AUTOMATED CLASSIFICATION OF GAME PLAYERS AMONG THE PARTICIPANT PROFILES IN MASSIVE OPEN ONLINE COURSES

ALI AL-TAEI

JANUARY 2015

AUTOMATED CLASSIFICATION OF GAME PLAYERS AMONG THE PARTICIPANT PROFILES IN MASSIVE OPEN ONLINE COURSES

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES OF
ÇANKAYA UNIVERSITY

BY
ALI AL-TAEI

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE
IN
THE DEPARTMENT OF
COMPUTER ENGINEERING

JANUARY 2015

Title of the Thesis: **Automated Classification of Game Players among the Participant Profiles in Massive Open Online Courses**

Submitted by **Ali AL-TAEI**

Approval of the Graduate School of Natural and Applied Sciences, Çankaya University.

Prof. Dr. Taner ALTUNOK
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

Prof. Dr. Müslim BOZYİĞİT
Head of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

Assist. Prof. Dr. Murat YILMAZ
Supervisor

Examination Date: 20.01.2015

Examining Committee Members:

Assist. Prof. Dr. Abdül Kadir GÖRÜR	(Çankaya Univ.)	
Assist. Prof. Dr. Murat YILMAZ	(Çankaya Univ.)	
Prof. Dr. Uğur HALICI	(METU)	

STATEMENT OF NON-PLAGIARISM PAGE

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 : Ali, AL-TAEI

Signature :

Date : 20.01.2015

ABSTRACT

AUTOMATED CLASSIFICATION OF GAME PLAYERS AMONG THE PARTICIPANT PROFILES IN MASSIVE OPEN ONLINE COURSES

AL-TAEI, Ali
M.Sc., Department of Computer Engineering
Supervisor: Assist. Prof. Dr. Murat YILMAZ

January 2015, 68 pages

In recent years, there has been an increasing interest in Massive Open Online Courses (MOOCs). This interest highlights the importance of understanding behavior, traits, and preferences of individuals. Developing such an understanding requires ways for improving the process of MOOC design by adapting innovative techniques such as personality profiling, which have been frequently employed in the field of game development. This study suggests a mechanism to classify MOOC participants into their correspondent Bartle's Massively Multiplayer Online Game (MMOG) player type by using Myers-Briggs Types Indicator (MBTI) as a personality reference. The goal is to explore the profiles of MOOC attendees by using both MBTI and Bartle's MMOG player types for the sake of delivering a distinctive view about the audience of MOOCs. To this end, an online questionnaire which is composed of three dimensions was administered: (i) demographics, (ii) MBTI personality assessment, and (iii) Bartle's player types. Respondent (N=75) replies showed a relationship between a group of personality types and MMOG playing styles. Furthermore, a machine-learning model was proposed to instantly classify the player types. Ultimately, results (N=67) showed that using Back Propagation (BP) neural network is acceptable for both the training process (performance=100%) and the testing process (performance=91.6%). The results suggest that our approach provides a novel way to asses participants of MOOCs in terms of Bartle's player types. Moreover, our approach of applying BP method provides a novel way to accurately classify participants of MOOCs in terms of Bartle's player types.

Keywords: Personality Assessments, Managing Participant Profiles, Player Types, Automated Classification, Artificial Neural Networks, Massive Open Online Courses.

ÖZ

KİTLESEL AÇIK ÇEVRİMİÇİ KURSLARDAKİ KATILIMCI PROFİLLERİ ARASINDAKİ OTOMATİK OYUNCU SINIFLANDIRMASI

AL-TAEI, Ali
Yüksek Lisans, Bilgisayar Mühendisliği Anabilim Dalı
Tez Yöneticisi: Yrd. Doç. Dr. Murat YILMAZ

Ocak 2015, 68 sayfa

Son yıllarda Kitlesel Açık Çevrimiçi Kurslara (KAÇK) artan bir ilgi söz konusudur. Bu ilgi bireylerin davranışları, özellikleri ve tercihlerinin anlaşılması öneminin altını çizmektedir. Böyle bir anlayış geliştirmek, sıklıkla oyun geliştirme alanında kullanılan kişilik profilleme gibi yenilikçi teknikleri uyarlayarak KAÇK tasarım sürecini geliştirmek için çeşitli yollar gerektirmektedir. Bu çalışma, bir kişilik referansı olarak Myers-Briggs Türü Göstergeler (MBTG) kullanılarak KAÇK katılımcılarının Bartle Kitlesel Çok oyunculu Çevrimiçi Oyunları (KÇÇO) oyuncu türü içinde sınıflandırmak için bir mekanizma ortaya koymaktadır. Amaç, KAÇK izleyicileri hakkında ayrıştırıcı bir bakış sunmak için KAÇK katılımcı profillerini hem MBTG hem de Bartle KÇÇO oyuncu türlerini kullanarak araştırmaktır. Bu amaçla, üç boyutlu bir çevrimiçi anket kullanılmıştır: (i) demografik özellikler, (ii) MBTG kişilik değerlendirmesi, ve (iii) Bartle oyuncu türleri. Muhatap (N=75) cevapları bir grup kişilik türleri ile KÇÇO oyun stilleri arasında bir ilişkinin

olduğunu göstermiştir. Dahası, bir makine öğrenimi modeli anında oyuncu türü sınıflandırması için önerilmiştir. Sonuçta, sonuçlar (N=67) Geri Yayılımlı (GY) sinir ağının hem eğitim süreci (performans=%100) hem de test süreci için (performans=%91,6) uygun olduğunu göstermiştir. Sonuçlar yaklaşımımızın Bartle oyuncu türleri açısından KAÇK katılımcılarını belirlemede özgün bir yol sağladığını ortaya koymaktadır. Ayrıca, GY yöntemi uygulama yaklaşımımız Bartle oyuncu türleri açısından KAÇK katılımcılarını doğru bir şekilde belirlemede özgün bir yol ortaya koymaktadır.

Anahtar Kelimeler: Kişilik Değerlendirmesi, Yönetici Katılımcı Profilleri, Oyuncu Türleri, Otomatik Sınıflandırma, Yapay Sinir Ağları, Kitlesel Açık Çevrimiçi Kurslar.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my thesis supervisor *Dr. Murat YILMAZ,* who has encouraged and guided me patiently throughout this thesis.

