MODELING STUDENT BEHAVIOURS IN A VIRTUAL CLASSROOM WITH INCORPORATION OF SOCIAL LEARNING THEORY INTO BELIEF-DESIRE-INTENTION MODEL

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MODELING STUDENT BEHAVIOURS IN A VIRTUAL CLASSROOM WITH INCORPORATION OF SOCIAL LEARNING THEORY INTO BELIEF-DESIRE-INTENTION MODEL

submitted by **CENK KÖKNAR** in partial fulfillment of the requirements for the degree of **Master of Science in Modeling and Simulation, Middle East Technical University** by,

Prof. Dr. Nazife Baykal
Dean, Graduate School of **Informatics Institute** _______________

Assoc. Prof. Dr. Hüseyin Hacıhabiboğlu
Head of Department, **Modeling and Simulation** _______________

Prof. Dr. Veysi İşler
Supervisor, **Computer Engineering, METU** _______________

Assist. Prof. Dr. Musa Ataş
Co-supervisor, **Computer Engineering, Siirt University** _______________

Examining Committee Members:

Assoc. Prof. Dr. Alptekin Temizel
Modeling and Simulation, METU _______________

Prof. Dr. Veysi İşler
Computer Engineering, METU _______________

Assist. Prof. Dr. Didem Akyüz
Elementary Education, METU _______________

Assoc. Prof. Dr. Hüseyin Hacıhabiboğlu
Modeling and Simulation, METU _______________

Assoc. Prof. Dr. Aslıhan Tüfekci
Computer and Instructional Tech. Edu., Gazi University _______________

Date: 08.06.2015

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: CENK KÖKNAR

Signature :

ABSTRACT

MODELING STUDENT BEHAVIOURS IN A VIRTUAL CLASSROOM WITH INCORPORATION OF SOCIAL LEARNING THEORY INTO BELIEF-DESIRE-INTENTION MODEL

Köknar, Cenk
M.S., Department of Modeling and Simulation
Supervisor : Prof. Dr. Veysi İşler
Co-Supervisor : Assist. Prof. Dr. Musa Ataş

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Serious game is a game type designed with the goal different than pure entertainment. A serious game is designed to provide certain skills to user according to the design purpose of it. This type of game is used actively in politics and military as a board game or card game even before the development of computer games. Today, serious game can be considered as a mental contest played with computer, prepared for training the player about desired areas including defense, education, scientific exploration, health care, emergency management, city planning, engineering and politics. In this thesis, a serious game is developed to train teachers about classroom management. The user performs the teacher's actions with keyboard and mouse, and tries to complete given tasks during simulation. The students are controlled by intelligent agents. The aim of the thesis is to create a student behaviour model which is highly realistic. There are several software models to design intelligent agent, and belief-desire-intention model is selected in this thesis. On the other hand a software model should be modified for the requirements of the software. The classroom is highly social environment, and BDI model should be upgraded to represent social interactions between students and teacher. To increase the realism of the behaviours of agents, social learning theory is integrated into the belief module of the intelligent agents. It is observed that the incorporation of the social learning theory into the intelligent agent increases the realism of student's behaviours.

Keywords: BDI, intelligent agent, social learning theory, student behaviour, serious game

ÖZ

SANAL SINIFTA ÖĞRENCİ DAVRANIŞLARININ SOSYAL ÖĞRENME TEORİSİ DAHİL EDİLMİŞ İNANÇ-İSTEK-AMAÇ MODELİ İLE MODELLENMESİ

Köknar, Cenk
Yüksek Lisans, Modelleme ve Simülasyon Bölümü
Tez Yöneticisi : Prof. Dr. Veysi İşler
Ortak Tez Yöneticisi : Yrd. Doç. Dr. Musa Ataş

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Ciddi oyun türü, kullanıcıyı yalnızca eğlendirmeyi hedeflemez. Ciddi oyun, tasarlanma amacına uygun şekilde kullanıcının gerekli becerileri kazanmasını amaçlar. Bilgisayar oyunlarının geliştirilmeye başlanmasından yıllar önce dahi siyaset ve askeri alanlarda tahta üzerinde oynanan oyunlar ve kart oyunları aktif olarak kullanılmıştır. Günümüzde ciddi oyunlar, bilgisayarda oynanan ve kişiyi istenilen alan üzerinde eğitmek için kullanılan zihinsel bir mücadele olarak düşünülebilir. Bu alanlara savunma sanayi, eğitim, bilimsel araştırma, sağlık, acil durum yönetimi, şehir planlaması, mühendislik ve politika örnek verilebilir. Bu tezin amacı gerçekçi bir öğrenci davranış modeli tasarlamaktır. Tez kapsamında öğretmenler için bir sınıf yönetim oyunu geliştirilmiştir. Kullanıcı, simülasyon boyunca öğretmen aksiyonlarını klavye ve fare aracılığıyla gerçekleştirir, verilen görevleri başarıyla tamamlamaya çalışır. Öğrenciler akıllı ajanlar tarafından kontrol edilmektedir. Akıllı ajan tasarımında çeşitli yazılım modelleri mevcuttur. Bu tez kapsamında inanç-istek-amaç modeli kullanılmasına karar verilmiştir. Öte yandan bir yazılım modeli, geliştirilen yazılımın ihtiyaçlarını karşılamak için modifiye edilmiştir. Sınıf ortamının sosyal bir ortam olmasından dolayı, öğrencilerin birbiriyle ve öğretmenle olan sosyal etkileşimlerinin gösterilebilmesi için seçilen yazılım modeline ekleme yapılmıştır. Ajanların davranışlarının gerçekçiliğinin arttırılması için inanç modülü içerisine sosyal öğrenme teorisi entegre edilmiştir. Akıllı ajanlara sosyal öğrenme teorisinin dahil edilmesi ile birlikte öğrencinin davranışlarının daha gerçekçi olduğu gözlemlenmiştir.

Anahtar Kelimeler: BDI, akıllı ajan, sosyal öğrenme teorisi, öğrenci davranışı, ciddi oyun

To my family and friends...

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

LIST OF ABBREVIATIONS

ABBRV	Abbreviation
TUBITAK	The Scientific and Technological Research Council of Turkey
GATES	Game Based Teacher Education System
ACTA	Applied Cognitive Task Analysis
AI	Artificial Intelligence
MAS	Multi Agent System
BDI	Belief-Desire-Intention
PALs	Pedagogical Agents as Learning Companions
UI	User Interface
NC	Noise Condition
EC	Energy Condition
AC	Attention Condition
DTC	Disruptive Talking Condition
IC	Involvement Condition
TC	Temper Condition
RTC	Respect Teacher Condition
USC	Understand Subject Condition
TAC	Teacher Authoritarian Condition
NE	Noise Effect
EE	Energy Effect
AE	Attention Effect
DTE	Disruptive Talking Effect
IE	Involvement Effect
TE	Temper Effect
RTE	Respect Teacher Effect
USE	Understand Subject Effect
TAE	Teacher Authoritarian Effect

CHAPTER 1

INTRODUCTION

Virtual training systems and serious games are trending educational tools because of their benefits. They offer realistic experience to the users on a specific issue. Providing controlled environment for the training, reducing cost of the training, and removing figure artist necessity are major benefits of virtual training systems[27]. Moreover, virtual training systems and serious games eliminate boredom of the learning task. It is observed that virtual training systems and serious games also increase the learning efficiency in terms of retention and memorization [8].

Realism of agents in a virtual environment affects the success of the simulation significantly. Hence, it would be valuable if a game based teacher training simulation could support a mechanism for real world interactions. Although user-agent interaction is the major consideration, agent-agent interaction of proposed models are minimal in previous studies that agents are modeled with belief-desire-intention (BDI) [2, 3, 13].

Game Based Teacher Education System (GATES), is an example to the serious games designed to train teachers which is granted by The Scientific and Technological Research Council of Turkey (TUBITAK). GATES is designed to train teachers about using technologically enhanced classrooms effectively. Moreover, the teachers classroom management skills are enhanced via various scenarios [20].

The contribution of this thesis is modeling student behaviours in a virtual classroom with incorporation of social learning theory into belief-desire-intention model. Our model provides social learning to student agents. Thanks to this, the agents can perform realistic behaviours in a social environment.

Social learning is incorporated into BDI model via modifying the belief module of the design. The developed model is analyzed in a serious game, which is developed as a test harness. It is observed that the students' behaviours in a classroom management game are more realistic when the intelligent agent models have social learning capability.

1.1 Outline

The thesis has been organized into the following chapters:

- Chapter 2 provides an overview of the concepts "intelligent agents", "multi-agent systems" and "social learning theory". The chapter explains the BDI architecture and social learning theory which are used during the thesis, and gives examples of applications and studies that use these architectures.
- Chapter 3 describes the proposed model to create a social learning student agents, the action working mechanism in the virtual classroom and the architecture of the system. Moreover, the chapter explains how student behaviours have been mapped to BDI format and social learning theory is incorporated into BDI model in details.
- Chapter 4 gives information about the user study. The user study is used to verify the results which are collected from the serious game that is designed in this study.
- Chapter 5 gives information about conceptual design of the virtual classroom. The chapter provides detailed information about the serious game designed in the scope of the thesis.
- Chapter 6 covers the case studies that demonstrate the accuracy of the system and the differences between various user behaviours in virtual classroom. This chapter also compares the results that obtained from serious game and user study.
- Chapter 7 concludes the study with a summary and the potential future works.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

This chapter provides information with related works about intelligent agents, multi-agent systems, BDI theory, serious games and social learning theory; which are used in this thesis.

Design procedure of an intelligent agent which demonstrates the human behaviour is highly complex. Modeling human behaviours is an interdisciplinary process that adopts theories from psychology and computer science. Moreover, the selected models should be implemented in a serous game by considering the game designing strategies.

There were several studies on the student personality model and software models separately in the literature [2, 3, 12, 13, 15, 25, 33]. However, there are few studies on combining them and creating a serious game to train teachers about classroom management [2, 13].

2.1 Intelligent Agents

2.1.1 Definition

Definition of agent differs among people who worked on computer science area. According to Russell and Norvig [36], anything can be considered as an agent if it perceives its environment with sensors and acts upon environment with effectors.

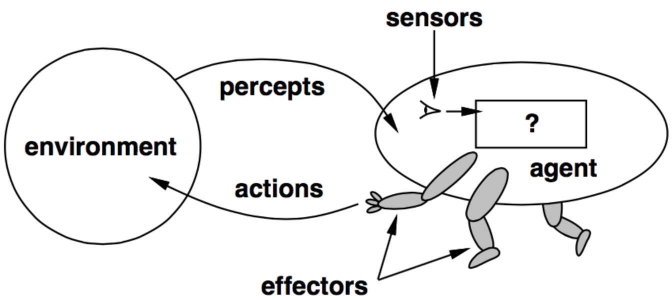

Figure 2.1: An agent interacts with environment through sensors and effectors.

According to previous explanation, any entity which obtain the output and convert it to its input with sensors and create output with its actions can be considered as intelligent agent; when an environment is designed to produce output and take input.

Maes [29] claims that, intelligent agents are computational systems that sense and act in a complex environment autonomously. Intelligent agents realize their set of goals and tasks in agreement with their design purposes. In this explanation, intelligent agent is defined as autonomous.

Smith et al [40] state that agents are not subroutines. They have decision mechanism and update their goals and priorities according to their design purposes. It is stated that an agent should have special purpose to achieve.

According to Franklin and Graesser [18], an intelligent agent is an entity in its environment which senses the environment, collects data and acts according to the collected data. It follows its own agenda and updates its agenda with respect to the future events. They have stated that humans and animals can be modelled as an intelligent agent and these are the high end of being an agent. Beside, they have also mentioned that a thermostat can be considered as a low end of being an intelligent agent, because it senses its environment and acts according to it.

2.1.2 Foundations of Intelligent Agents

An intelligent agent contains three attributes to satisfy its concept [46].

- Flexibility is one of these attributes. An intelligent agent can act both reactively and proactively. The agent responds to changes in its environment in an appropriate way, thus the agent is a reactive entity. On the other hand, an agent can make predictions and planning according to its goal. This characteristics shows that the agent is proactive. With the combinations of proactivity and reactivity, the agent is capable to handle unexpected events as well as acting according to its plan.

- An agent can interact with its environment, so the second attribute is interactivity. To achieve its goal, an agent can use or move the objects in an environment. This interaction is low-level interaction, because the agent is the only intelligent entity in this type of interaction. An agent can also perform high-level interactions. These interactions can be represented as agent-agent interaction and agent-human interaction. To perform these interactions, the agent should have higher social capabilities such as communication, cooperation and competition.

- Autonomy is the last attribute of an intelligent agent. An agent does not need any third party consultation or coordination to execute its actions. This means that the agent is free to choose its actions.

These three key attributes can be contained in an intelligent agent with different levels. If an intelligent agent is designed to act like a human being, this agent should have mental states. There are three types of mental states introduced to intelligent agents [46]:

- states that related with information such as knowledge, presumption and assumption
- connotative states such as intentions, plans and duties
- affective states such as desires, goals and preferences

2.2 Multi-Agent Systems

A multi-agent system is a multiple interacting intelligent agents within an environment. Multi-agent systems are designed to solve very complex problem, which cannot be solved by a single agent because of the problems compexity [9]. The combination of the agents and their environments create a multi-agent system. A multi-agent system may contain human groups and robots [23].

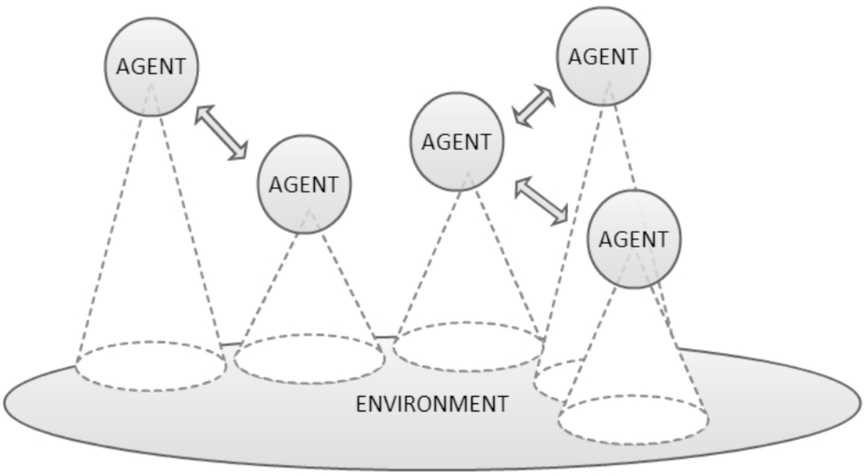

Figure 2.2: Structure of multi-agent system

Wooldridge [47] mentions that cooperation, coordination and negotiation are the required characteristics for the agents to create a multi-agent system. It is stated that the agents have several other characteristics:

- Autonomy: The agents are at least partially self-sufficient, self-aware and autonomous.
- Local view: The agents cannot have a global view on its environment because of the complexity of its environment.
- Decentralization: Creating a controller agent is avoided to eliminate the risk of reducing the system to the monolithic system. [34].

Agent environments are organized according to several aspects. An agent's capacity of gathering information from its environment determines the accessibility of the environment. Variability in consequences of same action is named as the determinism of an environment. The dynamics of an environment is about the entities that affect their environment at a certain time. Discreteness is the defined set of actions for agents in the environment are whether finite or not. Episodicity is a property that determines the agent action in a certain time periods influence other periods or not [36]. Dimensionality is about the decision mechanism of an agent that it regards the important factors in its environment to make decisions [37].

Multi-agent systems are used in different areas. Online trading [10], disaster response [38], modeling social structures [42], information management [28], process control [44], air traffic control [19], business process management [21], health monitoring [14] and computer games are some of the industries that use multi-agent systems actively.

2.3 BDI Theory

2.3.1 Definition

Belief-desire-intention model was first proposed by Michael Bratman [11] to understand and explain the intention and plans of human.

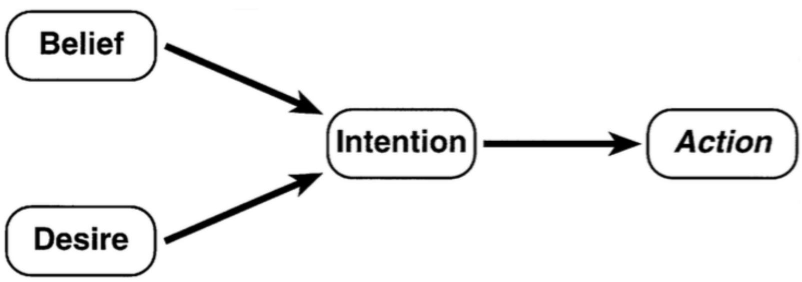

Figure 2.3: A schematic representation of belief, desire, intention and action

Figure 2.3 shows that a person has beliefs and desires. A person's beliefs are made by his/her mental state, and his/her desires are based on his/her wishes, hopes and wants. According to belief and desire, a person has set of intentions which are a planned and decided set of actions [30]. After making elimination among them, the person selects one of the intentions as an action [24].

Software engineering uses the BDI theory to model human behaviours. There are several video games that have intelligent agents designed by BDI software model [12, 13, 32, 33].

2.3.2 Related Works

2.3.2.1 Artificial Soccer

Artificial Soccer has a highly dynamic environment. An agent in Artificial Soccer has following beliefs. The agent's absolute position, velocity and direction are important inputs in game world. The agents also should estimate the other agents' future positions by using the relative visual information concerning lines, flags, and goals. In the developed model, the player's history is also logged. Ball position and wind are other inputs that agent should consider.

The agent has intuitive goals in Artificial Soccer. If the agent possess the ball, it can dribble or pass. If the agent does not possess the ball, it can defend, watch the situation or run to a certain location. In the paper, the writers have described these desires as goals, which may mislead the readers. The defined goals in Artificial Soccer are wishes of a soccer player in explained situations without any plans [30].

The agents have two stages of planning in Artificial Soccer, which are determining best strategy to achieve their intention, and updating their current parameters [12].

This study is a successful BDI implementation on an intelligent agent in video game. The agent can adapt itself in a fast paced environment. However, the team behaviours between agents are implicit, in other words are not defined explicitly. This situation might result in unwanted decisions in a team work.

2.3.2.2 Quake 2

The Quake 2 development team aims to use BDI agents to develop AI driven agents which are human-like players [32]. The expert players are modelled with BDI, but it is also discussed that completely original characters may be modelled with the same technique. Three expert players were analyzed to create Quake 2 bots. Two of them are explained in the paper. First playing style is sniper who stands in a safe spot to wait for the victims. The second playing style is more aggressive that the player travels in the environment to find the victims. The players' behaviours are modeled with Applied Cognitive Task Analysis (ACTA) [31]. Table 2.1 is designed to analyze professional players' belief and desires. According to the collected data via ACTA, basic features of Quake 2 agents are designed. Table 2.2 contains more specific questions that collects data on gameplay of professional players. The collected data via ACTA is also used in belief module of Quake 2 agents.

The designers have tried to model expert player beliefs and desires with extra questions. For example, Having a low health criterion is questioned between defensive playing style and aggressive playing style.

In the implementation stage, the designers have modelled the beliefs of the agents with the collected data via ACTA. On the other hand, they have modelled the desires as events instead of unplanned goals because of the limitations about their developing

Table 2.1: Sample first interview questions

When you play the game, do you perceive any distinct phases?
What are your main goals in each of these phases?
What are the relative priorities of these main goals?
Say you enter the new game, where you do not know the world map, and you may know some, but not all of the players. What are the first things that you do?
Do you make an effort to get to know the style of other players? How do you use that knowledge?

Table 2.2: Sample questions from later stages

You say the first stage of the game is when you do not know the map. When do you consider that you do know the map? Do you explore every nook and cranny?
What makes a good sniping spot?
If you'd just respawned and you could hear but not see a fight nearby, what would you do?
How important the sounds of the game to you? What sorts of things do you listen for?
What sort of things most clearly differentiate novice players from expert players?
Say you'd identified a particular opponent as being a better player than you. Would you make an attempt to actively avoid him/her?

tools. This situation is resulted in ambiguity in the agent's goal in a certain situation [33].

2.3.2.3 Modeling Student Behaviours in a Virtual Classroom Using Belief Desire Intention Model

In this related work, the student behaviours are modelled in a virtual classroom [13]. A student's beliefs are described as its observations and parameters. The observations are counters, which store the repetition count of the actions. Walking student count is an example to the observations. The observations are global, which means that they are same for each student. On the other hand, the parametric representation is unique for each student. There are 8 mental and 2 physical parameters. The parameters change with the events in the classroom and they affect each other. The relations between parameters are constructed with hypothetical reasoning, and implemented as the rules of the game. The relations between parameters could be defined more accurate. Talking with other student reduces the attention and increases the noise as a game rule. Noise affects attention negatively extra to the primary effect of the action. Thus, talking with other students decreases the attention two times because of its effect on agent's noise and attention. It is a hard task to design a rewarding system by considering secondary effects of parameter calculations. Naming of the parameters may also be selected more scientific. Desire to talk parameter is considered as disruptive talking action in classroom in this thesis. Nevertheless, increasing the desire to talk, in other words involvement, of the student is a goal of a teacher in classroom management [6].

It is stated that student desires are goals or options during the simulation. The table of student states is given and they are the only options for intelligent agent to be selected. This situation means that the set of desires of intelligent agents for each personality type are equivalent.

The variability in different student personality types is satisfied with the coefficients. Although, the naming of personality types are derived from a study, the coefficients of student personality types are determined with hypothetical reasoning, which reduces the correctness of the personality types. For example, the clever personality type has the second lowest social ability coefficient. Relation between academic intelligence and emotional intelligence is not validated significantly, and this generalization includes a questionable assumption [45]. Moreover, definition of comprehensive level coefficient is unclear.

When the results of the study are analyzed, it is seen that the overall system works correctly. However, relative distance between student and event is also not important in introduced mathematical model. According to construal level theory 2.6.2, the effect of an event should be inversely proportional with the distance to increase the realism. A virtual classroom is a social environment and the learning among agents are satisfied with counters in this study. It could be modelled more elaborate with modeling a suitable theory derived from psychology.

2.4 Serious Games

2.4.1 Definition

A serious game is a game designed for a primary purpose other than pure entertainment. Motivation of participants during a complex or boring task can be increased via serious games. A serious game has a challenging goal which can be scored. Moreover, a serious game is fun to play. It imparts to the user a desired skill, knowledge or attitude to train the user to the real world [8].

Figure 2.4 shows that the definition of serious games is different from other related concepts in terms of playing/gaming and parts/whole. Gamification can be differentiated from serious games with the help of parts/whole dimension. It means that the product of gamification is not a complete computer game, but serious game is. On the other hand playful design and toys are playable contents, but they are not computer games [16].

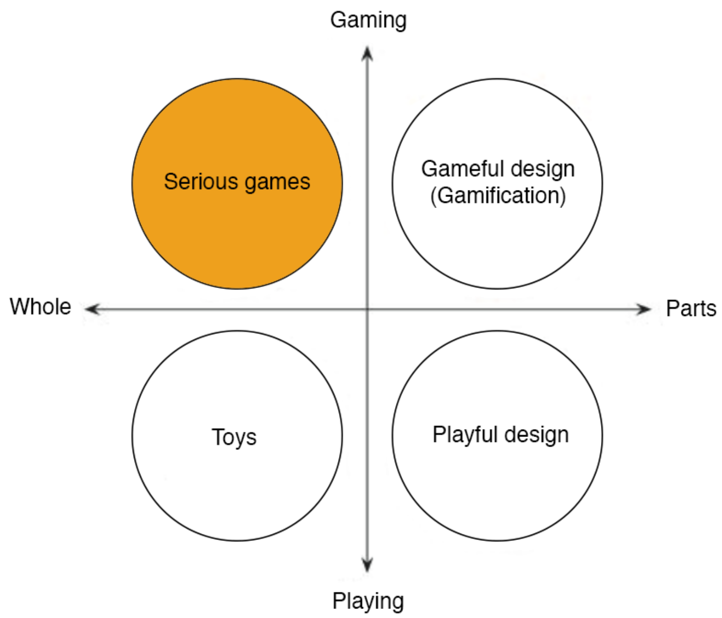

Figure 2.4: Characteristics of serious games among similar contents

Serious games are used in different fields. Activism games, advergames, business games, exergaming, health and medicine games, news games, game based learning and political games can be given as examples for serious games in different areas [8].

2.4.2 Related Game Based Teacher Training Simulations

2.4.2.1 simSchool

simSchool is a classroom simulation that trains teacher about analyzing student differences, adapting instruction to individual learner needs, gathering data about the impacts of instruction, and seeing the results of their teaching in a 2D virtual classroom. This simulation aims to train teacher on general teaching skill, using technology and teaching strategies for special needs students [2].

The ontology of simSchool is extensive that the teacher can perform any action in real world during simulation. Moreover, the agents have unique and elaborate background which is the unique feature of simSchool. However, if a teacher interacts with a student, the other students are not affected from this interaction. A classroom is a social environment and all of the actions should affect the students in the classroom.

2.4.2.2 TeachLivE

TLE TeachLivE is a mixed-reality classroom with simulated students that trains teachers to develop their pedagogical practice in a safe environment that removes the necessity of real student in training session. The students are simulated via avatars during session and they are controlled by other teachers. The immediate feedback is given by observers via in ear headphone which increases the efficiency [3].

TeachLivE is designed to analyze the teacher's classroom management skills. According to the collected data, the teacher trainers give feedback and improve the classroom management skills of the participants. The students in the virtual environment are controlled by human players. Player controlled characters can be easily replaced with intelligent agents which is done in our thesis. The use of intelligent agents decreases the required force of labor to operate simulation.

2.5 Student Personality Types

Role of student characteristics in a teaching environment is very important. Although computer science try to model student, defining and categorizing the process of student personalities are mostly performed by educational sciences. There are several theories on this topic, and the followings are suitable for creating an intelligent agent to perform student behaviours. Before continuing with related studies there is a term that important to understand the following studies. Latent class analysis [17] is statistical method for identifying unclassified class membership among subjects using categorical and/or continuous observed variables. For example, the students may be categorized with respect to their preparation behaviours before lecture start into different types of student characteristics.

