The simulation mechanics controls how agents interact with each other, how the environment changes as a result of the actions of the agent or external factors (e.g. a simulation protocol defining a change in the environment). The agent logic governs the dynamic interactions between the internal agent state, its behavior and its properties.

A screen shot of the simulation is shown in figure 4.1

4.1.1 The environment: a classroom

In our case the environment is a classroom that contains multiple tables for students to study individually and in small groups. In addition the environment is modeling the noise that is accumulating in the classroom resulting from the different actions performed by the agents. The noise model implemented, is accumulating the noise produced by the different actions performed by all agents in the classroom, whereby different Actions produce different amount of noise depending on the simulation configuration.
Agents are moving about in the classroom as part of the various actions they perform. The Unity3d Navigation Agent Infrastructure is used to control the movement of agents, including path finding and collision control.

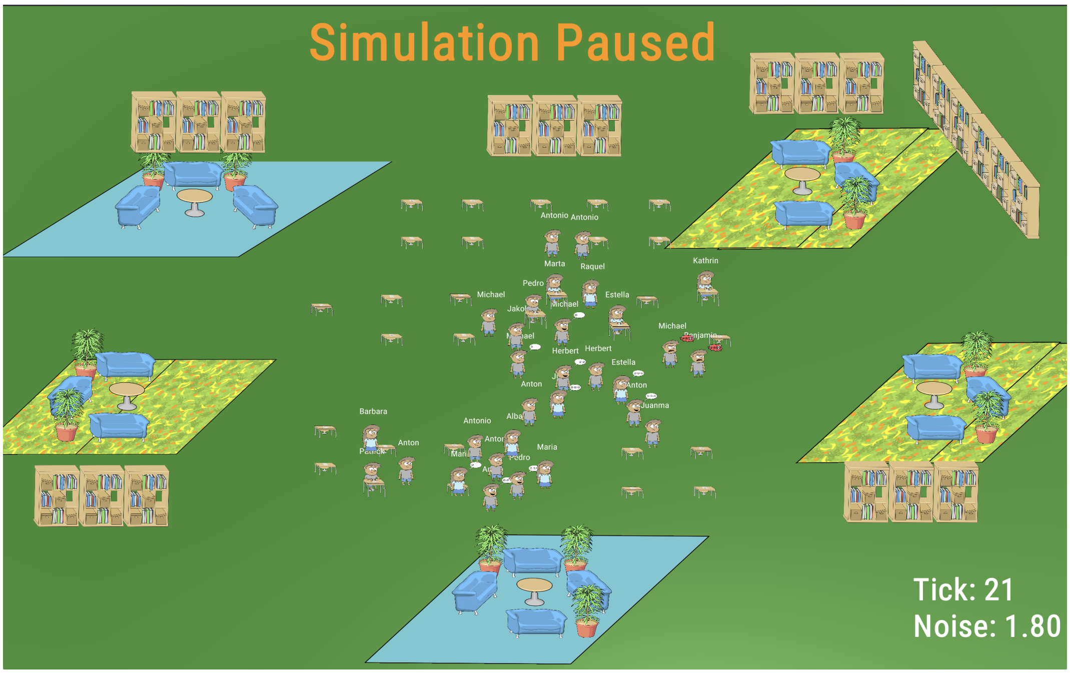


Figure 4.1: A screenshot of the running simulation.

4.1.2 The agents: school children

The agents are modeled to simulate school children of no specific age or physical property. Instead agents are characterized completely by their personality traits based on the Big Five Personality Traits model (see 4.1.3). In addition agents have several internal states and a set of possible behaviors they can perform (see 4.2).

The internal states modeled by the agent are **motivation** to study, **happiness** and **attention** during studies.

The behaviors available to the agents fall into one of three different types, being either

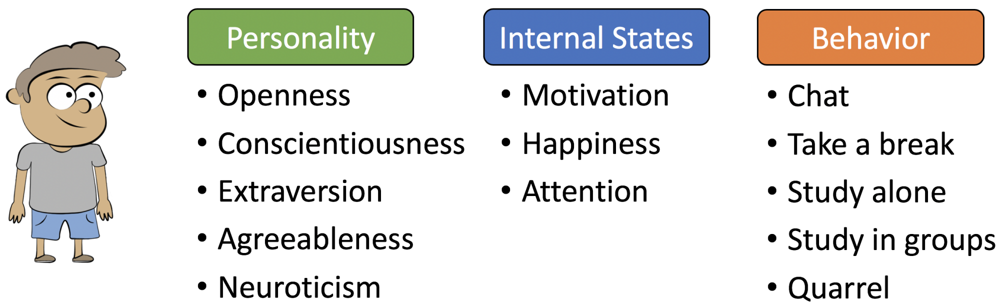


Figure 4.2: Agent Overview

educational, recreational or aggressive.

- **Chat:** Agents chat with another random selected agent in the classroom.
- **Take a break:** Agents take a break and start a random walk through the classroom.
- **Quarrel:** Agents start to quarrel with another random selected agent in the classroom.
- **Study alone:** Agents sit down on one of the individual tables and study by themselves.
- **Study in groups:** Agents take a spot on a group table and study with the other agents on the table.

Actions themselves have states, and an agent is always performing a single action in a specific state

- **Inactive:** The action is not active (This is needed because of implementation details).
- **Transition:** The agent is walking towards its goal in order to perform the action.
- **Waiting:** The agents is waiting for either some response of another agent or the environment in order to perform the action.
- **Executing:** The agent is executing the action.

The agents behavior depends on the internal states, as well as is affecting them. Each agent is itself a **dynamics systems** that is governed by the agent logic and based on its personality profile (see a visualization of this cycle in figure 4.3).

Dynamic Systems

As mentioned in the introduction, agent-based models are focus on the interaction *between* components of the simulation. As we have shown that the agents are themselves dynamics systems, complete system is therefore the result of the interaction of multiple dynamic systems (i.e. agents and environment) (see figure 4.4).

This **multi level dynamic system** can express very sophisticated behavior and dynamics, making it one of the main reasons agent-based models are such a powerful tool to

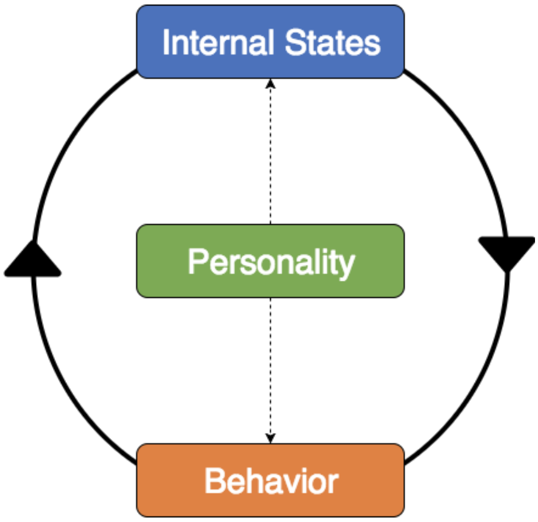


Figure 4.3: Agent Dynamics

study real world social phenomena. One of the most curious aspect of complex dynamic systems are **emergent phenomena**[17] which describe aspects of the complete system (i.e. classroom), absent in the individual (i.e. children) components.

One example of emerging properties is the *wetness* of Water that only appears in a ensemble of many water molecules, and not present in a single individual molecule. Another famous example is **Cowans Game of Life**[18] that shows the almost infinite complexity generated by a cellular automata simulating black or white cells on a infinite grid. Constructs generated by the simulation have emerging properties like *self replication*, *finite* and *infinite life cycles* and many more. None of those behaviors are obviously deducible from the initial basic interaction rules. Instead those properties emerge in the interaction between the components or agents following basic rules.

Agent homogeneity

One important axis along which to classify agent-based models is agent homogeneity[19]. In homogeneous agent models all agents share the same characteristic's and agent logic. Heterogeneous agent models on the other side can differ in the agents logic, its behavior or based on some parameters in its configuration.

In our case the simulation contains heterogeneous agents that differ, based on parameters in their Personality Traits. All agents follow the same logic and have the same capabilities.

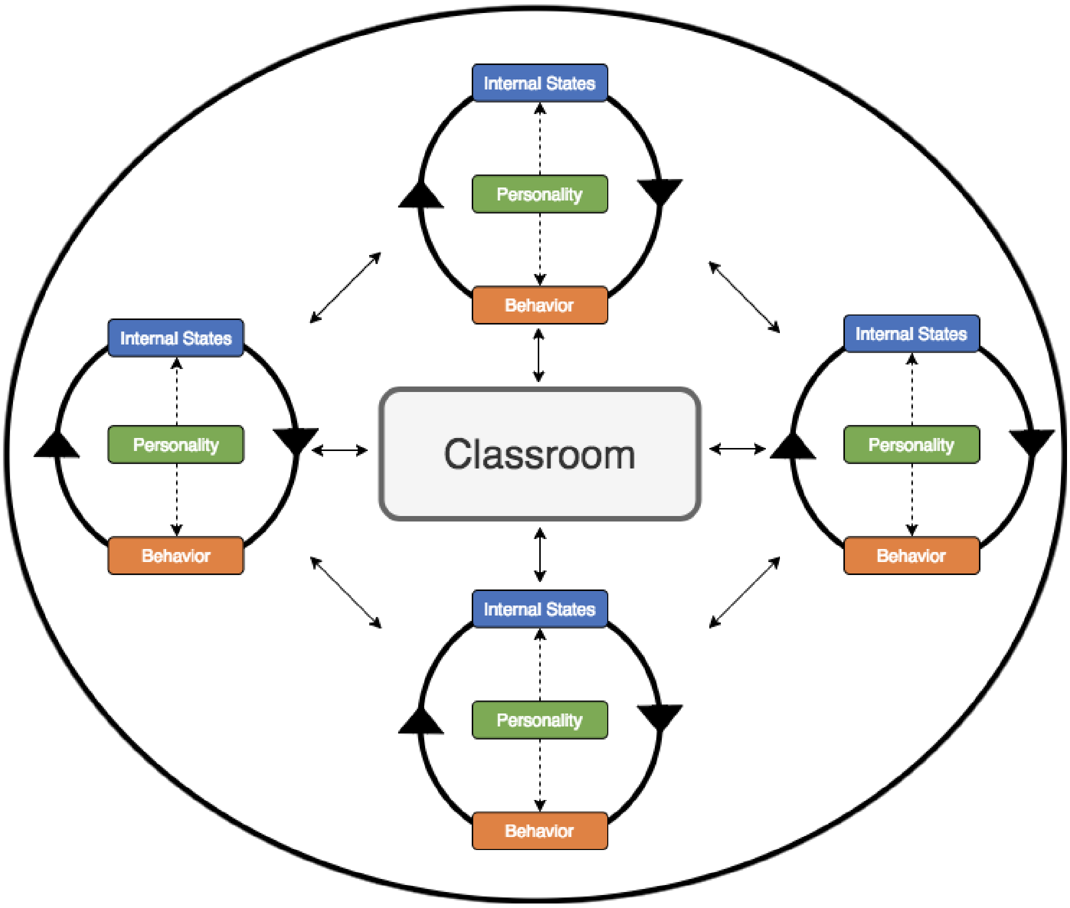


Figure 4.4: Group Dynamics

4.1.3 Agent Behavior Selection

The following are the different factors that influence agent behavior:

- **Environment:** The availability of tables, and the accumulated noise in the classroom.

- **Direct agent interaction:** Another agent that accepts ot rejects to chat or quarrel with the agent.

- **Internal states:** Based on internal states agent logic governs which action is more or less desired by the agent.

- **Peer Pressure:** The action an agent selects to perform is influenced by the average action preference of the group.

How peer pressure is modeled is discussed in more detail in 4.5.

4.2 Agent Personality Model

As described earlier agents differ between each other only in their Personality, witch is modeled on a set of **Personality Traits**.

It is not novel to use personality traits in ABM, but previous works[20] modeled very abstract personality traits that have no psychological bases.

We therefore where careful, to choose an established and widely used personality traits model. The **OCEAN** personality trait model([21], [22]), commonly known as the **Big-Five**, has been developed in the 1960s and has since been used in applied and theoretical psychology. It is based on factor analysis of empirical studies (mostly self description of patients about their behavior and self image).

4.3 The Big-Five

Its name is derived from the five orthogonal dimensions which are used to describe the personality of an individual, whereby the extremes of each dimension are associated with typical behaviors or thought patterns (see figure 4.5 for a graphical summary).

A short description of the different dimension has been taken from[1] can be found in the table 4.3.1.

4.3.1 Stability of Personality Traits

From the literature it is not clear how stable the personality traits described by the OCEAN model really are. Some studies ([23] [24]) show gender differences and systematic changes of traits during the lifetime of a person, and specially during adolescence. Other studies on the other side, found results([25], [26]) on the stability of personality traits for a very long time or even the complete life of an individual.

Independent of their stability over time, personality traits seem not to depend on hereditary factors alone, as studies[27] show different life factors like socio-economic status to be a powerful predictor of personality traits.

The concrete origins and dynamics of personality traits go beyond this work, and we decided there is enough evidence in the literature to justify the OCEAN model as a useful personality model and the personality traits are stable enough to be taken as constant for our purposes.

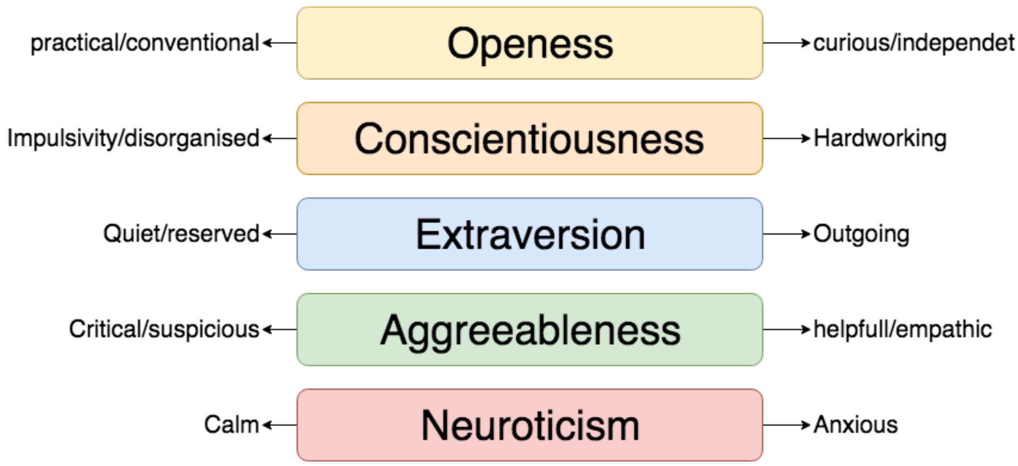


Figure 4.5: OCEAN Model

4.3.2 Big-five in the classroom

Various empirical studies have been performed in the past in order to investigate the association between Personality Traits, behavior and academic outcome in schools ([1], [28], [29]). We used those empirical found associations to define and tune agent logic as well as simulation parameters in order to reproduce agent behavior that is in agreement with those results.

As a summary of those findings we cite from [29] where the authors write.

Together, this literature review suggested the following hypothesis: neuroticism and low extraversion correlate with social inhibition, low agreeableness and low conscientiousness with aggressiveness, and conscientiousness and culture/intellect/openness with antecedents and outcomes of school achievement. These correlations are consistently found all throughout childhood.

Although it is well studied how the Big-Five behave on an individual level, we found very few studies that focused on group dynamics influenced by the Big-Five. One work that we did find[30] studied how the Big-Five influence the forming of new friendships in adolescence, but limited the study to pair wise interactions.

Another study [31] showed the effect of personality traits of members in a peer group on the academic achievement of the individuals. The investigators defined their own academic

Personality Trait	**Description**
Openess	*The general tendency to be curious about both inner and outer worlds. O includes the elements of an active imagination, aesthetic sensitivity, attentiveness to inner feelings, preference for variety, intellectual curiosity, and independence of judgment. A high O also includes individuals who are unconventional, willing to question authority, and ready to entertain new ethical and social ideas.*
Conscientiousness	*The general tendency to be able to resist impulses and temptations. The conscientious individual is purposeful, strong-willed, and determined. On the positive side, high C is associated with academic and occupational achievement; on the negative side, it may lead to annoying fastidiousness, compulsive neatness, or workaholic behavior, Low C's are not necessarily lacking in moral principles, but they are less exacting in applying them.*
Extraversion	*The general tendency to be outgoing. In addition, high E's prefer large groups and gatherings and are assertive, active, and talkative. They like stimulation and tend to be cheerful in disposition. They are upbeat, energetic, and optimistic.*
Agreeableness	*The general tendency to be altruistic. The high A is sympathetic to others and eager to help them, and believes that others will be equally helpful in return. By contrast, the low A is antagonistic and egocentric, skeptical of others' intentions, and competitive rather than cooperative.*
Neuroticism	*The general tendency to experience negative affects such as fear, sadness, embarrassment, anger, guilt, and disgust is the core of the N domain. However, N includes more than susceptibility to psychological distress. Perhaps because disruptive emotions interfere with adaptation, those who score high in N are also prone to have irrational ideas, to be less able to control their impulses, and to cope more poorly then others with stress.*

Table 4.1: Table: Ocean model factors taken from [1]

relevant personality traits and showed how more persistent peers elevate the academic performance of less persistent peers without costs to those peers or themselves.

To the best of your knowledge there is no previous work that uses the Big-Five personality trait model to study how group dynamics in a classroom are affected by different personality profiles.

4.3.3 Alternatives to the Big-Five

The Big-Five model is not the only popular personality trait model commonly used. Another model, specially popular in the area of management and labour market, is the Myers Briggs Type Indicator **MBTI**, which assigns each individual to one of 16 possible personality types. Although popular, there seems to be no scientific basis for the model and scientific investigation[32] revealed low predictive power and accuracy of the model.

The OCEAN model has therefore been preferred over any alternative.

4.4 Agent Logic

As mentioned before the simulation is using a heterogeneous agent model with agents that differ in their personality traits, but share the same logic and capabilities.
The logic is executed independently on each agent, and is implemented as an infinite loop, repeating the following steps

1. **Calculating action scores**
2. **Action selection**
3. **Action execution**
4. **Handling interactions**
5. **Updating internal states**

4.4.1 Calculating action scores

The agent can execute one of five actions (see the section 4.1.1 about available actions). In order to decide which action to execute, a score is calculated for each action independently. Section 4.5 covers the action score calculation in detail. The score of an action depends on the the internal states of the agent and its psychological profile.

Action Score Bias

Besides the action score, the agent is calculating an **action score bias** that is added to the score of the current action and subtracted from the score of the previous action. This mechanism is used to keep the agent from switching between actions too quickly. In addition, the added bias models the tendency to continue with an ongoing task and switching costs between tasks (similar to sustaining attention). Reducing the score of the previous action keeps the agent from looping between two of the possible actions, and cause a more diverse action selection.

The action score bias depends on the conscientiousness of the agent and is following an exponential decay curve, where time is the number of ticks the agent is performing the current action. The number of ticks is only taken into account while the action is executed, not in its other states, making sure that *Transitions* or *Waiting* do not affect the action score bias.

$$action - score - bias(a_i) = \alpha * e^{-(1.0-C)\beta*t} \tag{4.1}$$

with

- a_i is the action i
- where α is a simulation parameter defining the maximum bias
- where β is a simulation parameter defining a dampening factor scaling exponential decline
- where C is the agents conscientiousness
- where t is the number of ticks the current task is executed

4.4.2 Action selection

Based on the scores a single action is selected probabilistically, giving preference to the action with the highest score.

As mentioned shorty in the chapter on agent logic, the action selection does not only depended on the agents own desires, but is modulated by **peer pressure**. This aspect was included in the model by building the action score vector that is used to select an action, as a weighted sum of the action score vector of the agent plus the mean action score vector of the classroom (i.e. all agents in the classroom). The weight given to the classroom average is defined by a simulation parameter.

The probability for a action to be selected is defined by the square of the normalized action scores (see equation 4.2). Taking the squared action score makes sure that the highest rated score has a clear advantage over the other actions, but still gives other actions a chance to be selected.

$$p(a_i) = \frac{s_i^3}{\sum s_i^3} \tag{4.2}$$

with

- $p(a_i)$ is the probability of action i to be selected
- where s_i is the score for action i

4.4.3 Action execution

The selected action is evaluated if it can be performed, and if this is possible then the action is executed. If the action cannot be performed, the second *best* action is taken. In case the second action is not possible, the agent is forced to take a break. In addition if it is not possible to perform an action, the agent keeps track of what its desired action is, and what action is executed instead.

The complete decision sequence evaluated is shown in the decision tree at 4.6

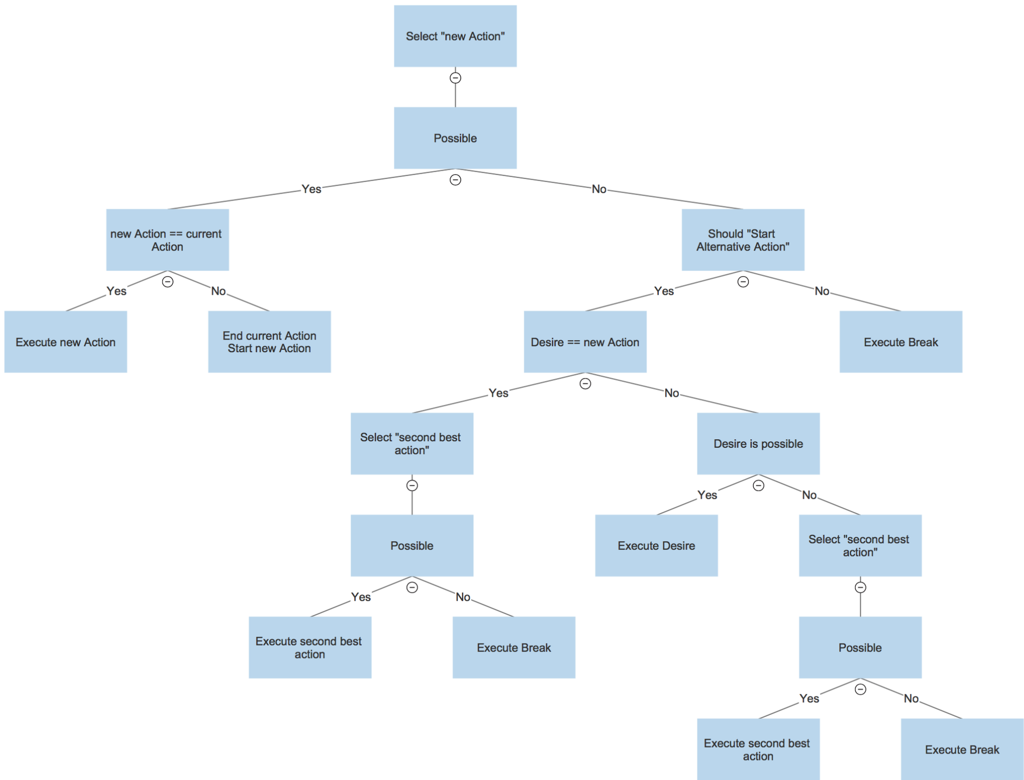


Figure 4.6: Action Selection Decision Tree

4.4.4 Handling Interaction

Some of the agent behaviors like *Chat* and *Quarrel* depend on direct interactions between agents. Meaning that if agent A wants to chat with agent B (who is randomly selected from the available agents), then Agent A depends on B *accepting* its invitation to chat. This mechanism is implemented by agent A who is sending a request for chatting to agent B, and agent B in return decides to either accept or reject the invitation.