And I am thankful to the examining committee members for their kindness, comments, and suggestions during the presentation of this thesis.

Also, I would like to express my deep gratitude to my family for their infinite love and support throughout the years.

TABLE OF CONTENTS

LIST OF FIGURES

FIGURES

FIGURES

LIST OF TABLES

TABLES

LIST OF ABBREVIATIONS

MOOC	Massive Open Online Course
MMOG	Massively Multiplayer Online Game
MMORPG	Massively Multiplayer Online Role Playing Game
MUD	Multi User Dungeon
ANN	Artificial Neural Network
MLP	Multi Layer Perceptron
MBTI	Myers Briggs Type Indicator
SVM	Support Vector Machine
DT	Decision Tree
DNN	Deep Neural Network
BP	Back Propagation
DGD	Demographic Game Design
CART	Classification And Regression Trees
WoW	World of Warcraft
HMM	Hidden Markov Model
BCI	Brain Computer Interface
EEG	Electro Encephalo-Graphy
GNS	Gamist/ Narrativist/ Simulationist
MDA	Mechanics Dynamics Aesthetics
KTS	Keirsey's Temperament Sorter

CHAPTER 1

INTRODUCTION

1.1 General Overview

The emergence of MOOCs is considered as an important event in the open learning culture for the next decade [1]. More recently, however, literature offers contradictory findings about its benefits where some researchers considered MOOCs trend as disruptive to the existing approaches of learning and to the whole learning system [2, 3]. In fact, MOOCs achieved a notable success within short period of time and gained acceptance from a wide range of participants, scholars, well known universities and research institutions [4]. In addition, MOOCs overcome the constraints of traditional online courses (e.g. geographical limitation, funding, and number of participants) [5, 6] by combining and using both of the learning styles that were employed in xMOOCs[1] [7] and the connectivist pedagogical techniques that were used in cMOOCs[2] [8]. The success of and growing interest in MOOCs, expand the scope toward exploring innovative models and pedagogies [9, 10].

So far, however, there has been little discussion about the problems (e.g. pedagogical, technological, logistical, and financial) that can be encountered in both designing and operating a MOOC [11]. From the pedagogical viewpoint, instructors concurrently deal with a massive amount of participants from various locations and countries, who have distinctive personalities with different goals and motivations [6]. Additionally, new learning approaches should be discovered and employed to improve learner

[1] In xMOOCs, the letter 'x' represents the general characteristics of this type of MOOCs such as scalability, open access to contents and materials, and closed licensing.

[2] In cMOOCs, the letter 'c' represents the general characteristics of this type of earlier MOOCs such as concerns with connectivity, and open access and licensing.

autonomy [12] and the relationship between learners [13]. Therefore, there seems to be an increasing concern that different personalities, motivations, and autonomy of participants play an important role in the design process of a MOOC.

In general, games are powerful artifacts, which are mostly successful in engaging and motivating participants [14, 15]. There are several commonalities between the design process of a MOOC and a MMOG. Firstly, both can be regarded as socio-technical systems, which have interrelated social and technical components that serve a large number of users with different personalities, goals and motivations. Secondly, they are open systems where participants can join and leave freely. Thirdly, they both can be regarded as services. Thus, exploring the preferences, personal traits, motivation and interests of MOOC audience and using game design methodologies to create more engaging MOOCs might be a reasonable assumption to be tested.

A typical innovative game design process starts with designing user experiences and aesthetics rather than its mechanics [16]. This approach evokes participants' motivation and supports individuals to stay in an optimal state during the game [17, 18]. To investigate and explore the social aspects of MOOCs, designers need to fully understand the target audience by using a set of assessments and tools. Myers-Briggs Type Indicator (MBTI) and Bartle's game player types are the most common tools for conducting such operations [19]. Bartle [20] suggests a model to classify MMOG players based on the variance of players' behavior, interests and motivations. In Bartle's model, players were classified into 4 different categories: achievers (seeking for achievement), explorers (motivated by exploration, imagination, and learning of new things), socializers (motivated by cooperation, interaction, and communication with other players), and killers (motivated by competition, and fighting other players) [21]. Bartle's player typology is used as a fundamental framework in MMOGs/MMORPGs[3] research and MMOGs/MMORPGs design studies [22]. Players in the same category have similar characteristics and somehow behave in the same way. In other words, each player type represents an independent (unique) behavior pattern [23]. Furthermore, the patterns might be useful to address some of the issues

[3] Massively Multiplayer Online Role Playing Game (MMORPG) is a genre of Massively Multiplayer Online Game (MMOG).

in artificial intelligence. For instance, they might be useful for creating complex artificial behavioural models (see [24]).

1.2 Objectives

The goal of this research study is to investigate the personality characteristics, demographics (e.g. age, gender, level of education) and experience of the participants of MOOCs using MBTI assessment and Bartle's player types test. In other words, we first try to explore temperaments and preferences using the information acquired from personality types and game playing types. Secondly, in the light of the collected information, we hypothesize (i.e. train and test) a machine-based classifier to reveal the personality types of players with incomplete information. This research seeks to address the following questions:

RQ1: *Is it possible to explore objective characteristics (e.g. age, gender, etc.) and subjective characteristics (personality types, and player types) of MOOC participants?*

RQ2: *Is it possible to automatically classify participants into equivalent game player types using BP-ANN?*

1.3 Organization of the Thesis

The remainder of this research study is organized as follows:

Chapter 2 reviews the background and related previous studies on the topic of this study. Key studies about personal preferences and MBTI, MMOG Bartle's player types and test, MOOCs, machine learning, artificial neural networks and basics of multi-layer perceptron (MLP) method with backpropagation (BP) algorithm are reviewed and explained.

Chapter 3 details the suggested research methodology. It explains the steps used for exploring personality types, Bartle's player types, and applying back propagation method as a tool to classify individuals into their equivalent Bartle's player types.

Chapter 4 discusses the study and our approach. In addition, the results are shown under different titles (demographic information, personality preferences and types, Bartle's player types, and the machine-based (i.e., BP) classifier). Furthermore, validation of results and the model are examined through different experiments and are presented in detail. Lastly, limitations and threats to validity are explained.