2.5.1 Study of Carl Jung

According to Jung [22], there are several characteristics to categorize people. First of them is how a person obtain an energy. There are two extremes which are termed as introversion and extraversion. Introvert people are energized by their own ideas and thoughts. Extrovert people are energized by interacting with others. Second item in Jung's theory is about the person's information acquiring strategy. There are two terms introduced as sensing and intuition. Sensing people acts according to their observations. On the other hand, intuitive people act according to their instincts. Lastly two characteristics are defined according to decision mechanism of people which are thinking and feeling. Thinkers make decisions with objective and analytical thinking with blocking their feelings. In contrast, feelers make decisions subjectively and considers the outcomes and how it affect the others.

2.5.2 Study of Rita Coombs Richardson and Emily Arker

This study is carried on to recognize the students' personality styles and learning styles. The aim is to provide information about student for teacher to select the best instructional method to satisfy student's individual needs. To defined student personalities are constructed on Carl Jung's Personality Theory. In the study there are four styles and their characteristics [35]:

- Energizers are full of excitement, optimistic and eager to enjoy the life. They enjoy being with other energizers.
- Bridge builders enjoy communicating with others and maintaining relationships.
- Bottom liners have tendency to take risk. They are also confident in showing their feelings in any situation.
- Thinkers are analytical and subjective persons. Most of them are perfectionists.

It is stated that with the awareness of those personalities, healthy teacher/student relationships can be constructed.

2.5.3 Study of Tina Seidel

The defining student characteristics process in this study is based on the observations in high school science classes. 50 classes in Germany and 32 classes in Switzerland are observed during lectures, which are selected randomly. According to Seidel [39], latent class analysis have shown that there are five basic student characteristics in terms of student's:

- General cognitive ability
- Content pre-knowledge in subject domain
- Interest towards subject domain
- Self-concept ability in subject domain

Characteristics	Smart	Uninterested	Underestimating	Overestimating	Struggling
Group size %	24	12	29	16	19
Cognitive ability	High	High	High	Low	Low
Pre-knowledge	High	Intermediate	High	Intermediate	Low-Intermediate
Interest	High	Very low	Intermediate	High	Low
Self-concept	High	Intermediate	Low	High	Low

Figure 2.5: Student characteristics in detail

The personality definition of Jung is not limited with students and can be used to model any personality [22]. Coombs et. al. [35] not only defines the student personalities, but also defines teacher personalities. The teacher personalities are out of scope of this thesis. The student characteristics of Seidel is used in this thesis, because the student personalities are suitable to be modelled via belief desire intention model.

2.6 Social Learning Theory

Social learning theory is used to model student behaviours in this thesis. The brief information and related researches will be shared in this section.

2.6.1 Definition

According to Bandura [7], learning is a cognitive process in a social environment. It can ben occur with observing or direct instructions. Rewarding and punishment are also trigger the learning in social context, which is known as observational learning. Several conditions should be satisfied to trigger social learning. A person should give an attention to the other person and the person's action. A person's characteristics such as sensory capacities, arousal level, perceptual set, past reinforcements affect the attention of him/her. Moreover, the person should remember the observed person's behaviour which is called retention. After a while, the person should reproduce the same behaviour to use social learning, which requires a motivation to perform. In other words, the person should have a good reason to imitate the other people's behaviours.

The following theories are from social psychology that play role in social learning.

2.6.2 Construal Level Theory

Construal level theory is a theory in social psychology which expresses the relationship between psychological distance and people's thinking [43]. The theory describes that the more distant an object or event from individual, the more abstract it will be thought of. On the other hand, the closer an object or event is, the more concretely it will be thought of. According to theory, there are several types psychological distance:

- temporal distance: time
- spatial distance: physical distance
- social distance: interpersonal distances, such as distance between two groups who have counter-views
- hypothetical distance: imaging that an event is possible or not possible

Although there are several psychological distances, only spatial distance is modelled in proposed method because of the limited schedule. Remaining types of psychological distance are planned to model in future work which is shared in Chapter 7.

2.6.3 Operant Conditioning

According to Skinner [41], human mind is more productive to study observable behaviour rather than internal mental events. Skinner believed that understanding the cause-effect relationship of a behaviour is the best way to understand it. This approach is called as operant conditioning. Operant conditioning is changing the subject's behaviour with using reinforcement which is given after the subject's desired response. Skinner stated that three operant is available in use which are given in Table 2.3.

Table 2.3: Three responses or operant can follow subject's behaviour to create operant conditioning

Operant type	Effect on probability to occur
Neutral operant	Does not change
Reinforcer	Increase
Punisher	Negative

The operant conditioning occurs in different types. Positive reinforcement and negative reinforcement is used to increase probability to perform the behaviour. This condition is also valid for punishment. The detailed example for operant conditioning is given in Figure 2.6. Operant conditioning is modelled in serious game that is developed in the scope of the thesis to explain the teacher's rewarding and punishment on students.

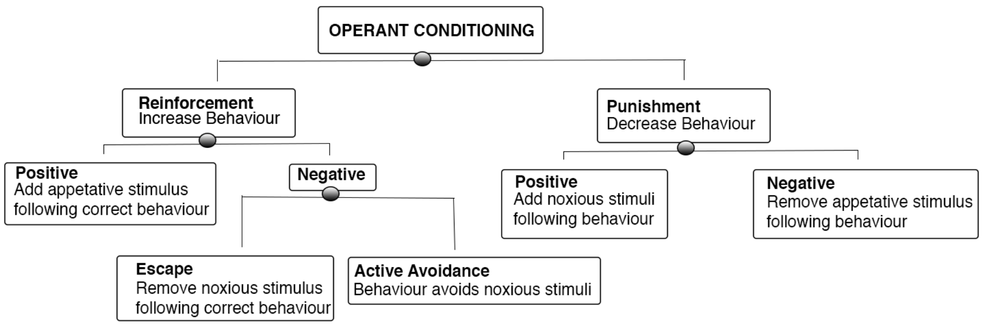

Figure 2.6: Operant condition types with examples

2.6.4 Related Works

2.6.4.1 Intelligent Social Learning

In this study, a heuristic is proposed to model the intelligent social agent. According to the Conte and Paolucci [15], there are eight steps to design an agent which has social learning:

- Social mental representations should be modelled which should include social beliefs, social desires and intentions, including the desire to imitate others.
- External and internal features of an agent should affect the others.
- Let agent reason upon social beliefs, which results in generating new beliefs that should be took into account while acting and imitating.
- Social goals should be linked to social beliefs.
- An agent should compare its knowledge with other agents.
- Decide whether to imitate, solving potential conflicts goals among the goal to imitate and not to imitate, according to some criterion.
- An agent should decide that imitating a behaviour is a solution or not to solve potential conflicts according to goal's criteria.
- An agent should adopt external criteria for selective imitation, which is introduced as social desirability.
- An agent should decide which agents to imitate.

The proposed heuristic have not been implemented in a serous game or simulation. On the other hand, the shared heuristic is explicit and sufficient to guide a designer to implement an intelligent agent which has a social learning.

2.6.4.2 A Social-Cognitive Framework for Pedagogical Agents as Learning Companions

In this article, artificial companions are designed as the partners of the users during learning process. The authors call their agents as pedagogical agents as learning companions (PALs) [25]. The study does not aim to replace the people with PALs, but explores the effect of companions in learning. Social cognitive theories are implemented on agents including distributed cognition, social interaction, and Bandura's social cognitive theory.

It is emphasized that teaching and learning are highly social activities and interactions with teachers, peers, and instructional materials affects the efficiency in learning process. Social cognitive ability is an important key feature, because PALs are designed to learn with the users as a real companion which makes learning a social process. It is stated that human beliefs and knowledge is shaped in social context with communication. Moreover, social interaction is added to the PALs to make computer-based learning more meaningful.

Implementation of social-cognitive theory identifies three modes of human agency which are personal, proxy and collective. PALs are responsive partners thus they only satisfy the learner's request that result in increasing in the learner's self-efficacy beliefs in the task. The user can use the PALs' knowledge when he/she needs it, and they can work together to accomplish the given tasks [25].

CHAPTER 3

RESEARCH METHODOLOGY

The research methodology which is followed throughout the study is given in this chapter. The research methodology starts with the problem statement which is followed by the proposed solution's software architecture. The proposed software method is used in a serious game whose design process and user interfaces (UI) are explained in detail in Section 4. At the end of the chapter, the implementation process of the software architecture is given.

3.1 Problem Statement

As discussed in previous sections, serious games are powerful tools to train the user on desired skills. If the desired skills are trained in social environments, the agents in the game should be modeled elaborately to give the user a realistic experience which increases the efficiency.

As we mentioned before, there are several serious games designed to train teacher in a virtual classroom environment. It is analyzed in related works that social learning between intelligent agents are ignored or omitted in these studies. However, a classroom environment is highly interactive and social learning occurs among students in real life. To provide a realistic experience for teachers, in other words users, the student agents should have the characteristics in real life including social learning.

This thesis aims to model student behaviours in a virtual classroom. There is a study which presents a belief-desire-intention software model to produce student behaviours [13]. The belief-desire-intention model is upgraded to represent social learning among intelligent agents in this study. It is observed that, the intelligent agents modify their intentions according to their interactions with the teacher and other agents during lecture. The agents should reconsider their intentions according to their observations and beliefs, which may result in imitating the other person's behaviour.

Problem definition can be stated explicitly that the social learning theory will be incorporated into belief-desire-intention software model to increase realism in intelligent agents' behaviours.

3.2 Software Architecture

3.2.1 Use Case

It is shown in Figure A.1 that there are two actors in the serious game that designed in the scope of the thesis, which are student and teacher. The teacher is controlled by the user and can affect the virtual classroom. The teacher can choose among the lecturing options to carry on the lecturing process and give feedback on selected student's behaviour. On the other hand, the student is controlled by intelligent agent. There are five type of actors as a student in virtual classroom which are given in Table 3.1. According to Wray and Laird [48], the agents should have different personalities to increase the realism. The student chooses its actions autonomously. If the teacher shares his or her opinion on the student's action, the student might change its action's priority via social learning. The personalities are derived from study of Tina Seidel [39] that is described in Section 2.5.3. Although the teacher count is limited with one, there can be more than one student having one of the defined personality types. A personality type determines the initial beliefs and desires for that intelligent agent.

Table 3.1: Five types of personalities who are the actors as students

Smart
Uninterested
Overestimating
Underestimating
Struggling

3.2.2 Action Algorithm

An action can be defined as the activity performed by an actor in the virtual classroom, whose effect may change the game environment. There are two actors that are explained in 3.2.1, which are student and teacher.

3.2.2.1 Student Actions

The autonomous student agents perform student actions during game simulation. The student actions are categorized into two groups which are misbehaviours and good behaviours. The defined misbehaviours are shared in Table 3.2, and the defined good behaviours are shared in Table 3.3. Performing criteria of these actions are determined as the game rules which are shared in Table B.1. The effects of student actions are also shared in Table B.2. The student actions have conditions that agent's belief should be suitable to perform the action. A student action affects not only student's self-belief, but also neighbour students' beliefs. The outcome of each student action is unique. The formula to calculate the effect of an action on belief of an agent was given in

Equation (3.3) in 3.2.3.1. The effect of an action is inversely proportion with the Gaussian distance according to construal level theory which is explained in 2.6.2.

Table 3.2: Defined misbehaviours in designed serious game

Daydream
Sleep
Sing
Laugh
Draw on book
Write text message

Table 3.3: Defined good behaviours in designed serious game

Idle
Take note
Do activity
Read
Listen
Participate

3.2.2.2 Teacher Actions

Teacher actions are performed by user which plays the teacher role during game. The possible actions are offered to the user via UI. There are two types of teacher actions which are dealing and lecturing. Each lecturing action has unique effect on the game world. The lecturing action affects all of the students in the classroom equally. The set of lecturing actions are given in Table 3.4. Fail action is defined as a challenge of the game, and it is not selectable by the user.

Table 3.4: Defined lecturing actions designed serious game

Intro
Cover from book
Cover via activity
Summary
End lecture
Fail

The dealing actions are rewarding/punishment of the teacher on a student, which triggers the operand conditioning and social learning. A dealing action only affects the selected student's belief parameters directly, but affects all the students' belief via social learning. The defined dealing actions and their effect on a student action are given in Table 3.5. Rewarding and punishment have stronger effects as compared with approve behaviour or disapprove behaviour and explain why. On the other hand, disapprove behaviour and explain why action increases the student's respect towards teacher that leads the student to perform the good behaviours.

Table 3.5: Priming effect of dealing actions on student action

Action	Priming effect on student
Ignore behaviour	No priming on student action
Reward Behaviour	Positive priming on student action
Punish behaviour	Negative priming on student action
Approve behaviour	Positive priming on student action
Disapprove behaviour and explain why	Negative priming on student action

The teacher actions and their effects on game world are given in Table C.1. In addition to belief parameter effects, dealing actions increase or decrease the student's actions belief parameter effects. The secondary effect and the student's action effect are reflected on a student's belief separately. For example, if a student performs action A which increases its attention 10 and the teacher approves this action, extra 5 attention is added to the student because of the secondary effect of approve behaviour action. The secondary effects of the dealing actions are given in Table 3.6.

Table 3.6: Secondary effects of dealing actions

Action	Secondary effect on student
Ignore behaviour	Student action effect $*(-0.25)$
Reward Behaviour	Student action effect $*(1.0)$
Punish behaviour	Student action effect $*(-1.5)$
Approve behaviour	Student action effect $*(0.5)$
Disapprove behaviour and explain why	Student action effect $*(-0.5)$

In addition to Table 3.6, if a good behaviour is ignored, the students are are exposed to $Fail * (0.25)$. If a good behaviour is disapproved or punished, the students are are exposed to $Fail * (0.5)$.

3.2.3 Belief Desire Intention Algorithm

Figure A.2 contains the information about proposed artificial intelligence algorithm. The intelligent agents are acting as students in a virtual classroom. Student agents are designed with belief-desire-intention model. A student class possesses a belief object, desire object, intention object and personality object. Personality object is used for initiation of belief and desire of a student according to its personality.

3.2.3.1 Belief Module

Belief module holds parameters to represent the intelligent agent's mental state as parametric model. Although some of the parameters have correlation between each other, their calculations are performed separately. The "Parameter" is a defined class which has four items that can be seen in Table 3.7.

Table 3.7: Elements in parameter class

isolated
agentInteraction
actionInteraction
total
parameterType

Isolated holds the value of a parameter whose source is only the student's personality. This variable is updated in the beginning of the simulation and does not change during the simulation.

AgentInteraction is calculated only when the social learning is activated among intelligent agents. An agent might affect the other's mental state with its presence via this variable. For example, if student 1 has high attention and student 2 has low attention, student 2 will decrease the attention level of student 1 via agentInteraction and student 1 will increase the attention of student 2 by their presence. The effect of this variable is inversely proportional with distance between student 1 and student 2 according to construal level theory which is explained in Section 2.6.2. The formula to calculate the agent interaction on a student agent is given in Equation (3.1). In the formula, D (3.2) represents the Euclidian distance coefficient that is calculated by the distance between source student i_0 and relative student i_n. η is used for representing a mental parameter, and this formula is used for calculating the agent interaction element of each mental parameter. Δx is the minimum significant distance in the game, which is determined by the distance between adjacent students. X stands for the position of a game object in game world. σ and α are the coefficients to tune the internal effect of an agent interaction, which are optimized by trial-and-error method. $\sigma = 0.6$ and $\alpha = 0.1$ in the proposed software model.

$$\sum_{i=1}^{n} i = D * (\eta(i) - \eta(i_0)) * \alpha \tag{3.1}$$

where

$$D = \sigma^{|X(i_0) - X(i)|/\Delta x} \tag{3.2}$$

ActionInteraction stores the value which is created by action. This element can be considered as experience part of the parameter. If an agent performs action, its actionInteraction parameter is updated with the value of its action. Moreover, surrounding agents are update their actionInteraction values with respect to the source agent's action effect value. For example, if an agent laughs during lecture, the neighbour agents' attention decrease inversely proportional with their Euclidian distance between the agent that laughs according to construal level theory which is explained in 2.6.2. The formula to calculate the agent interaction on a student agent is given in Equation (3.3). ActInt is the action interaction element in BP, which stands for belief parameter. In the formula, D (3.4) represents the distance coefficient that is calculated from the distance between source student i_0 and relative student i_n. λ represents the action and $\lambda(BP)$ is the effect of action in terms of selected belief parameter. Equation (3.3) is used for each belief parameter to reflect action's complete effect. Δx is the minimum significant distance in the game, which is determined by the distance between adjacent students. X stands for the position of a game object in game world. σ is the coefficient to tune the external effect of action interaction, which is optimized by trial-and-error method. $\sigma = 0.35$ in the proposed software model.

$$ActInt(BP) = ActInt(BP) + D * \lambda(BP) \tag{3.3}$$

where

$$D = \sigma^{|X(i_0) - X(i)|/\Delta x} \tag{3.4}$$

Total is calculated with the sum of other three elements in parameter class. The formula to calculate total is given in Equation (3.5).

$$Total = Isolated + AgentInteraction + ActionInteraction \tag{3.5}$$

ParameterType is an enumerator that marks the parameter as negative or positive. This information is important during calculation and visualization of parameters on UI.

In Table 3.8, the physical parameters have shown. The physical parameters are used for representing the environmental effect on an intelligent agent's belief. The agent's physical condition is also affects its belief, and it is represented with the physical parameters.

Table 3.8: Physical parameters in belief module

Noise
Energy

Noise is a negative parameter which increases with the misbehaviours. The teacher should keep the students' noise value low by selecting proper classroom management strategies.

Energy is important for intelligent agent to perform certain actions. The misbehaviours such as singing, laughing and the good behaviours such as participating, doing activity require high level of energy. The teacher should keep student's other parameters in desired region. A student with high energy and low attention may easily perform misbehaviour. The entire desired student actions require at least mid energy level and energy is a positive parameter because of this situation.

The mental parameters are shared in Table 3.9. The mental parameters are selected as a subset of human perception to model a student's beliefs in a classroom environment. These parameters hold information about the entity's belief about teacher, lecture and other students. Some of the parameters give information about agent's emotional situation.

Table 3.9: Mental parameters in belief module

Attention
Disruptive Talking
Involvement
Temper
Respect Teacher
Understand Subject
Teacher Authoritarian

Attention is a positive parameter that gives information about the agent's attention level during simulation. Attention is one of the key parameter that leads the agent to perform a misbehaviour or a good behaviour.

Disruptive talking represents the agent's tendency to talk with teacher and other agents independent from the lecture topic. Disruptive talking is a negative parameter and should be kept low.

Involvement affects the agent's tendency to participate in lecture. If an intelligent agent starts to participate during lecture, it affects the neighbour agents positively which is highly desired.

Temper gives information about agent's mental situation. An agent with high temper cannot focus on lecture and cannot perform good behaviours. Excessive punishing may lead high temper on an agent.

Respect teacher parameter is important during simulation. The agent may listen the teacher and obey the direction of the teacher. Moreover, the student avoids to perform a misbehaviour. If the students have high respect to their teacher, the teacher can be qualified as authoritative [26], because the teacher should be demanding and warm to have high respect teacher parameter.

Understand subject parameter triggers the desired student actions. If a student understands the subject, he or she starts to listen, participate, and execute the given tasks.

Teacher authoritarian parameter forces student to avoid performing a misbehaviour, even if the student does not show respect to teacher. The students have high teacher authoritarian parameter if the teacher punishes the students several times during the lecture. The authoritarian teacher is demanding and distant to the students [26].

The predefined student personality types have different beliefs. It can be considered as different initial parameter values for different personalities. The starting values are given in Table 3.10 which are selected to satisfy the information given in Figure 2.5.

Table 3.10: Starting beliefs for five types of personalities

Parameter Name	Smart	Unint.	Underest.	Overest.	Strug.
Noise	0	0	0	0	0
Energy	70	70	50	70	30
Attention	70	10	40	70	30
Disruptive Talking	10	70	30	50	30
Involvement	50	10	30	60	10
Temper	30	10	50	30	30
Respect Teacher	70	10	70	40	50
Understand Subject	70	70	70	30	10
Teacher Authoritarian	0	0	0	0	0

3.2.3.2 Social Learning in Belief Module

Social learning is incorporated into belief module of belief-desire-intention model, because social learning affects the personal beliefs by imitating surrounding beings. The student agents store their observations in a list which can be seen in Figure A.2. A student agent updates its list with imitating other agents and considering the teacher's feedback.

The intelligent social learning is implemented by using the heuristics of Conta and Paolucci [15]. The eight steps to design an agent which has social learning has modified and reduced to five steps which are:

- A student's social mental representation is modelled via belief-desire-intention model
- External and internal features of student agents are affected from each other with proposed model. A student action affects the other students and changes their belief. Their internal states affect each other via agentInteraction element of the parameter which is explained in 3.2.3.1.

- Observations are stored in lists to generate new beliefs that the list named as perception list.
- There are certain criteria for agent to imitate other behaviours. A student should have low attention to imitate other students who perform misbehaviour. On the other hand, if a student has high attention, it has a tendency to imitate good behaviours during lecture.
- A student has to have high respect teacher or teacher authoritarian value to take teachers rewarding or punishment into account. If a student agent does not respect teacher or fear from teacher, it ignores the response of teacher on certain action.

The teacher feedback on a certain action is an operand conditioning. It is explained in 2.6.3 that operand conditioning is built on rewarding and punishment. Rewarding increases the student's probability to perform an action. Punishment decreases student's wish to perform an action. Repetition of rewarding and punishment reinforces the learning about that action. The student's learning has five states which are shared in Table 3.11.

Table 3.11: Degrees of social learning

Should not
May not
Neutral
May
Should

For example, a student may participate during lecture whose priority is "neutral". If the teacher rewards this action, the students who respect to teacher or fear from teacher promote the priority of participate action to "may". During the reasoning process, the student prefers to perform this action which has higher priority rather than other actions. Priming may also be triggered without response from teacher. If a student has high attention, it has a tendency to imitate the other students who are performing a good behaviour. If a student has low attention, imitation is sourced by the other students whose action is a misbehaviour.

3.2.3.3 Desire Module

The desires change among different personality types. However, the set of desire for a specific personality does not change during simulation time. In real world, the desires may also change in time, but it is assumed as constant in this simulation as a game rule to observe the effect of the social learning.

According to Figure 2.5, the smart students have high cognitive ability, pre-knowledge in subject domain, interest towards subject domain and self-concept. Thus, the smart student's desires are related with the lecture. The set of desires for a smart student is shared in Table 3.12.

Table 3.12: Set of desires for smart personality

Listen
Read
Take note
Do activity
Participate

The uninterested students have high cognitive ability, intermediate level of pre-knowledge in subject domain and self-concept and very low interest towards subject domain. Although, the uninterested students has sufficient knowledge and cognitive ability, they have not got a suitable set of desires to participate in lecture and has extremely low attention. The set of desires for an uninterested student is shared in Table 3.13.

Table 3.13: Set of desires for uninterested personality

Daydream
Sleep
Sing
Laugh
Draw on book
Write text message

The underestimating students have high cognitive ability and pre-knowledge in subject domain, intermediate interest towards subject domain and low self-concept. This student type is interested in lecture topic. However, they underestimate their pre-knowledge in subject domain, so they fear from participating or doing activity which requires interaction with others. The underestimating students avoid interacting with others during lecture because of their low level of confidence on subject domain even though they have sufficient pre-knowledge. The set of desires for an underestimating student is shared in Table 3.14.

Table 3.14: Set of desires for underestimating personality

Listen
Read
Take note

The overestimating students have low cognitive ability, intermediate level of pre-knowledge in subject domain, high interest towards subject domain and self-concept. The overestimating students overestimate their pre-knowledge in subject domain. This type of student may do activities during lecture, but its set of desires is not suitable to listen, read or take note during the lecture. The set of desires for an overestimating student is shared in Table 3.15.

Table 3.15: Set of desires for overestimating personality

Do activity
Sing
Laugh
Draw on book
Write text message

The struggling students have low cognitive ability, pre-knowledge in subject domain, interest towards subject domain and self-concept. This type of students wants to be good at subject domain. Nevertheless, their knowledge and mental state are not suitable to be a successful student. They are aware of this situation and have tendency to isolate them from classroom environment. The set of desires for a struggling student is shared in Table 3.16.

Table 3.16: Set of desires for struggling personality

Listen
Read
Daydream
Sleep

3.2.3.4 Intention Module

Intention algorithm is designed to assign a current action to agent after the reasoning process. In belief-desire-intention model, the intention is the process that a person assigns new goal based on his/her beliefs and desires. The intention of the agent is updated with the change in beliefs during simulation.

Update process of intention is explained in Figure 3.1. According to it, the first elimination among the alternatives is executed according to the belief parameters of an agent. For example, an agent with high energy cannot decide to sleep, because the sleeping action is not performable because of the agent's energy parameter level. Square, pentagon and hexagon are performable actions in this example. After the first elimination, the social learning set in to manipulate the agent's decision. If one of the alternatives has higher priority than others, this action is added to possible action list. If there is more than one action with high priority, all of them are added to the possible actions list. Only the pentagon has the highest priority which is determined by the agent's observations in social environment, and hence pentagon is the only alternative in refined possible actions list. After these eliminations, the student agent's personal desires kick in to make final decision. If there were any desired action in the list, this action would have higher priority. If there were more than one desired actions in the list, the current action is selected randomly among these actions. In this example there is no desire in refined possible actions, and pentagon action is set as the intention of the agent.