In case the request is accepted both agents perform the action (i.e. Agent B will interrupt its current action), and if rejected, the sending agent A will retry either sending another request to the same agent B, or start over with another agent.

Agent B decides its response depending on a random factor and its personality traits. In case of chat the relevant personality trait is *conscientiousness* and in case of quarrel *agreeableness*. The random factor is a number between 0.0 and 1.0 that is randomly generated and compared to the personality trait. Is that number equal or bigger than the corresponding personality trait, the agent will accept the interaction.

This mechanism reflect empirical findings that agents with a high level of conscientiousness are less likely to be distracted from their current task, and a high level of agreeableness, reducing the chance to quarrel, as it is associated with less involvement in conflicts.

4.4.5 Updating internal states

At the end of each cycle, the agent is updating its internal states, whereby from the three internal states (i.e. motivation, attention and happiness), only attention and happiness are updated at this point.

- **Happiness:** is increased if the current action is not quarrel, and the executed action is the desired action. In case the agent is executing a not desired action happiness is decreased by a factor (a simulation parameter) that is scaled by the agents neuroticism. In addition happiness is effected by different actions (discussed later).
- **Attention:** is calculated in case the agent is studying (either alone or in a group). It is calculated by taking the sum of its motivation adding conscientiousness and subtracting the noise in the classroom.

As *motivation* is concerned, this internal state is altered by the current action performed.

4.5 Actions

As mentioned before, agents have the capability to perform one of five actions (i.e. Chat, Quarrel, Break, Study alone and Study in groups), with each action being in one of four states (Inactive, Transition, Waiting and Execution) at each moment in time.
All actions follow a similar structure, and have three main functions:

- **Test Feasibility:** Test if it is possible to execute an action. This includes to test for the availability for resources in the environment (e.g. for example if there is a free individual table available) or the availability of other agents (e.g. in case of a group study if there are other agents at the table willing to study).

- **Action scoring:** Calculates a score for the action based on the internal states and the personality of the agent.

- **Action execution:** Makes the agent perform different behaviors based on the state of the action (e.g. in Transition it makes the agent walk toward its goal). This is the point in which the internal state motivation is altered according to the simulation mechanics.

Before describing the exact mechanics for the different actions we have a look at how to calculate the action scores.

4.6 Actions Scores

As mentioned before each action is scored independently, taking into account the internal states and the personality traits of the agent. The score calculated reflects how appropriate the specific action is for the personality and the internal state of the agent.
The generated score is a continuos value between 0 and 1.0, where high values are given if the action is in correspondence with the simulation mechanics, and low values otherwise. Although the scoring differs between the specific actions, all of them make use of the same basic building blocks.

Those blocks are an exponential growing, an exponential decaying function and a function calculating the weighted sum of three components (see equation 4.3 and a visualization in figure 4.6). The weights for the sum correspond to the importance given to personality, motivation and happiness in calculating the score. The weights are simulation parameters and stay constant for the simulation. The components summed are the exponential growing or decaying function, depending on the internal state and the personality of the agent. The exponential functions have been defined to stay within a range of 0.0 to 1.0 for values of x between 0.0 and 1.0. In addition, the result of the scoring function is cutoff to stay within 0.0 and 1.0.

As mentioned before, the internal states happiness and motivation are effected by the action the agent is performing. How the internal states are affected, depend on the state of the action, and differs between *Waiting, Transition* and *Execution*. Where for *Waiting* and *Transition* the effect strength on happiness is modulated by the agents neuroticism and agreeableness, and during *Executing* motivation and happiness are changed by a constant factor that is defined as a simulation parameter.

$$E_{grw}(x) = \frac{e^{x^2} - 1}{e - 1} \tag{4.3a}$$

$$E_{dec}(x) = \frac{e^{(1-x)^2} - 1}{e - 1} \tag{4.3b}$$

$$weighted_{sum}(\alpha, x, \beta, y, \gamma, z) = (\alpha * x) + (\beta * y) + (\gamma * z) \tag{4.3c}$$

with

- α the weight of personality

- β the weight of motivation
- γ the weight of happiness

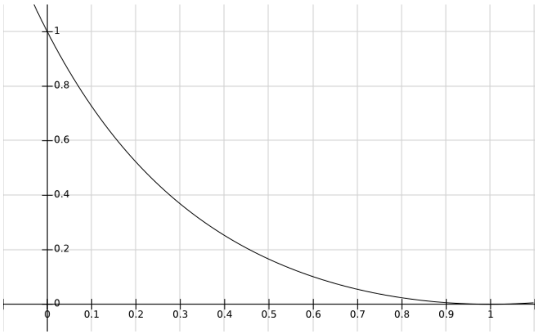


Figure 4.7: Exponential Decay

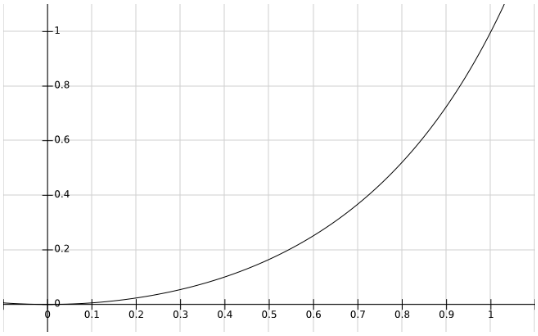


Figure 4.8: Exp Growth

Chat

The intention of *Chat* is to recover the motivation of the agent, preferred by agents with high rates on extroversion. In order to chat, the agent will randomly select another agent in the classroom to chat with, and approach that agent. If the other agent accepts the invitation, and both agents are next to each other, the agents will start chatting. If the request was rejected, the agent will repeat to send requests for a specific number of times, before giving up and start the second best scored action.
The action scored is calculated using the following scoring function

$$weighted_{sum}(extroversion, w_{per}, E_{dec}(motivation), w_{mot}, E_{grw}(happiness), w_{hap}) \quad (4.4)$$

While the agents are chatting, they will produce a bit of noise adding the accumulated noise in the classroom.

Taking a break

The intention of this action is to recover motivation, for agents with low rates on extroversion (working as an alternative to chatting). When taking a break, agents don't depend on any other agent, and will start to wander around in the classroom randomly, performing a random walk, causing no noise while doing so.

The action score is calculated using the following scoring function

$$weighted_{sum}(1.0 - extroversion, w_{per}, E_{dec}(motivation), w_{mot}, E_{grw}(happiness), w_{hap}) \tag{4.5}$$

Quarrel

Quarreling is the result of an agent's happiness being very low and being at least medium to highly motivated. In order to quarrel the agent has to find another agent to do so. Similar to Chat the agent will select another agent randomly and starts to quarrel with that agent if accepted. If the other agent refuses, the unhappy agent will repeat its request a fixed number of times before giving up and evaluate another action.

Once the agents start quarreling, their motivation and happiness will fall drastically. In addition quarreling produces a lot of noise that is added to the accumulated noise in the classroom. When the agents stop to quarrel as special mechanism is invoked, immediately increasing the happiness of the agent by a fixed value (simulation parameters).

The action score is calculated using the following scoring function

$$weighted_{sum}(agreeableness, w_{per}, E_{grw}(motivation), w_{mot}, E_{dec}(happiness), w_{hap}) \tag{4.6}$$

Studying alone

If the agent is motivated and happy, it will start to study, preferring to study alone in case of low levels of extroversion. In order to study alone the agent needs access to a free individual table, and that the noise in the classroom is not too high. The acceptable noise level for an agent is depending on its conscientious, sustaining higher noise levels with higher rates of conscientious. Studying alone increases the noise levels slightly.

The action score is calculated using the following scoring function

$$weighted_{sum}(1.0 - extroversion, w_{per}, E_{grw}(motivation), w_{mot}, E_{grw}(happiness), w_{hap}) \tag{4.7}$$

Studying in groups

Agents with high extraversion rates, motivation and happiness, will start to study in groups. What agents need to do so, is a seat on a group table and other agents at the table that are willing to study. Groups studying increase the noise level in the class by a medium amount.
The action score is calculated using the following scoring function

$$weighted_{sum}(extroversion, w_{per}, E_{grw}(motivation), w_{mot}, E_{grw}(happiness), w_{hap}) \quad (4.8)$$

Chapter 5

Data Analysis

In this chapter we will present how the simulation is run and how the results are analyzed.

5.1 Running the simulation

In order to run a simulation three things are needed:

- **simulation software:** Which is a binary file of the simulation software available for Mac/Win/Linux
- **Simulation Parameters:** A JSON text file that defines simulation parameters
- **Classroom Profile:** A JSON text file that specifies the psychological profiles of students in the class

The simulation can be run interactively making it possible to observe the progression of the simulation, or in headless mode, where no visualization is generated. The later one is particularly useful when combined with a increased simulation speed, in which case many different simulations can be run in a **batch mode** [1] like manner.

Independent of the way the simulation is run, a CSV output file will be generated that documents the progress of the simulation. That CSV file can be opened in any arbitrary tabular data processing software (e.g Excel) for manual inspection, but is made to be analyzed by a set of python scripts developed for the purpose, and included with the simulation software stack.

[1] Batch mode means that a series of simulations are run consecutively without any human supervision or interaction.

How those scripts are used and what results they generate is described in the following chapter.

5.2 Data Analysis Pipeline

The Data Analysis performed for the complete thesis is split into three parts, each having a distinct focus, answering a different set of questions.

1. **Simulation:** The goal of the simulation is to study the behavior of a particular classroom and combination of agent profiles. Providing insights into the behavior of a single agent and the aggregated and averaged behavior of the group as a whole.

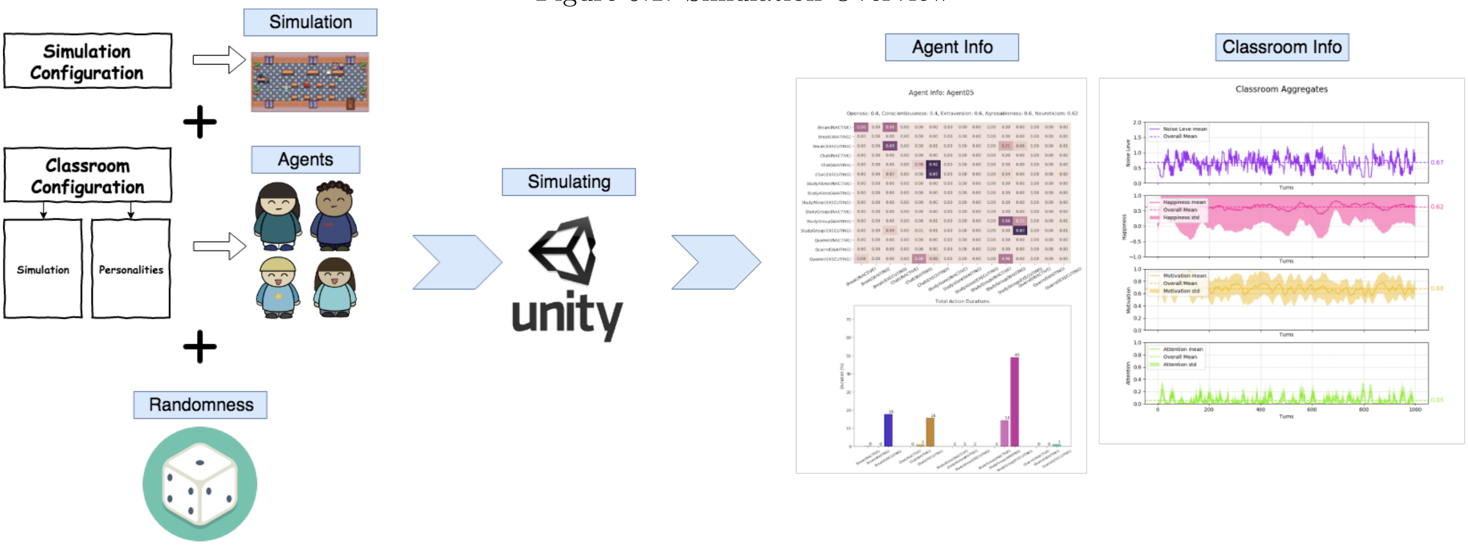
2. **Experiment:** The *Experiment* studies how much variation is there between multiple runs of the simulation of the same classroom, slightly changing the classroom profiles and random elements of the simulation.

3. **Study:** Having a expectation on how a specific classroom profile behaves, the *Study* phase asks the question how two different profiles compare to each other, and how alterations of the personality profile affect group averages.

In the following sections we will have a look at each step of the pipeline individually, as it is not necessary to run the complete pipeline but based on the question one tries to answer only one or two of the first steps are necessary.

5.3 Simulation

Figure 5.1: Simulation Overview



Simulation is the first step of the analysis, answering the question how a specific classroom of agents behaves.

The simulation program takes three input arguments. The simulation config, is defining all simulation relevant parameters that govern how the simulation mechanism works, the classroom configuration that defines the psychological profile of students, and a random seed that is used to initialize the random number generator used during the simulation.

Examples files of the simulation config and classroom config can be found as part of the appendix (see A and A.1).

The classroom configuration must contain a set of Personality Types and the number of students of each type. When the simulation is run, a classroom is dynamically generated and filled with agents as defined.

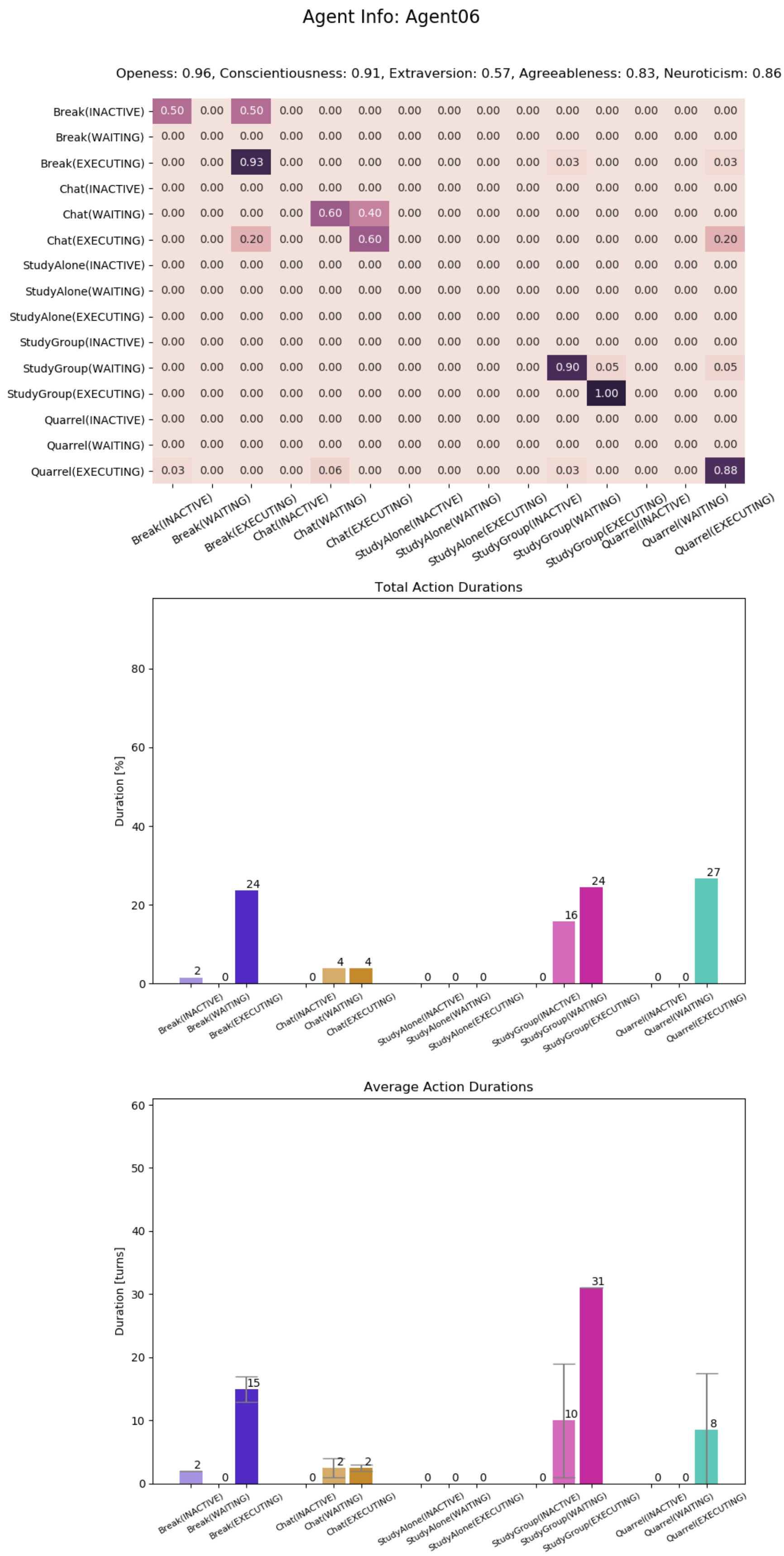
The python analysis scripts for the simulation will process the CSV file produced after the simulation is completed and will generate a set of figures containing information about each individual agent, the classroom as a group and a new CSV file that contains aggregated information.

5.3.1 Agent Info

One of the results of the simulation step is the **Agent Info** figure (see 5.3.1 showing three different agent infos) that is generated for each agent, and contains information about the distribution and transitions between different behaviors performed by the agent. This figure is used to study how a specific instance of a psychological type behaves in the given classroom. One can observe how much of the overall time an Agent spends Studying alone or how long on average a single study session lasts.

It is interesting to observe the different patterns with which the personality traits affect the behavior distribution of the individual agents. One could for example observe that agents high on conscientiousness, on average have longer learning sessions than agents that are low on conscientiousness.

Figure 5.2: Agent Info



5.3.2 Classroom Aggregates

The second result produced by the simulation analysis is a figure showing classroom aggregated features over time (see figure 5.3.2 as an example). This figures contains information like the aggregated noise, average happiness, motivation and attention of a class, in addition to information about how many of the students are studying or quarreling at a specific moment during the simulation.

This kind of figure is useful to study how personality profiles effect the group as a whole, and can be used to search for emerging social phenomena.

5.4 Experiment

The experiment is the second phase of the data analysis pipeline and is focused on evaluating the variance between simulations of the same classroom configuration.

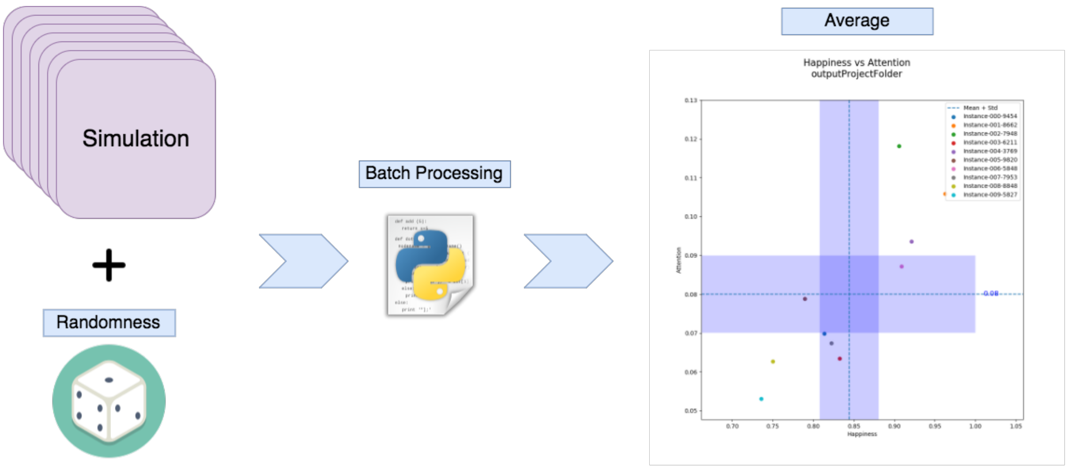
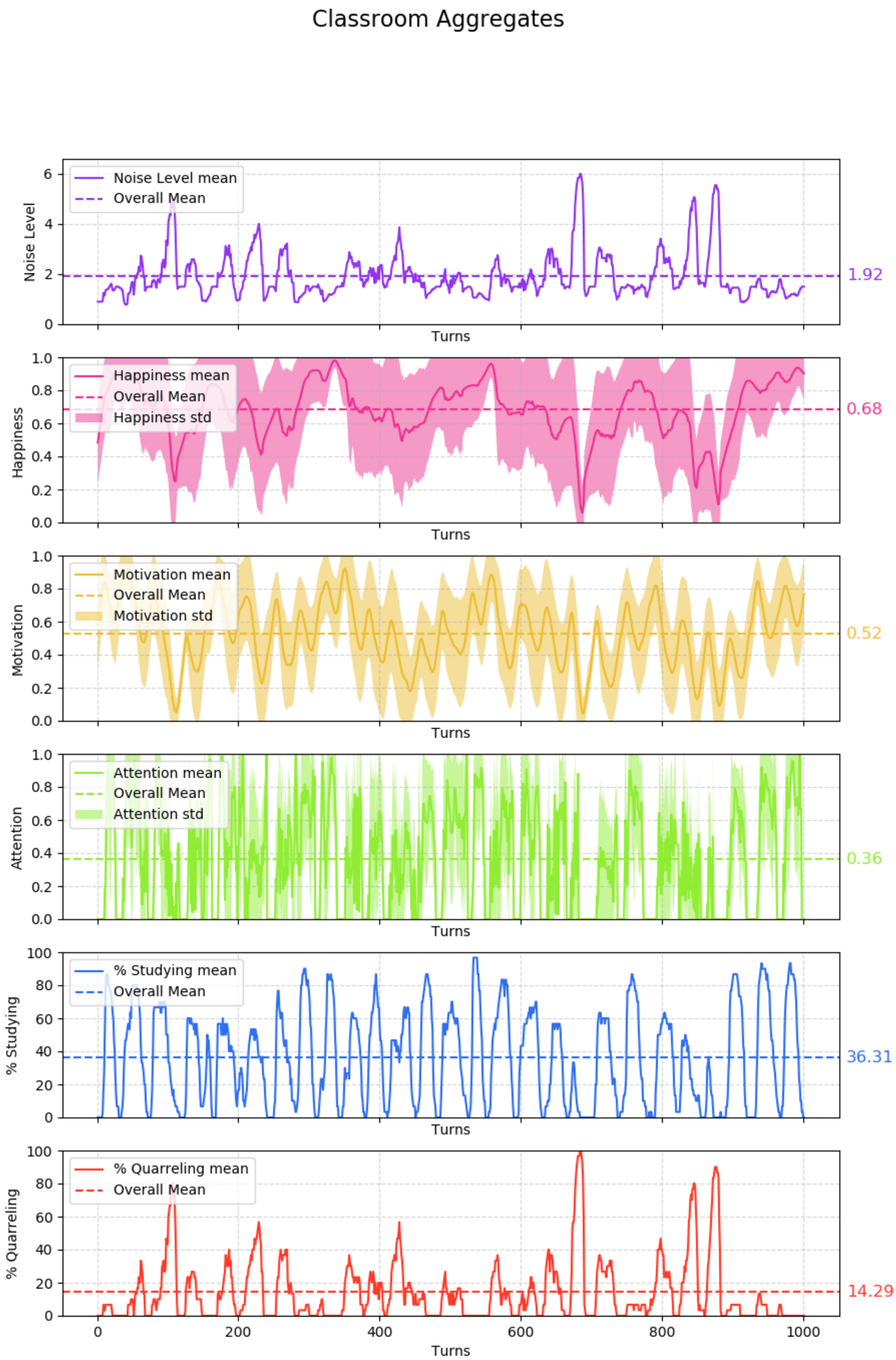


Figure 5.4: Experiment Overview

In order to have a statistical description of the simulation results, one has to run multiple instances of the same simulation (identical simulation and classroom configs) but different seed values for the random number generator used during the simulation.