Chapter 5 presents conclusions and implications of this study. Additionally, based on the findings and contributions of this research study, suggestions are given for future studies.

CHAPTER 2

BACKGROUND

2.1 Introduction

This chapter discusses the personality basics, MBTI assessment and the personality types, Bartle's player types and game player types test (i.e. Bartle's player test). Also machine learning and classification, artificial neural networks and basics of Multi Layer Perceptron ANN, and the Back Propagation algorithm are explained. And lastly, some of the previous related studies will be reviewed.

2.2 Personality Basics and MBTI assessment

The term *personality* is derived from the Latin word *persona* which is used to refer to mask works produced by theatre performers in order to play different roles or to hide their real characters [25]. There are many definitions of personality that are based on a variety of theories, and these theories can be categorized into four different standpoints [25, 26]:

- **Psychoanalytic standpoint:** This approach was founded by Freud, and focuses on the importance of unconscious and childhood experiences.

- **Humanistic standpoint:** This approach emphasizes human nature concepts such as personal awareness, free will, and psychological growth.

- **Trait standpoint:** This approach focuses on understanding, describing, and measuring the traits that shape personality.

- **Social cognitive standpoint:** This approach focuses on the importance of conscious mind concepts such as learning from observations, self-efficiency, social activities, and cognitive procedures.

However, personality can be defined as the set of psychological experiences, traits, cognition, and emotional and cultural characteristics that shape the behaviour pattern of an individual [25, 26, 27, 28].

2.2.1 Personality types: MBTI assessment

Since people are different in their personalities and behaviours, many assessments and tests are established to determine the type of personality such as Big Five Factor Model [29], Minnesota Multiphasic Personality Inventory (MMPI) [30], and self report inventory [31].

Jung's theory of psychological types proposed four functions (i.e. personality characteristics) that constitute different personalities [32]. Based on Jung's theory, Myers and Briggs submitted an indicator called MyersBriggs Type Indicator (MBTI) to assess personality type. Depending on four dichotomies, MBTI produced 16 different types of personalities. These four dichotomies represent differences and preferences of people, and they might be described as follows [33]:

- **Extraversion - Introversion (E/I):**

  This dichotomy represents the preferred way in which individuals collect their energy, in extraversion or introversion.

  Extraverted (E) individuals prefer to receive energy from external environment such as social interaction with people, objects, and actions. Introverted (I) individuals, on the other hand, prefer to get energy from privacy, introspection, segregation, and reflection [34].

- **Sensing - Intuition (S/N):**

  This dichotomy represents the preferred way of individuals to collect information/ knowledge, on a sensing or intuition scale.

Sensing (S) personalities have a preference to collect information objectively and in an ordered way. They use their senses to collect information [35], and believed that this information is true and reliable [34]. Individuals with intuitive (N) personalities, on the other hand, have the preference to convert this information further into potential possibilities, modulations, and associations. Additionally, people with intuitive (N) personalities prefer to look at the big picture without paying much attention to the details [35].

- **Thinking - Feeling (T/F):**

This dichotomy represents the preferred way of taking and/or making decisions. It determines whether individuals prefer to depend on their thinking skills more than their feeling or vice versa, to take decisions.

Personalities with thinking (T) type seem to prefer logical and analytical approach in making decisions. They do not let their emotions affect their judgments and decisions [34, 35]. On the other hand, personalities with feeling (F) preference seem to prefer making their decision subjectively based on their personal values and principles, and considering the potential impacts of their decision on others [35].

- **Judging - Perceiving (J/P):**

The function of this dichotomy is to determine an individual's dominant preference which could be judging (J) during decision making process or perceiving (P) during information collecting process [35]. In particular, this dichotomy aims to explore how individuals with different personalities behave as far as decisions, deadlines, schedules, and organization are concerned. Those who prefer the judging (J) direction like to have a life-style in which they can put and accomplish plans and schedules, be firm with deadlines and ready to make decisions quickly and objectively [35]. On the other hand, people who prefer the perceiving (P) option like to know and collect information, without making judgments if they do not have to. They prefer a life style of flexibility, simplicity, and spontaneity [35].

Figure 1 shows the four dichotomies through which different types of personalities can be indicated [36, 37]:

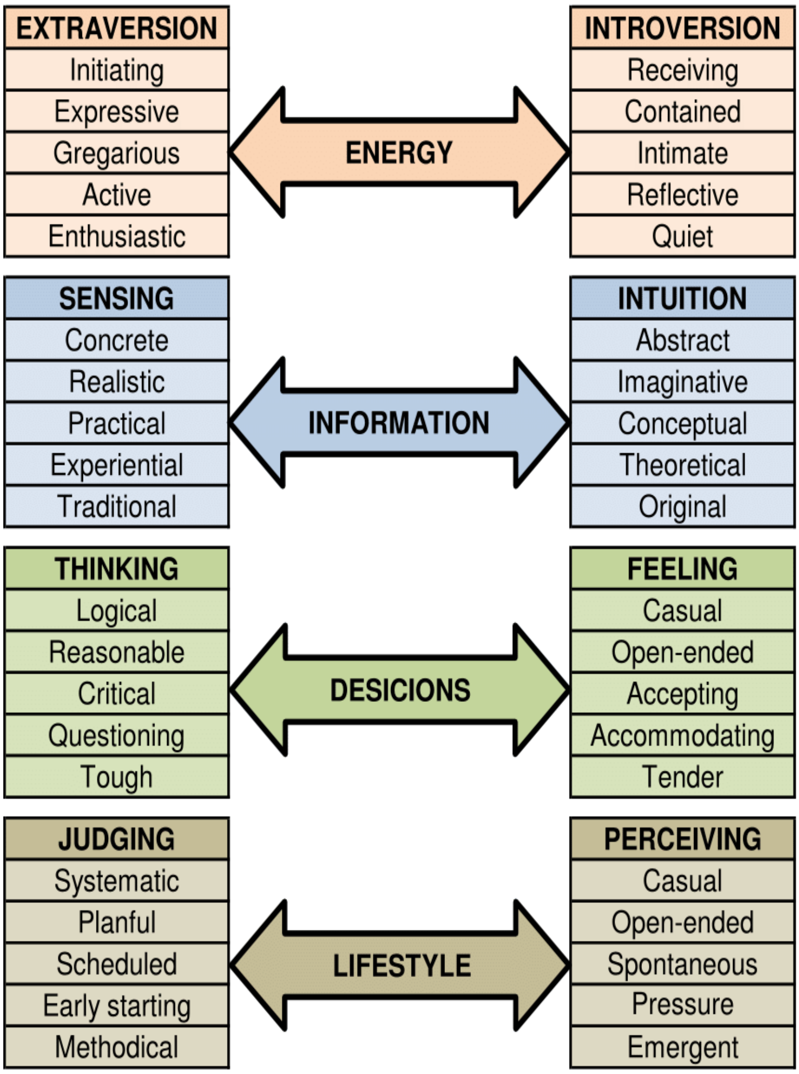

Figure 1 The MBTI assessment and four dichotomies

Each individual has different preferences from the opposing poles of each factor, which, in total, represents an individual's personality type [36]. Accordingly, a combination of these 16 personality types can be formed as shown in Figure 2 (adopted from [37]):

			Sensing Types		Intuitive Types	
			Thinking	Feeling	Feeling	Thinking
			ST	SF	NF	NT
Introvert	Judging	I / J	ISTJ	ISFJ	INFJ	INTJ
Introvert	Perceiving	I / P	ISTP	ISFP	INFP	INTP
Extravert	Perceiving	E / P	ESTP	ESFP	ENFP	ENTP
Extravert	Judging	E / J	ESTJ	ESFJ	ENFJ	ENTJ

Figure 2 MBTI personality types

The four functions discussed above provide 16 different types of personalities. The 16 different types of MBTI are listed below with a brief definition for each type [35, 37]:

- People with **ISTJ** personality type are natural organizers dealing with the world in concepts of tactile facts (Sensing) that they objectively handle (thinking) over structure (judging). Oftentimes, others consider them as discreet and cool (introverted).
- People with **ISFJ** personality type are committed and feel obliged to finish their job. They are comfortable, accurate and quiet workers (introverted) in a structured environment (judging). They have a pragmatic and realistic personality (sensing), and make decisions depending on interpersonal factors (feeling).
- **INFJ** individuals are creative, and reflective (introvert), and see the world as full of chances and potentials (intuitive). They consider these potentials and possibilities and implement them orderly and in a scheduled style (judging) in order to make their decisions subjectively (feeling).
- **INTJ** people are independent thinkers, and have great power in achieving their goals and ideas (introvert) in a world of endless possibilities from their own point of view (intuitive). By implementing these possibilities and ideas out of a structured order (judging), they can take decisions objectively (thinking).
- **ISTP** individuals have well-known abilities to achieve their goals. They are hard to understand (introverted), and mostly deal with the world in concepts

of tactile facts (sensing), and live the life focusing on present time. In addition, people in this category take decisions objectively (thinking) based on the current moment (perceiving).

- **ISFP** individuals speak through their work and actions far more than their words, and conceive that it is better to carry out plans and actions orderly (introverted). Although they see the world in concepts of tactile facts (sensing), they make decisions subjectively (feeling). Also, they prefer to keep all options open (perceiving).
- **INFP** people are gentle, idealistic, and prefer thinking (introverted) and imagination (intuitive). They make decisions based on their personal values (feeling), and prefer to keep everything flexible (perceiving) more than fixed.
- People with **INTP** type personality prefer to ravel out problems by making decisions objectively (thinking) and reflecting upon different possibilities (intuitive). They are also tranquil and flexible (perceiving).
- **ESTP** people are pragmatic and focus on the immediate moment of the external world (extraverted) in a grounded and realistic manner (sensing). They take decisions objectively, by giving more attention to what is happening now-and-here (perceiving), as they do not like conceptual and theoretical explanations (thinking).
- **ESFP** people are friendly, flexible, open, love to have fun and comfort in dealing with the external world (extraverted), and have a pragmatic forestation (sensing). They make decisions subjectively (feeling) and flexibly (perceiving).
- Individuals with **ENFP** personality type are social and warm (extraverted), and look for everlasting possibilities (intuitive). They prefer to keep all their options open (perceiving), and make their decisions based on their social connections and communication abilities (feeling).
- **ENTP** individuals are brilliant, stimulating, and derive fun from life (extraverted), and the everlasting possibilities of conceptual and theoretical relations (intuitive). These conceptual connections are filtered objectively (thinking) to keep the options open (perceiving).
- **ESTJ** individuals are natural organizers, and the managers of people and other resources (extraverted) although they prefer to deal with the world through a

pragmatic and practical approach (sensing). They make analytical, direct decisions (thinking), and have the ability to fulfil these decisions quickly in a structured way (judging).

- People with **ESFJ** personality type are reliable and cooperative friends, and have the ability to interact with others facilely (extraverted). They give careful attention to personal specifics and details (sensing), and interact and make decisions in an interpersonal (feeling) but scheduled manner (judging).
- **ENFJ** individuals are naturally convincing people with social preference and skills (extraverted). They make decisions subjectively (feeling) after considering all possibilities carefully (intuitive). They prefer using their characteristics in a structured way (judging), which help them be considered as excellent communicators and networkers.
- Individuals with **ENTJ** personality type are natural leaders who have the ability to interact with people skillfully (extraverted). They consider possibilities and connections (intuitive), which enables them to make analysis objectively (thinking) and to accomplish things through an organized approach.

It is recommended by the Myers and Briggs Foundation [38] to deal with MBTI tool as an indicator to explore preferences of people rather than as a psychiatric measure or test. Since its early release in 1962, hundreds of research studies had examined the MBTI and proved that it is a valid and reliable tool [38]. Each year, there are millions of individuals who take this test for different reasons [38]. MBTI is one of the most widely-used tools all over the world and it is available in 24 different languages [39]. Additionally, MBTI tool is applicable and useful in such fields as management and leadership (see [39, 40, 41, 42]), computer science and software development (see [43, 44, 45, 46]), spiritual and personal growth (see [47, 48, 49, 50, 51, 52]), relationships and family affairs (see [53, 54, 55, 56, 57, 58]), and education and learning (see [59, 60, 61, 62, 63, 64, 65]).