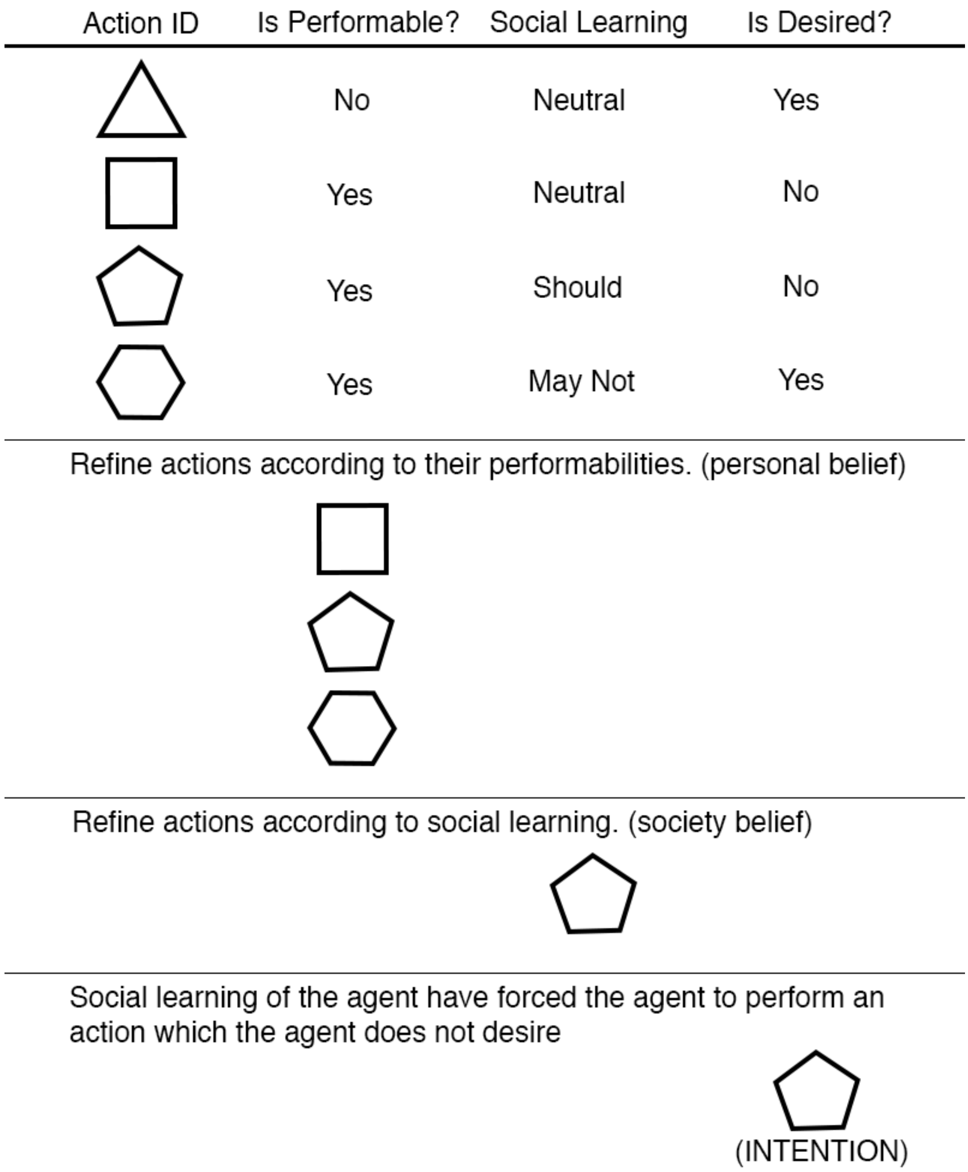

Figure 3.1: Reasoning process of student agent

CHAPTER 4

GAME DESIGN

The game is developed with Unity Engine. Unity [4] is one of the trending game engine which offers 2D and 3D game development opportunities. The game is developed with 2D graphics. Unity is built on Mono [1] framework which is an open source implementation of Microsoft's .NET Framework. Moreover, Mono framework allows developers to build the cross-platform applications. The Unity is selected in this thesis, because it supports C # and has outnumbering community who are glad to support other developers. Proposed method for student agents are implemented in C # language.

When the game is started, the first game scene is the main menu where you can select which experiment to execute. Moreover, you can modify the prepared experiments from this UI. The main menu is shared in Figure 4.1.

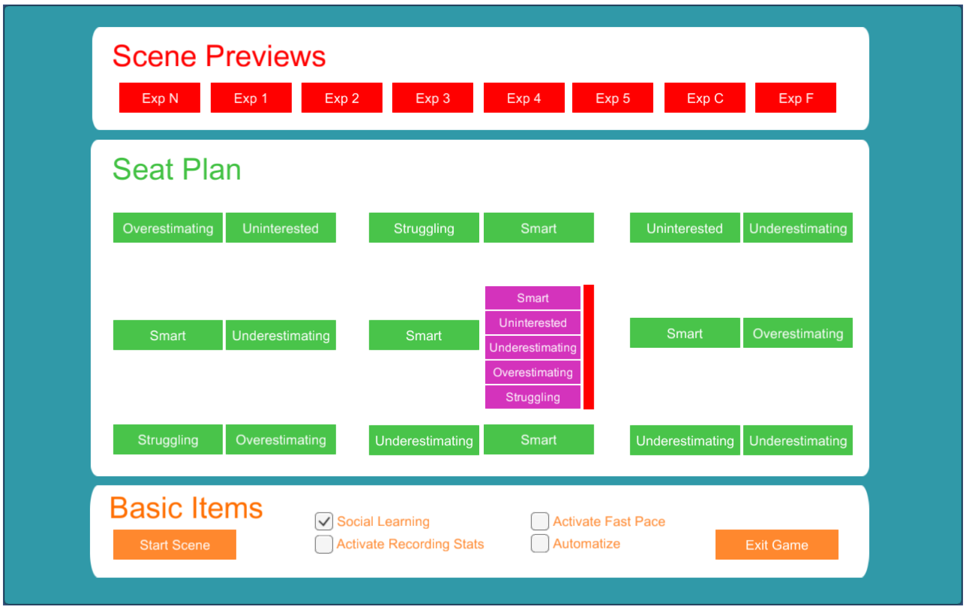

Figure 4.1: Main menu of designed serious game

When the simulation is started, the scene is replaced with the virtual classroom environment. The teacher can access to the lecturing actions menu from UI, which is given in Figure 4.2. The teacher can also request from class to perform a certain action via Request menu to reinforce the occurrence of this action. For example, a teacher may request from students to take note while he or she is covering the subject from book.

When the user clicks on a student, the basic information of selected student is shown on game screen. The user can reward or punish the student's action from this interface. The explained interface is given in Figure 4.3.

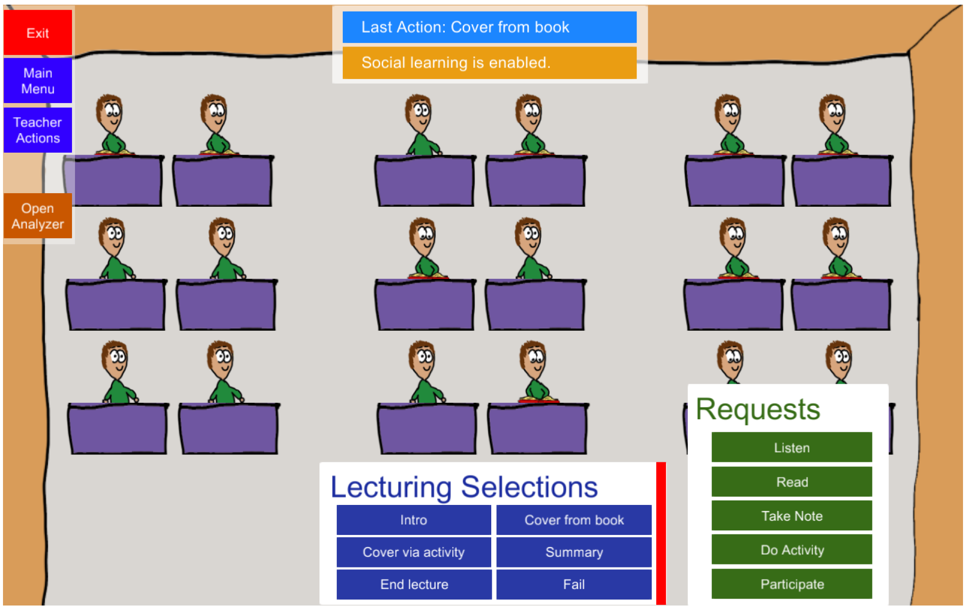

Figure 4.2: Lecturing menu of designed serious game

It is explained in Chapter 3 that the student's belief is composed of many elements. The selected student's isolated parameter values, agent interaction values, action interaction values, social learning and reasoning are given in analyzing window which can be accessed via UI. The analyzing window is given in Figure 4.4.

Figure 4.3: Dealing menu for selected student of designed serious game

Figure 4.4: Analyzing window of selected student of designed serious game

CHAPTER 5

USER STUDY

5.1 Purpose

The aim of the user study is to prove that our student behaviour model is realistic. A Likert scale questionnaire is prepared for teachers to reflect their experiences on the behavioural and mental effects of the social learning on students. The subjects are selected as teachers who are actively lecturing in an elementary school or a high school.

5.2 Questionnaire

The questionnaire is designed with the combination of multiple choice questions and a Likert scale questionnaire which has 5 scaling options. The multiple choice questions are prepared to collect the demographic data of the participants. The boundary values are Strongly disagree(1) and Strongly agree(5). Normal classroom, smart classroom, uninterested classroom, underestimating classroom and overestimating classroom definitions are given in 6. The questionnaire is given in Appendix E.

5.3 Demography of Participants

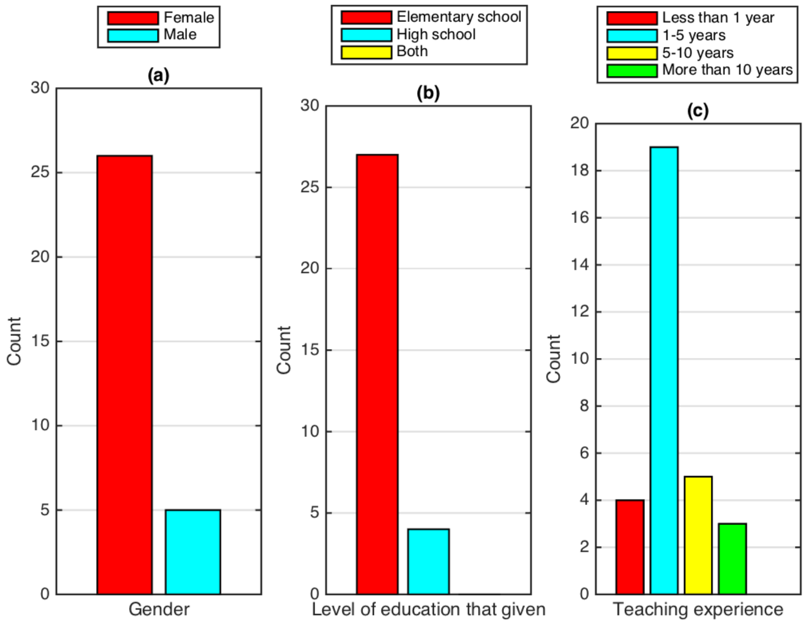

Figure 5.1: (a) Gender distribution among participants (b) Level of education that participant give to the students (c) Participant's teaching experience

5.4 Analysis

The questions and the statements are independent from each other in the questionnaire. Each question's or statement's mean is calculated to demonstrate the central tendency of the responses. To satisfy the minimum sample size of Central Limit Theorem, subject number is selected as 31 which is bigger than 30. The results are shared in the bar charts, and compared with the results of the serious game designed in the scope of the thesis.

CHAPTER 6

RESULTS AND DISCUSSION

The experiments are designed to prove that the social learning student agents increase the realism in reasoning mechanism of the agents. To satisfy this situation, the experiments are repeated in a normal classroom distribution with the social learning is activated, specific classroom distribution with the social learning is activated and specific classroom distribution with the social learning is deactivated. Normal classroom distribution is designed according to group size data for different student personality types in Tina Seidel's study 2.5.3.

In the experiments, the classrooms are named according to following informations:

- Smart classrooms consist of 17 smart students plus a student that has different personality type.
- Uninterested classrooms consist of 17 uninterested students plus a student that has different personality type.
- Underestimating classrooms consist of 17 underestimating students plus a student that has different personality type.
- Overestimating classrooms consist of 17 overestimating students plus a student that has different personality type.
- Struggling classrooms consist of 17 struggling students plus a student that has different personality type.
- Normal classrooms consist of 3 overestimating, 2 uninterested, 3 struggling, 5 underestimating and 5 smart students.

The following game missions are completed to execute the related experiment:

- The missions in Table 6.1 are completed to execute Experiment 6.2, Experiment 6.3, Experiment 6.4, Experiment 6.5, Experiment 6.6, Experiment 6.7.
- The missions in Table 6.2 are completed to execute Experiment 6.8.
- The missions in Table 6.3 are completed to execute Experiment 6.9.
- The missions in Table 6.4 are completed to execute Experiment 6.10.

The test harness is automatized to execute the tasks in scenarios identically. Each scenarios have been repeated 30 times, and mean of the results is shared in histograms. The results are given in following sections. The results of the experiments are verified by the user study, which is explained in 5.

Table 6.1: Required tasks to perform Experiment 6.2, Experiment 6.3, Experiment 6.4, Experiment 6.5, Experiment 6.6, Experiment 6.7.

Lecture: Intro
Request: Read
Lecture: Cover via book
Lecture: Fail
Request: Do activity
Lecture: Cover via activity
Lecture: Fail
Request: Take note
Request: Participate
Lecture: Summary
Lecture: End

Table 6.2: Required tasks to perform Experiment 6.8.

Lecture: Intro
Request: Read
Lecture: Cover via book
Lecture: Fail
Interaction: Punish 3 misbehaviours
Request: Do activity
Lecture: Cover via activity
Interaction: Approve 3 good behaviours
Lecture: Fail
Interaction: Punish 3 misbehaviours
Request: Take note
Request: Participate
Lecture: Summary
Lecture: End

Table 6.3: Required tasks to perform Experiment 6.9.

Lecture: Intro
Request: Read
Lecture: Cover via book
Lecture: Fail
Interaction: Disapprove 3 misbehaviours and explain why
Request: Do activity
Lecture: Cover via activity
Interaction: Reward 3 good behaviours
Lecture: Fail
Interaction: Disapprove 3 misbehaviours and explain why
Request: Take note
Request: Participate
Lecture: Summary
Lecture: End

Table 6.4: Required tasks to perform Experiment 6.10.

Lecture: Intro
Request: Read
Lecture: Cover via book
Lecture: Fail
Interaction: Approve 3 misbehaviours
Request: Do activity
Lecture: Cover via activity
Interaction: Ignore 3 good behaviours
Lecture: Fail
Interaction: Approve 3 misbehaviours
Request: Take note
Request: Participate
Lecture: Summary
Lecture: End

6.1 Teacher Point of View on Social Learning Between Students

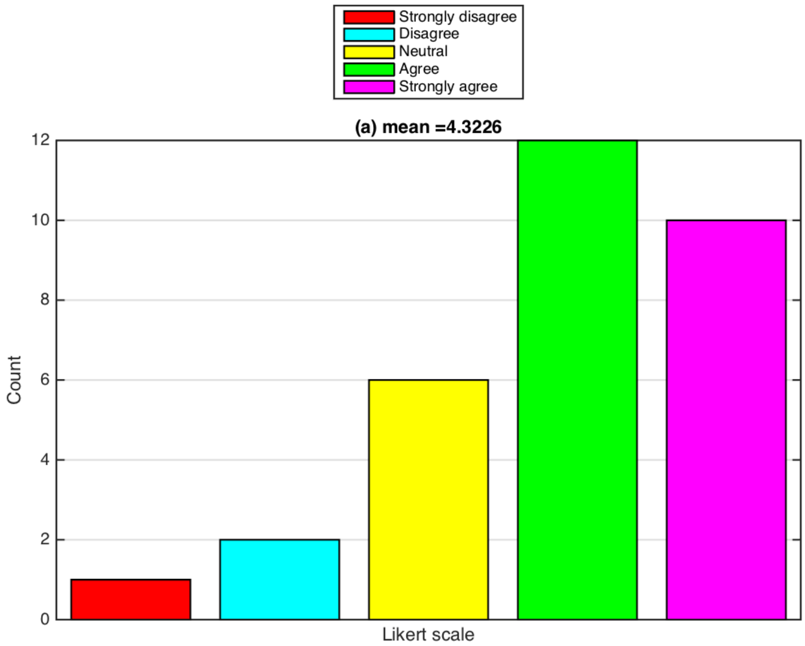

Figure 6.1: Collected data on statement 4, "The students observe and imitate each other in classroom." in Section 5.2

The results are given in Figure 6.1 which verifies the concept of social learning among student. The central tendency of the data is larger than neutral and strongly agree answer has the highest frequency among the responds that are collected by user study.

6.2 Social Learning of Smart Student Experiment

6.2.1 Game Results

This experiment consists of three sessions. In first session, a smart student is placed in an uninterested classroom without social learning. In second session, the first session experiment is repeated with the social learning. In the last session, a smart student is analyzed in a normal classroom distribution.

When the social learning is disabled, the smart student follow its desires even if the classmates are not have same beliefs and desires (Figure 6.2, 6.3, 6.4). On the other hand, the smart student imitates the uninterested student's behaviours when the social learning is enabled. Moreover, the smart student's belief parameter values converge to the uninterested belief parameter values (Figure 6.5, 6.6, 6.7). A smart student's behavioural and parameter analysis results are similar in a normal classroom (Figure D.1, D.2) and uninterested classroom with the social learning is disabled.

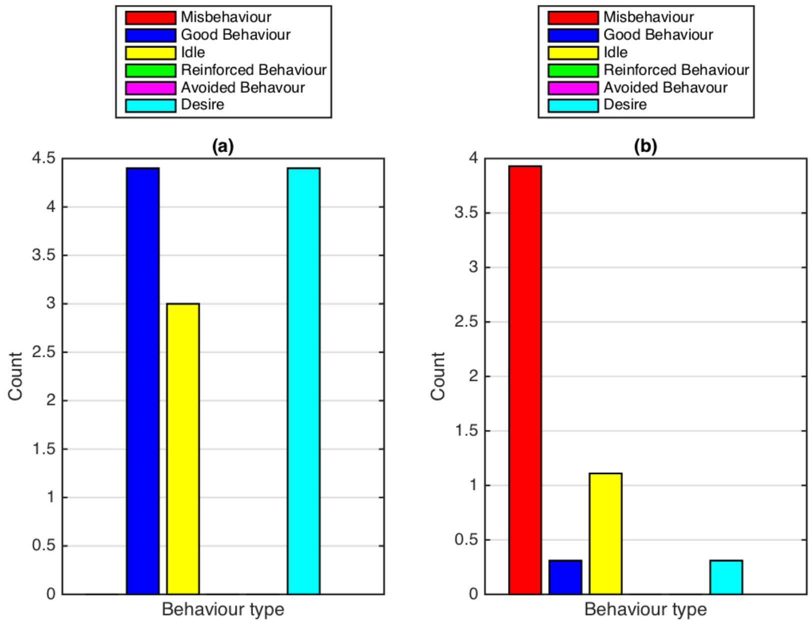

Figure 6.2: (a) Smart student behaviour histogram when social learning is disabled (b) Classroom average behaviour histogram when social learning is disabled

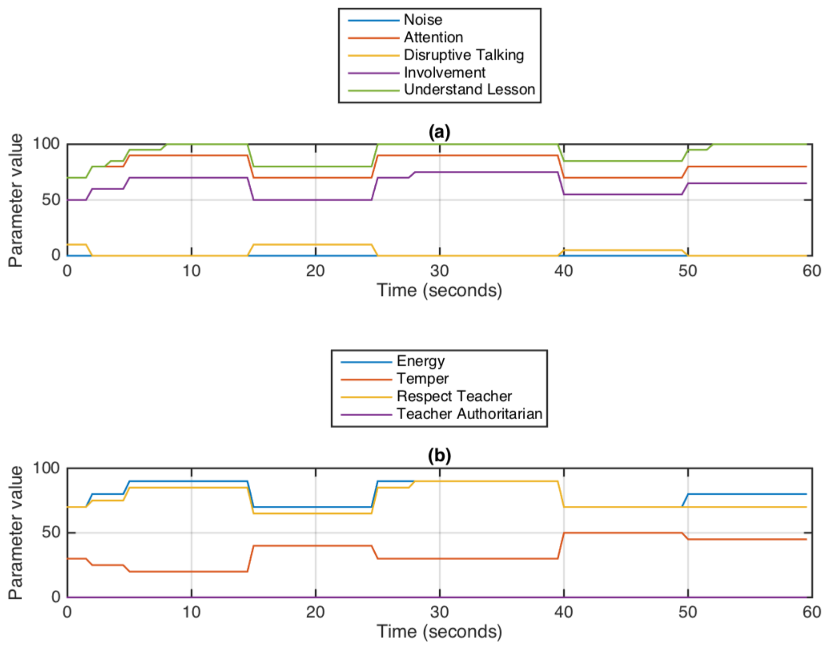

Figure 6.3: (a) Smart student academic performance parameters graph when social learning is disabled (b) Classroom average academic performance parameters graph when social learning is disabled

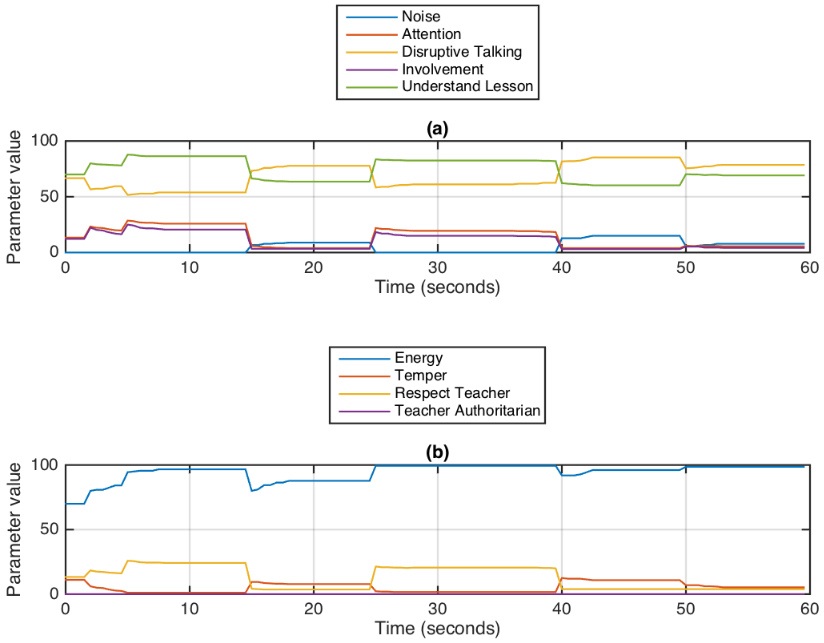

Figure 6.4: (a) Smart student human relations parameters graph when social learning is disabled (b) Classroom average human relations parameters graph when social learning is disabled

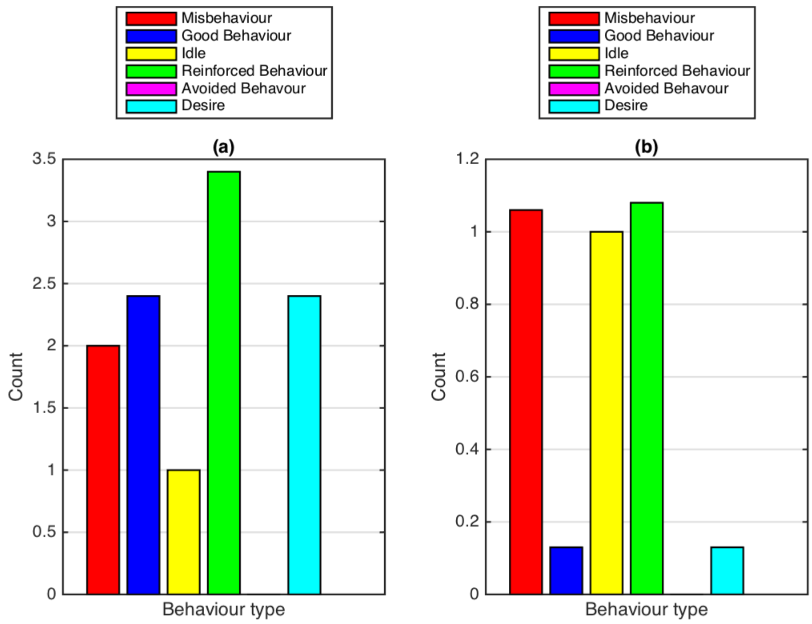

Figure 6.5: (a) Smart student behaviour histogram when social learning is enabled (b) Classroom average behaviour histogram when social learning is enabled

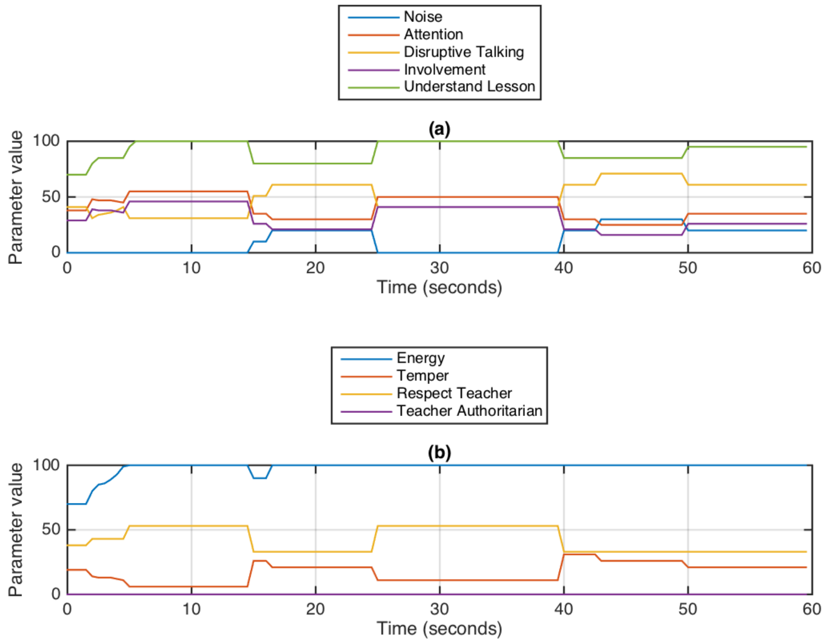

Figure 6.6: (a) Smart student academic performance parameters graph when social learning is enabled (b) Classroom average academic performance parameters graph when social learning is enabled