There are several random elements in the simulation. Depending on the classroom configuration, agent personality can be partially randomized. The actions selection process has a random element, and agent interactions are effected by the output of a random number generator.

Figure 5.3: Classroom Aggregates



The result of the experiment phase is a single **HA-Plot**, named after its axis Attention and Happiness. The plot shows a a single point for each simulation instance, with its position being based on the average attention and happiness of the corresponding classroom over the complete simulation.

In addition the average happiness and attention over all instances is indicated with two solid lines, and the corresponding standard deviation with semi transparent bars.

The plot helps to identify the spread between different instances of the simulation, and could be used to detect outliers and estimate the stability of a specific classroom configuration.

In addition to the HA-Plot a CSV file is generated that contains the average happiness and attention for each agent and classroom for all simulation instances. This dataset is the numeric equivalent to the generated HA-Plot.

5.5 Study

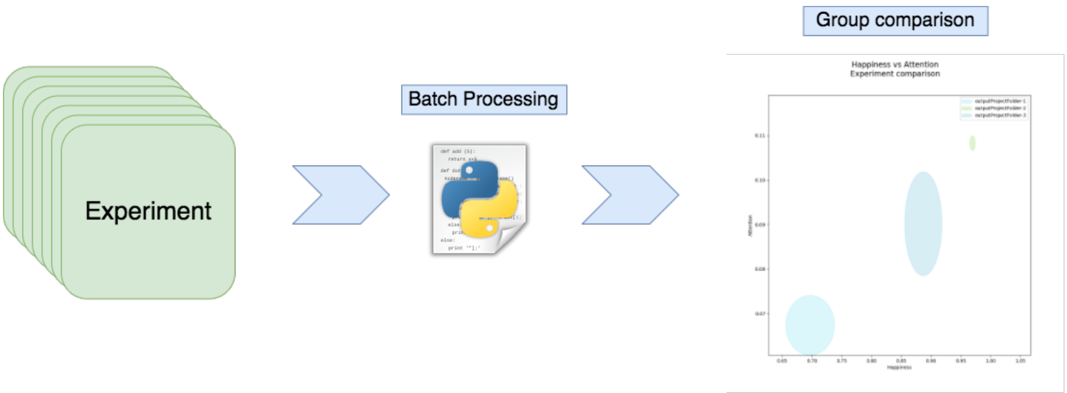


Figure 5.5: Study Overview

The last step in the data analysis pipeline is focused on comparing different classroom profiles.

In this phase of the analysis the CSV generated during the Experiment phase is analyzed to generate a HA-Plot that contains one ellipse for each classroom profile simulated. The ellipse center and size are defined by the mean and standard deviation of all individual agents of the corresponding classroom profile.

This plot gives an visual overview how the different classroom profiles compare to each other, and can be used to study the strength and direction of change one profile has compared to another.

In addition the plot contains a statistical analysis of the relation between classroom profiles and the correlation between happiness, attention and the different personality dimensions. The statistical analysis includes a MANOVA analysis indicating if there is a significance difference between groups along the dimensions Happiness and Attention, in addition to a pair wise ANOVA analysis to indicate if each classroom profile paar is significantly different to each other.

An example of the plot can been seen as part of the results presented in the next chapter (see figure 6.1).

Chapter 6

Study and Results

In this chapter we will present the study that has been performed and the results generated using our simulation.

6.1 ADHD and Personality Traits

A recent study [33] shows that the world wide prevalence for anxiety disorders within children and adolescents to be around 6.5%, and Attention-deficit hyperactivity disorder **(ADHD)**[34] being one of the most common childhood behavioral disorder, ranging between 5% and 10% [35].

Because of the high prevalence of anxiety disorders in the general population, and the availability of studies correlating ADHD with personality traits, we decided to study the effect of children with personality profiles that match those of ADHD patients on the class as a whole.

The primary reference for how ADHD symptoms relate to personality traits, we took from [28], where the authors write

... our findings for the two major symptom domains suggest the following conclusion: overall ADHD symptoms are related to low Conscientiousness, low Agreeableness, and high Neuroticism.

6.2 Study Description

The study we performed had the objective to simulate how an increasing number of students with ADHD symptoms would affect the group dynamics. This was achieved by the following steps.

- We defined three types of students (*ADHD, Normal, Ambitious*)
- Created several classroom profiles varying the ratio of the different student types present
- Run a Simulation study comparing the classroom profiles to each other

6.2.1 Student Types

The student types chosen have been inspired by the literature, whereby we took defined a ADHD student using results from [28], a normal type using [23] and Ambitious students from [29].
At this point it is worth to note that the defined student types are prototypical in nature. There exists no *normal* nor *ADHD* personality trait type. The Big-Five model is a continuos scale in all five dimensions. The different personality types have been defined as a shorthand to simplify the analysis of results and highlight the divergence between groups. The concrete personality profiles used for each type are found in table 6.1

Student Type	**O**	**C**	**E**	**A**	**N**
ADHD	RND	0.20	RND	0.20	0.80
Normal	0.75	0.60	0.55	0.65	0.50
Ambitious	0.80	0.80	RND	0.80	0.20
Random	RND	RND	RND	RND	RND

Table 6.1: Table with Student types composition groups
RND indicates a random value from a uniform distribution between [0, 1]

6.2.2 Groups

Based on the student types we created various classrooms that where compared to each other. Each group consisted of 30 students, varying the % of each Student type per group (see table 6.2).

The ratio of ADHD students is very high and does not correspond directly to empirical findings (see [35] who estimates ratios to be between 5-10%). We have chosen those high values because ADHD is no black or white form of psychological disorder, but rather a spectrum that can vary strongly in its intensity and persons behavior. Similar to the student types, the different groups have been defined to exemplify tendencies and highlight differences.

In addition the group 'Random' serves as a form of estimation how strong the simulation output is affected by the classroom profile.

Group	**ADHD**	**Normal**	**Ambitious**	**Random**
ADHD-Low	7%	93%	0%	0%
ADHD-Medium	17%	83%	0%	0%
ADHD-High	33%	66%	0%	0%
ADHD-VeryHigh	50%	50%	0%	0%
ADHD-None	0%	100%	0%	0%
ADHD-None-Ambitious	0%	50%	50%	0%
ADHD-Low-Ambitious	7%	46%	46%	0%
ADHD-Medium-Ambitious	20%	40%	40%	0%
ADHD-VeryHigh-Ambitious	50%	0%	50%	0%
Random	0%	0%	0%	100%

Table 6.2: Groups composition studied

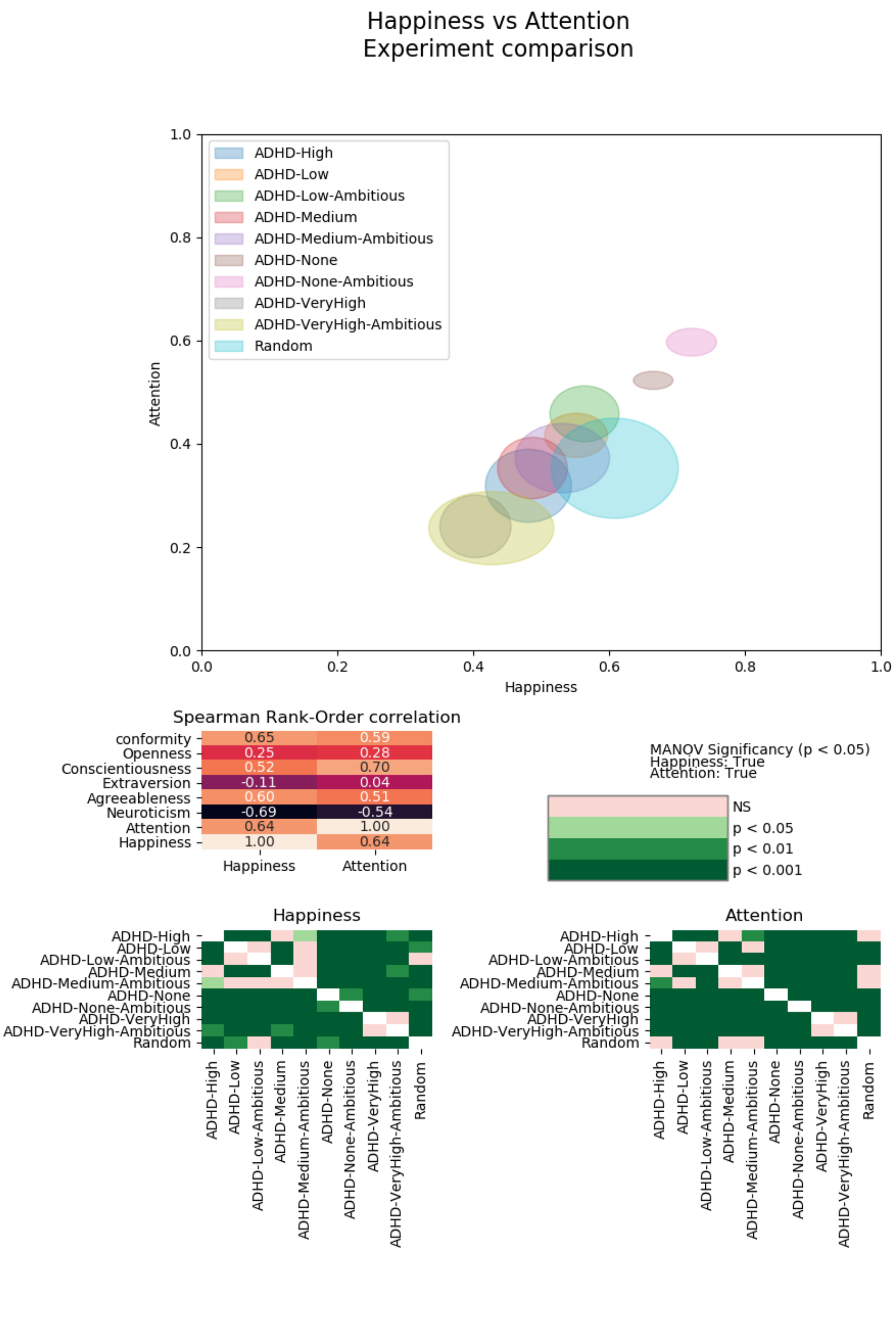
RND indicates a random value from a uniform distribution between [0, 1]

6.3 Results

We have been simulation each of the groups defined above using 5 replicates, initiated with different seed values.

The HA-Plot is generated by the last step of the Data Analysis is shown in figure 6.1.

Figure 6.1: HA-Plot comparing the different classroom configurations



Classrooms with ADHD students had a strong effect in all groups. The general tendency seems to be that the higher the ratio of ADHD students, less happy and attentive the class as a whole becomes. The ambitious students on the other side cause the exact reverse effect, increasing happiness and attention.

6.3.1 ADHD Effect

Given this dynamic, specially the groups containing a mixture of ADHD and ambitious students is interesting. Comparing the groups *ADHD-Low-Ambitious*, *ADHD-Medium-Ambitious* and *ADHD-VeryHigh-Ambitious* show that ADHD type students have a far stronger effect than their ambitious counterparts.

This effect is most visible in the *ADHD-Low-Ambitious* group, in which only very few ADHD students, reduce mean happiness and attention compared to the *ADHD-None* group despite the presence of many more ambitious students.

ADHD and Personality traits

To investigate this further, we have calculated the correlation between student personality traits and happiness, attention and conformity. The correlation matrix is part of the HA-Plot of the final result 6.1. In addition we have calculated two more correlation matrices, that contain all ADHD classrooms in one matrix, and all None ADHD classes in the other (see figure 6.2).

It appears that for None-ADHD Classrooms, the different personality traits are equally correlated with the mean happiness and attention of the students. For the ADHD classrooms on the other side there is a strong correlation for some of them, but not for others. Happiness and Attention correlates strongly with Conscientiousness, Agreeableness and Neuroticism; which by the way are the main personality traits for the ADHD student type. This strong correlation between the key ADHD personality traits and the HA axis explain the direction of the effect.

Concerning the strength of the effect, it is interesting to look at the HA-Plots showing the individual agents of a single simulation Instance. Comparing the classroom configurations *ADHD-Low-Ambitious*, *ADHD-Medium-Ambitious* and *ADHD-VeryHigh-Ambitious* contained in the A, one can see clearly that there are two clusters of agents. The ADHD agents in the lower left and the None-ADHD agents in the upper right region of the plot. As the ratio of ADHD students increases, the None-ADHD cluster is shifting towards the lower left (less happy, less attention), while the ADHD cluster remains where it was.

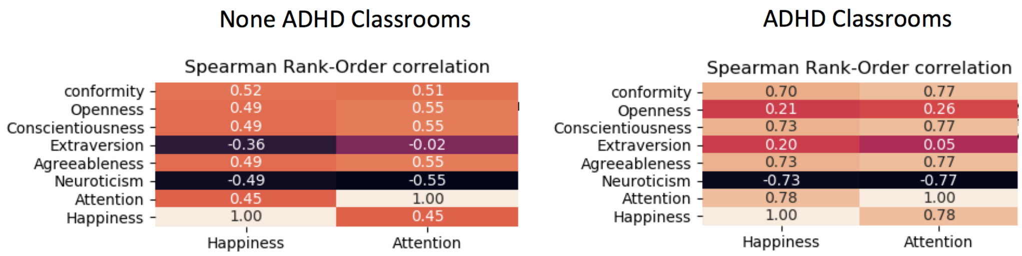


Figure 6.2: Comparing change in correlation between ADHD and None-ADHD Classrooms

It appears that the ADHD students cause a strong shift in behavior of the None-ADHD agents, without altering or adapting their own.

6.3.2 Classroom riots

Finally we want to shortly compare the classroom aggregate plots of the classroom configurations *ADHD-High*, *ADHD-None*, *ADHD-None-Ambitious* and *ADHD-Low-Ambitious*.

It appears that the *ADHD-High* class compared to the *ADHD-None* has less regular cycles of studying and breaks, while increasing the number of class wide episodes of quarrel (i.e. classroom riots). Those class wide quarrels are an interesting phenomena that can be observed in all classroom configurations.

Comparing the effect of few ADHD students in an ambitious classroom (groups *ADHD-None-Ambitious* and *ADHD-Low-Ambitious*) one immediately notices the increased number of class wide quarrels. In addition it is interesting to see that the *ADHD-None-Ambitious* has a tendency to be in one of two extreme cases of either none or almost everyone quarreling.

Chapter 7

Conclusion and outlook

In this chapter we will draw our final conclusions, including an outlook on possible directions to continue and improve the work done so far.

7.1 Conclusion

As part of the thesis we have developed a multi-agent model that is simulating a virtual classroom.

We have devised a Agent Logic that is based on the established Big-Five Personality Trait model and that produces agent behavior consistent with empirical studies.

We have developed a data analysis pipeline that makes it possible to efficiently run multiple simulations in a batch mode, enabling a statistical analysis of the simulation results.

We chose to compare how students with prototypical ADHD personality traits affect the classroom dynamics, and therefore defined multiple classrooms varying in ratio between none to a high number of ADHD students.

We found that students have a very strong effect on the average happiness and attention of the class. It appears that ADHD students affect the behavior of None-ADHD Students without changing their won. In addition we found that even a low number of ADHD students cause more frequent riots, specially in classrooms with very ambitious students.

The simulation software, the data analysis scripts and all content presented in this thesis is available freely under the MIT License from the github repository https://github.com/mapa17/breakfastclub.

7.2 Outlook

As mentioned shortly in the chapter on Objectives some initial objectives had to be dropped during the development of the thesis in order to stay within the available time frame.

The following is a list of possible improvements, as well as ideas for follow up projects.

- **Improve classroom analysis:** The HA-Plot for different classroom configurations is a very concise representation of multiple instances of the same classroom configuration. Many of the temporal dynamics shown in the classroom aggregate plot are not visible in the HA-Plot. In addition there is no direct way to compare classroom aggregate plots.

  Methods from Time series analysis could be used to extract information about the signal dynamics (like periodicity, entropy, moments, ...) in order to compare instances of the same classroom configuration or between different configurations.

  It would be particularly useful extract a *typical* classroom aggregate showing the classroom dynamics for an configuration and not only an instance.

- **Interactive Simulation:** On way to extend how the simulation can be used, is to make the simulation interactive. Doing so would provide the user with the option to force agents to perform certain actions, expulse students from the classroom, call for silence or similar interactions. This would make it possible to develop a teacher training program, based on the simulator, similar to commercial solutions like TLE TeachLive [14] or simSchool [15] but open source and with agent behavior that is based on a psychological model.

  In order to support learning and provide a novel visualization of the effect of user interaction with the simulation we envisioned a system that is able to track the effect of each user interaction onto the final result of the simulation. This could be achieved by creating a clone of the running simulation when ever the user is performing an action. That clone instance would continue until the end of the simulation unperturbed, and could be compared to the all other clones generated in the same way. This would make it possible to evaluate the effect of each user interaction onto the final result of the simulation, and visualize it as a trace instead of a dot in the HA-Plot.

- **Reinforcement trained teacher:** At the moment the simulation is consisting of students that behave like an autonomous study group. With the teacher interactions described in the previously, one could train a virtual teacher using reinforcement learning (RL) with the objective to maximize happiness and attention of the class.

  As there is a fast amount of literature on different teaching methodologies, it would be interesting to study if the RL trained teacher applies any of the known methodologies or applies new ones. Another interesting aspect would be to study the effect different classroom profiles have on the trained teacher, with other word, how different classroom profiles form and shape teacher behavior.

- **Screening of classroom profiles:** One obvious extension based on the batch processing capabilities of the simulation is to perform a kind of screening studying. One would systematically evaluate a high number of personality profiles, similar to screening studies in Bioinformatics, comparing thousands of combination in order to find interesting tipping points, extremes and curious singularities.

- **Dominance hierarchy:** The current simulation when calculating the peer pressure on a individual agent is modeling a flat social hierarchy. One could extend this to a more realistic Dominance Hierarchy, giving different agents different weights in controlling the classroom interest. Such a Dominance hierarchy in place one could extend its effect on other actions like chat or quarrel, making the outcome of interactions depend as well on the position of agents in the dominance hierarchy.

- **Learning Agents:** Because of simplicity the agents have no capability to learn and adapt their behavior over time. One could prevent some simple learning mechanisms, that would open a wide range of new questions one can study, concerning the dynamics of agent and group behavior over longer durations of time.

7.3 Acknowledgement

We especially want to thank Prof. Dr. Michael Kickmeier-Rust for his continuos support and mentoring. Without him this work would have not been possible.

Chapter 8

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Chapter 9

Article

Contact

cia, España

el.pasieka@protonmail.ch

b.com/mapa17

din.com/in/manuelpasieka

scount

Skills

tware Development

chine Learning

a Analysis

blem Solving

nguages

German

Python

English

I am eager to work with other machine learning experts to solve problems of automatic decision making and general artificial intelligence (e.g. learning, search and pattern recognition).

Experience & Education

Scientific Software Engineer
present - 2012

Biocomp / Vienna Biocenter Core Facilities

Developing serval data analysis applications used by neuroscience researchers to study the amygdala circuit in the mouse brain.

In particular application to automatically quantify and analyze animal behavior, and software to process and analyze neuronal activity.

- Programming in Python, Matlab, R
- Data Visualization: matplotlib, seaborn
- Data Processing: numpy, pandas
- Data Analysis: scipy, scikit-learn

Master in Artificial Intelligence
present - 2018

Universidad Internacional de La Rioja

Master Thesis: "The effect of personality traits on attention and happiness in a virtual classroom"

- Cognitive Neuroscience
- Automatic reasoning and planing
- Natural Language Processing
- Deep Learning

Research Assistent
2012 - 2011

Universidad Politécnica de Valencia

Developing a simulation environment controlled by a stationary replica of a autonomous vehicle.

- Programming in Python, C
- Developing simulation software

Master in Parallel and Distributed Computing
2012 - 2010

Universidad Politécnica de Valencia

Master Thesis: "Peer selection and Bandwidth allocation methods in BitTorrent Systems"

- Distributed Systems
- P2P Networks
- Parallel Computing
- High performance computing

Embedded System Engineer
2010 - 2007

Adaptivia GmbH

Programming of 16 bit low power SoC devices for wireless underground sensor networks.