2.3 Bartle Player Types

Based on his experience in MUDs, Bartle suggested a model to classify MUD/MMOG players, considering the variance of players' behavior, interests and motivation in gameplay [20]. According to Bartle's typology, there are four different types of players [20, 21]:

- **Achievers:** are the individuals who are seeking achievements and levels by collecting points.
- **Explorers:** are the people who are motivated by exploration, imagination, and learning of new things.
- **Socializers:** are a participant type who prefers cooperation, interaction, and communication with other players.
- **Killers:** are the players who love competition, and enjoy killing other players in games.

Figure 3, as adopted from [66], illustrates player types as suggested by Bartle based on in-game interests [21].

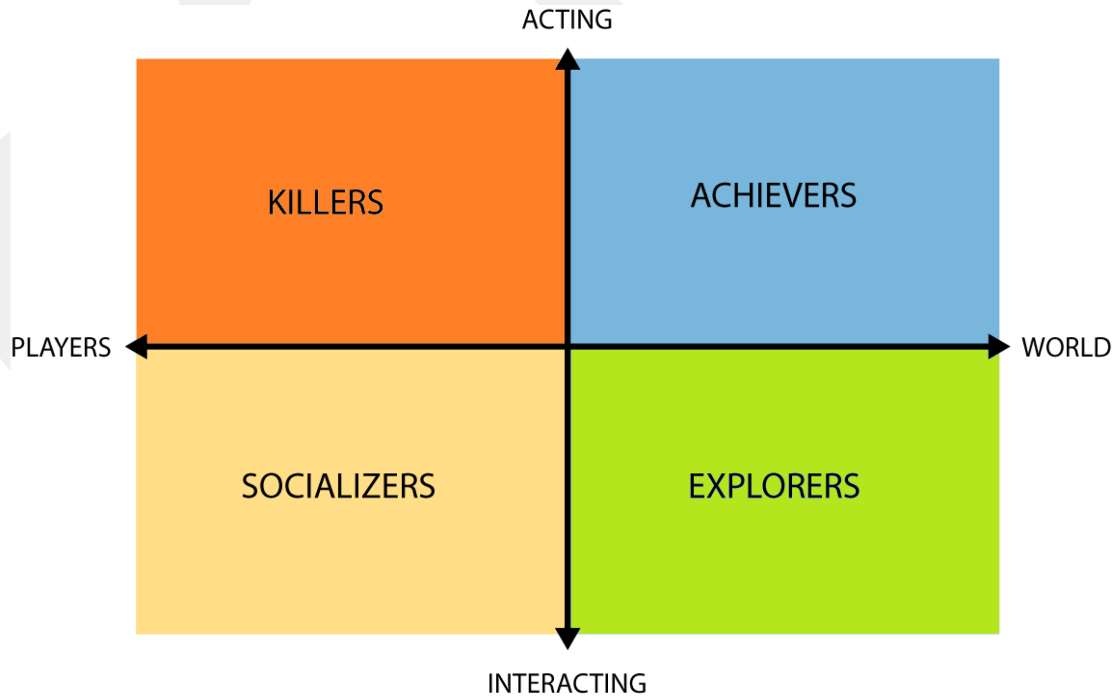

Figure 3 Bartle's player types' interests

The interactions/actions of each distinct player type with other players and/or with the world (the game) are different in many ways. That is, players 'play' or behave according to their interests, goals, and motivation. Lazzaro's (see [67]) and Yee's (see [68]) studies yielded similar results to those of Bartle's. Figure 4 below maps the goals of each Bartle player type onto similar results obtained from [67] and [68], as adopted from [66].

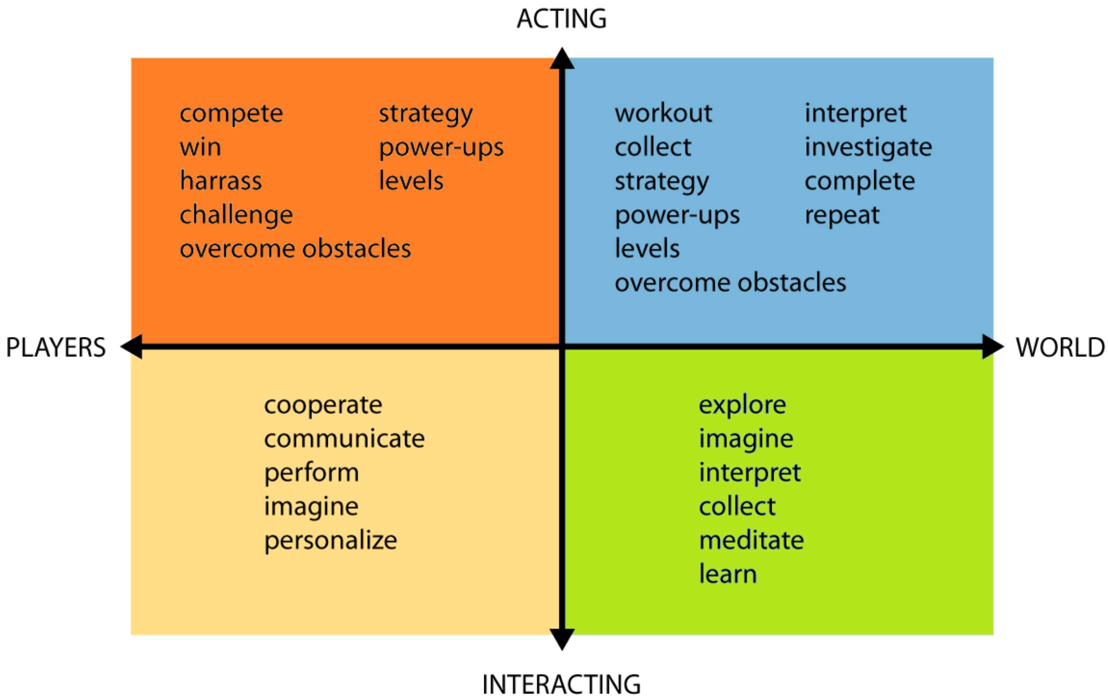

Figure 4 Motivation (engaged-by) of players

This understanding of the player types highlights proper ways to deal with participants and to improve the abilities of game designers by considering and employing suitable mechanics and contents. The aim is to fulfill the needs and motivation of each individual type and to keep balance (equilibrium) between them (e.g. contents might be suitable for achievers more than for socializers or killers, which means that they feel demotivated). In other words, this approach provides a comprehensive understanding to motivate players and to keep them in optimal state of engagement (*"flow"*), and demonstrates the suitable elements that should be employed [17, 21, 67].