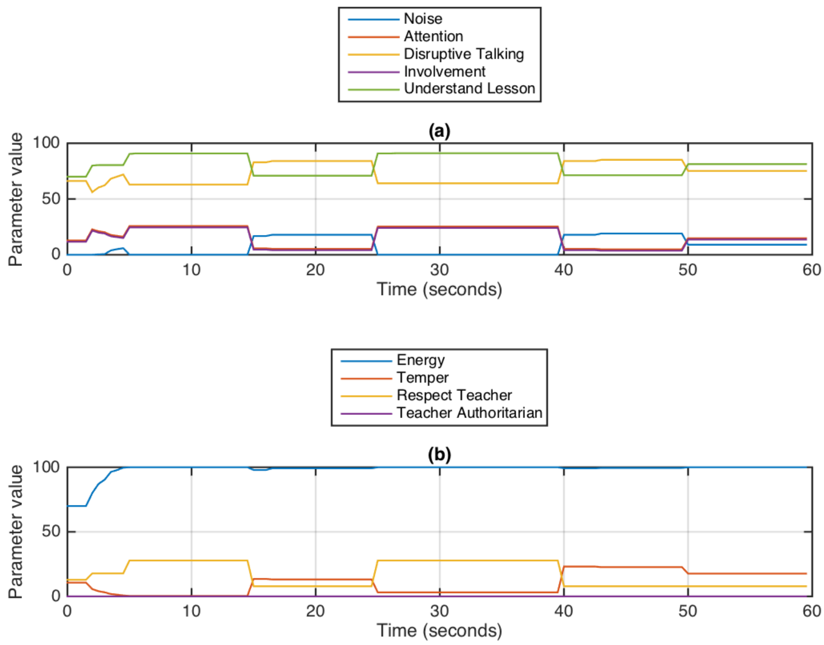

Figure 6.7: (a) Smart student human relations parameters graph when social learning is enabled (b) Classroom average human relations parameters graph when social learning is enabled

6.2.2 User Study Results

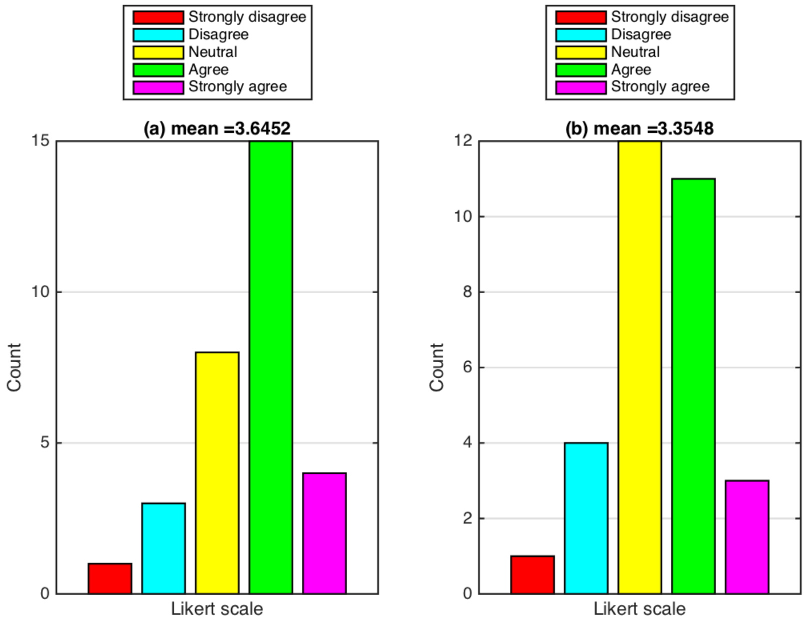

Figure 6.8: (a) Collected data on statement 6, "When a smart student is located at uninterested classroom, the smart student feels and thinks like uninterested students." in Section 5.2 (b) Collected data on statement 7, "When a smart student is located at uninterested classroom, the smart student imitates uninterested students' behaviours." in 5.2

Figure 6.8 Part (a) shows that the teachers agree with the statement which supports the idea that a smart student has similar belief to uninterested students in an uninterested classroom. The central tendency of the data is above neutral level. Agree has the highest frequency among the answers that are collected by user study.

Figure 6.8 Part (b) shows that the teachers slightly agree with the statement which supports the idea that a smart student has similar behaviours to uninterested students in an uninterested classroom. The central tendency of the data is above neutral level. Neutral has the highest frequency among the answers that are collected by user study.

The game experiment results are parallel with the user study results which means the social learning module is successfully implemented for a smart student in proposed model.

6.3 Social Learning of Uninterested Student Experiment

6.3.1 Game Results

This experiment consists of three sessions. In first session, an uninterested student is placed in a smart classroom without social learning. In second session, first session experiment is repeated with the social learning. In the last session, an uninterested student is analyzed in a normal classroom distribution.

When the social learning is disabled, the uninterested student follow its desires even if the classmates are not have same beliefs and desires (Figure 6.9, 6.10, 6.11). On the other hand, uninterested student imitates the smart student's behaviours when the social learning is enabled. Moreover, the uninterested student's belief parameter values converge to the smart belief parameter values (Figure 6.12, 6.13, 6.14). An uninterested student's behavioural and parameter analysis results are similar in a normal classroom (Figure D.3, D.4) and uninterested classroom with the social learning is disabled.

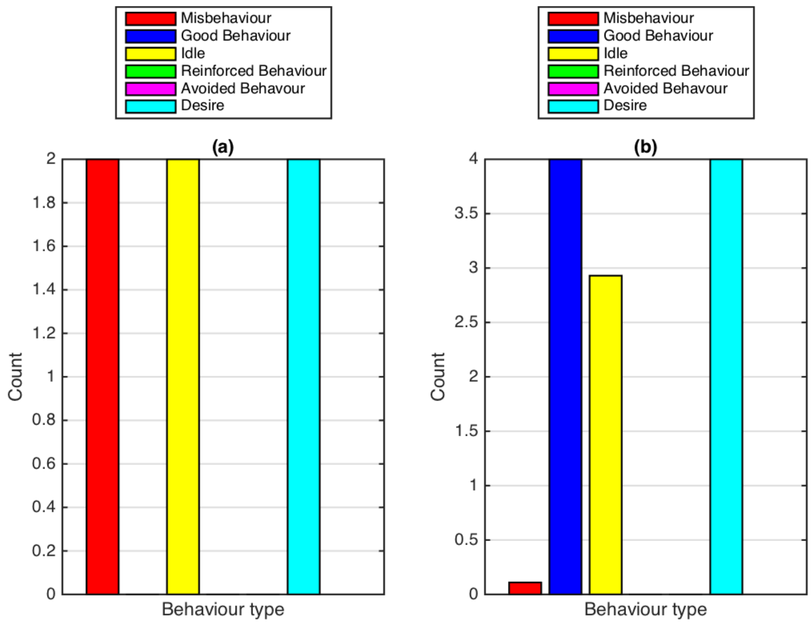

Figure 6.9: (a) Uninterested student behaviour histogram when social learning is disabled (b) Classroom average behaviour histogram when social learning is disabled

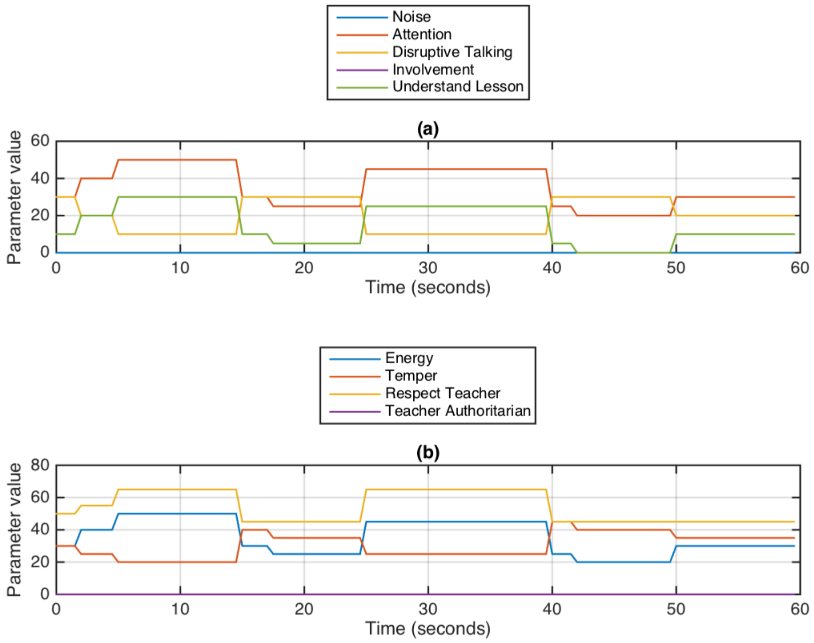

Figure 6.10: (a) Uninterested student academic performance parameters graph when social learning is disabled (b) Classroom average academic performance parameters graph when social learning is disabled

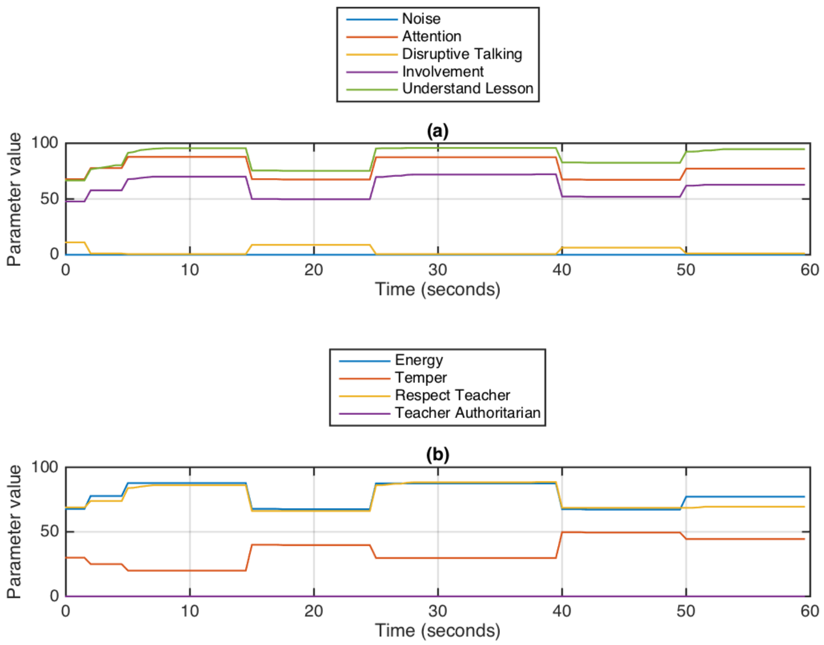

Figure 6.11: (a) Uninterested student human relations parameters graph when social learning is disabled (b) Classroom average human relations parameters graph when social learning is disabled

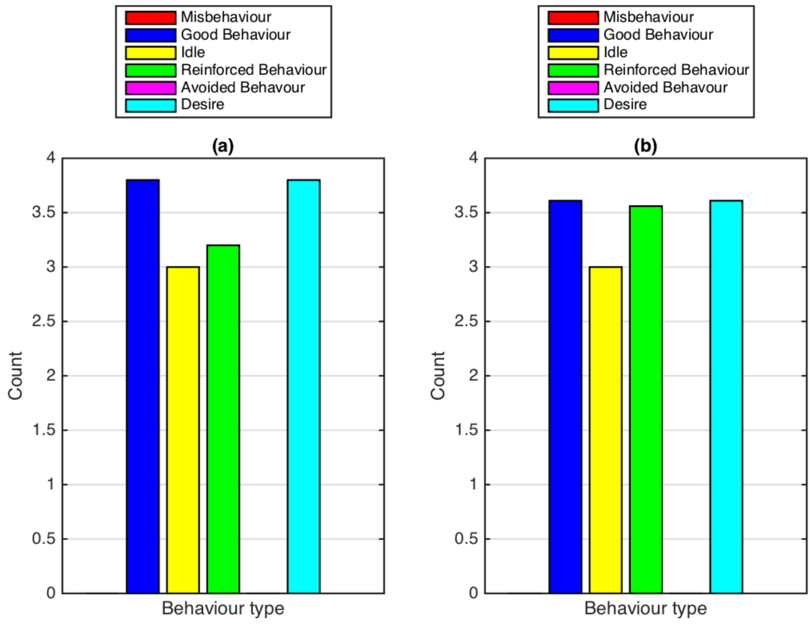

Figure 6.12: (a) Uninterested student behaviour histogram when social learning is enabled (b) Classroom average behaviour histogram when social learning is enabled

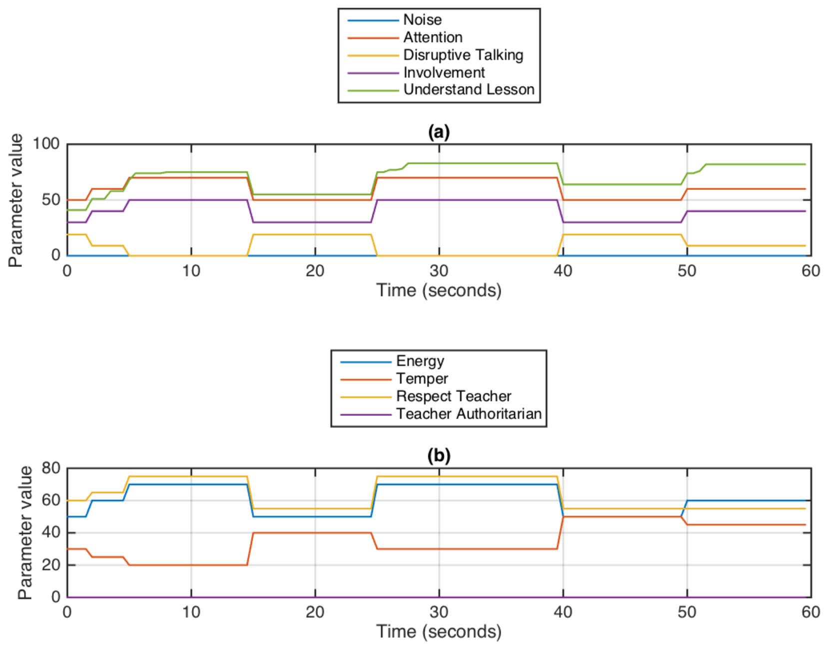

Figure 6.13: (a) Uninterested student academic performance parameters graph when social learning is enabled (b) Classroom average academic performance parameters graph when social learning is enabled

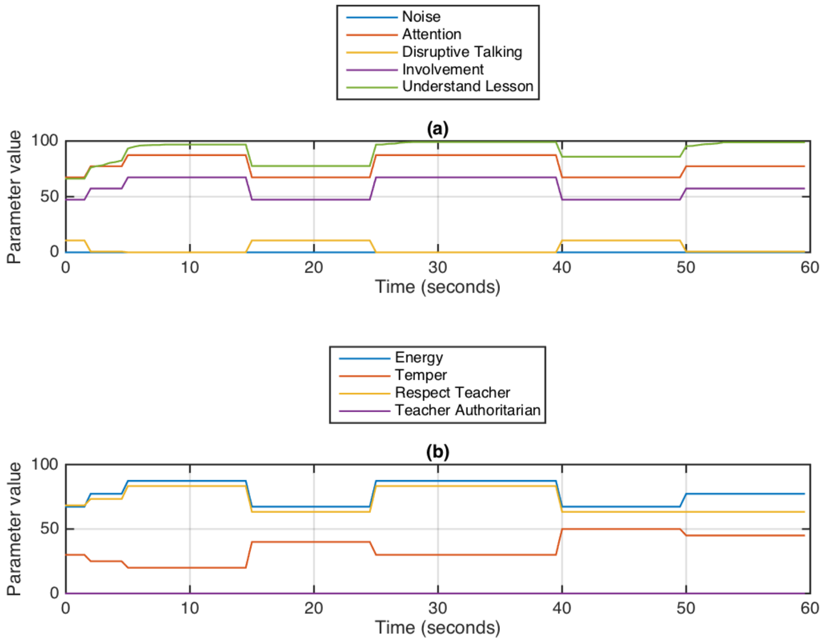

Figure 6.14: (a) Uninterested student human relations parameters graph when social learning is enabled (b) Classroom average human relations parameters graph when social learning is enabled

6.3.2 User Study Results

Figure 6.15 Part (a) shows that the teachers agree with the statement which supports the idea that an uninterested student has similar belief to smart students in a smart classroom. The central tendency of the data is above neutral level. Agree has the highest frequency among the answers that are collected by user study.

Figure 6.15 Part (b) shows that the teachers slightly agree with the statement which supports the idea that an uninterested student has similar behaviours to smart students in a smart classroom. The central tendency of the data is above neutral level. Agree has the highest frequency among the answers that are collected by user study.

The game experiment results are parallel with the user study results which means the social learning module is successfully implemented for an uninterested student in proposed model.

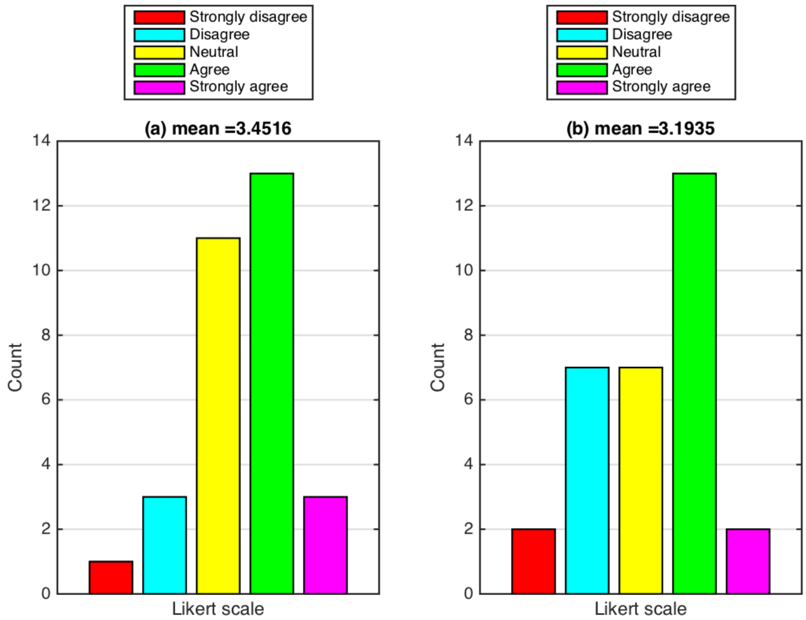

Figure 6.15: (a) Collected data on statement 10, "When an uninterested student is located at smart classroom, the uninterested student feels and thinks like smart students." in Section 5.2 (b) Collected data on statement 11, "When an uninterested student is located at smart classroom, the uninterested student imitates smart students' behaviours." in 5.2

6.4 Social Learning of Struggling Student Experiment

This experiment consists of three sessions. In first session, a struggling student is placed in a smart classroom without social learning. In second session, first session experiment is repeated with the social learning. In the last session, a struggling student is analyzed in a normal classroom distribution.

When the social learning is disabled, the struggling student follow its desires even if the classmates are not have same beliefs and desires (Figure 6.16, 6.17, 6.18). On the other hand, struggling student imitates the smart student's behaviours when the social learning is enabled. Moreover, the struggling student's belief parameter values converge to the smart belief parameter values (Figure 6.19, 6.20, 6.21). A struggling student's behavioural and parameter analysis results are similar in a normal classroom (Figure D.5, D.6) and struggling classroom with the social learning is disabled.

6.4.1 Game Results

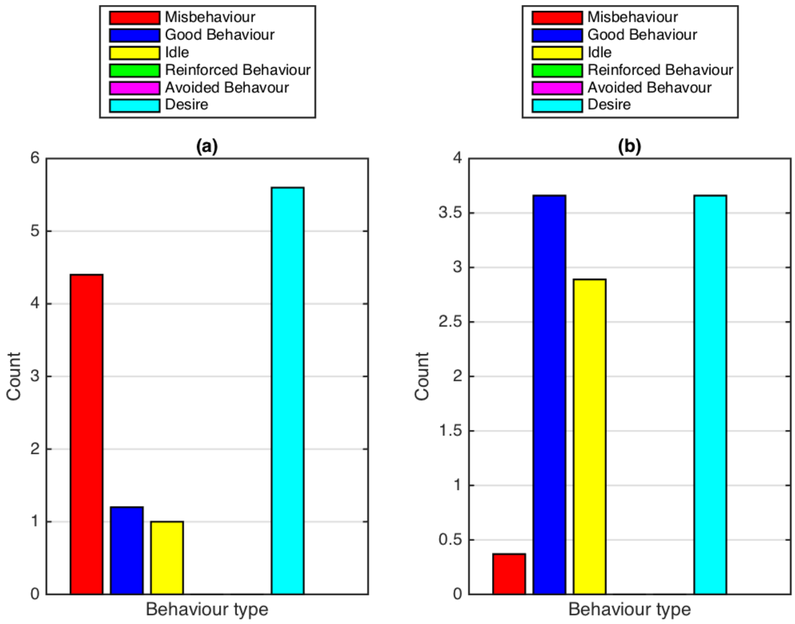

Figure 6.16: (a) Struggling student behaviour histogram when social learning is disabled (b) Classroom average behaviour histogram when social learning is disabled

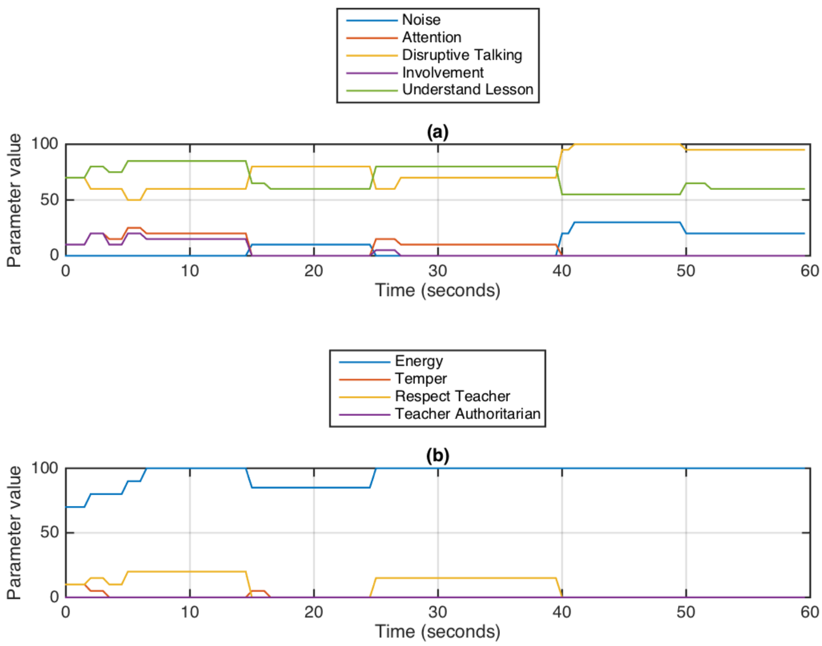

Figure 6.17: (a) Struggling student academic performance parameters graph when social learning is disabled (b) Classroom average academic performance parameters graph when social learning is disabled

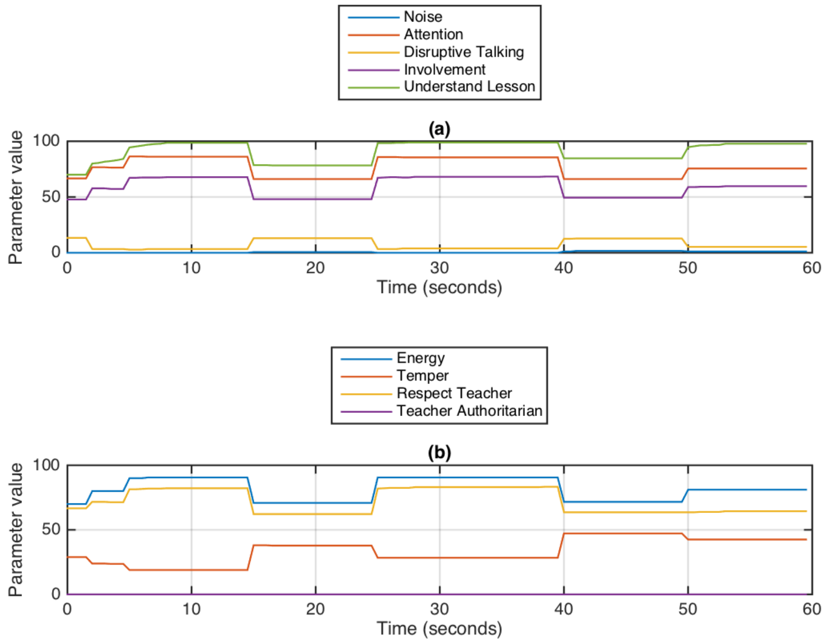

Figure 6.18: (a) Struggling student human relations parameters graph when social learning is disabled (b) Classroom average human relations parameters graph when social learning is disabled

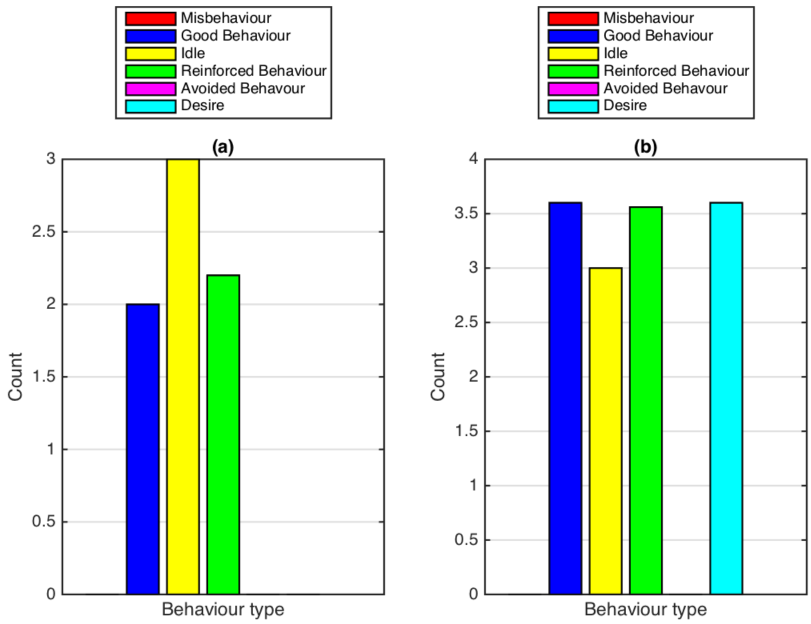

Figure 6.19: (a) Struggling student behaviour histogram when social learning is enabled (b) Classroom average behaviour histogram when social learning is enabled