- Embedded system engineering
- Programming in C
- System and Network design

Bachelor of Technical Informatics
2009 - 2005

Technical University Vienna

Bachelor Thesis: "Course Timetabling using Constraints satisfaction programming"

- Software Development
- Embedded system engineering
- Computer Theory

Various Internships
2007 - 2000

Database Developer
System Administrator
Infrastructure Maintances
Warehouse clerk
Project Assistant

Publications

Pliota, P., Böhm, V., Grössl, F., Griessner,J., Valenti, O., Kraitsy, K., Kaczanowska, J., **Pasieka, M.**, Lendl, T., Deussing, J. M. and Haubensak, W. (2018) 'Stress peptides sensitize fear circuitry to promote passive coping', *MolecularPsychiatry.*

Dr. Johannes Griessner , **Manuel Pasieka** , Mr. Vincent Boehm , Mr. Florian Grössl , Mrs. Joanna Kaczanowska , Dr. Pinelopi Pliota , Mr. Dominic Kargl, Ms. Barbara Werner , Dr. Nadia Kaouane , Ms. Sandra Strobelt , Dr. Silke Kreitz , Prof. Andreas Hess and Haubensak, W. (2018) 'Central amygdala circuit dynamics underlying the benzodiazepine anxiolytic effect', *MolecularPsychiatry.*

Appendix A

Appendix

A.1 Simulation Config


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    ],
    "Agent":
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        {"field":"NOISE_THRESHOLD", "value": 3.00},