Bartle's work [20] discusses the interactions between each player type and the way they work dynamically (e.g. how killers affect other types and killers also). These interactions can be summarized as listed in Table 1 below:

Player Type	INCREASE	DECREASE
Achievers	Slightly decrease killers. If killer numbers are high, increase the number of explorers.	Increase killers. Decrease explorer players if killer players are few.
Killers	Increase achiever players. Reduce explorers massively. Increase the number of socializers.	Reduce achiever players. Increase explorers massively. Decrease the number of socializers.
Explorers	Increase explorer players.	Increase killer players massively.
Socializers	Reduce killer players slightly.	Increase killer players slightly. Increase achiever players massively.
	Increase socializer players.	Decrease achiever players massively. Reduce socializer players.

Table 1 Connections Between and Reflections of Bartle Player Types

For a better understanding of Table 1, Figure 5 shows the graphical view of the influence of each player type [20, 21].

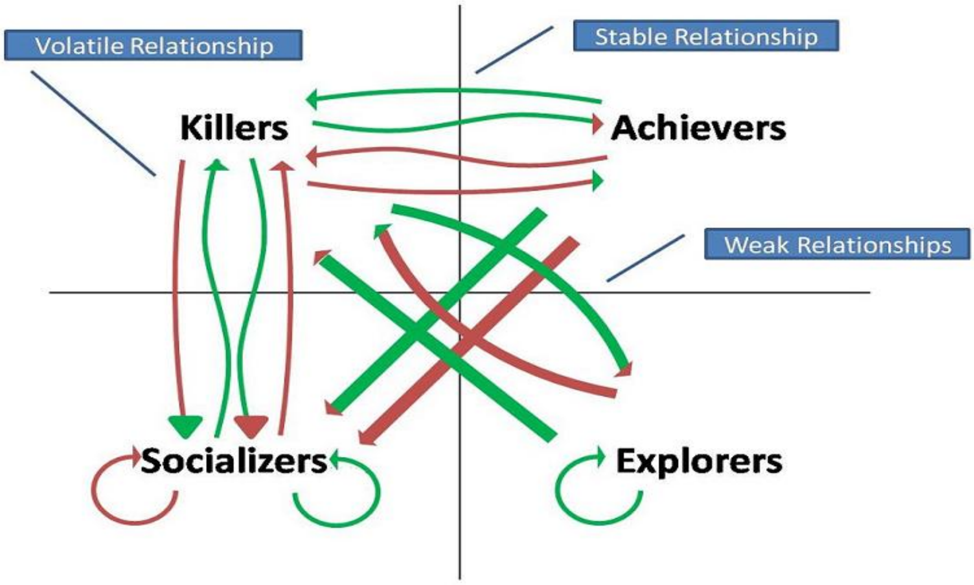

Figure 5 Flow of players

In the graph, green lines indicate the increasing numbers while the red ones show decreasing numbers. Thickness of lines indicates the size of change (e.g. a thick line means there is a big change). The size of arrow-heads indicates the amount of the flow of change(s) occuring in a specific group. Curves, on the other hand, indicate loops.

Bartle's study confirms two general approaches to provide the stability of the game based on the analysis of the relationships between player types:

1. Keep balance between all types, which is the most difficult to be achieved.
2. Players of a specific type(s) dominate the game, shaping it into their favourite flavour of 'fun' (i.e. the game is more likely to be a faction-oriented game if there is equilibrium between killers and achievers, while it is more likely to be a social game if there is stability between socializers) [20, 21, 69].

Bartle's player typology has been employed in game industry to assist designers to understand the motivation and personality of the targeted audience [70]. It is used as a base model for exploring audiences in gamification [71], which is a new promising field that aims to *properly employ game design tools and game elements in non-game related contexts* from marketing and services [72], to education [73, 74].

2.3.1 Game player types test

Bartle's player types test was initiated in 1999 by Andreason and Downey based on Bartle's approach to classify MUD players [21, 75].

Bartle test is available online[4], and more than 840,000 people especially gamers have been exposed to this assessment (gamerdna.com) [76]. The test contains 30 questions, and individual answers are calculated to reveal the player type also called Bartle quotient. Bartle quotient is a total 200% of all four preferences/dichotomies, and the maximum level of each single type is 100% [77].

The test is designed by putting equal number of questions in each category or preference (achiever, explorer, killer, and socializer). The type is determined through the dominant preferences (i.e. from the highest to the lowest preference score) and is denoted by the first capital letter of each preference[5].

2.3.1.1 Working example

As mentioned earlier, to calculate Bartle quotient Bartle's player types test should contain equal number of questions (or choices) for each dichotomy. In other words, if Bartle's player types test consists of 30 questions, and if there are 2 choices per single question; we have 60 choices in total, meaning there are 15 choices per single dichotomy (i.e. achiever, explorer, killer, and socializer). More specifically, if an individual selects 10 choices out of 15 for a specific dichotomy, it means that we can consider this individual as a person who prefers such a dichotomy with a percentage of 66.6%.

Consequently, let us assume that 2 persons answered the test questions and their scores on four dichotomies were as follows (Table 2):

---

[4] http://www.gamerdna.com/quizzes/bartle-test-of-gamer-psychology/take?cobrand=
[5] http://www.andreasen.org/bartle/

Achiever	Socializer	Explorer	Killer	Bartle's Type
20%	70%	80%	30%	ESKA
70%	20%	60%	50%	AEKS

Table 2 Bartle Quotient of Player Types

Obviously, Bartle's type for the first person (in the first row) will be calculated as E.S.K.A (Explorer, Socializer, Killer, and Achiever) and for the second person (in the second row) as A.E.K.S (Achiever, Explorer, Killer, and Socializer) [77].