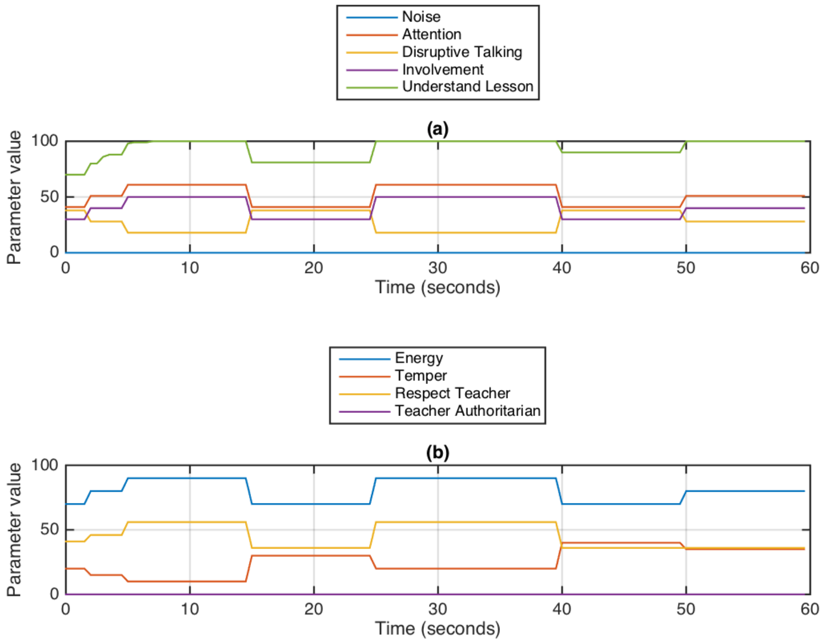

Figure 6.20: (a) Struggling student academic performance parameters graph when social learning is enabled (b) Classroom average academic performance parameters graph when social learning is enabled

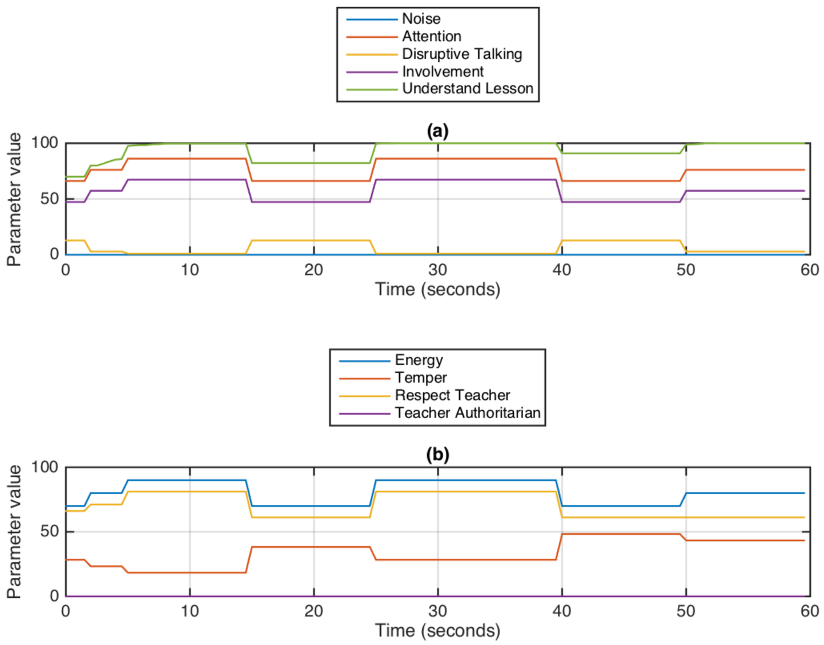

Figure 6.21: (a) Struggling student human relations parameters graph when social learning is enabled (b) Classroom average human relations parameters graph when social learning is enabled

6.4.2 User Study Results

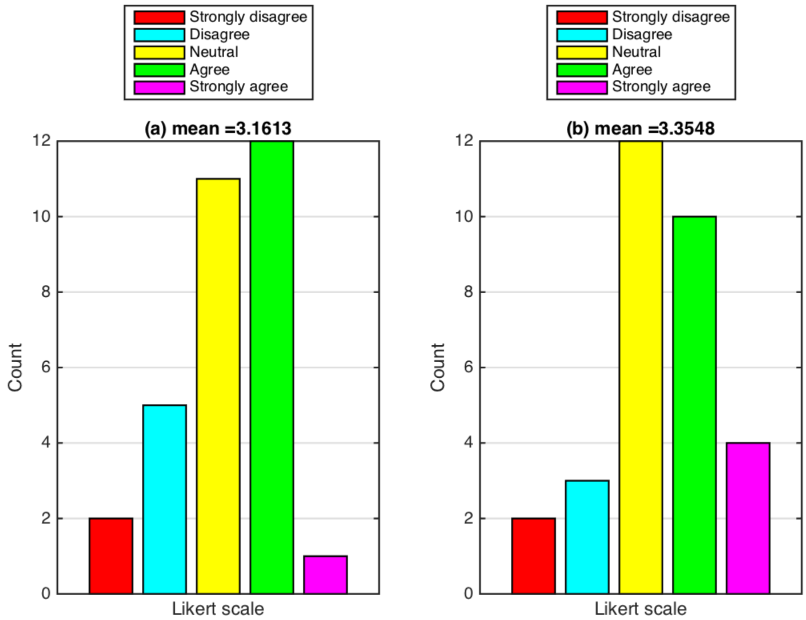

Figure 6.22: (a) Collected data on statement 8, "When a struggling student is located at smart classroom, the struggling student feels and thinks like smart students." in Section 5.2 (b) Collected data on statement 9, "When a struggling student is located at smart classroom, the struggling student imitates smart students' behaviours." in 5.2

Figure 6.22 Part (a) shows that the teachers slightly agree with the statement which supports the idea that a struggling student has similar belief to smart students in a smart classroom. The central tendency of the data is above neutral level. Agree has the highest frequency among the answers that are collected by user study.

Figure 6.22 Part (b) shows that the teachers agree with the statement which supports the idea that a struggling student has similar behaviours to smart students in a smart classroom. The central tendency of the data is above neutral level. Neutral has the highest frequency among the answers that are collected by user study.

The game experiment results are parallel with the user study results which means the social learning module is successfully implemented for a struggling student in proposed model.

6.5 Social Learning of Overestimating Student Experiment

6.5.1 Game Results

This experiment consists of three sessions. In first session, an overestimating student is placed in an underestimating classroom without social learning. In second session, first session experiment is repeated with the social learning. In the last session, an overestimating student is analyzed in a normal classroom distribution.

When the social learning is disabled, the overestimating student follows its desires where some of them are parallel with underestimating student (Figure 6.23, 6.24, 6.25). Overestimating student has not imitated the underestimating student's behaviours which requires interaction with other agents when the social learning is enabled. On the other hand, the overestimating student's belief parameter values converge to the underestimating belief parameter values (Figure 6.26, 6.27, 6.28). Overestimating student's good behaviour count is increased, because the underestimating students increases the overestimating student's understand lesson parameter. This experiment showed that underestimating students does not encourage the overestimating students to participate during lecture when social learning is on.

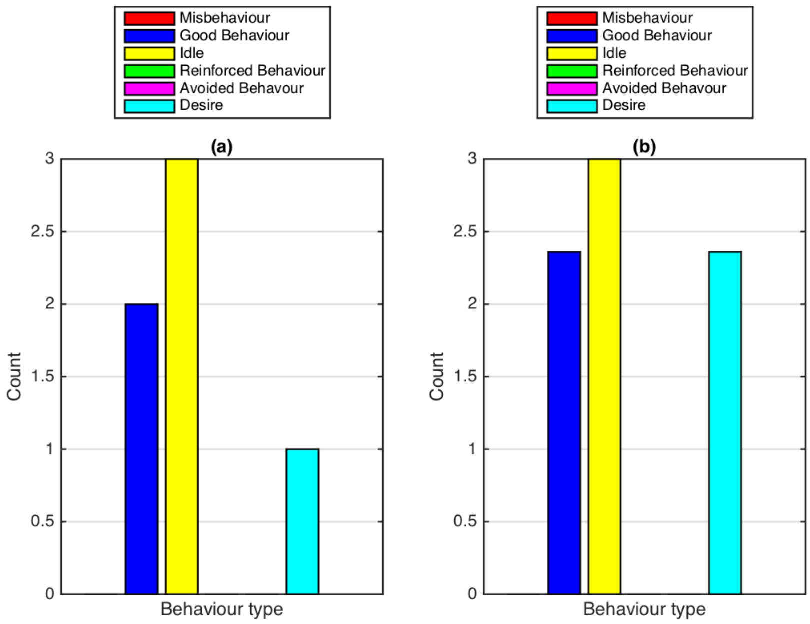

Figure 6.23: (a) Overestimating student behaviour histogram when social learning is disabled (b) Classroom average behaviour histogram when social learning is disabled

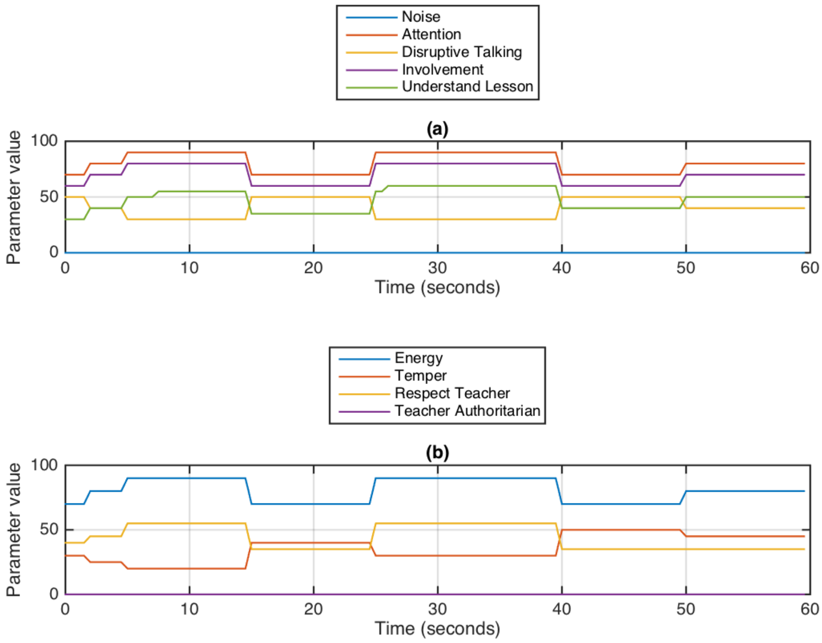

Figure 6.24: (a) Overestimating student academic performance parameters graph when social learning is disabled (b) Classroom average academic performance parameters graph when social learning is disabled

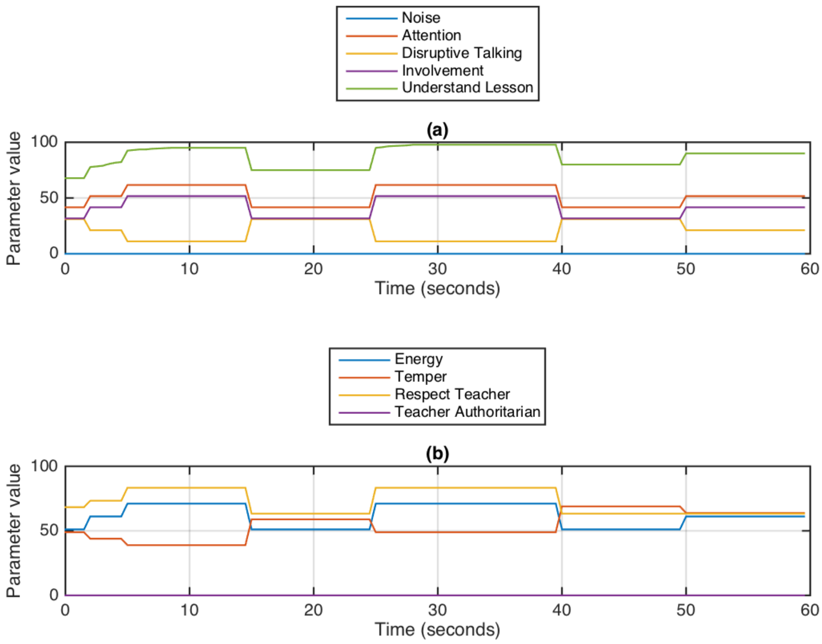

Figure 6.25: (a) Overestimating student human relations parameters graph when social learning is disabled (b) Classroom average human relations parameters graph when social learning is disabled

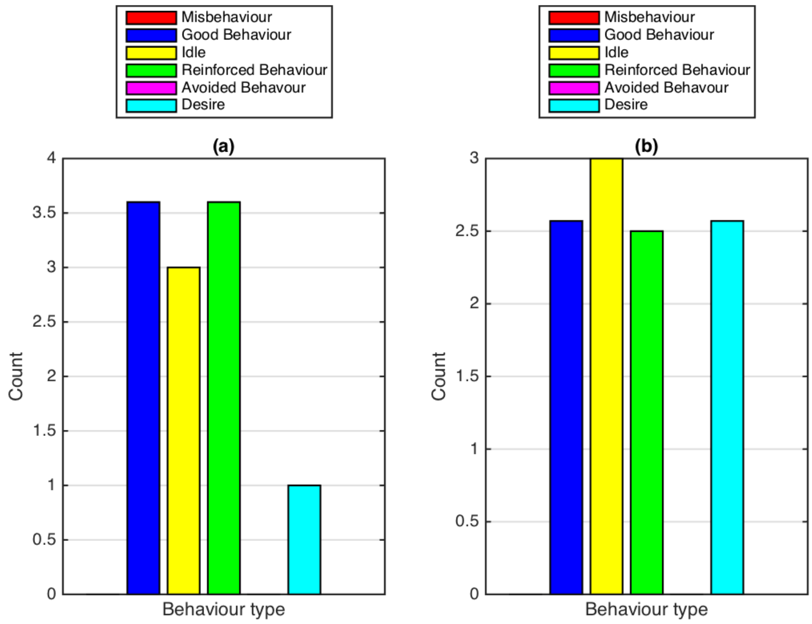

Figure 6.26: (a) Overestimating student behaviour histogram when social learning is enabled (b) Classroom average behaviour histogram when social learning is enabled

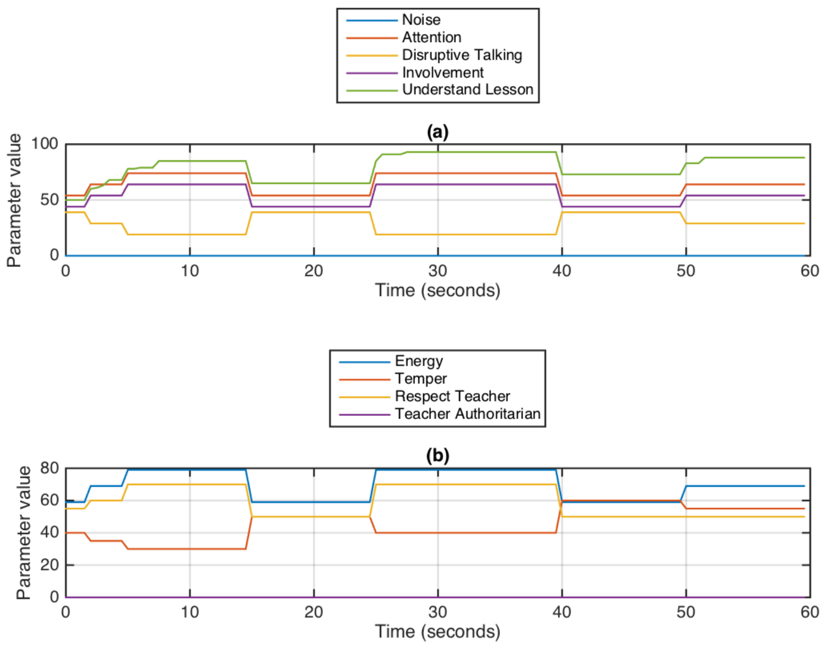

Figure 6.27: (a) Overestimating student academic performance parameters graph when social learning is enabled (b) Classroom average academic performance parameters graph when social learning is enabled

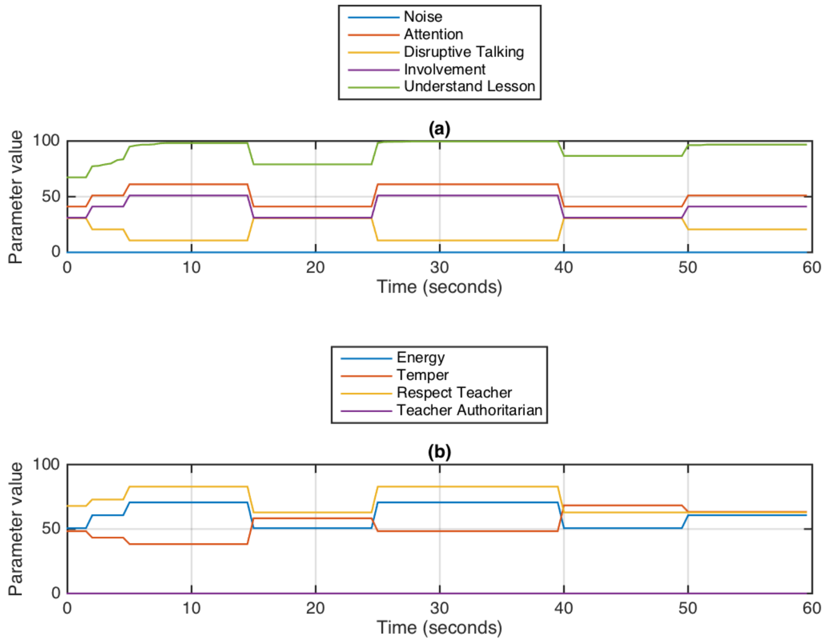

Figure 6.28: (a) Overestimating student human relations parameters graph when social learning is enabled (b) Classroom average human relations parameters graph when social learning is enabled

6.5.2 User Study Results

Figure 6.29 Part (a) shows that the teachers agree with the statement which supports the idea that an overestimating student has similar belief to underestimating students in an underestimating classroom. The central tendency of the data is above neutral level. Agree has the highest frequency among the answers that are collected by user study.

Figure 6.29 Part (b) shows that the teachers slightly agree with the statement which supports the idea that an overestimating student has similar behaviours to underestimating students in an underestimating classroom. The central tendency of the data is above neutral level. Agree has the highest frequency among the answers that are collected by user study.

The game experiment results are parallel with the user study results which means the social learning module is successfully implemented for an overestimating student in proposed model.

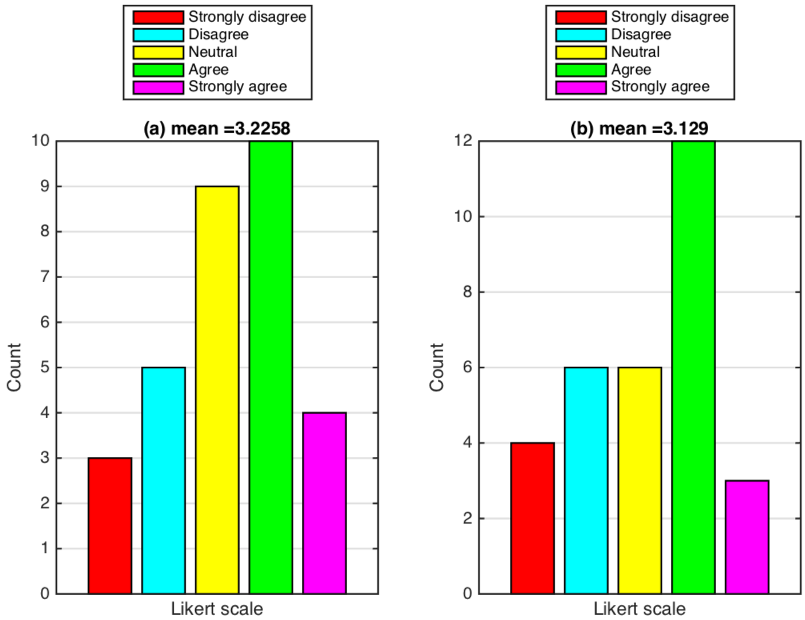

Figure 6.29: (a) Collected data on statement 12, "When an overestimating student is located at underestimating classroom, the overestimating student feels and thinks like underestimating students." in Section 5.2 (b) Collected data on statement 13, "When an overestimating student is located at underestimating classroom, the overestimating student imitates underestimating students' behaviours." in 5.2

6.6 Social Learning of Underestimating Student Experiment

6.6.1 Game Results

This experiment consists of three sessions. In first session, an underestimating student is placed in an uninterested classroom without social learning. In second session, first session experiment is repeated with the social learning. In the last session, an underestimating student is analyzed in a normal classroom distribution.

When the social learning is disabled, the underestimating student follow its desires even if the classmates are not have same beliefs and desires (Figure 6.30, 6.31, 6.32). On the other hand, underestimating student imitates the smart student's behaviours when the social learning is enabled. Moreover, the underestimating student's belief parameter values converge to the uninterested belief parameter values (Figure 6.33, 6.34, 6.35). An underestimating student's behavioural and parameter analysis results are similar in a normal classroom (Figure D.9, D.10) and underestimating classroom with the social learning is disabled.

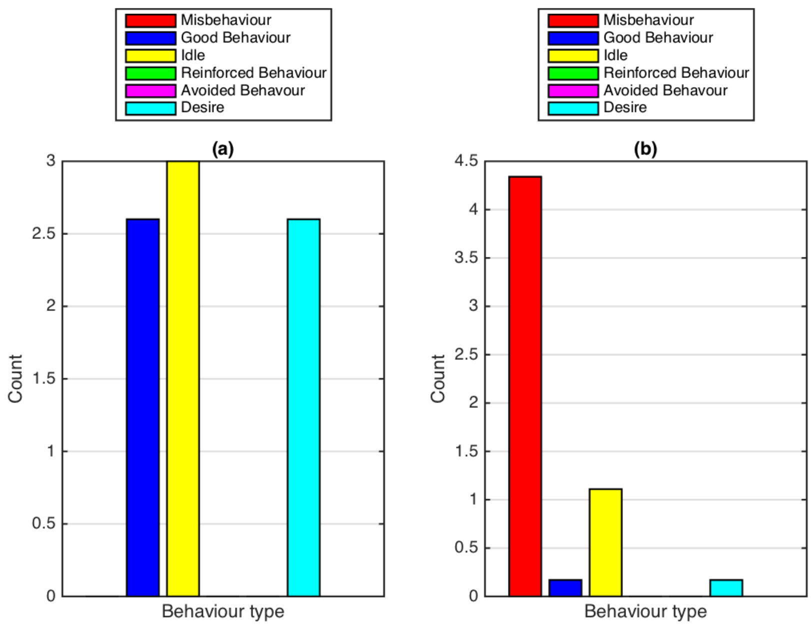

Figure 6.30: (a) Underestimating student behaviour histogram when social learning is disabled (b) Classroom average behaviour histogram when social learning is disabled

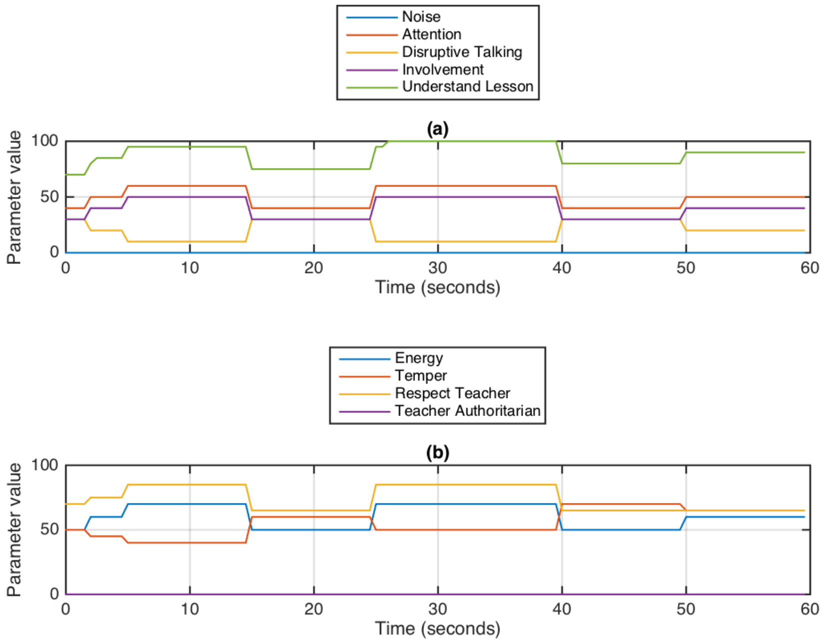

Figure 6.31: (a) Underestimating student academic performance parameters graph when social learning is disabled (b) Classroom average academic performance parameters graph when social learning is disabled