        {"field":"PERSONALITY_WEIGHT", "value": 0.40},
        {"field":"MOTIVATION_WEIGHT", "value": 0.30},
        {"field":"HAPPINESS_WEIGHT", "value": 0.30}
    ]
}
```

A.2 Classroom Config

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        {"name":"Normal", "openess":0.75,"conscientousness":0.6,"extraversion
            ":0.55,"agreeableness":0.65,"neuroticism":0.50},
        {"name":"Ambitious", "openess":0.8,"conscientousness":0.8,"
            extraversion":-1.0,"agreeableness":0.8,"neuroticism":0.2}
```

```
        ],
        "nAgents":[2, 14, 14]
    }
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A.3 Results

A.3.1 ADHD-Low

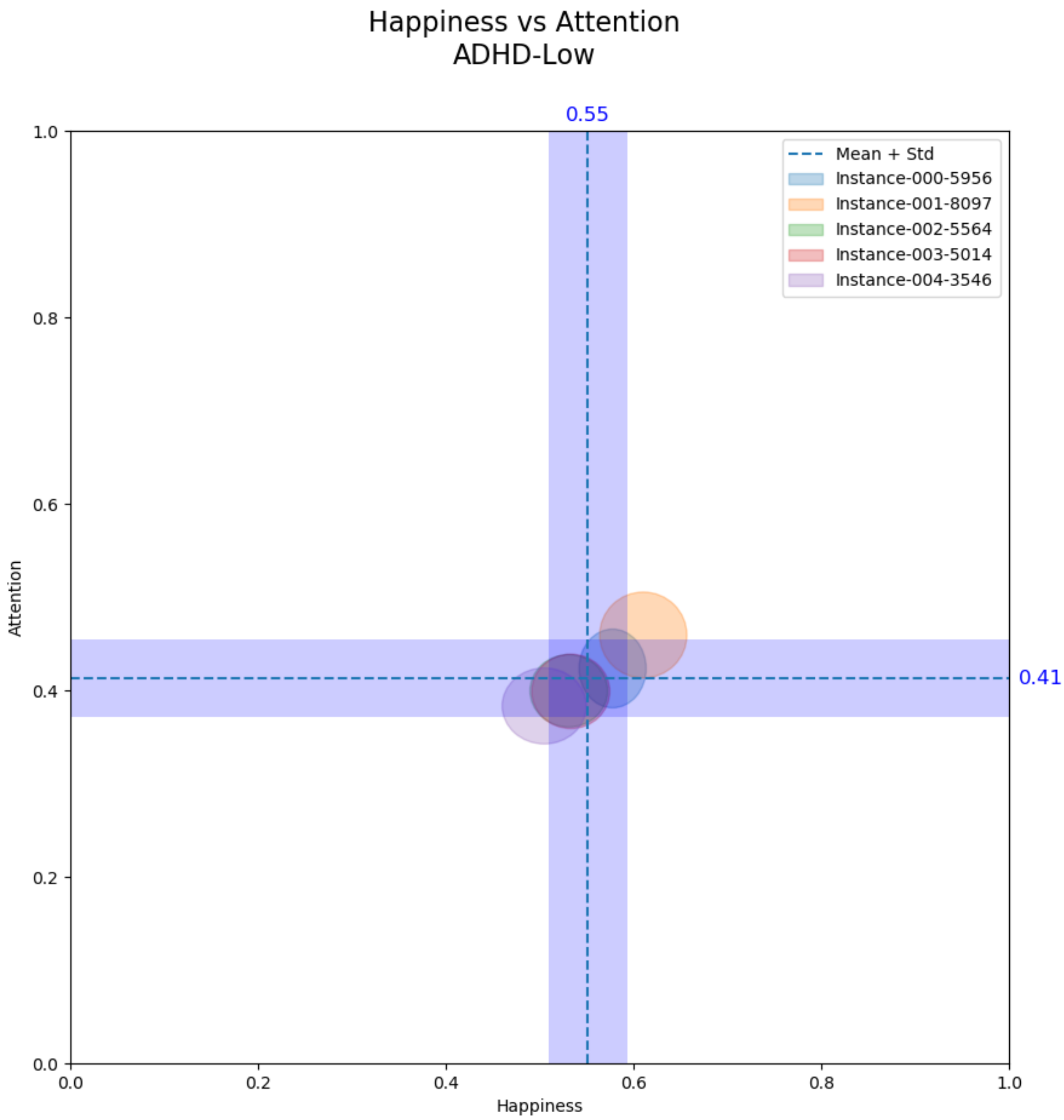

Figure A.1: HA Plot for complete experiment

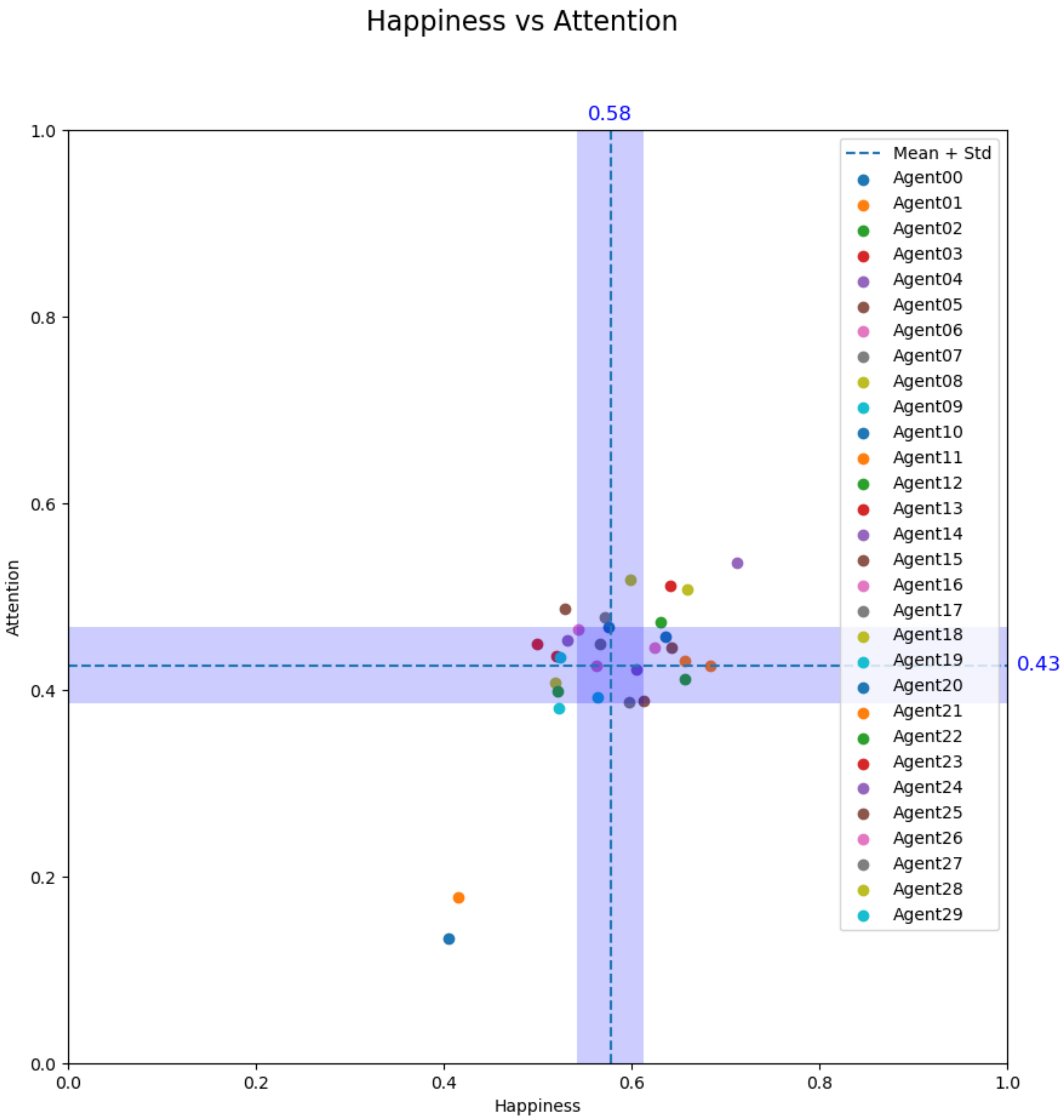

Figure A.2: HA Plot for first instance

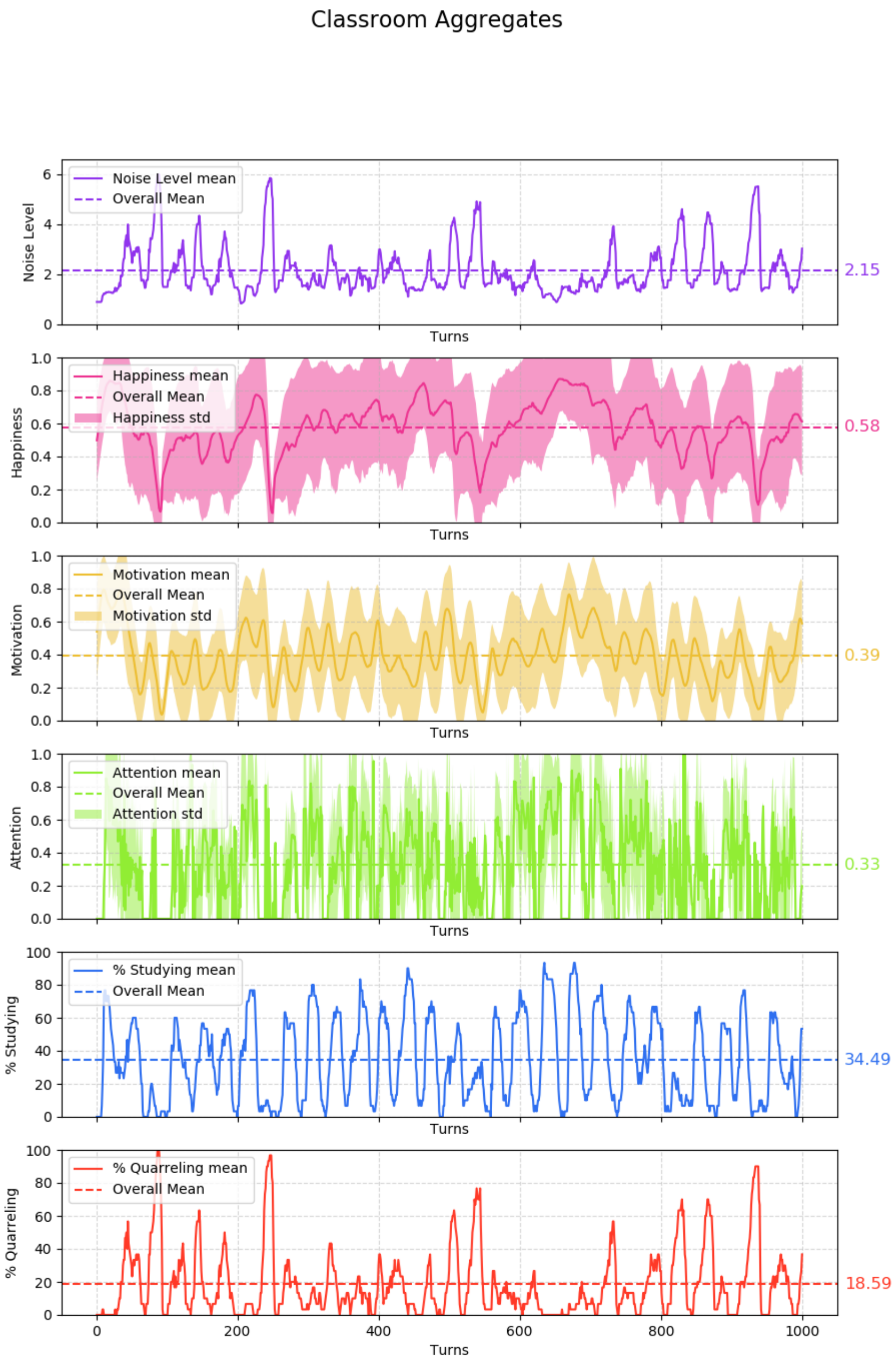