2.4 Machine Learning and Classification

2.4.1 Machine learning

Machine learning can find out how to achieve significant tasks by generalizing from data samples [78], which is highly practical and cost-effective. Also, there is lately availabe data that can address more problems [78]. Machine learning is commonly and widely used in the fields that depend on knowledge extraction (i.e., pattern recognition [79, 80], computer vision [81, 82], bioinformatics [79, 83], games [84, 85], and natural language processing and speech recognition [86, 87]. According to [88] machine learning might be described as a combination of three contents or stages:

- *Representation*, meaning that the classifier should be formed by using formal language that should be understandable and processable by the machine. Consequently, if the space of the problem does not match with the classifier's capabilities, then the classifier will not be able to learn.
- *Evaluation* (also called scoring function) is a level of learning, in which good and bad classifiers will be discriminated.
- *Optimization* is the final level, in which it is paramount to highlight the optimum classifier from the good ones that have been distinguished (i.e., from the previous level).

There are many perspectives and methods that are dedicated to achieve the aim of machine learning (i.e., artificial neural network (ANN), support vector machine (SVM), decision tree (DT), Naive Bayes, and k-means) [78]. In general, machine learning algorithms might be classified into three major types, namely, un-supervised, supervised and reinforcement learning algorithms. In addition to these major types, a new type named semi-supervised learning algorithm was derived from the supervised learning algorithm [89]. The differences between each of these types might be illustrated as follows:

- Unsupervised Learning Algorithm: In this type of learning methods, training datasets are not required. In other words, the output can be simply and directly concluded and delivered from the inputs (i.e., the incoming dataset). In addition, implementing the input data of such tasks is an easy and a rapid process. However, the accuracy of such methods is still limited due to the absence of relations to the taken data samples [78, 89].
- Semi-supervised Learning Algorithm: This algorithm is between unsupervised and supervised learning. It was founded to solve the problems that cannot be solved properly through supervised learning algorithms. The algorithms here are provided with unlabelled training data along with some supervising information [89].
- Supervised Learning Algorithm: This type of algorithm is able learn the structure of the algorithm and parameters based on labelled training dataset. In other words, such types of algorithms are able to predict the solution by learning from input data samples. Therefore, supervised learning is more flexible than unsupervised learning. Supervised learning is also called classification, which is the most commonly used technique in data mining [91]. There are many methods of supervised learning such as artificial neural networks, support vector machine, and decision trees [89, 92].
- Reinforcement Learning Algorithm: This type focuses on the idea of learning by trying to maximize the rewards when dealing with uncertain environment. It is inspired by behaviorism theory which assumes that individuals might learn from the outcome (e.g. rewards) of their actions. However, in machine

learning and artificial intelligence branches, selecting the most proper (rewarding) method can be considered as reinforcement learning method [90].

2.4.2 Artificial neural networks

Inspired by human nervous system, artificial neural network models have been introduced and used to achieve results and learning especially in areas where traditional approaches are not feasible [79, 88, 95]. Basically, an ANN consists of two main components: nodes (neurons) and weighted connections between nodes [79, 88]. Nodes are represented in layers [79, 88]. These nodes are connected by weighted connections between nodes of each layer to its previous layer [79, 92]. A typical neuron consists of three general functions: accumulation, activation, and output functions [93]. Figure 6 shows a typical artificial neuron[6].

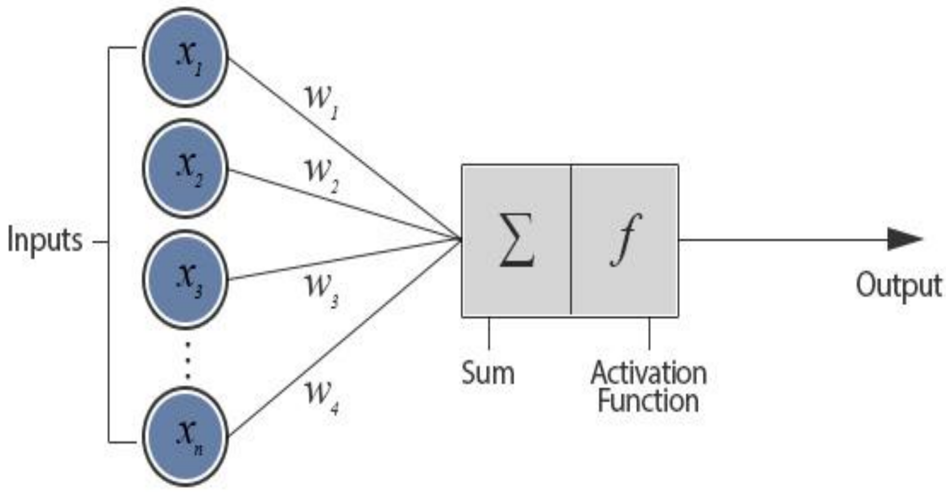

Figure 6 Typical artificial neuron node

The typical neural network is shown in Figure 7:

[6] Figures 6 and 7 are adopted from http://www.theprojectspot.com/tutorials/page/1.

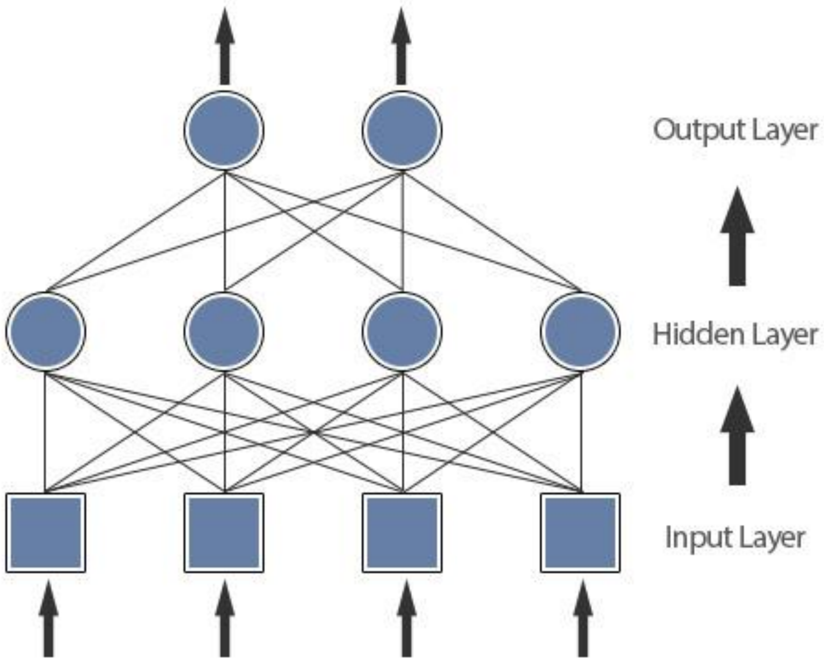

Figure 7 Neural network graph

However, ANN models differ from each other in three main parameters: (i) the approach of connections, (ii) the learning procedure and updating of weights, and (iii) the type of activation function [78, 93].