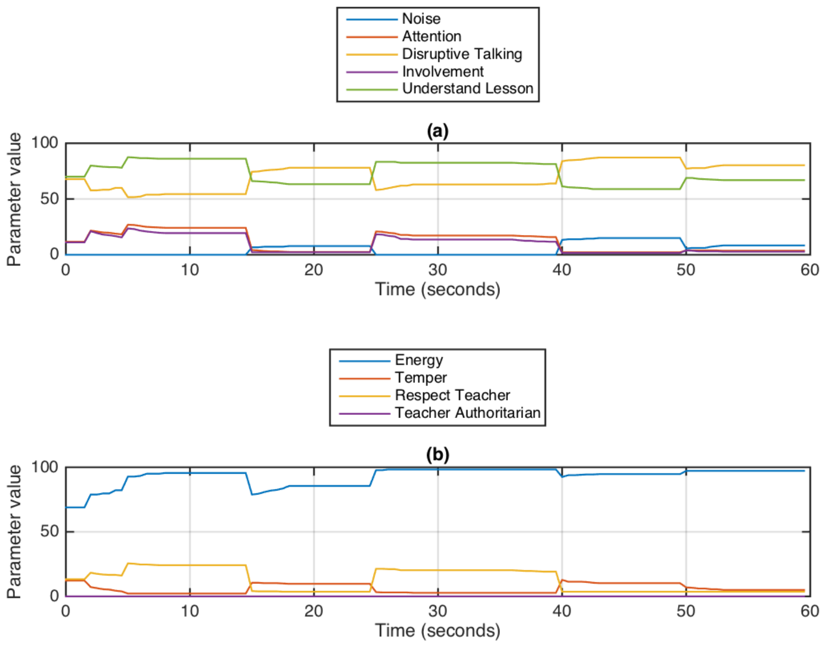

Figure 6.32: (a) Underestimating student human relations parameters graph when social learning is disabled (b) Classroom average human relations parameters graph when social learning is disabled

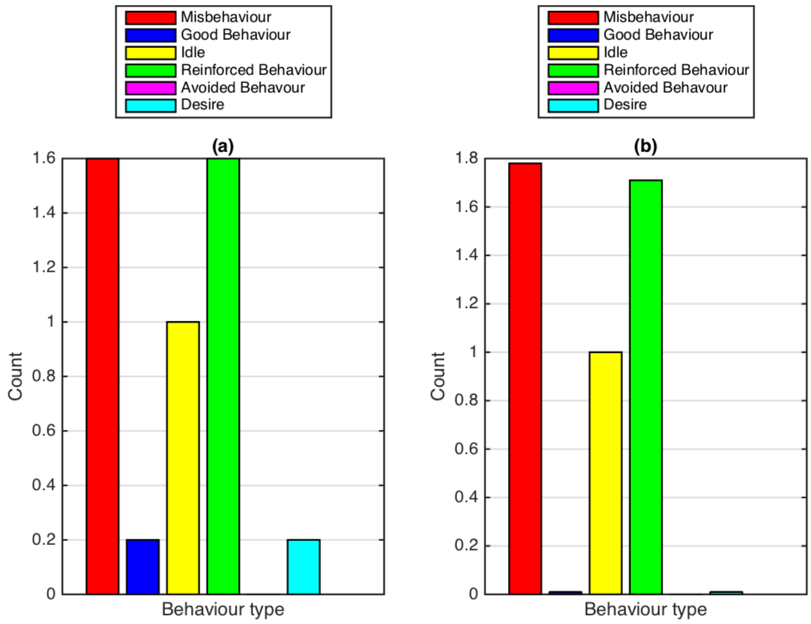

Figure 6.33: (a) Underestimating student behaviour histogram when social learning is enabled (b) Classroom average behaviour histogram when social learning is enabled

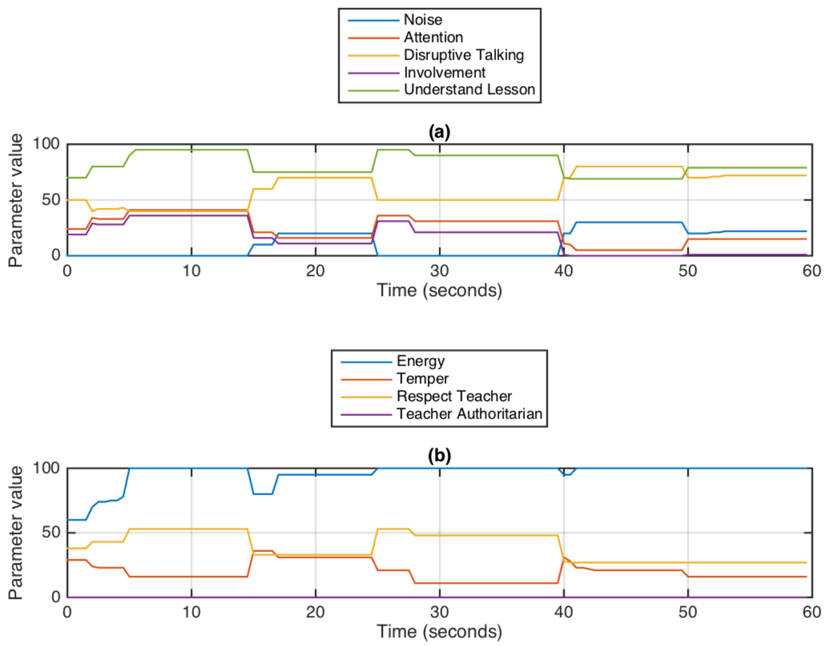

Figure 6.34: (a) Underestimating student academic performance parameters graph when social learning is enabled (b) Classroom average academic performance parameters graph when social learning is enabled

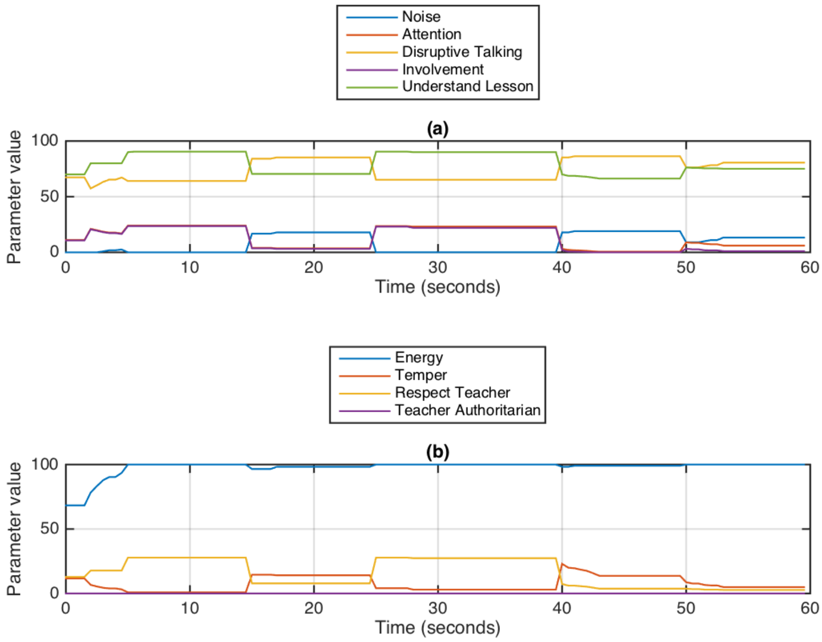

Figure 6.35: (a) Underestimating student human relations parameters graph when social learning is enabled (b) Classroom average human relations parameters graph when social learning is enabled

6.6.2 User Study Results

Figure 6.36 Part (a) shows that the teachers do not agree with the statement which supports the idea that an underestimating student has similar belief to smart students in a smart classroom. The central tendency of the data is on the neutral level. Neutral has the highest frequency among the answers that are collected by user study.

Figure 6.36 Part (b) shows that the teachers slightly agree with the statement which supports the idea that an underestimating student has similar behaviours to smart students in a smart classroom. The central tendency of the data is above neutral level. Neutral has the highest frequency among the answers that are collected by user study.

The game experiment results are not parallel with the user study results which means the social learning module implementation has some fault or detailed user study is needed to verify the game experiment for an underestimating student. The detailed user study will be shared in Future Works 7.

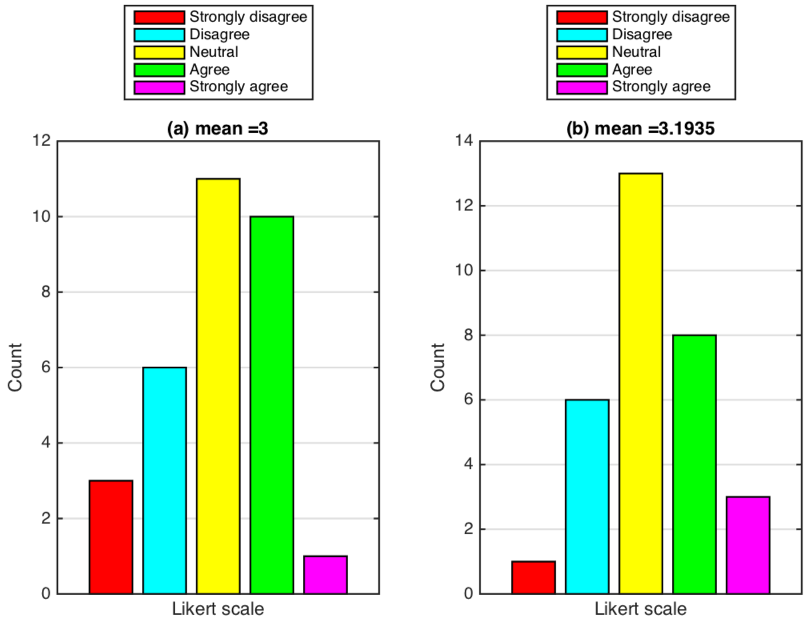

Figure 6.36: (a) Collected data on statement 14, "When an underestimating student is located at smart classroom, the underestimating student feels and thinks like smart students." in Section 5.2 (b) Collected data on statement 15, "When an underestimating student is located at uninterested classroom, the underestimating student imitates uninterested students' behaviours." in 5.2

6.7 Interaction Distance Effect on Social Learning Experiment

6.7.1 Game Results

This experiment consists of two sessions. In first session, a smart student and an uninterested student are placed side by side in an empty classroom. In second session, a smart student is placed at the left side of the classroom and an uninterested student is placed at the right side of the classroom to increase the distance between them. According to the results, the effect is stronger when the students are close to each other.

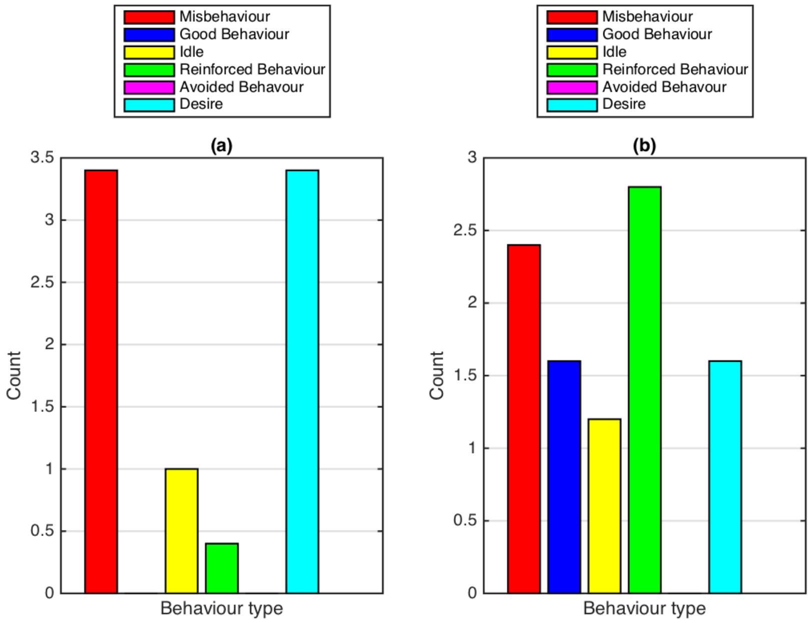

Figure 6.37: (a) Uninterested student behaviour histogram when distance between uninterested and smart student is short and social learning is enabled (b) Smart student behaviour histogram when distance between uninterested and smart student is short and social learning is enabled

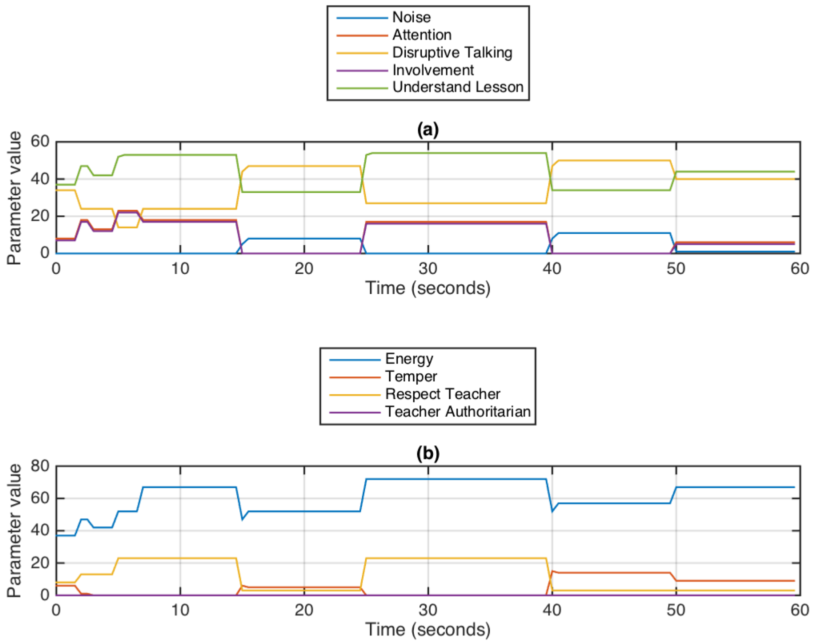

Figure 6.38: (a) Uninterested student academic performance parameters graph when distance between uninterested and smart student is short and social learning is enabled (b) Smart student academic performance parameters graph when distance between uninterested and smart student is short and social learning is enabled

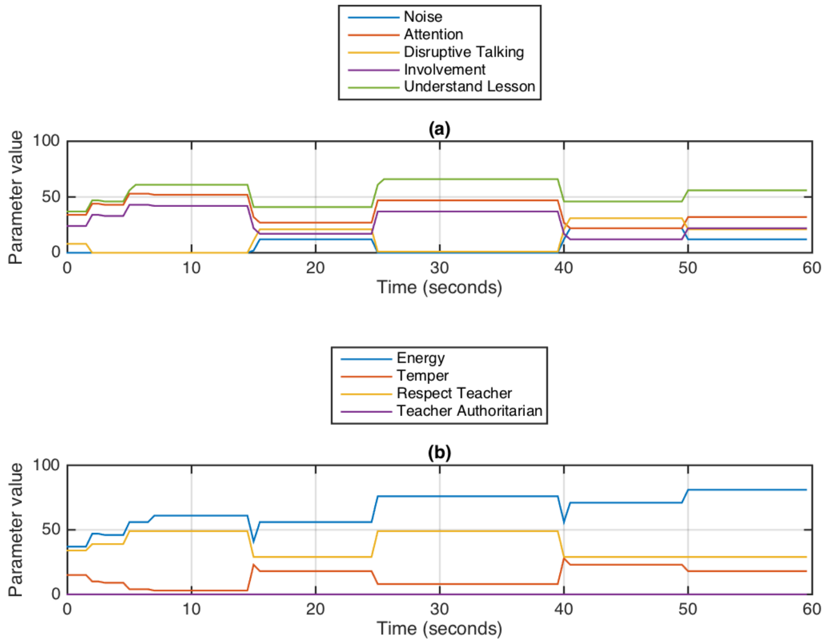

Figure 6.39: (a) Uninterested student human relations parameters graph when distance between uninterested and smart student is short and social learning is enabled (b) Smart student human relations parameters graph when distance between uninterested and smart student is short and social learning is enabled

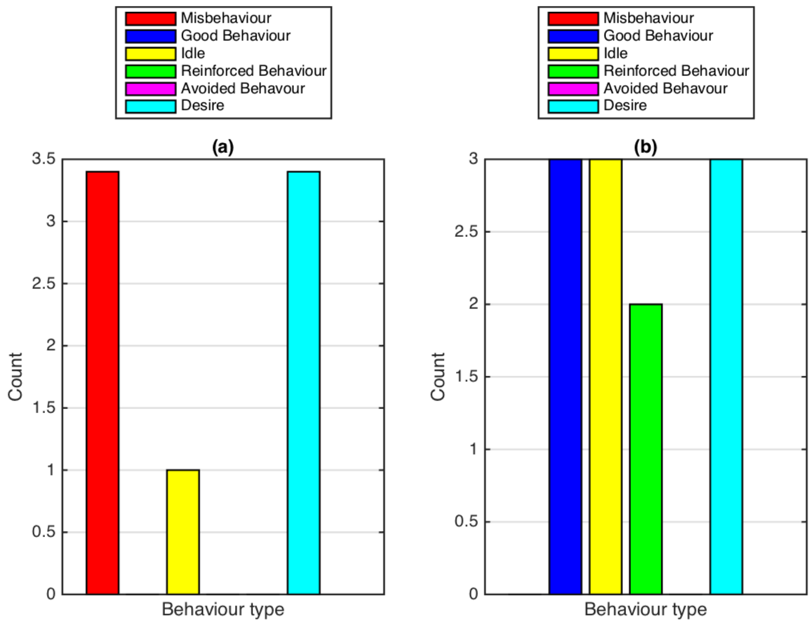

Figure 6.40: (a) Uninterested student behaviour histogram when distance between uninterested and smart student is long and social learning is enabled (b) Smart student behaviour histogram when distance between uninterested and smart student is long and social learning is enabled

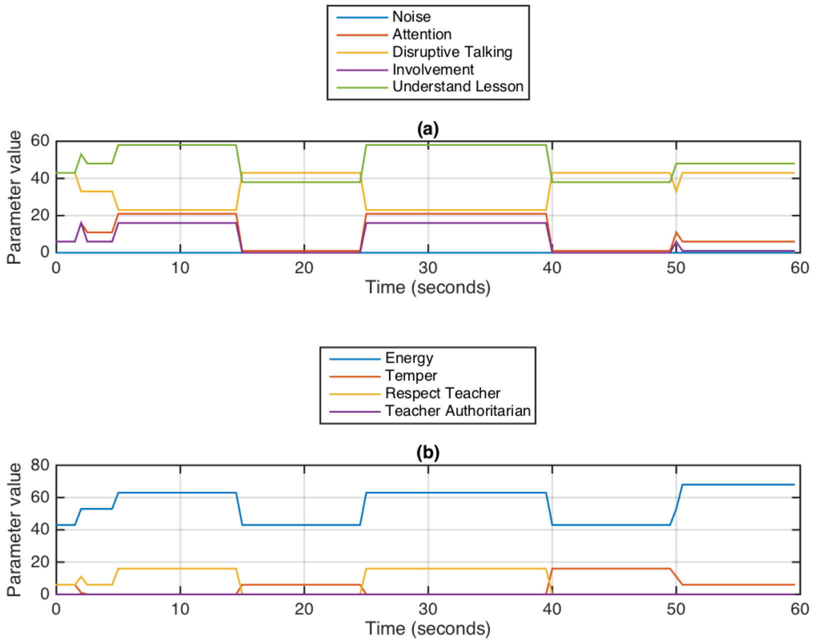

Figure 6.41: (a) Uninterested student academic performance parameters graph when distance between uninterested and smart student is long and social learning is enabled (b) Smart student academic performance parameters graph when distance between uninterested and smart student is long and social learning is enabled

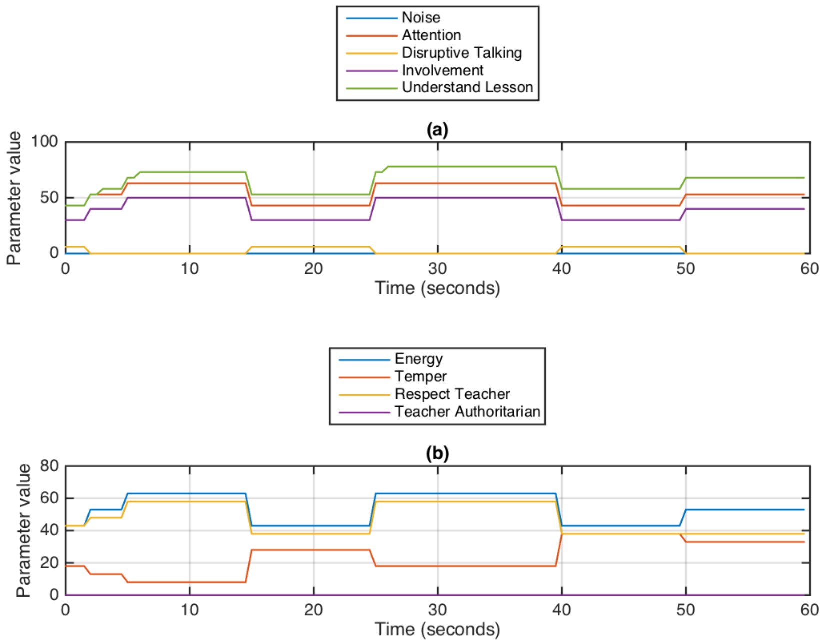

Figure 6.42: (a) Uninterested student human relations parameters graph when distance between uninterested and smart student is long and social learning is enabled (b) Smart student human relations parameters graph when distance between uninterested and smart student is long and social learning is enabled

6.7.2 User Study Results

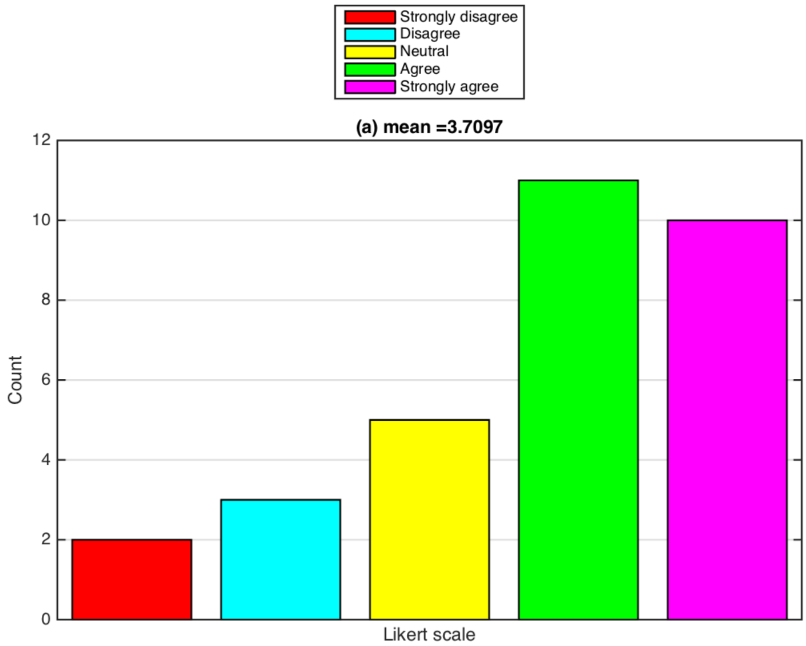

Figure 6.43: Collected data on statement 5, "A student's probability to observe and imitate the other students who is close to him/her is higher than the students who is far from him/her." in Section 5.2

The results are given in Figure 6.43 which verifies the construal level theory. The central tendency of the data is larger than neutral and agree answer has the highest frequency among the responds that are collected by user study.

The game experiment results are parallel with the user study results which means construal level theory is successfully implemented in proposed model.

6.8 Authoritarian Approach Effect on Social Learning Experiment

6.8.1 Game Results

This experiment is completed with a single session. Punishment on misbehaviour is resulted in the avoidance on punished behaviour. Approving the good behaviour has slightly encouraged students to repeat it. On the other hand, authoritarian approach has increased the temper and teacher authoritarian parameters of the students, which leads misbehaving students to stay idle rather than encouraging them to perform good behaviour.

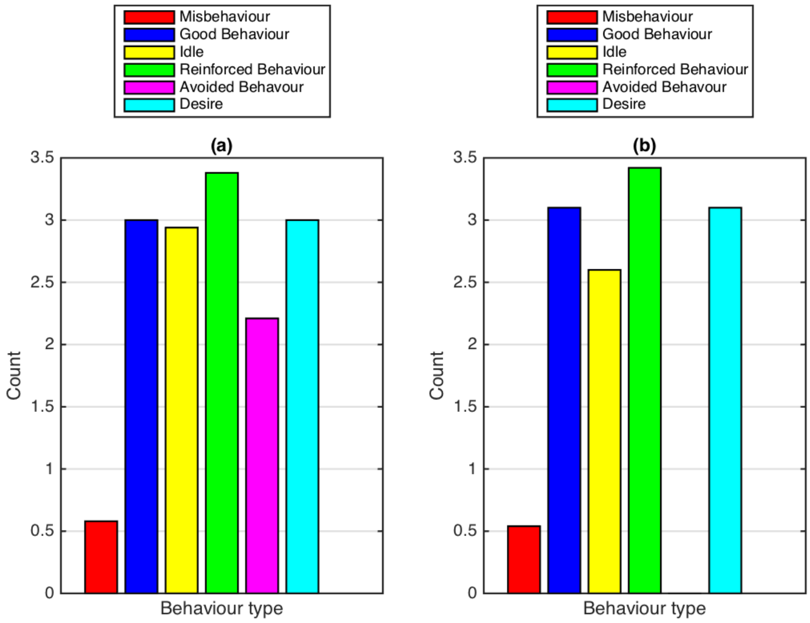

Figure 6.44: Classroom average behaviour histogram when authoritarian management is selected and social learning is enabled

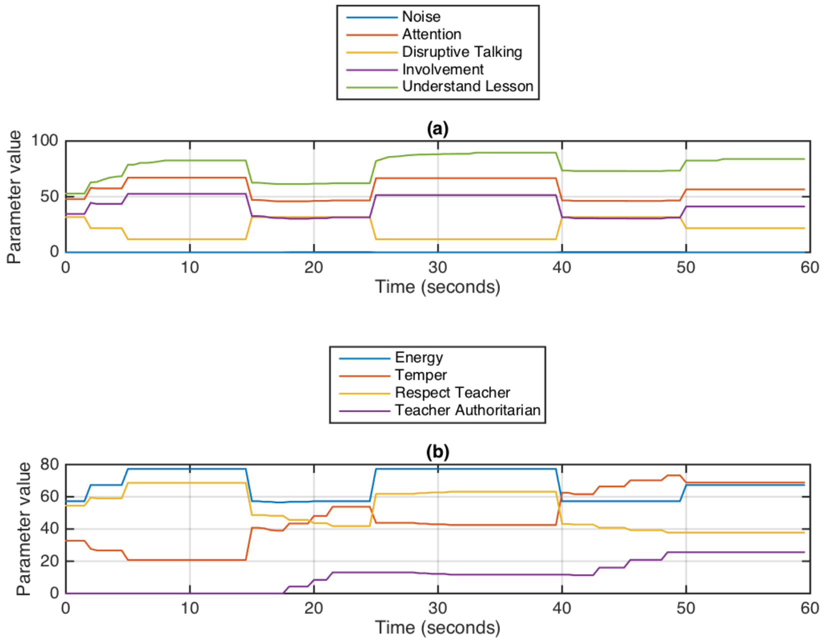

Figure 6.45: (a) Classroom average academic performance parameters graph when authoritarian management is selected and social learning is enabled (b) Classroom average human relations parameters graph when authoritarian management is selected and social learning is enabled

6.9 Authoritative Approach Effect on Social Learning Experiment

6.9.1 Game Results

This experiment is completed with a single session. Disapproving the misbehaviour and explaining the reason is resulted in the avoidance on disapproved behaviour. Rewarding the good behaviour has encouraged students to repeat it. This approach has not increased the student's temper and teacher authoritarian parameter levels while increasing the respect teacher parameter, which motivates misbehaving students to perform good behaviours.