Figure A.3: Classroom aggregates for first instance

A.3.2 ADHD-Medium

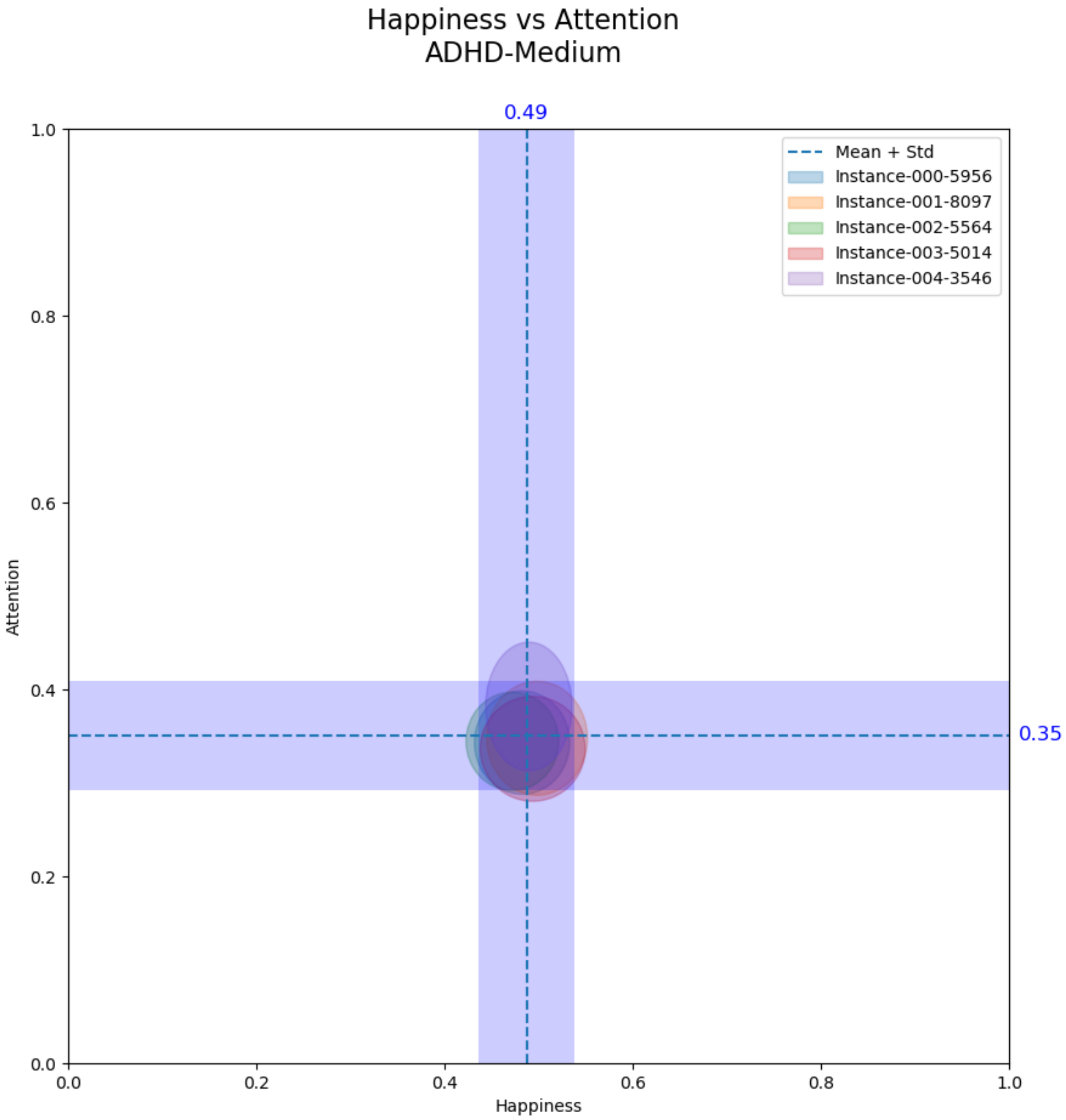

Figure A.4: HA Plot for complete experiment

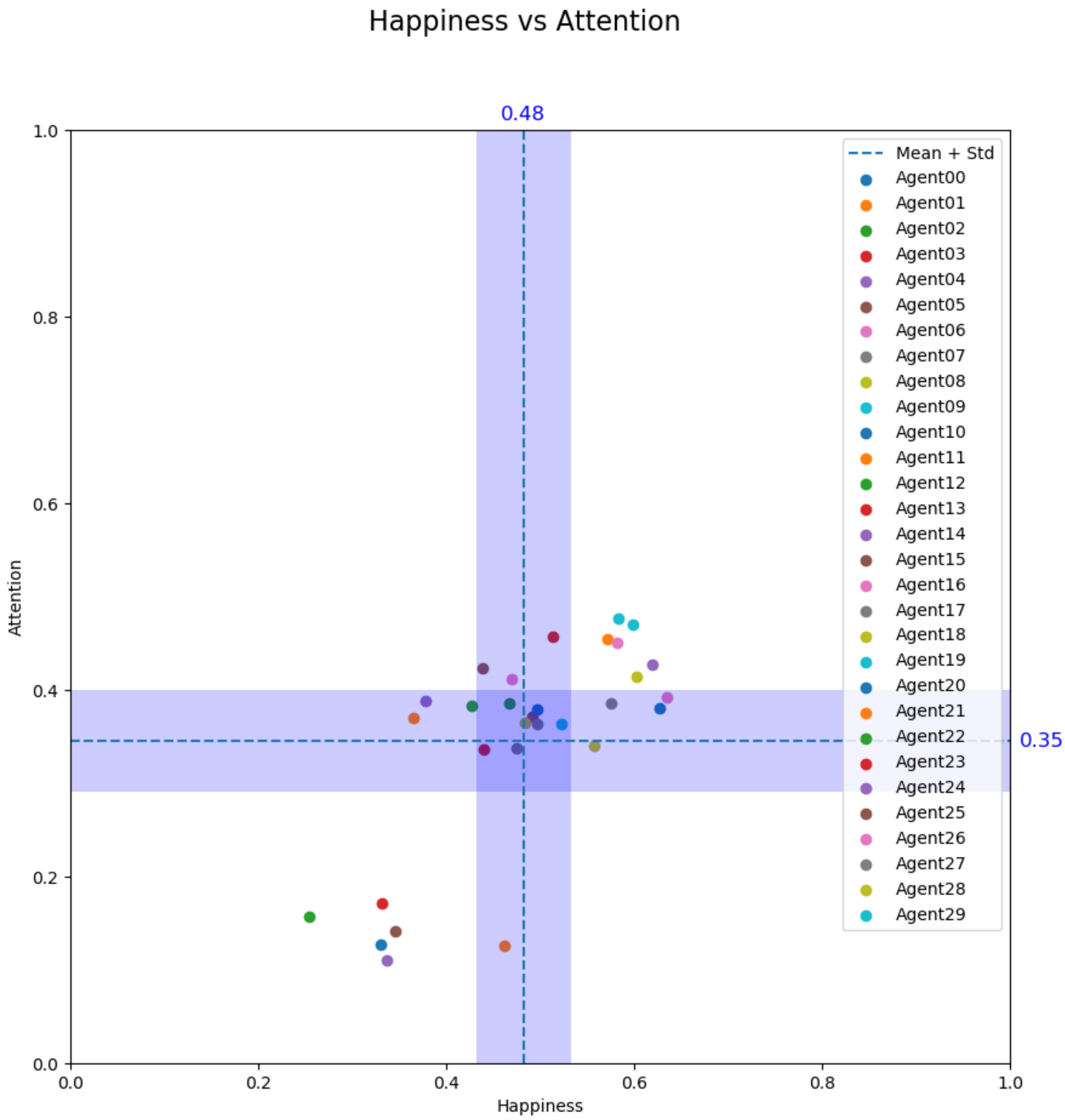

Figure A.5: HA Plot for first instance

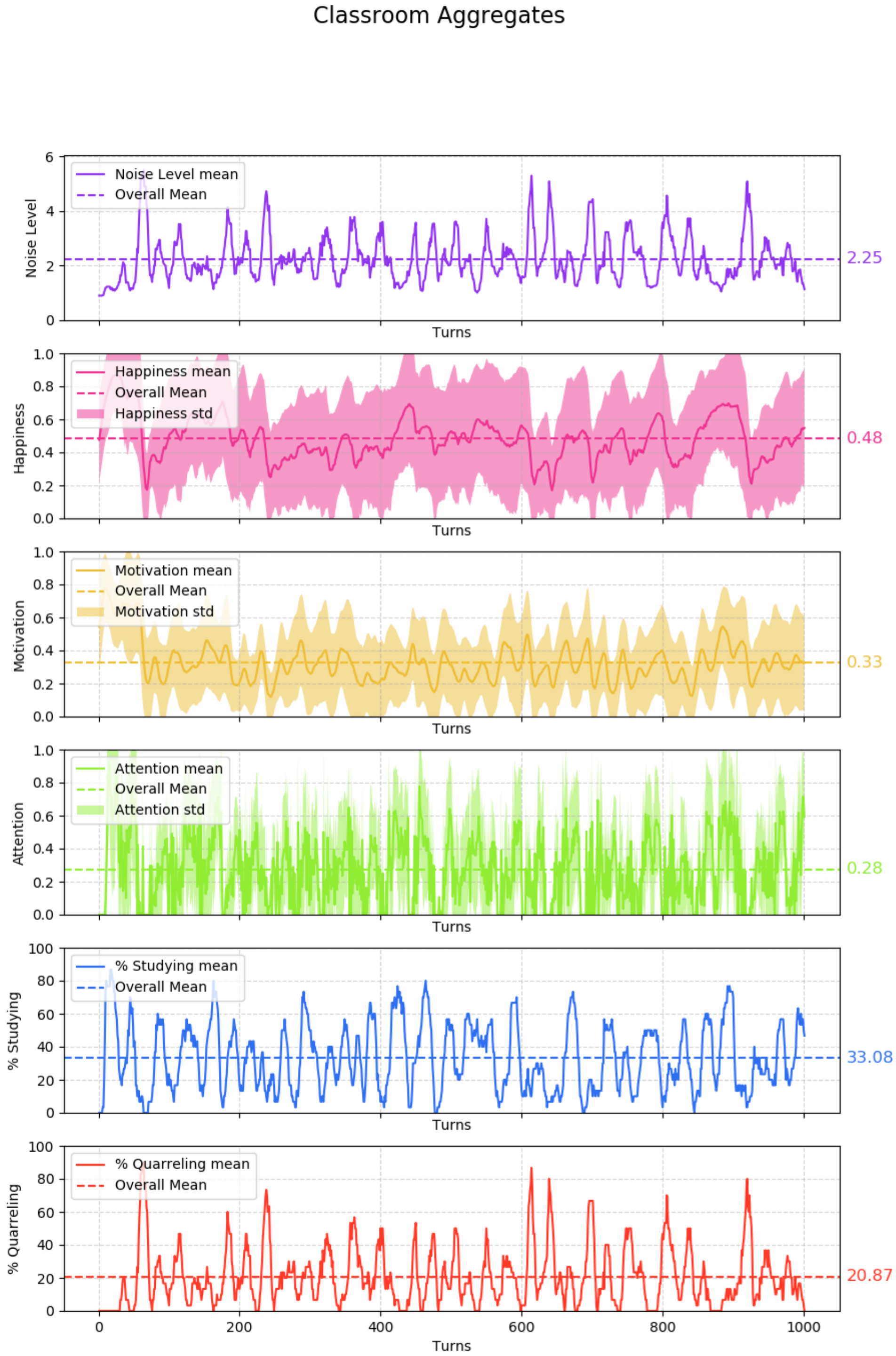

Figure A.6: Classroom aggregates for first instance

A.3.3 ADHD-High

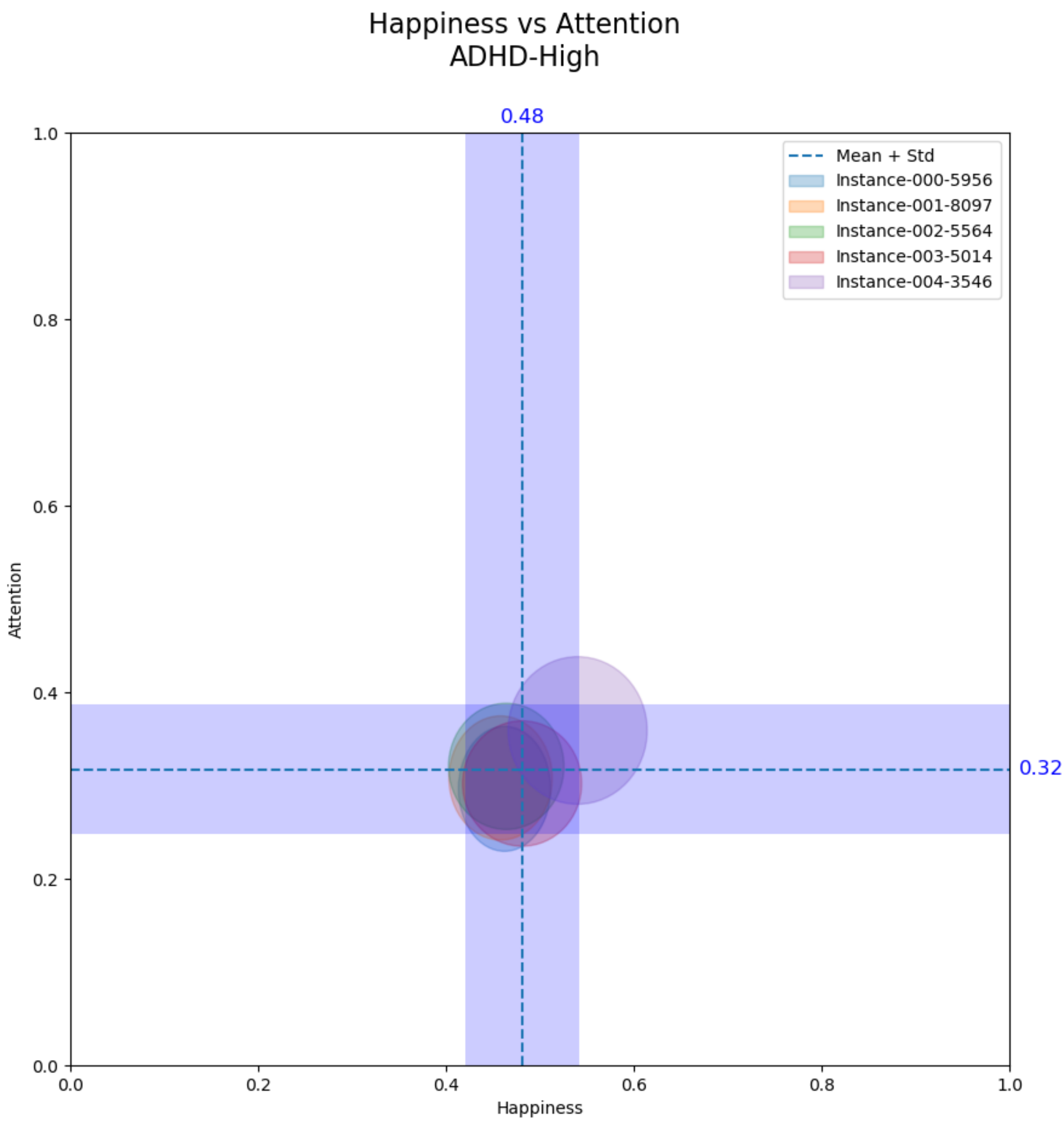

Figure A.7: HA Plot for complete experiment

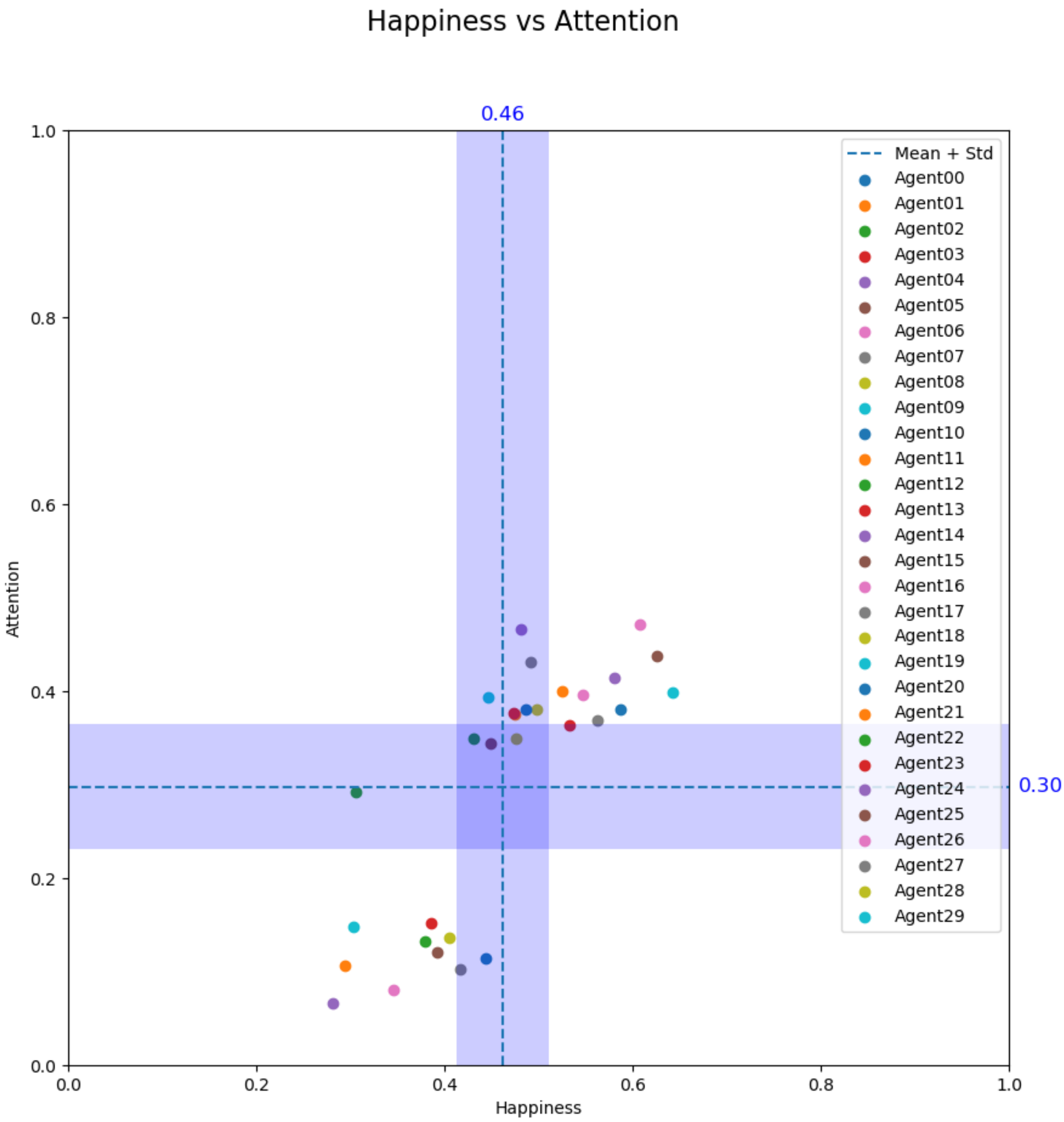

Figure A.8: HA Plot for first instance

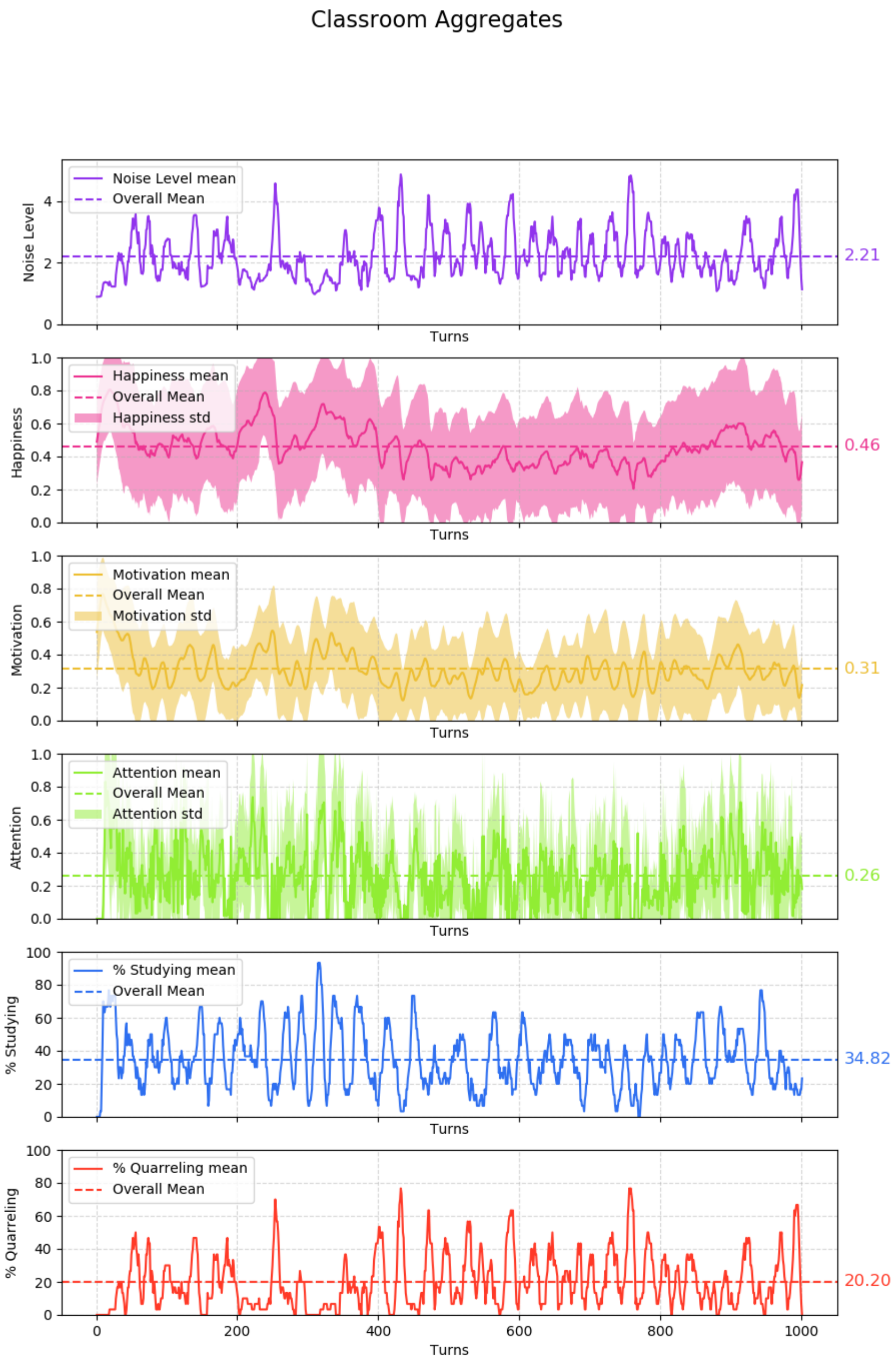

Figure A.9: Classroom aggregates for first instance

A.3.4 ADHD-VeryHigh

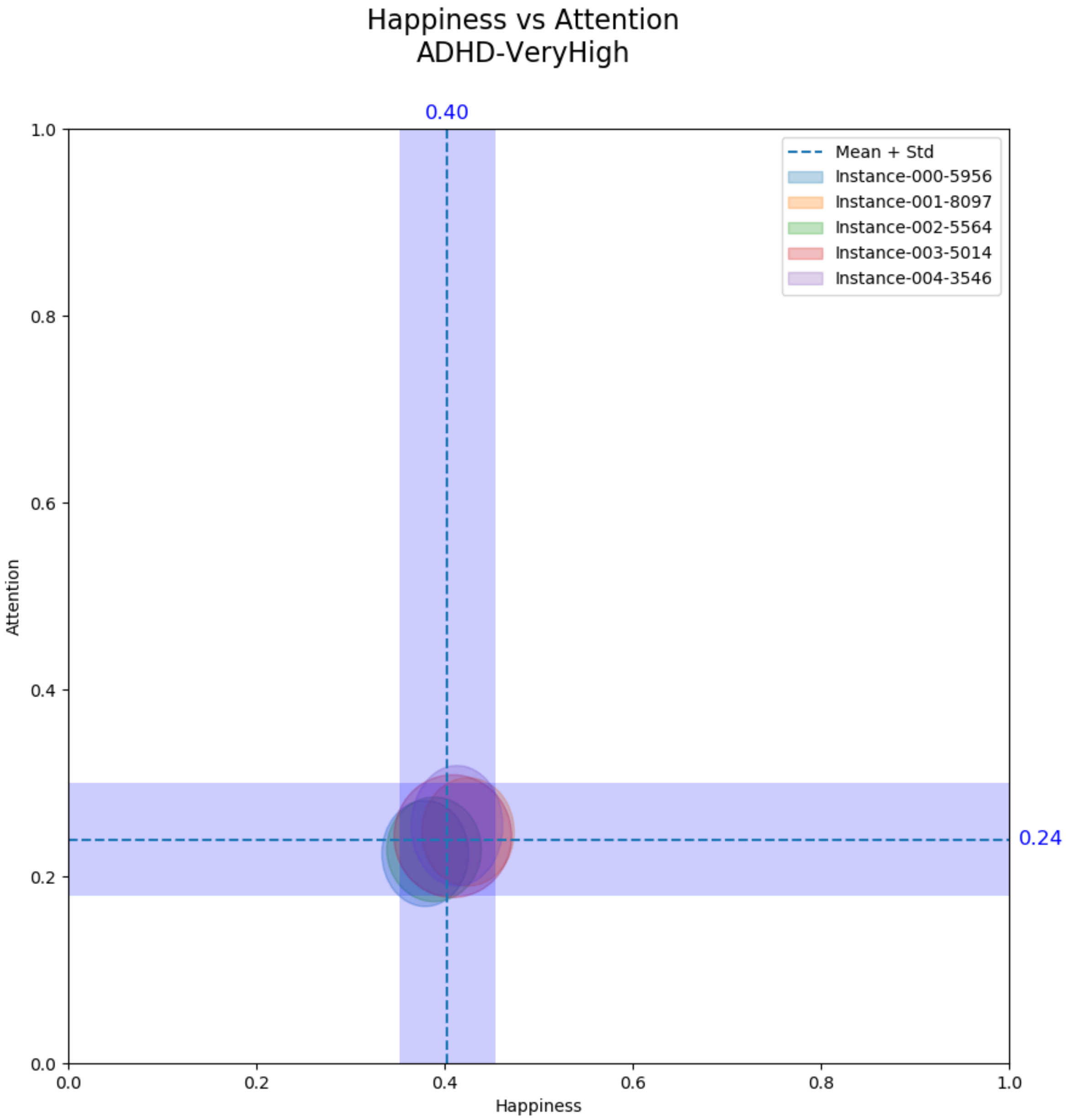

Figure A.10: HA Plot for complete experiment

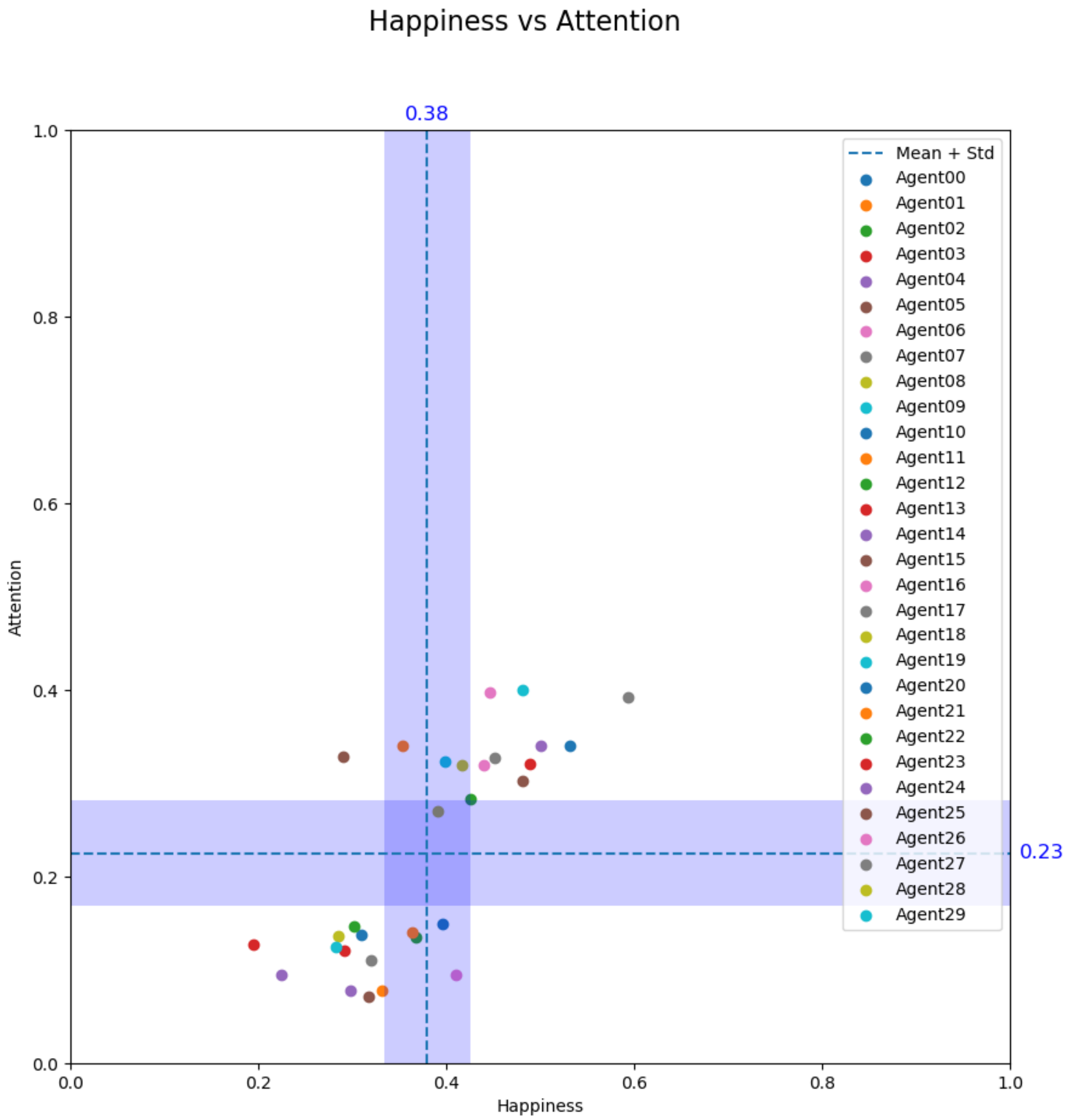

Figure A.11: HA Plot for first instance

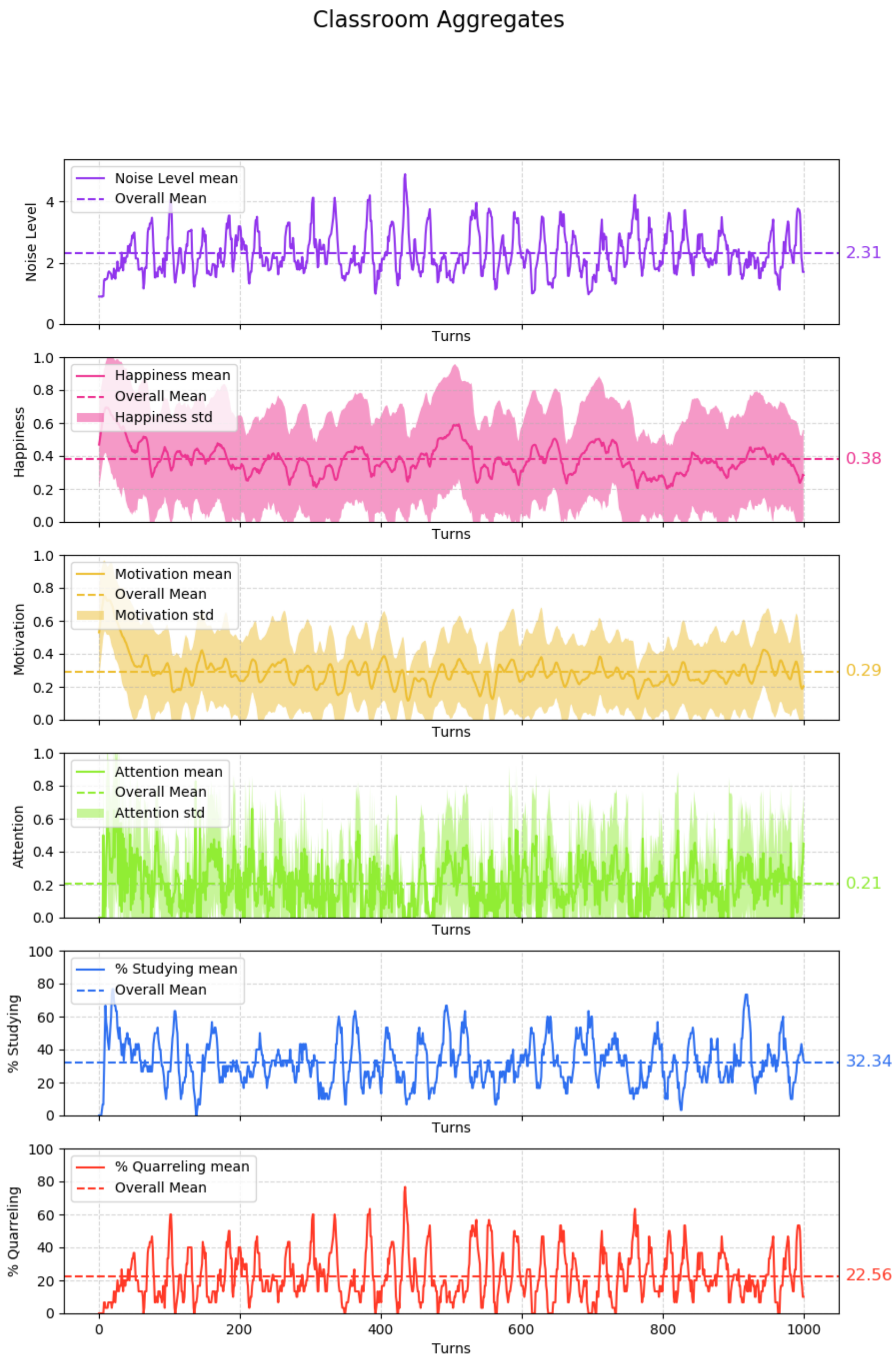

Figure A.12: Classroom aggregates for first instance

A.3.5 ADHD-None

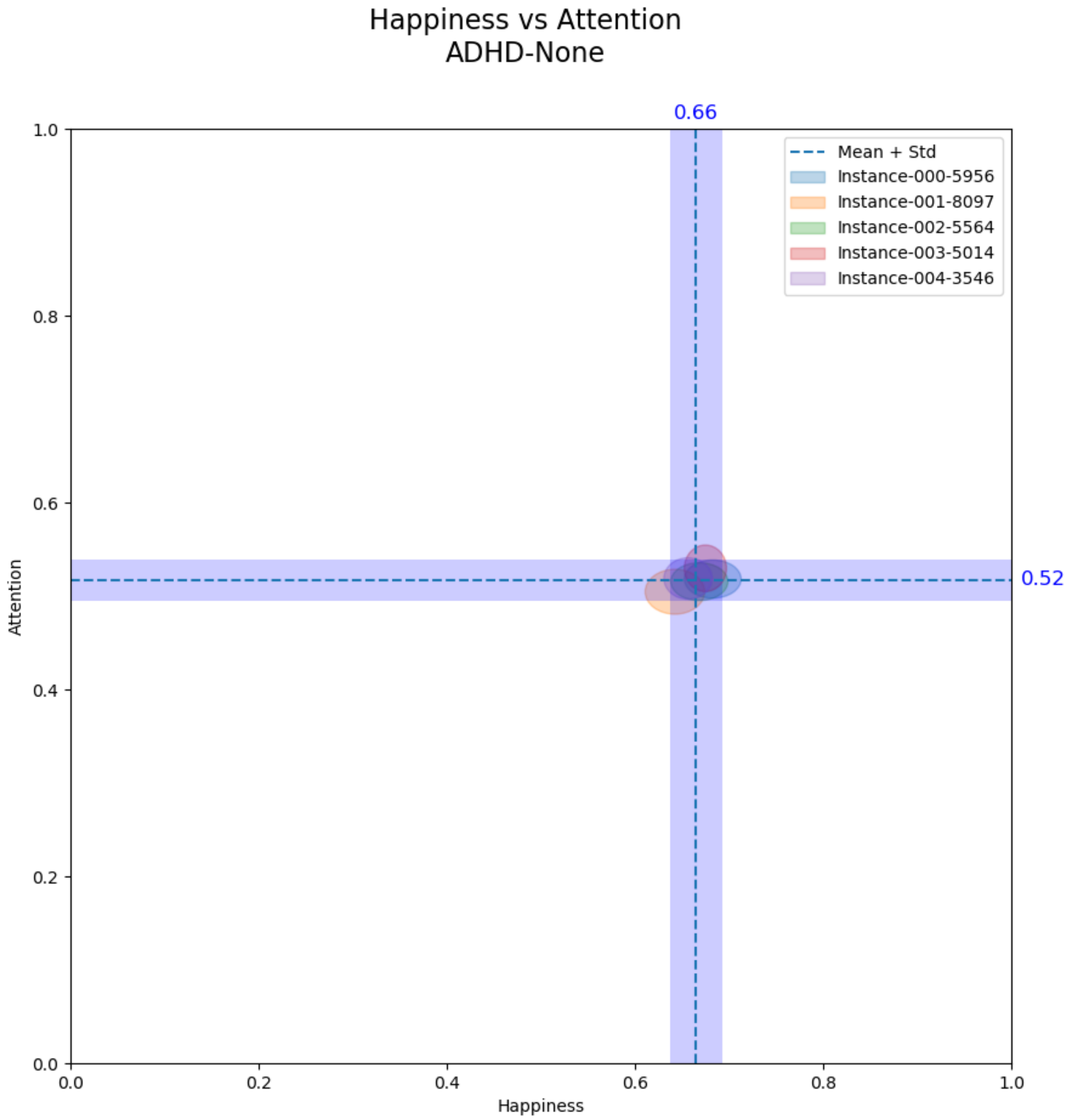

Figure A.13: HA Plot for complete experiment

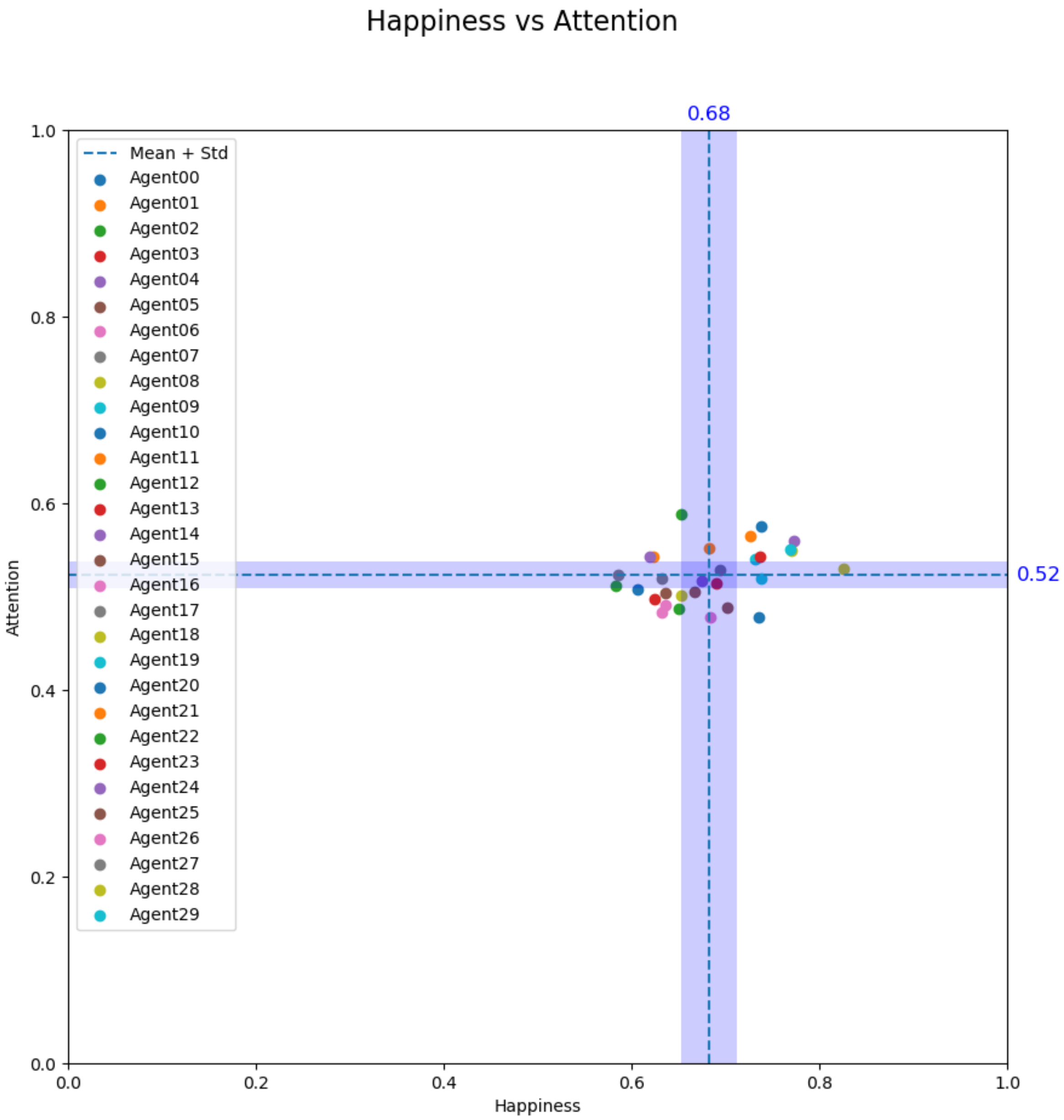

Figure A.14: HA Plot for first instance

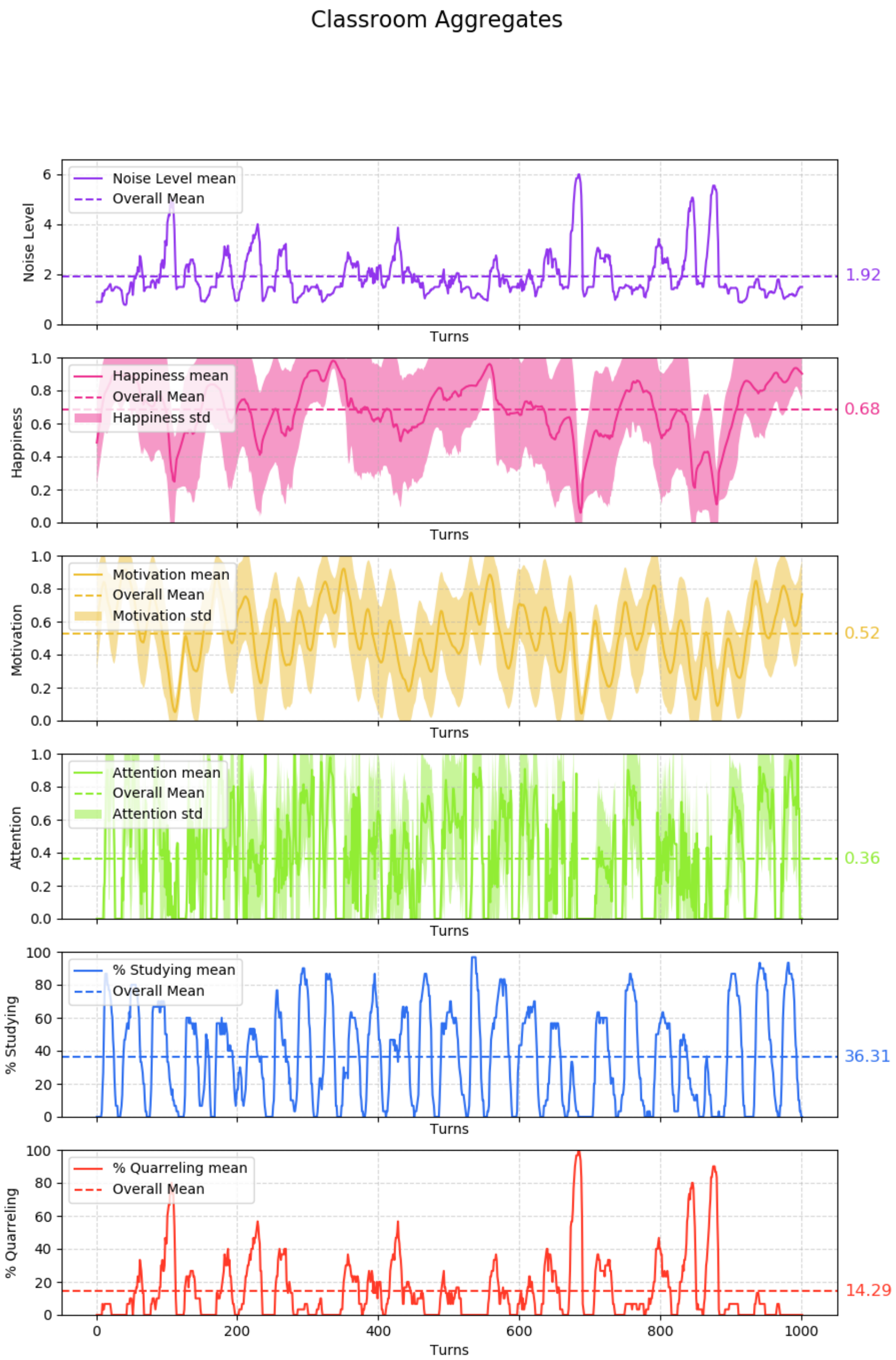

Figure A.15: Classroom aggregates for first instance

A.3.6 ADHD-Low-Ambitious

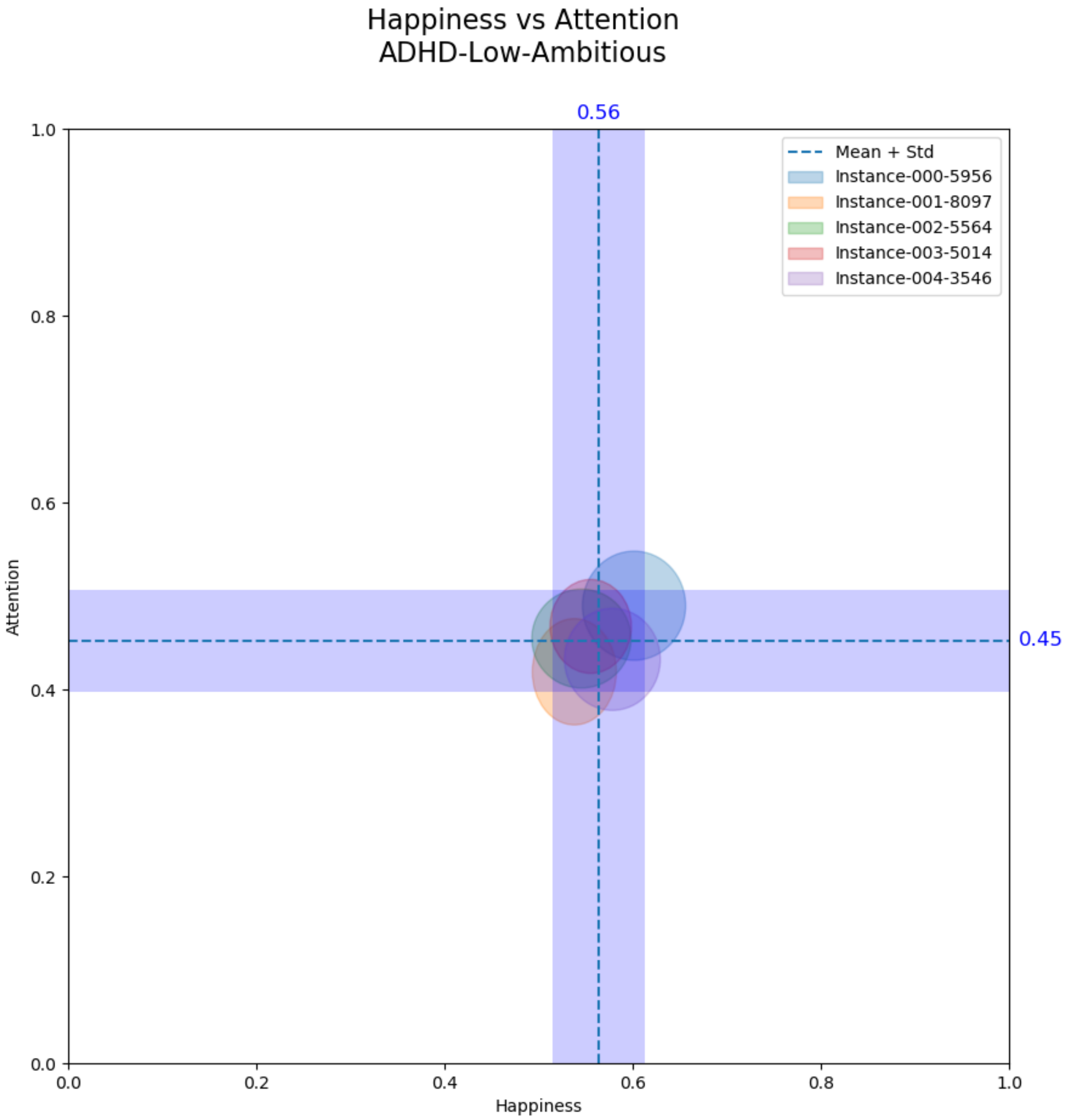

Figure A.16: HA Plot for complete experiment

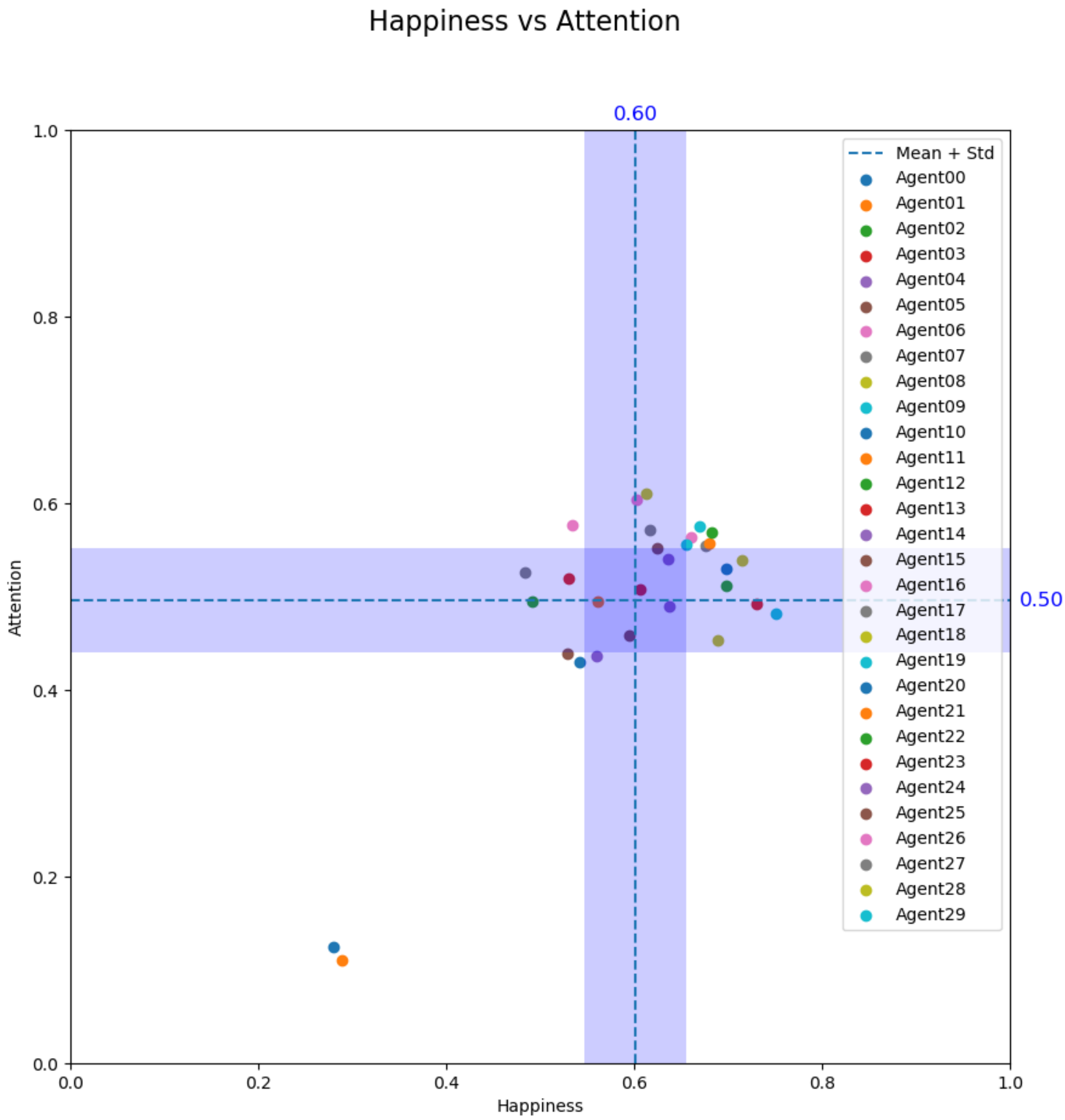

Figure A.17: HA Plot for first instance

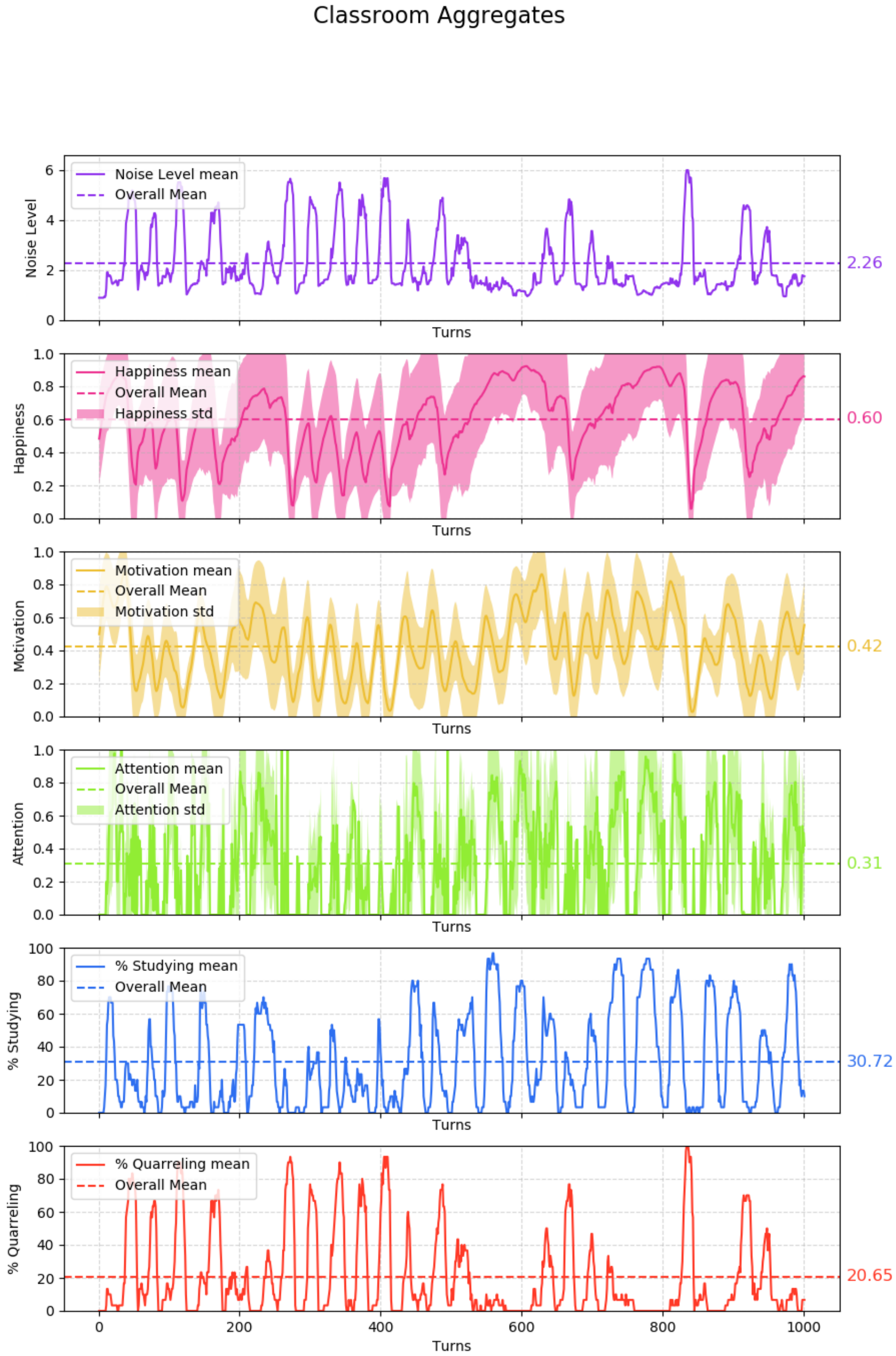

Figure A.18: Classroom aggregates for first instance

A.3.7 ADHD-Medium-Ambitious

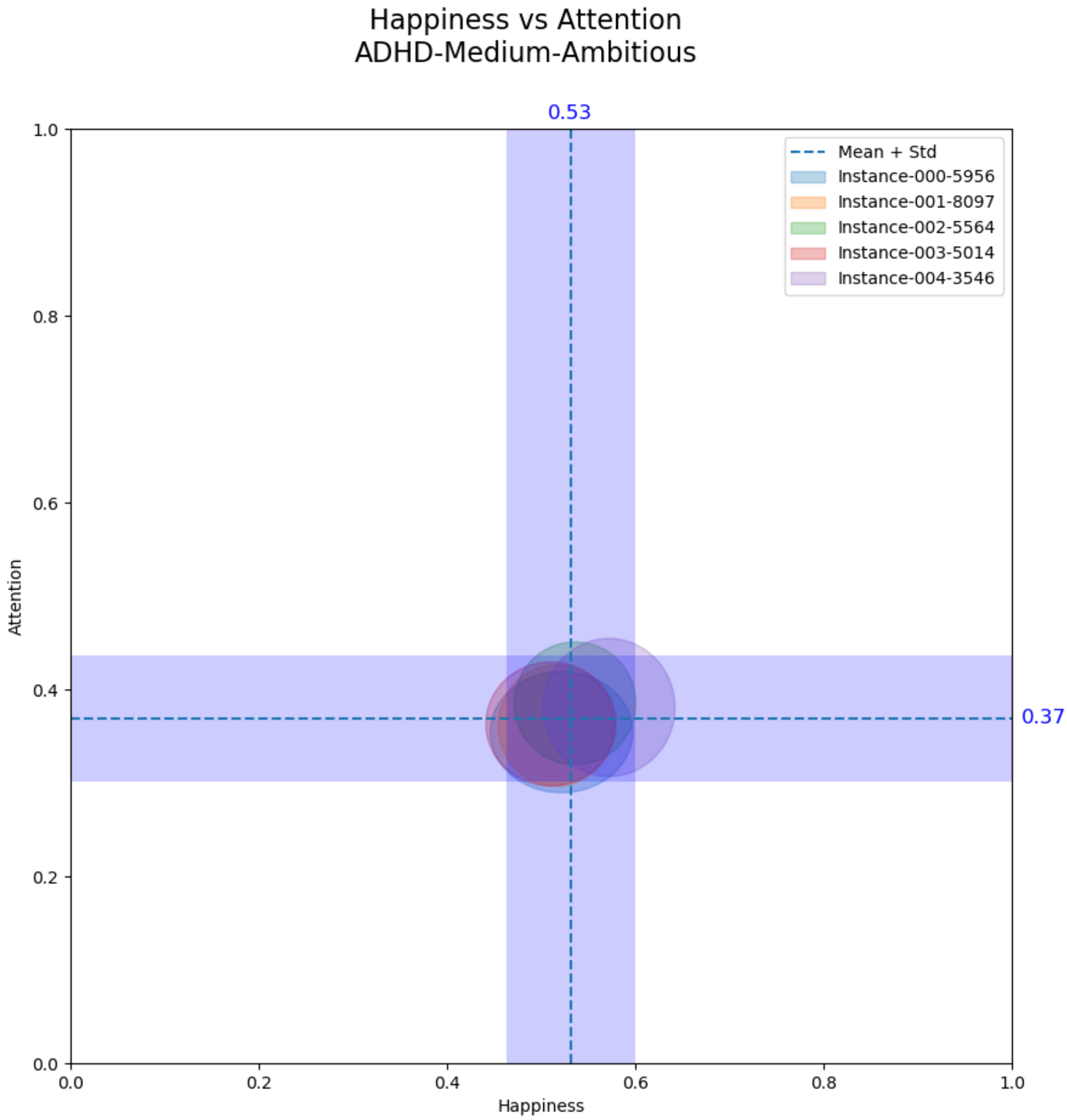

Figure A.19: HA Plot for complete experiment

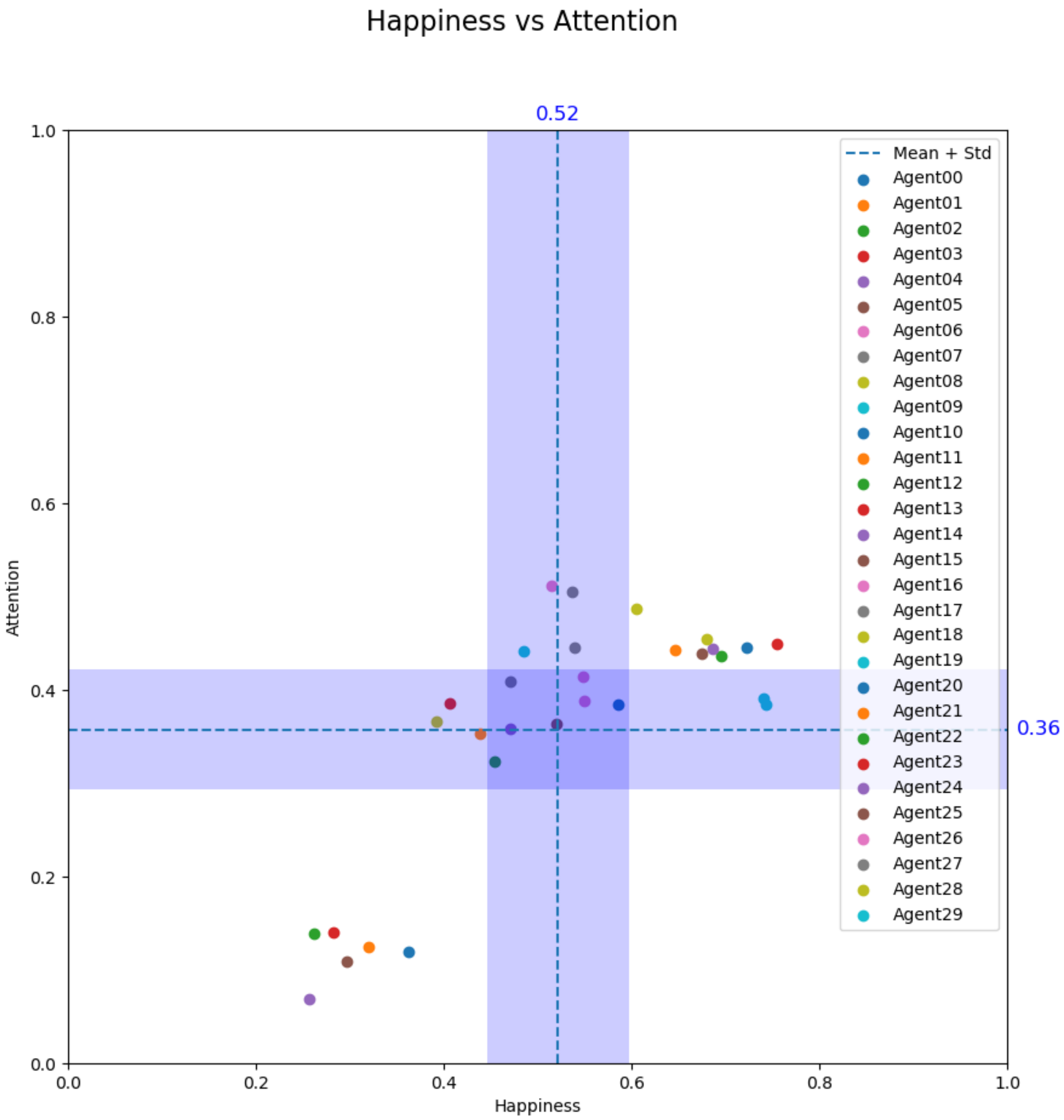

Figure A.20: HA Plot for first instance

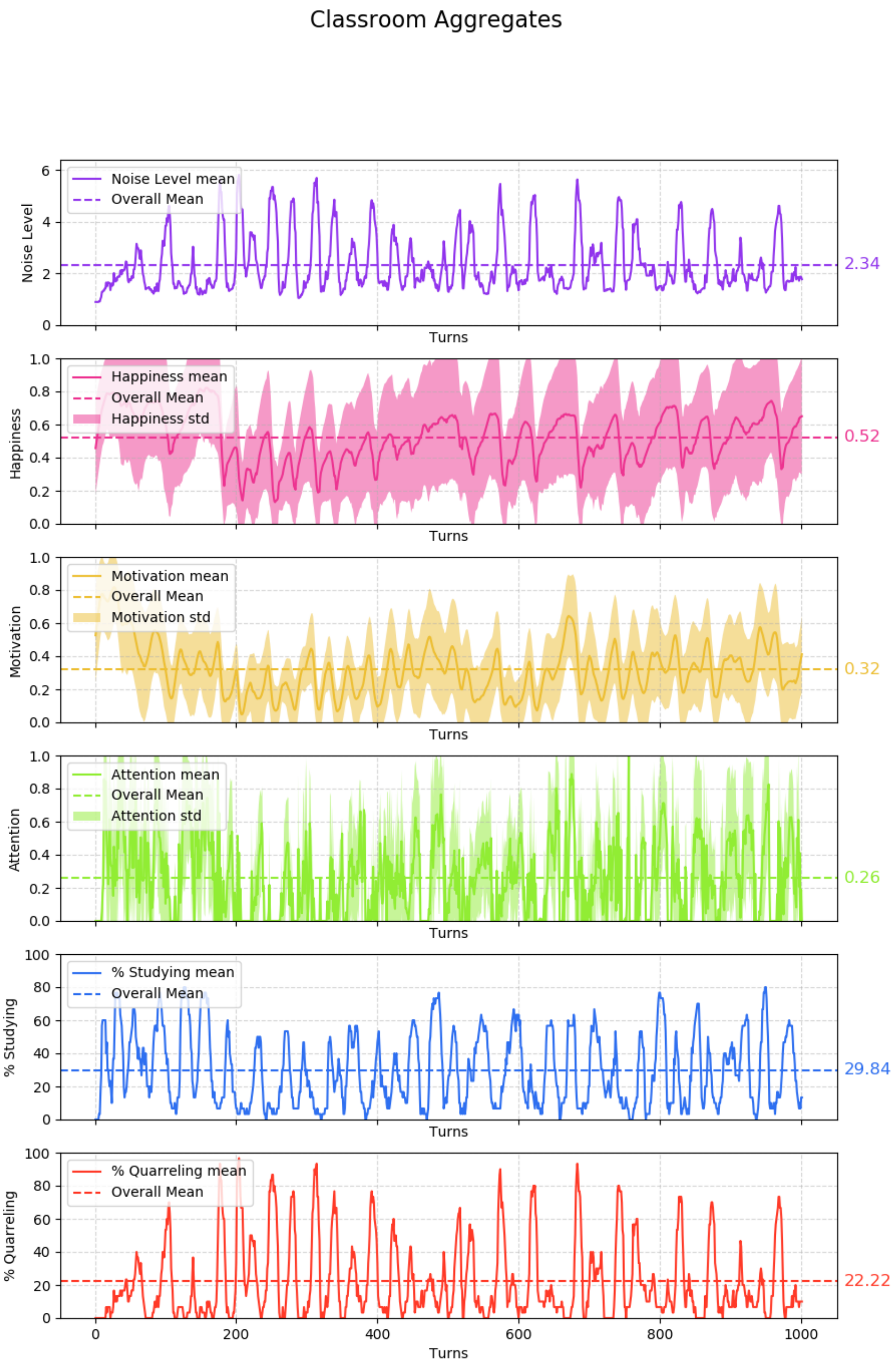

Figure A.21: Classroom aggregates for first instance