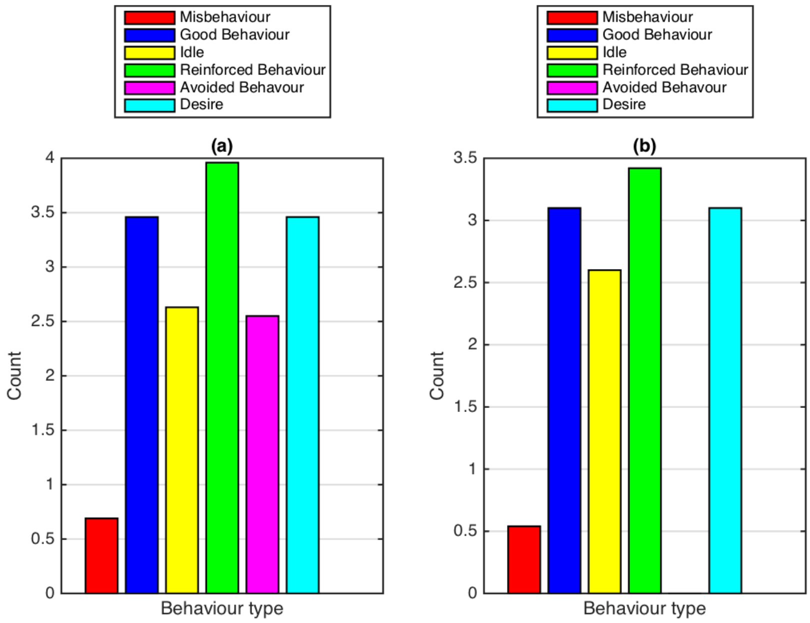

Figure 6.46: Classroom average behaviour histogram when authoritative management is selected and social learning is enabled

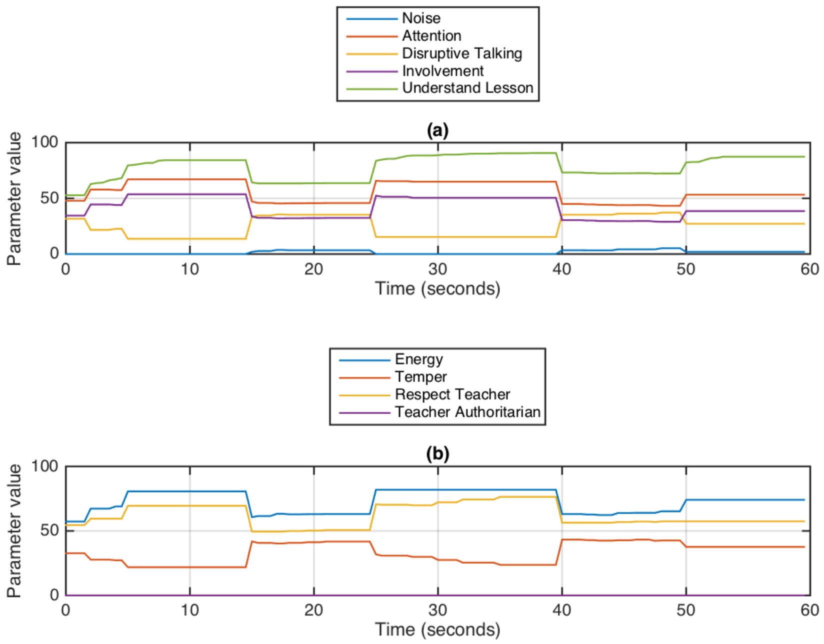

Figure 6.47: (a) Classroom average academic performance parameters graph when authoritative management is selected and social learning is enabled (b) Classroom average human relations parameters graph when authoritative management is selected and social learning is enabled

6.10 False Classroom Management Effect on Social Learning Experiment

6.10.1 Game Results

This experiment is completed with a single session. Approving/tolerating the misbehaviour has encouraged students to repeat approved behaviour. Ignoring the good behaviour has decreased the students respect to their teacher. This situation leads students to prefer misbehaviours rather than good behaviours.

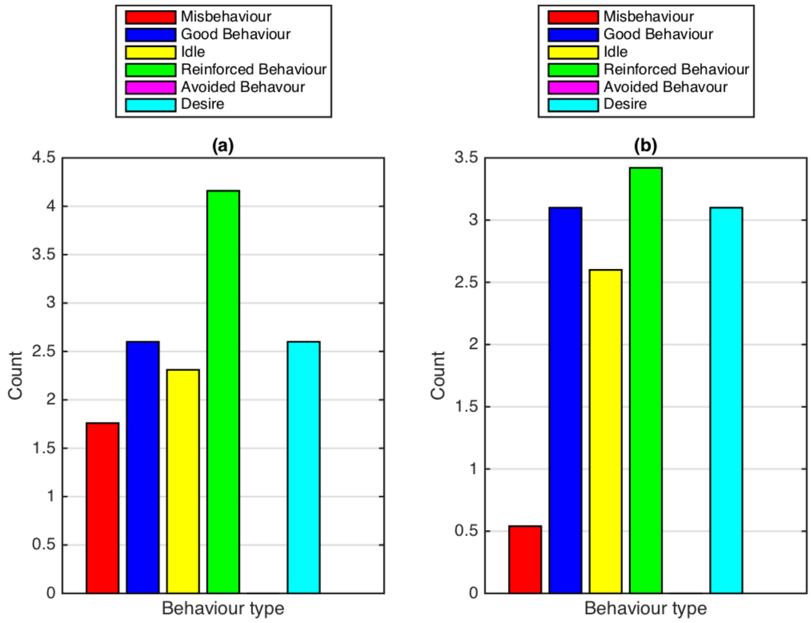

Figure 6.48: Classroom average behaviour histogram when false management is selected and social learning is enabled

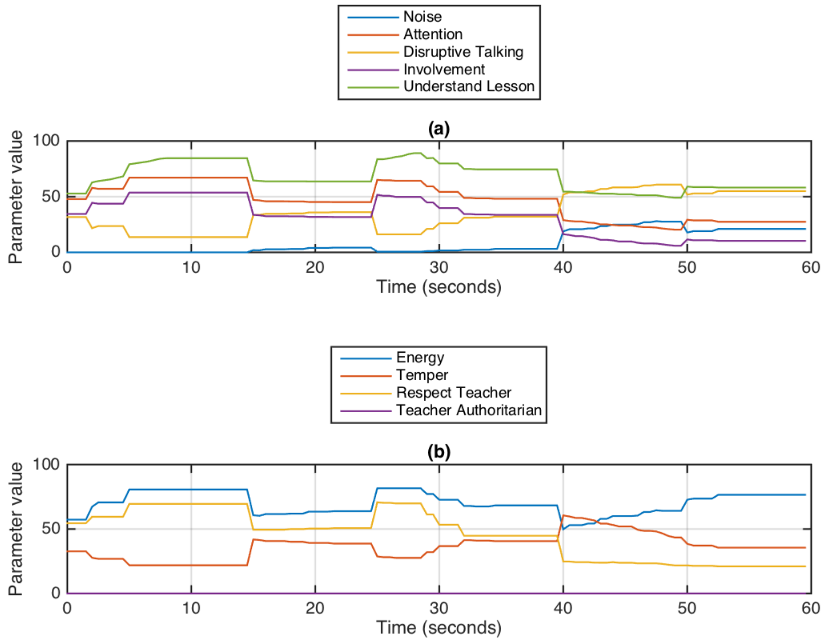

Figure 6.49: (a) Classroom average academic performance parameters graph when false management is selected and social learning is enabled (b) Classroom average human relations parameters graph when false management is selected and social learning is enabled

6.10.2 Teacher Classroom Management User Study Results

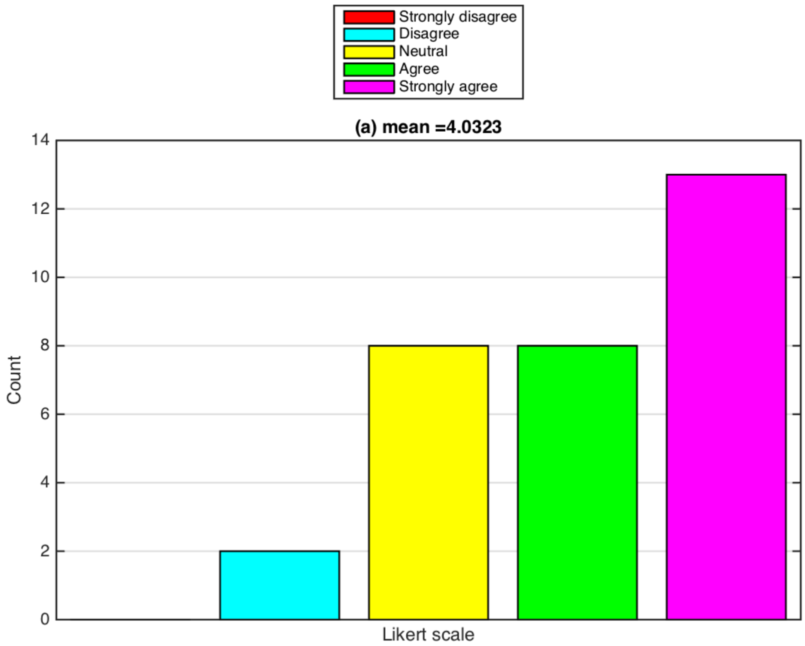

Figure 6.50: Collected data on statement 16, "If a teacher rewards or approves the students' desired behaviours, the students' possibility to perform same action increases." in Section 5.2

The results are given in Figure 6.50 shows that the teachers agree with the statement which supports the idea that rewarding or approving a good behaviour motivates students to repeat the same behaviour. The central tendency of the data is larger than agree, and strongly agree answer has the highest frequency among the responds that are collected by user study. The game experiment results are parallel with the user study results which means the rewarding mechanism of operant conditioning is successfully implemented in proposed model.

The results are given in Figure 6.51 shows that the teachers agree with the statement which supports the idea that punishing or disapproving a misbehaviour leads students to avoid misbehaving. The central tendency of the data is larger than neutral, and agree answer has the highest frequency among the responds that are collected by user study. The game experiment results are parallel with the user study results which means the punishing mechanism of operant conditioning is successfully implemented in proposed model.

The results are given in Figure 6.52 shows that the teachers agree with the statement which supports the idea that false management leads students to misbehave. The central tendency of the data is larger than agree, and strongly agree answer has the highest frequency among the responds that are collected by user study. The game experiment results are parallel with the user study results which means Operant Conditioning is successfully implemented in proposed model.

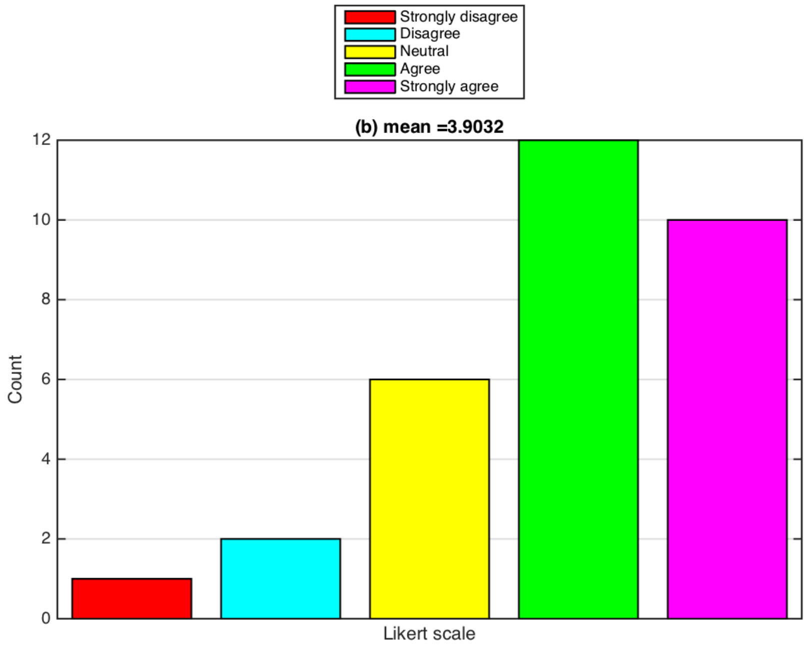

Figure 6.51: Collected data on statement 17, "If a teacher punishes or disapproves the students' misbehaviours, the students' possibility to perform same action decreases." in Section 5.2

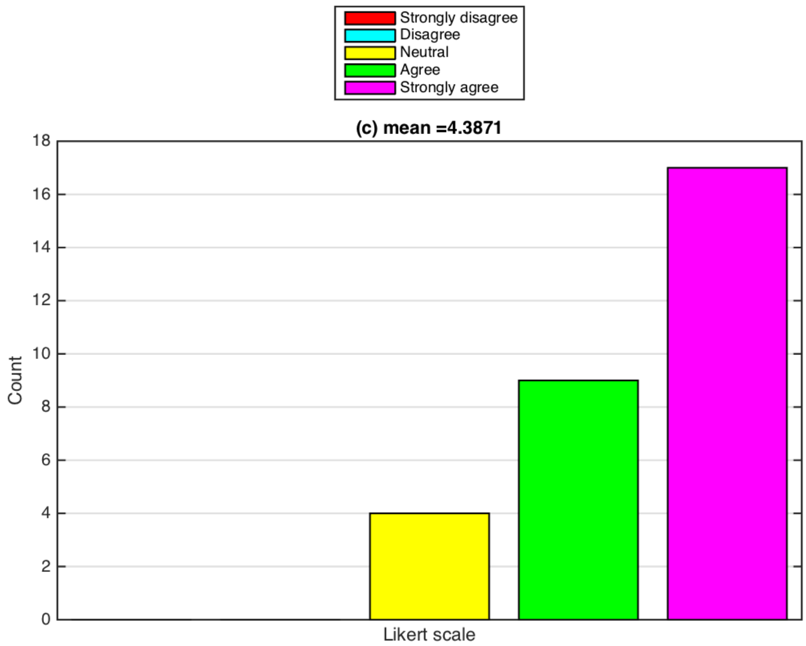

Figure 6.52: Collected data on statement 18, "If a teacher ignores students' desired behaviours and tolerates their misbehaviours, the students' possibility to misbehave increases." in Section 5.2

CHAPTER 7

CONCLUSION AND FUTURE WORK

This thesis has aimed to model student agents which are capable of social learning. The proposed model is simple yet sufficient to represent the social learning among students. The mental representation of student is successfully implemented with belief-desire-intention model. The different personalities behave according to their beliefs and desires, which are given in normal classroom experiment results in Appendix D. Moreover, external and internal features of student agents were affected by each other. In the experiments, an agent has changed its beliefs and behaviours according to its environment. Hence, it could be said that our five steps to model a social learning student agent is valid in Section 3.2.3.2.

The internal and external effects of the agent interaction only change with the spatial distance. It is given in Section 2.6.2 that there are three other psychological distances; which are temporal distance, social distance and hypothetical distance. They are not modelled in this thesis, because the designed game's simulation time is about 3 minutes. The simulation time should be long enough to observe the effects of these psychological distances.

The first future work is assigned because of the following reasons. Although the majority of teachers agree that social learning is an important element in a classroom via statement 4, "The students observe and imitate each other in classroom." in Section 5.2, neutral answer of Likert scale has the highest frequency for statement 7, 9, 14 and 15 in Section 5.2. There are two possible reason for these results. First, the social learning might be different for different student personality types which means that our model should be revised. Second, the authority or the respectfulness of the teacher who have participated to the user study might be high. This situation can be identified with an additional user study. The teacher's students should be the subjects of new user study that rank their teacher's authoritarian and respectfulness level. If the teachers who disagree with statement 7, 9, 14 and 14 in Section 5.2 are authoritarian or authoritative, the results will strengthen our model's accuracy. In our model, it is stated that social learning between students is blocked, the students have high respect teacher or teacher authoritarian parameter values. This user study could not be completed because of the schedule, and it is recorded as future work.

The effect mechanism of the actions in game world can be improved. The actions have constant effects on game world in our model. It could have been more realistic, if their effect changes according to the previous events. Moreover, the actions have constant effects on different personalities. It can be upgraded by extending the rewarding system that provides unique action effect values for each personality. The explained improvements on action working mechanism are not focus of this thesis; and simple yet sufficient rewarding system is modeled because of busy schedule.

Incorporation of theory of planned behaviour into the current proposed model is another future work. Social learning is triggered with the stimuli from actors in proposed model. The subjective norms may be constructed by learning in time which affect a persons decision in social environments. For example, the smart student imitates the uninterested student's behaviours when an uninterested student is in the classroom. In real world, a norm can be constructed by learning, which motivates the students to misbehave without active stimuli. A smart student may misbehave because of the norm without the uninterested student [5].

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APPENDIX A

SOFTWARE ARCHITECTURE

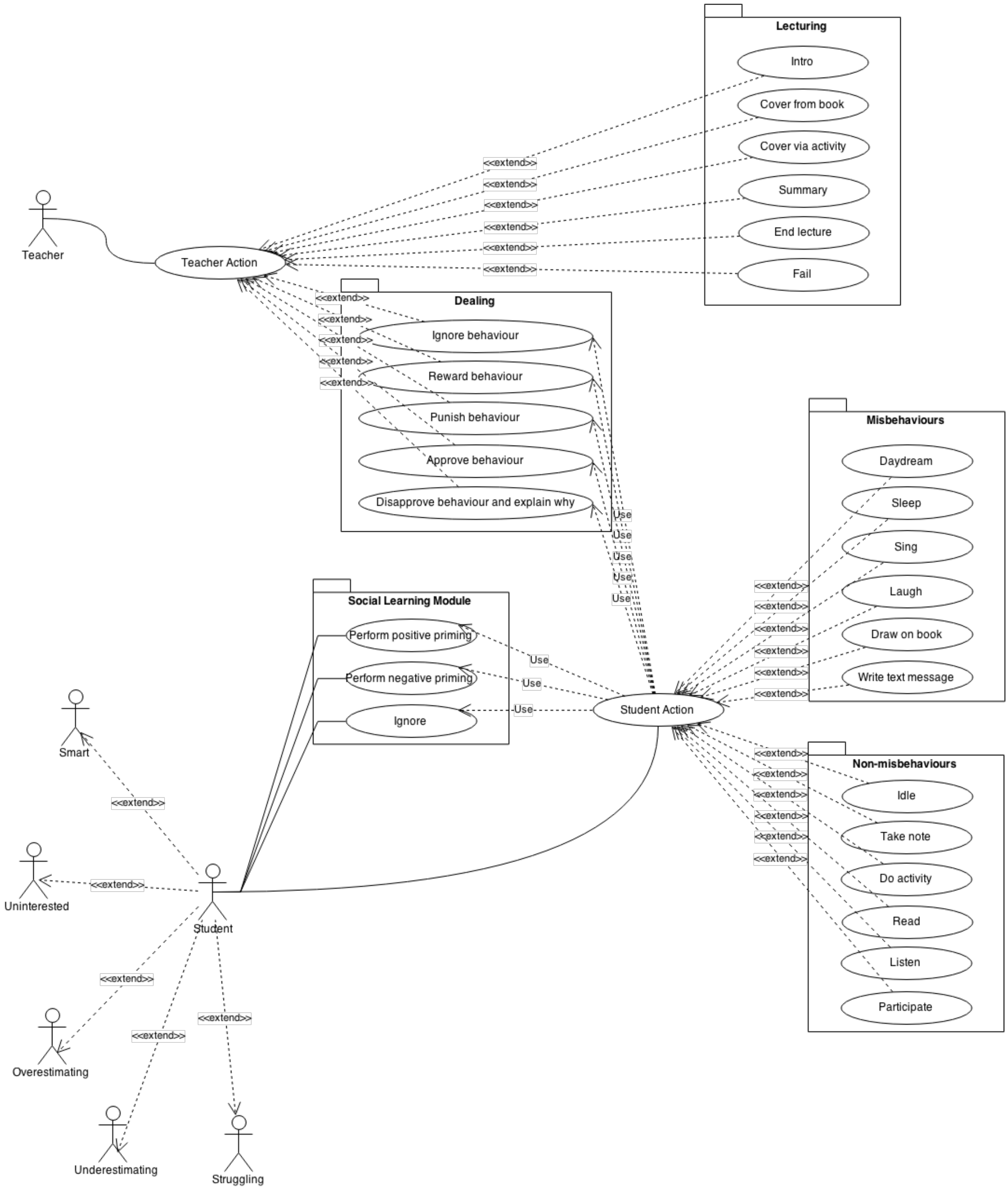


Figure A.1: Use case diagram

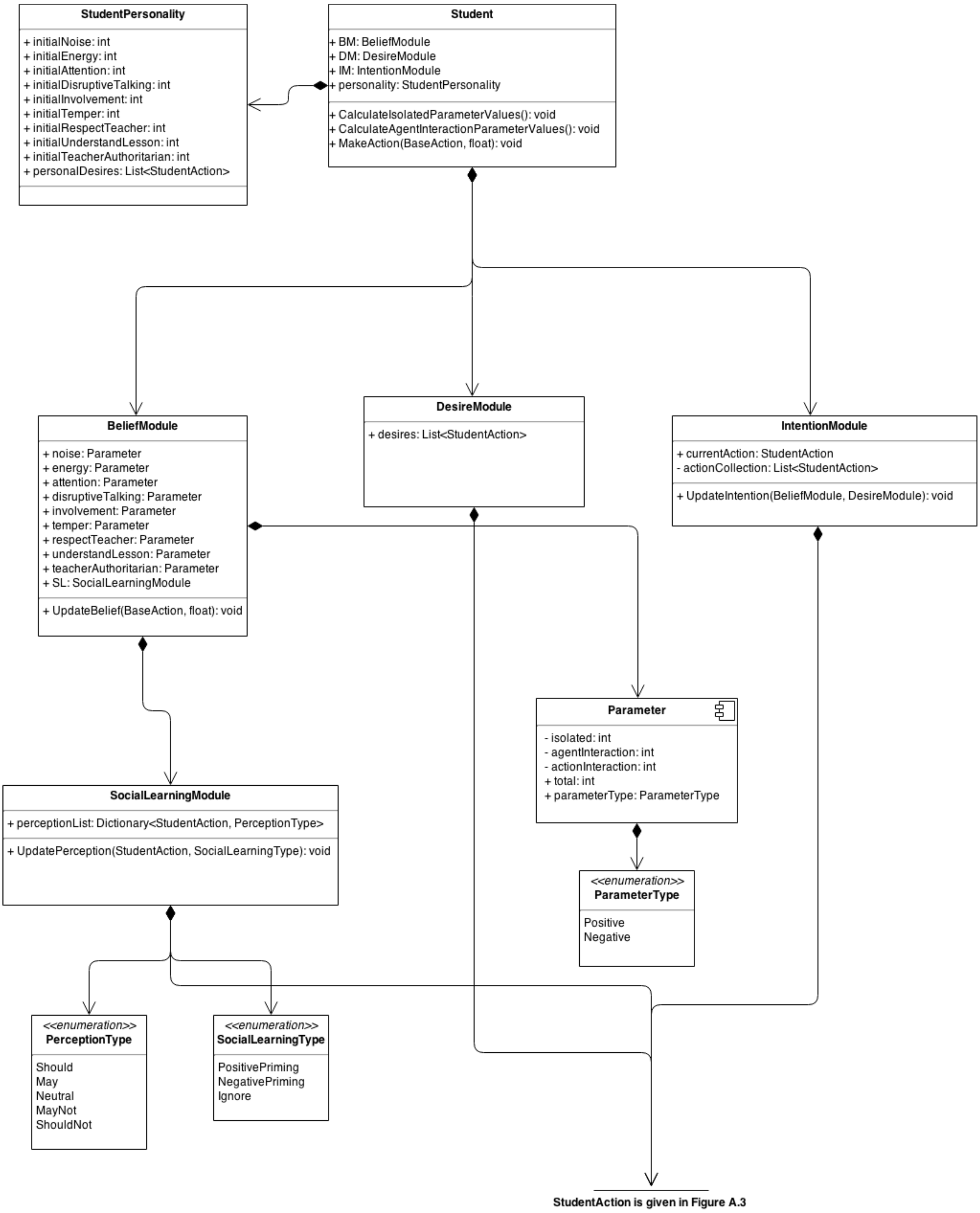


Figure A.2: Class diagram of student

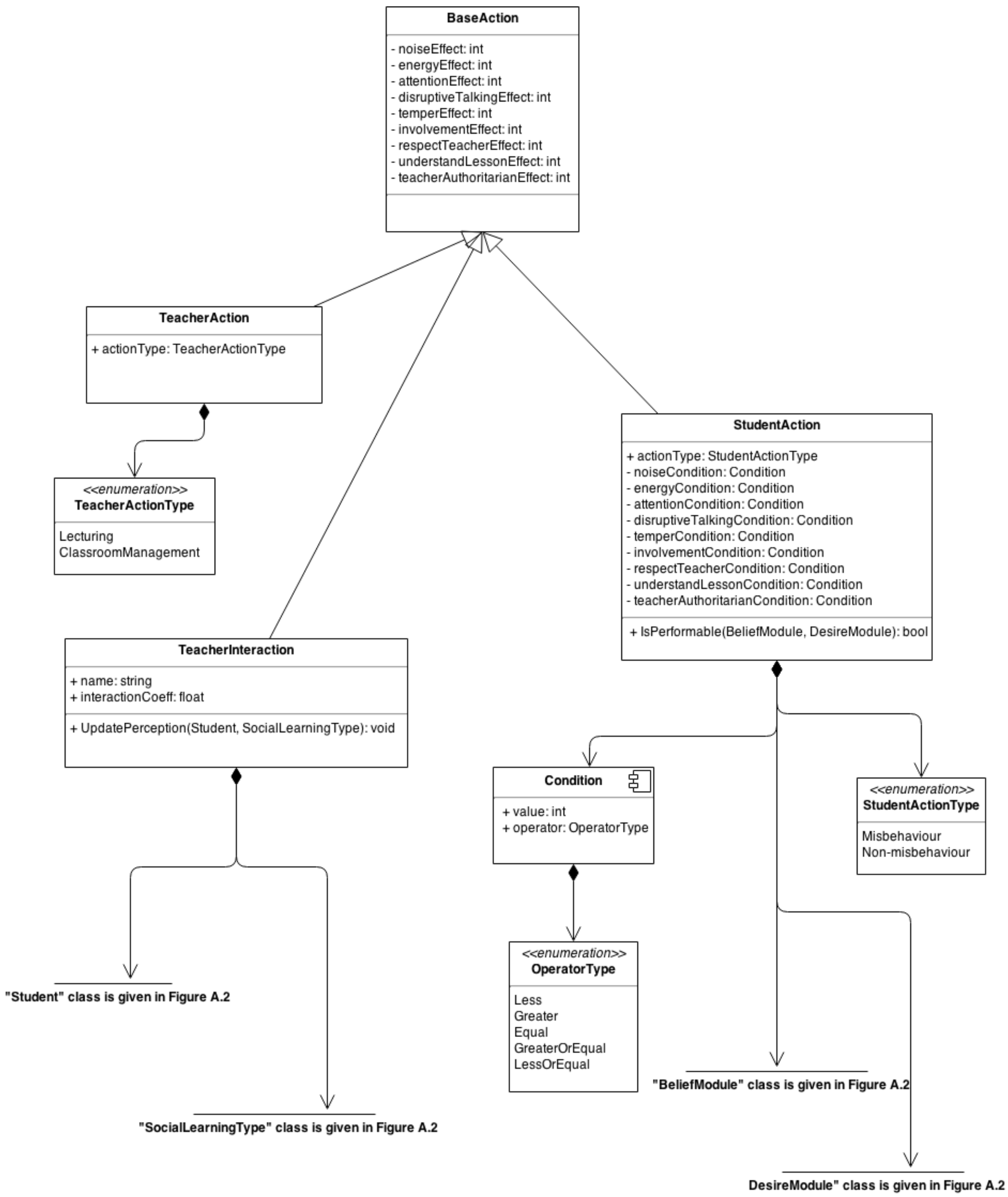


Figure A.3: Class diagram of base action, teacher action and student action

APPENDIX B

REWARDING SYSTEM - STUDENT ACTIONS

Table B.1: Conditions for student actions

Action	NC	EC	AC	DTC	IC	TC	RTC	USC	TAC
Daydream	-	<60	<40	-	-	<60	-	-	<60
Sleep	-	<40	<40	-	-	-	<40	-	<30
Sing	>60	>40	<40	-	-	-	<30	-	<30
Laugh	-	>40	<40	-	-	-	<40	-	<40
Draw on book	-	-	<40	-	-	-	<60	-	<40
Write text message	-	-	<40	>60	-	-	<40	-	<40
Idle	-	-	-	-	-	-	-	-	-
Take note	-	>40	>60	<60	-	<60	>40	>40	-
Do activity	<40	>60	>40	<50	>40	<60	>40	>40	-
Read	-	>40	>40	<60	-	<60	>40	>40	-
Listen	<40	>40	>40	<40	-	<60	>40	>30	-
Participate	<40	>40	>40	<40	>60	<60	>40	>30	-

Table B.2: Effects of student actions on source student

Action	NE	EE	AE	DTE	IE	TE	RTE	USE	TAE
Daydream	-5	-5	-5	0	-5	-5	0	-5	0
Sleep	0	-10	-10	-5	0	0	-5	-10	0
Sing	15	10	-10	10	-10	0	-20	-10	-10
Laugh	10	15	-5	10	-5	-5	0	0	-5
Draw on book	0	0	-5	0	-10	-10	-5	-5	-5
Write text message	0	10	-5	5	0	0	-5	-5	-5
Idle	0	0	0	0	0	0	0	0	0
Take note	0	0	0	0	0	0	0	5	0
Do activity	0	0	0	0	0	0	0	5	0
Read	0	0	0	0	0	0	0	5	0
Listen	0	0	0	0	0	0	0	5	0
Participate	0	0	0	-5	5	0	5	5	0

APPENDIX C

REWARDING SYSTEM - TEACHER ACTIONS

Table C.1: Effects of teacher actions

Action	NE	EE	AE	DTE	IE	TE	RTE	USE	TAE
Intro	-10	10	10	-10	10	-5	5	10	0
Cover from book	-10	10	10	-10	10	-5	10	10	0
Cover via activity	-20	20	20	-20	20	-10	20	20	0
Summary	-10	0	10	-10	10	-5	0	10	0
End lecture	0	10	0	0	0	0	0	0	0
Fail	20	-20	-20	20	-20	20	-20	-20	0
Ignore behaviour	0	0	0	0	0	0	-25	0	-10
Reward behaviour	0	0	0	0	0	-20	20	0	-10
Punish behaviour	0	0	0	0	0	40	-20	0	40
Approve behaviour	0	0	0	0	0	-5	5	0	-5
Disapprove behaviour and explain why	0	0	0	0	0	5	5	0	-5

APPENDIX D

STUDENT RESULTS IN NORMAL CLASSROOM

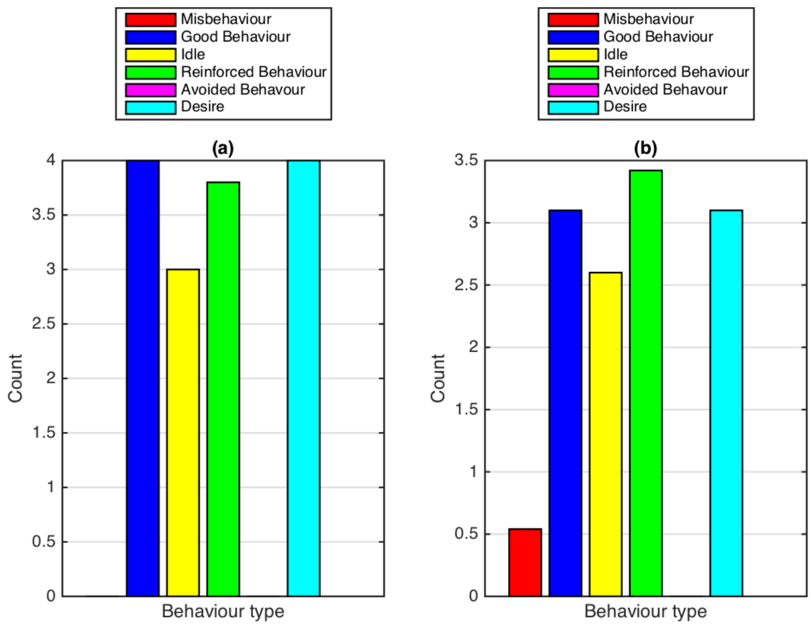


Figure D.1: Smart student behaviour histogram in normal classroom when social learning is enabled (b) Classroom average behaviour histogram in normal classroom when social learning is enabled

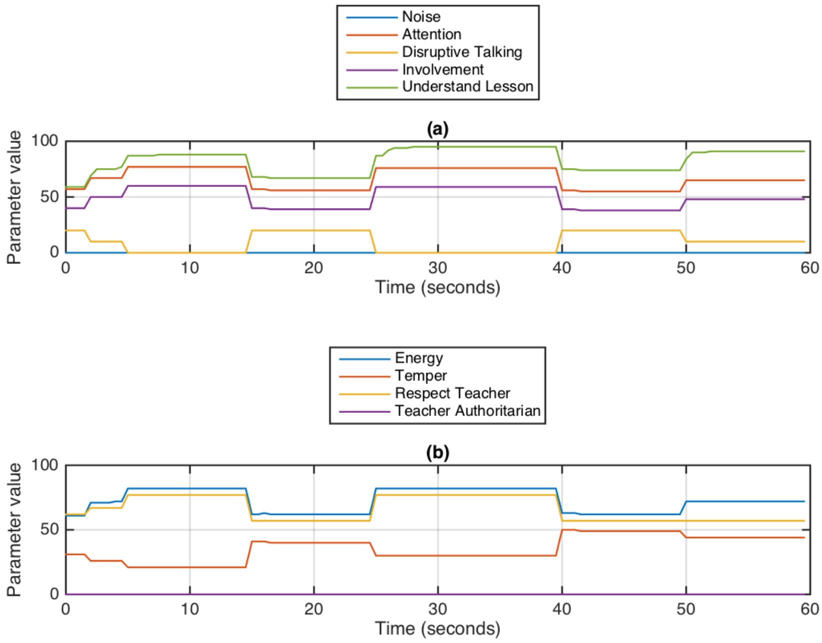


Figure D.2: (a) Smart student academic performance parameters graph in normal classroom when social learning is enabled (b) Smart student human relations parameters graph in normal classroom when social learning is enabled

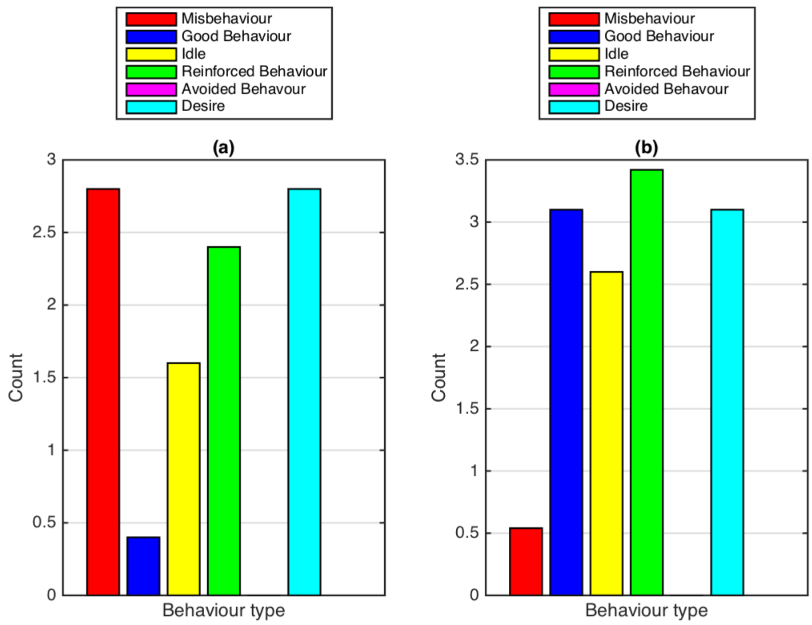


Figure D.3: Uninterested student behaviour histogram in normal classroom when social learning is enabled (b) Classroom average behaviour histogram in normal classroom when social learning is enabled

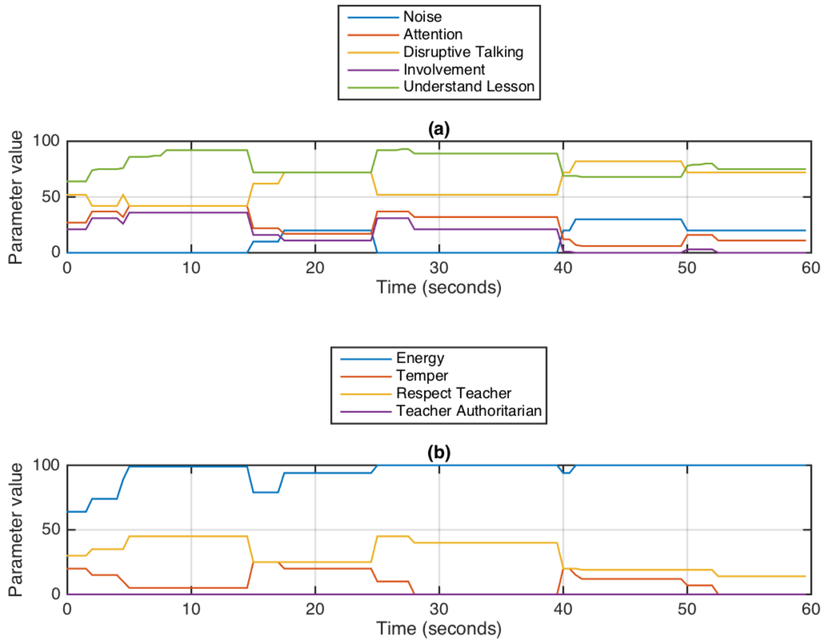


Figure D.4: (a) Uninterested student academic performance parameters graph in normal classroom when social learning is enabled (b) Uninterested student human relations parameters graph in normal classroom when social learning is enabled

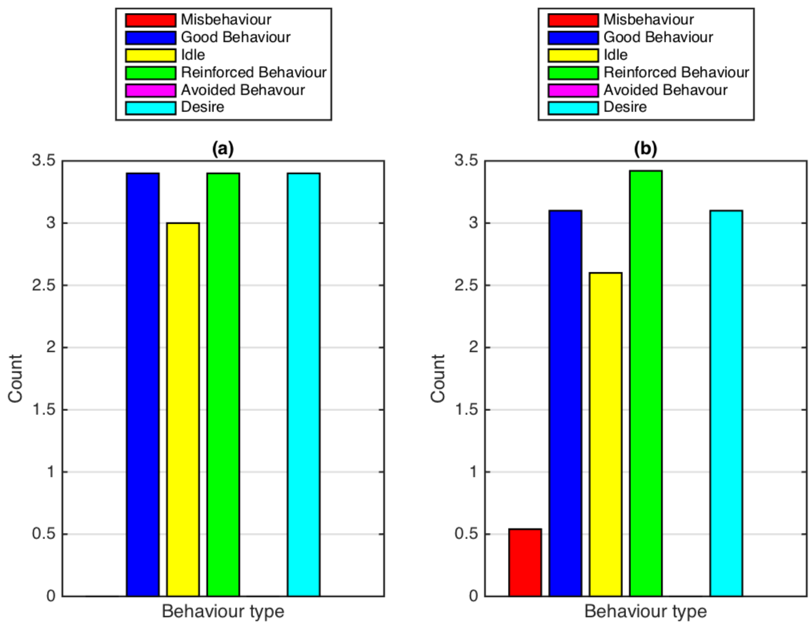


Figure D.5: Struggling student behaviour histogram in normal classroom when social learning is enabled (b) Classroom average behaviour histogram in normal classroom when social learning is enabled

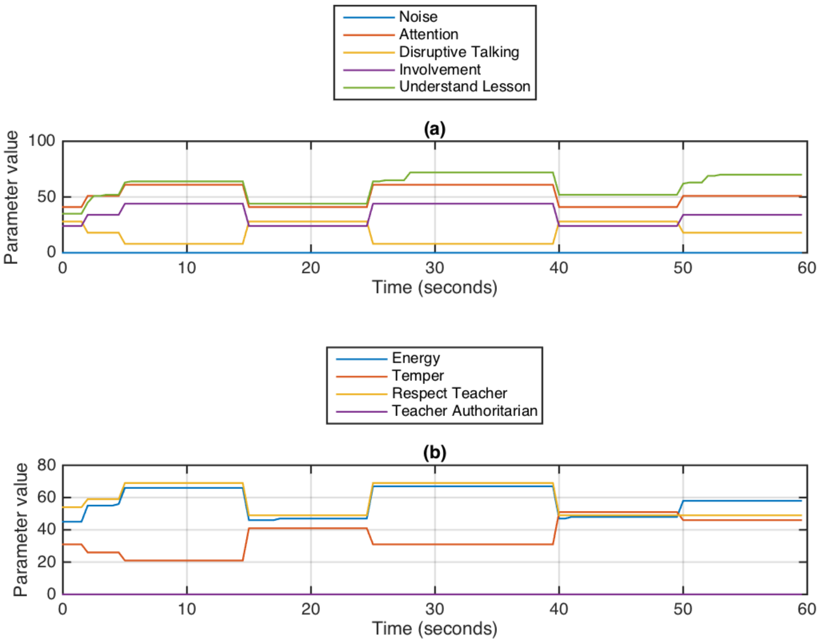


Figure D.6: (a) Struggling student academic performance parameters graph in normal classroom when social learning is enabled (b) Struggling student human relations parameters graph in normal classroom when social learning is enabled

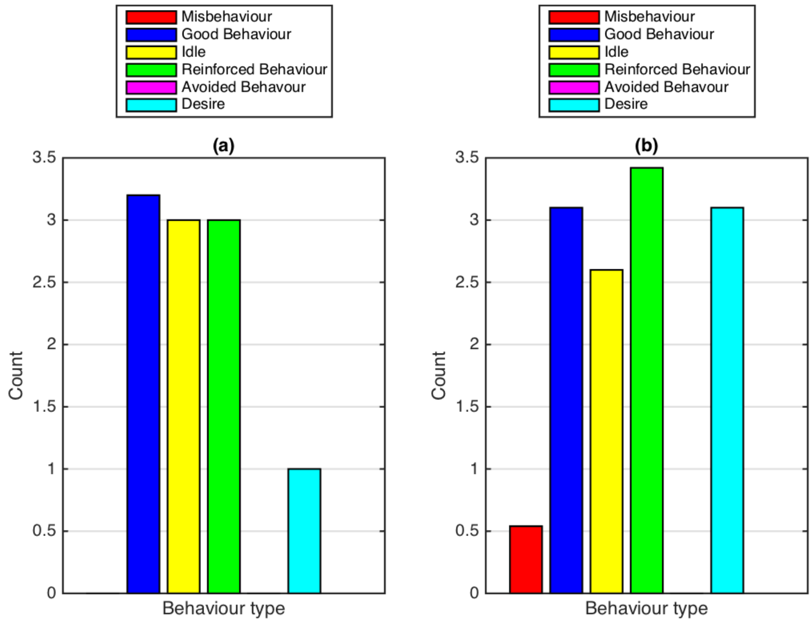


Figure D.7: Overestimating student behaviour histogram in normal classroom when social learning is enabled (b) Classroom average behaviour histogram in normal classroom when social learning is enabled

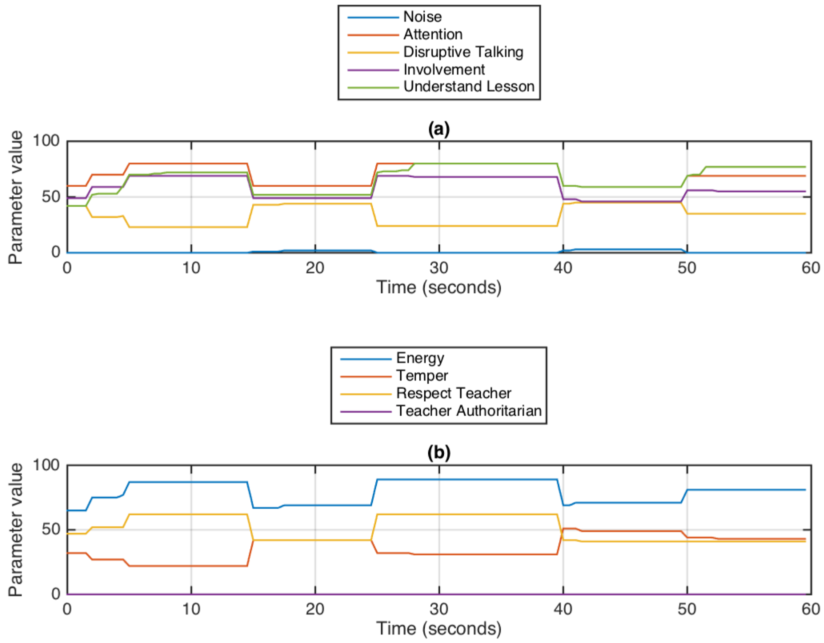


Figure D.8: (a) Overestimating student academic performance parameters graph in normal classroom when social learning is enabled (b) Overestimating student human relations parameters graph in normal classroom when social learning is enabled

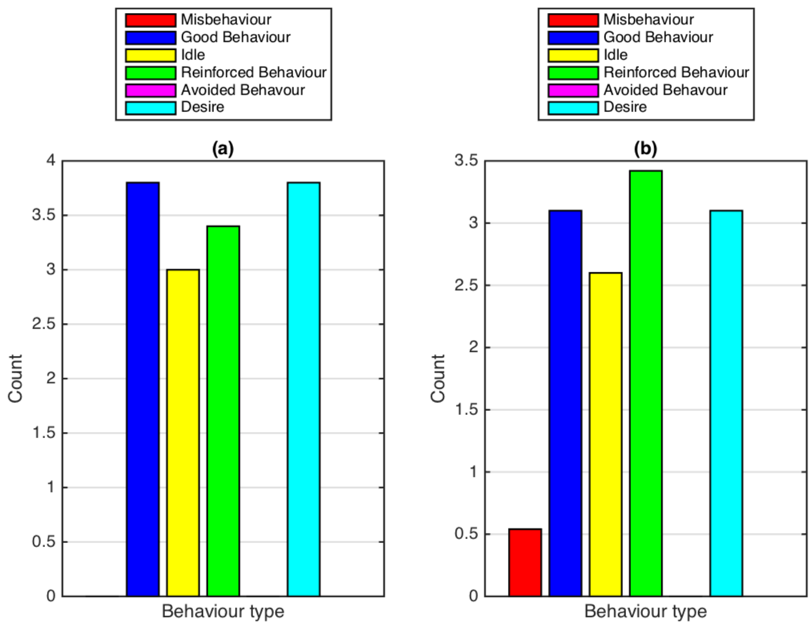
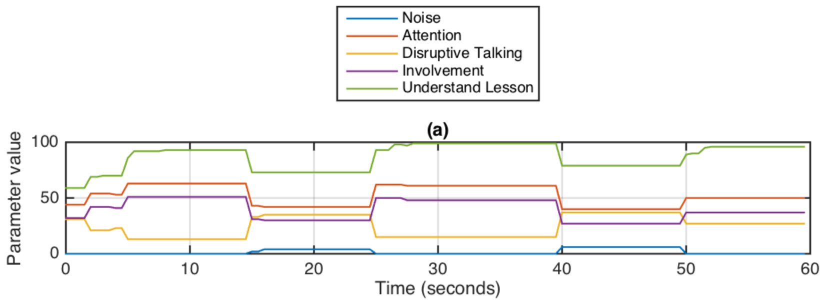


Figure D.9: Underestimating student behaviour histogram in normal classroom when social learning is enabled (b) Classroom average behaviour histogram in normal classroom when social learning is enabled



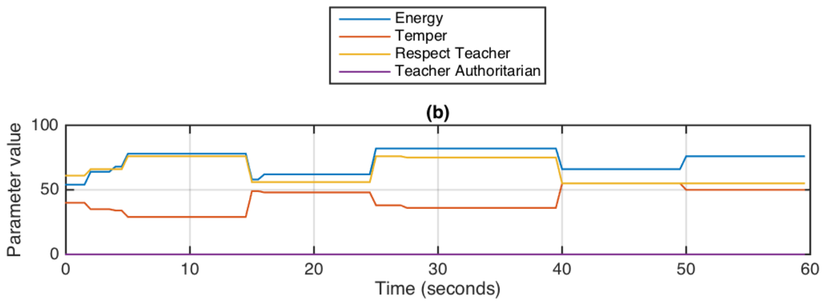


Figure D.10: (a) Underestimating student academic performance parameters graph in normal classroom when social learning is enabled (b) Underestimating student human relations parameters graph in normal classroom when social learning is enabled

APPENDIX E

QUESTIONNAIRE

1. Gender?
   (a) Male
   (b) Female

2. Which level of education you are giving?
   (a) Elementary school
   (b) High school
   (c) Both

3. What is your teaching experience in terms of year?
   (a) Less than 1 year
   (b) 1 - 5 years
   (c) 5 - 10 years
   (d) +10 years

4. The students observe and imitate each other in classroom.

5. A student's probability to observe and imitate the other students who is close to him/her is higher than the students who is far from him/her.

6. When a smart student is located at uninterested classroom, the smart student feels and thinks like uninterested students.

7. When a smart student is located at uninterested classroom, the smart student imitates uninterested students' behaviours.

8. When a struggling student is located at smart classroom, the struggling student feels and thinks like smart students.

9. When a struggling student is located at smart classroom, the struggling student imitates smart students' behaviours.

10. When an uninterested student is located at smart classroom, the uninterested student feels and thinks like smart students.

11. When an uninterested student is located at smart classroom, the uninterested student imitates smart students' behaviours.

12. When an overestimating student is located at underestimating classroom, the overestimating student feels and thinks like underestimating students.

13. When an overestimating student is located at underestimating classroom, the overestimating student imitates underestimating students' behaviours.
14. When an underestimating student is located at uninterested classroom, the underestimating student feels and thinks like uninterested students.
15. When an underestimating student is located at uninterested classroom, the underestimating student imitates uninterested students' behaviours.
16. If a teacher rewards or approves the students' desired behaviours, the students' possibility to perform same action increases.
17. If a teacher punishes or disapproves the students' misbehaviours, the students' possibility to perform same action decreases.
18. If a teacher ignores students' desired behaviours and tolerates their misbehaviours, the students' possibility to misbehave increases.