A.3.8 ADHD-VeryHigh-Ambitious

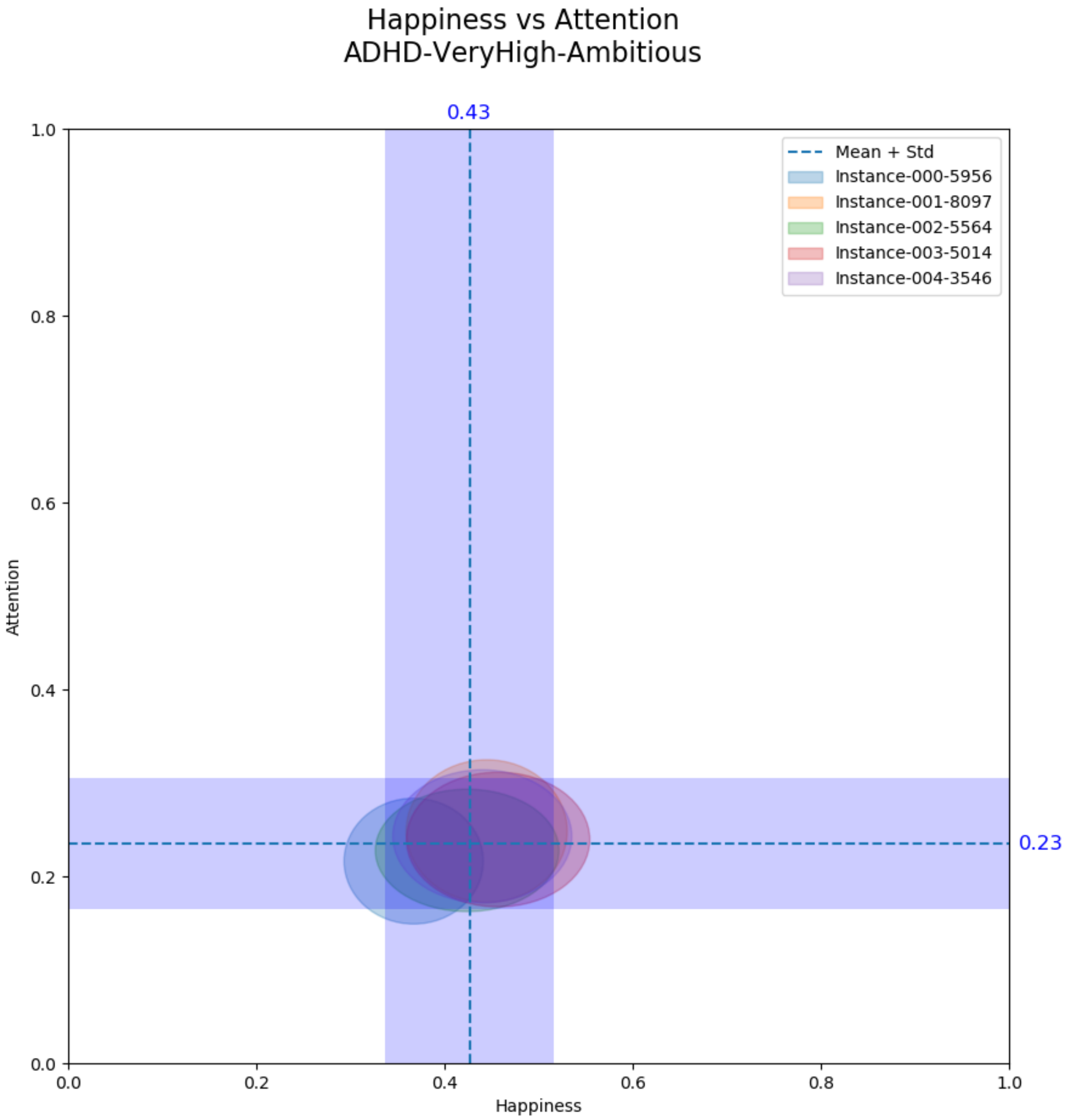

Figure A.22: HA Plot for complete experiment

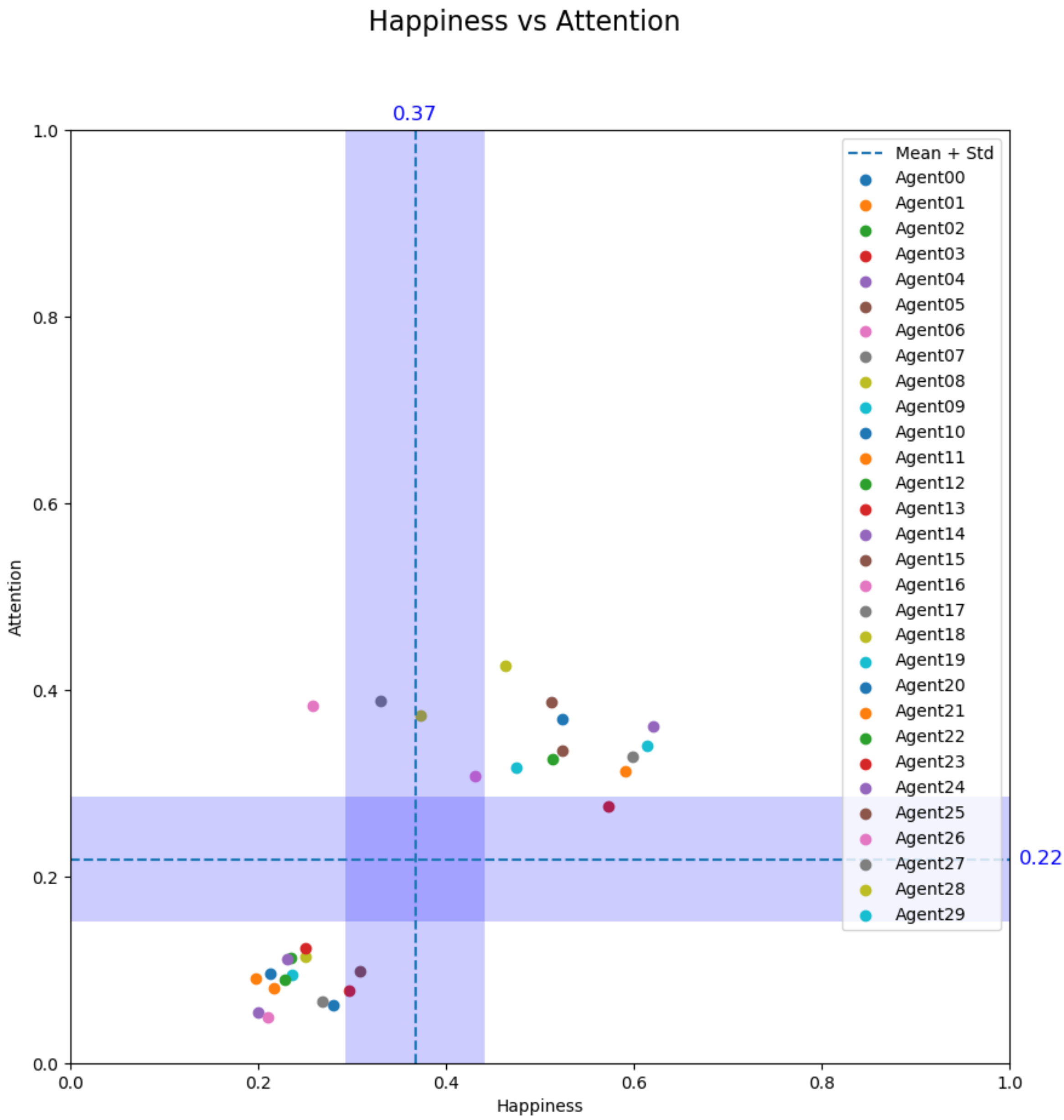

Figure A.23: HA Plot for first instance

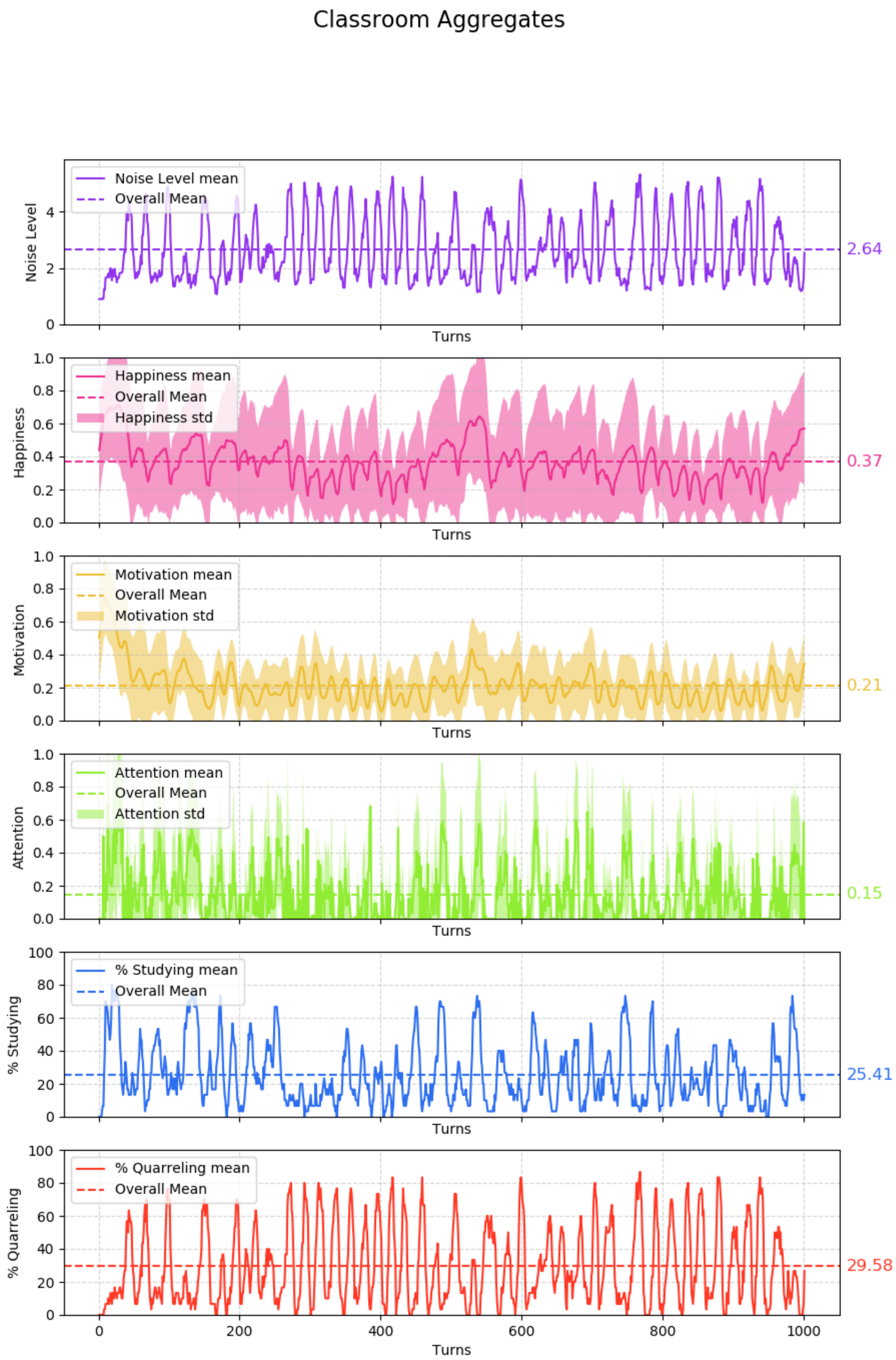

Figure A.24: Classroom aggregates for first instance

A.3.9 ADHD-None-Ambitious

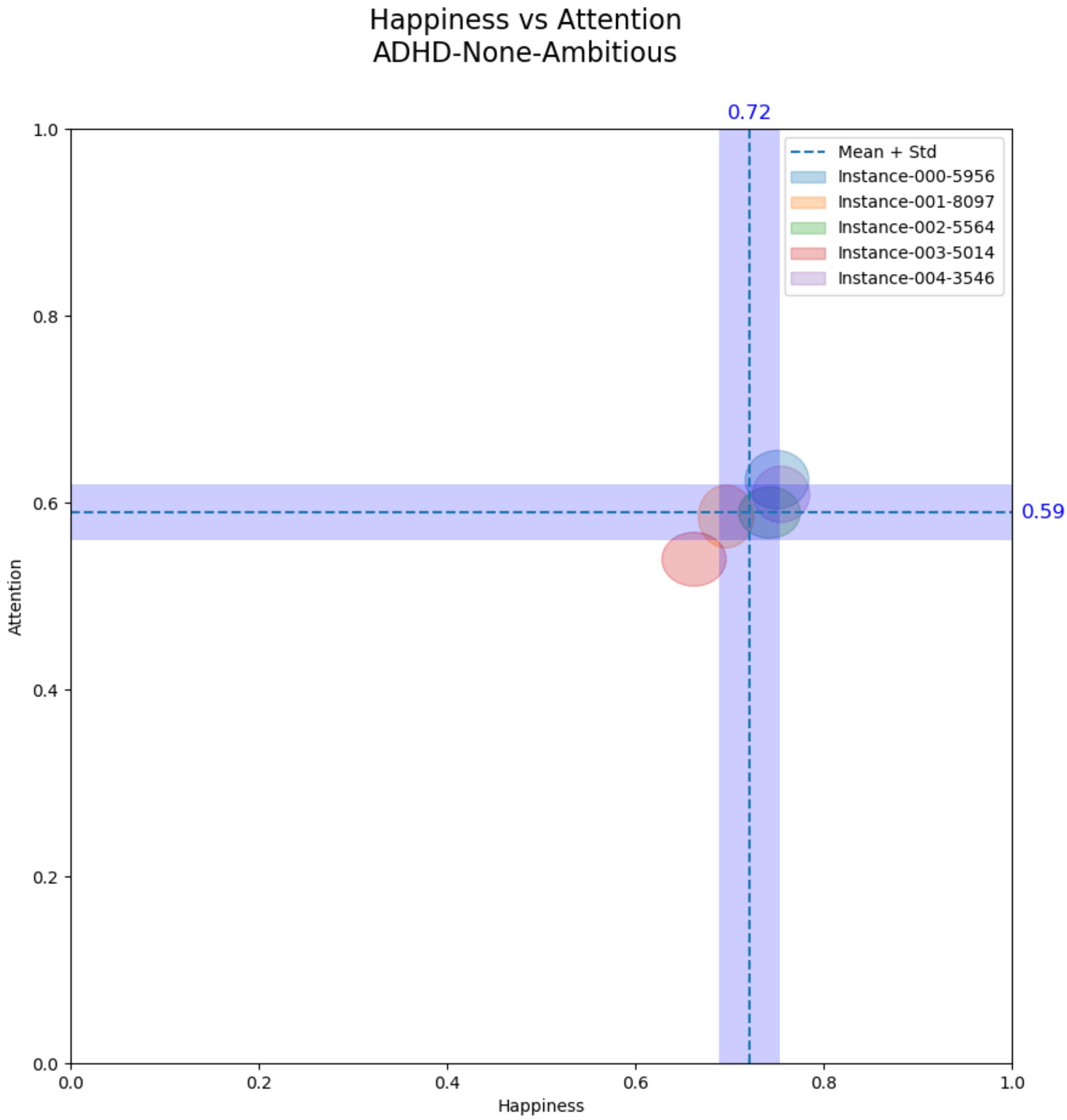

Figure A.25: HA Plot for complete experiment

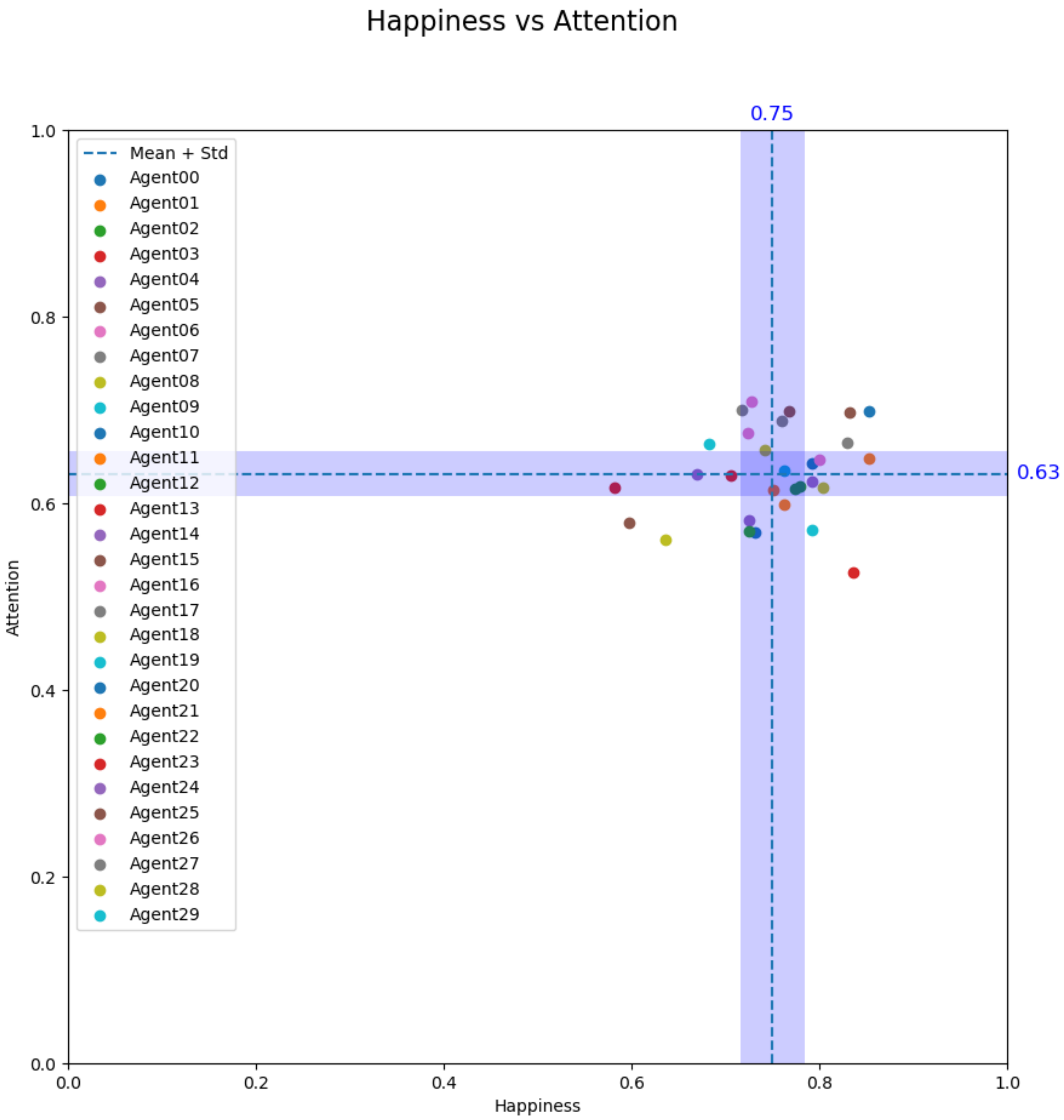

Figure A.26: HA Plot for first instance

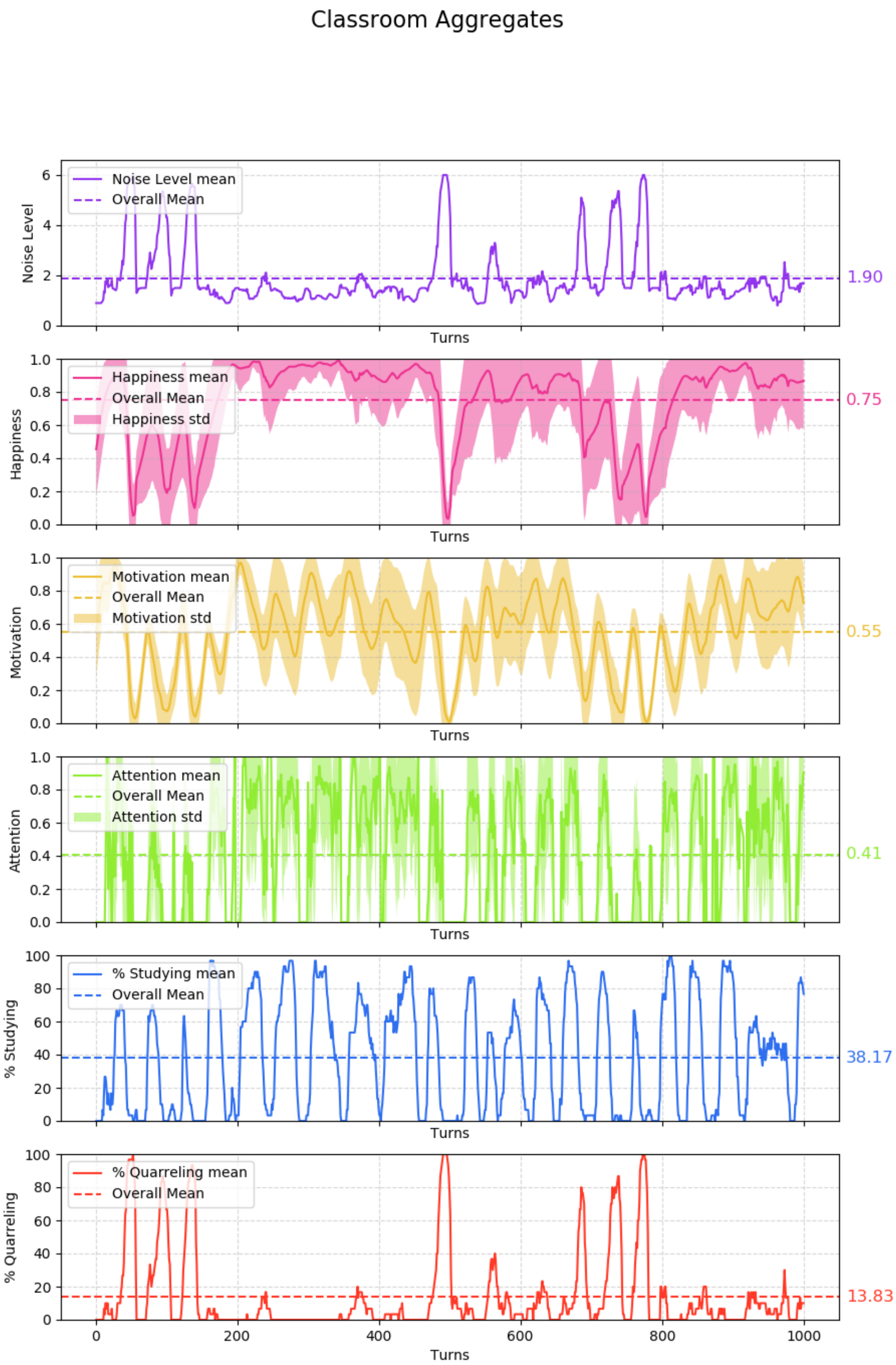

Figure A.27: Classroom aggregates for first instance

A.3.10 Random

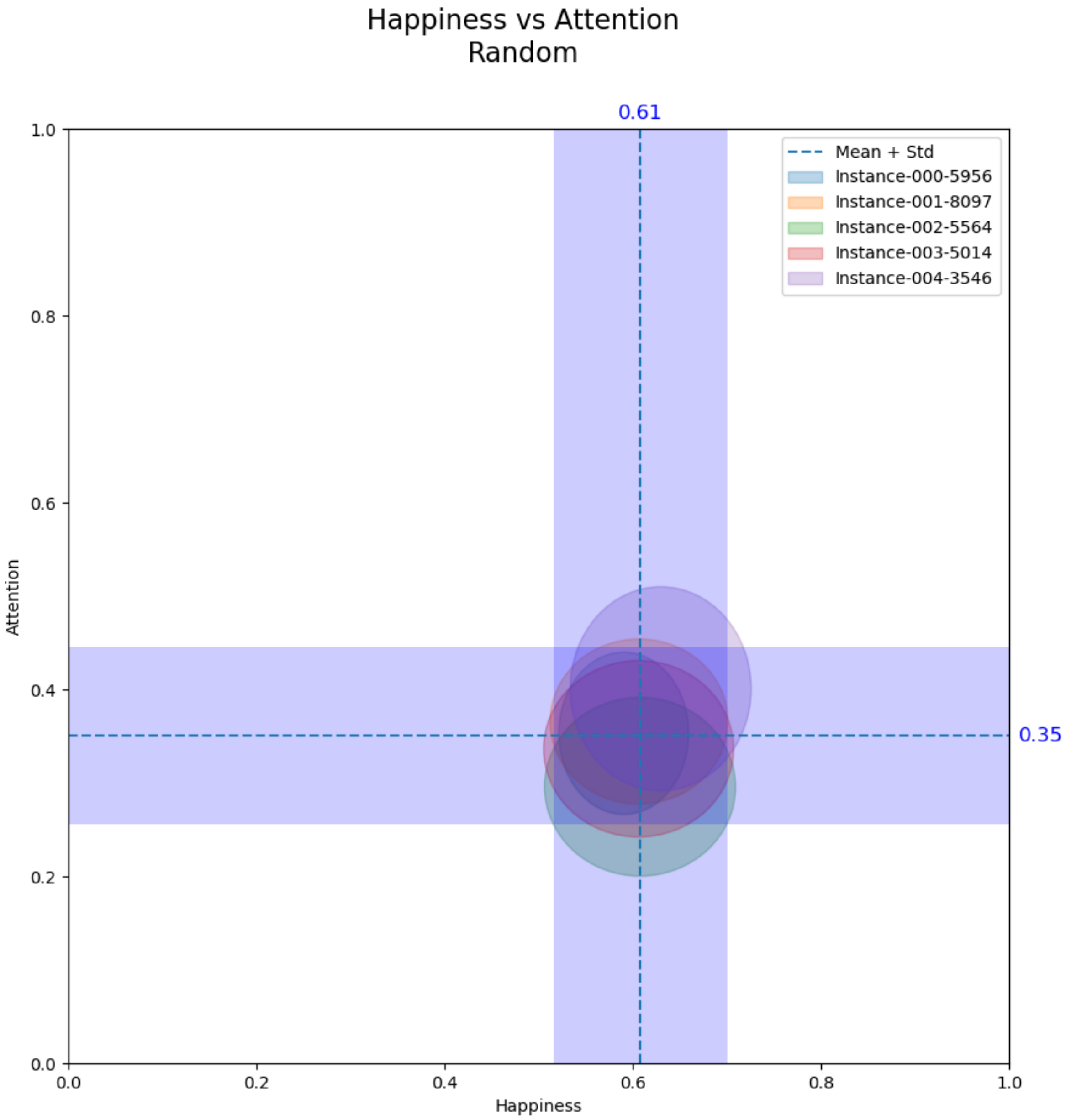

Figure A.28: HA Plot for complete experiment

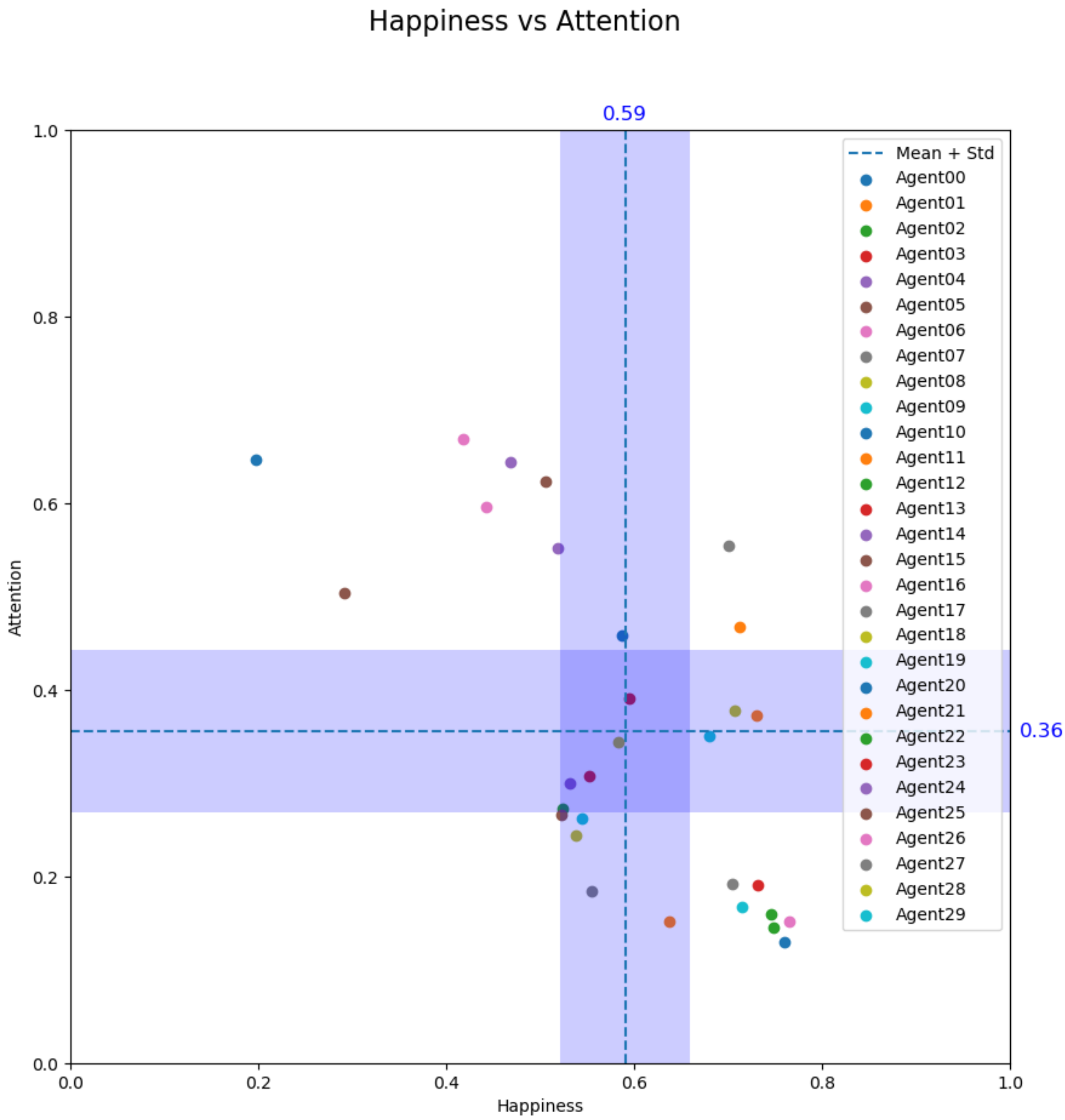

Figure A.29: HA Plot for first instance

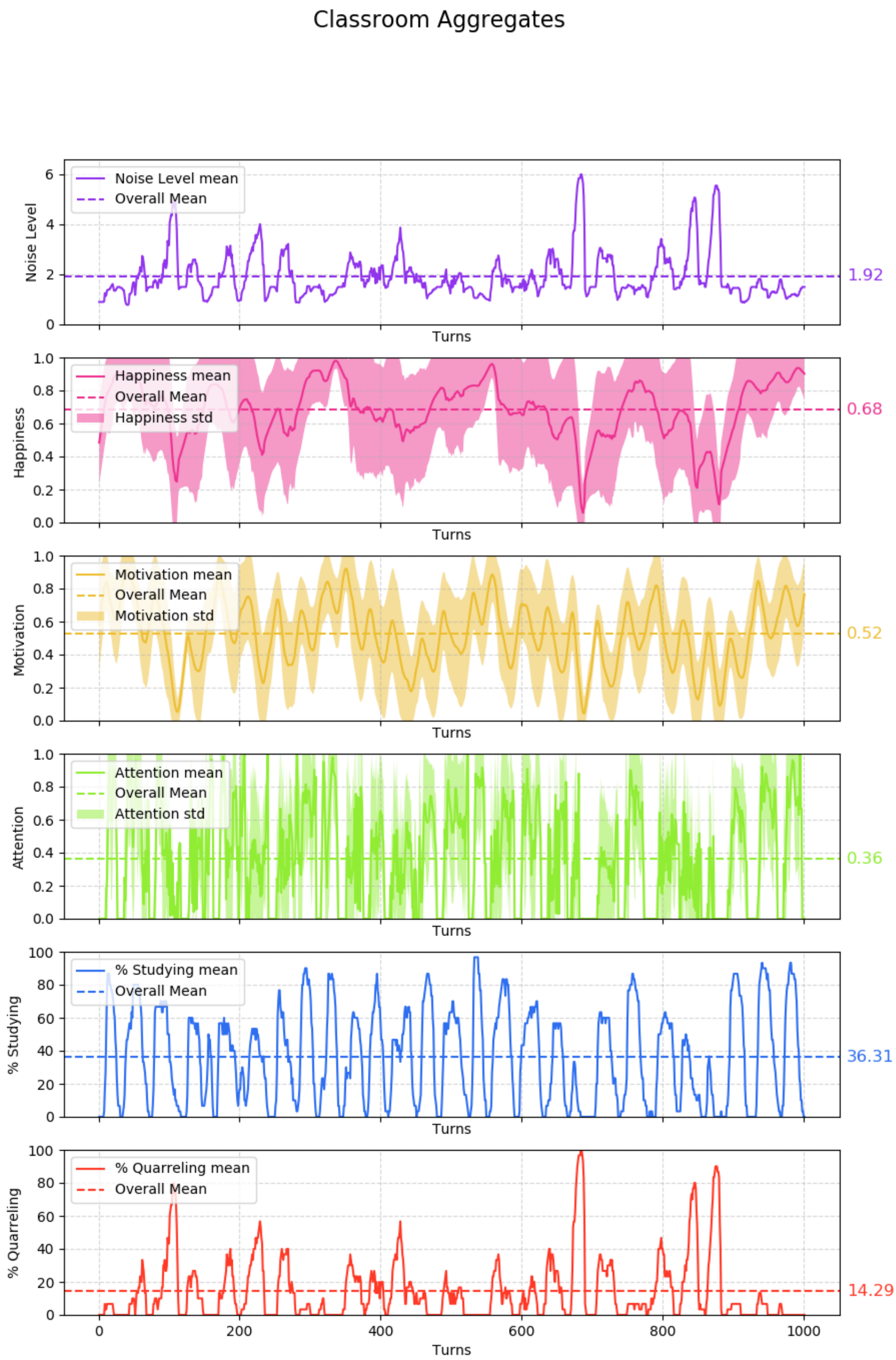

Figure A.30: Classroom aggregates for first instance

[EOF]