2.4.3 Multi layer perceptron neural networks

Multi Layer Perceptron (MLP) is one of the most popular and commonly used neural network methods especially in pattern recognition and classification for its high ability to learn complex patterns [93, 94].

MLP model consists of 3 connected layers: input layer, one (or more) hidden layer(s), and output layer. These layers are connected together by weighted connections. The input of each node in layer k+1 is the summation of all outputs from nodes in layer k (see figure 7). The number of nodes in input layer is equal to the number of attributes in the input vector[7]. Hidden layer(s) and nodes in each layer are up to the designer as they are variable parameters and should be managed carefully for better efficiency.

[7] Vector is a pair of input: desired-output pattern that is used to learn BP model

And the final output from the output layer nodes represents the predicted class (each node in output layer represents a single class) [79, 94, 95].

Generally, in MLP models with BP learning algorithm, input data goes forward to the output layer with no feedback. Hidden layer nodes transfer data to the nodes of the next layer based on the result of activation function of each node. Frequently, MLP method uses sigmoid function as an activation function, and error back propagation as a learning rule algorithm. In other words, BP model first initiates with small random weights, and a desired error rate. The learning process is achieved by using input: desired-output pair vectors to adjust the weights in order to minimize the error rate (i.e. calculate the difference between the real error and the desired error rates for all nodes in output layer). Next, back propagation process corrects the weights [94, 95, 96].

The algorithm of BP is presented in the following section [93] in the form of pseudo code.

2.4.3.1 BP algorithm

1. Weights initialization: Initialize the weights matrix by giving small random numbers (ranging from 1.0 to -1.0). And set the other required parameters (i.e. learning rate, error rate, maximum iterations, and threshold).
2. Forward propagate the input vectors (from *I*) with corresponding target vector (from *T*).
3. Compute the input and output of each node in all hidden and output layers. Input to nodes in hidden layer (e.g. node *j*) can be calculated using the following equation:

$$I_j = \sum_{i=1}^{p} W_{ij}\, O_j + \Theta_j \tag{2.1}$$

   And the output from node *j* can be computed via the following equation:

$$O_j = \frac{1}{1 + e^{-Ij}} \tag{2.2}$$

   Consequently, output values from hidden layer nodes are the input values to the nodes of output layer (as in our case we have only one hidden layer). Input to nodes in output layer (e.g. node *j*) can be calculated using the following formula:

$$I_j = \sum_{i=1}^{q} W_{ij}\, O_j + \Theta_j \tag{2.3}$$

And the output from node *j* can be computed by using (2.2).

4. Back-propagation of the error: The error is fed backward with respect to the weights and threshold. The error of a unit *j* in output layer can be computed using the following equation:

$$Error_j = O_j\left(1 - O_j\right) O_j\left(T_j - O_j\right) \tag{2.4}$$

And the error of unit *j* in hidden layer can be computed using the following equation:

$$Error_j = O_j\left(1 - O_j\right) \sum_{k=1}^{r} Error_k\, W_{jk} \tag{2.5}$$

5. Update weights and threshold. Weights can be updated using the following equations:

$$\Delta W_{ij} = \delta Error_j O_j \tag{2.6}$$

And

$$W_{ij} = W_{ij} + \Delta W_{ij} \tag{2.7}$$

And threshold can be updated using the following equations:

$$\Delta\Theta_j = \delta Error_j \tag{2.8}$$

And

$$\Theta_j = \Theta_j + \Delta\Theta_j \tag{2.9}$$

6. Check for stop:

   If (max-iteration), then Return (weights) and Exit. Else

   If (Error of vectors) less than (error rate), then Return (weights) and Exit. Else go to step: 2.

where,

I_j : Input to node *j*.

O_j : Output of node *j*.

Θ_j: Threshold of node *j*.

T_j : Target output from node *j*.

W_{ij} : Weights matrix that connects unit *i* in layer *L* to unit *j* in layer *L+1*.

$Error_j$: Error of unit j.

δ: Learning rate.

p, q, r: Represent the numbers of input nodes, hidden nodes, and output nodes, respectively.

2.5 Related Literature

The investigation of psychometric properties (e.g. traits, motivation, and personal preferences) of individuals has been studied and employed in many different disciplines such as software engineering [45], game development [97], economics [98, 99]. Different methods have been utilized to assess personality types of participants such as MBTI [36], Keirsey's Temperament Sorter (KTS) [100], and Bartle's player type [21].

Yee [101] surveyed online about 30.000 MMORPG users to investigate their motivations, evoked experiences, and demographics. Results show that MMORPGs engage wide range of users of different ages 22 hours/week on average. Additionally, it was observed that the motivations of users were affected by five factors: achievements, immersion, escapism, relationships, and manipulation. Male users were found to be engaged more by factors of achieving and manipulation, while female users prefer relationship factor. As a conclusion, MMORPG environment is an interesting and powerful field to be further researched and implemented.

MUDs have also used in new areas such as corporate and educational platforms and environments for distance learning [102], which deserve more investigation.

Cowley et al. [103] state that employing machine learning methods to explore gameplay experience/player type is in its infancy. In their study, they trained two flavours of Decision Tree method (i.e. CART and C5.0) and DGD player taxonomy on Pac-Man gamers to select appropriate rules for the classification. Training set contained 100 instances, while the testing set contained 37 instances; and the validation testing performance of classifier was about 70%.

Drenman and Keeffe [104] suggest considering economic issues together with in-game player behaviours. They point to the investigation of different products and services and the offering-consuming behaviors of players according to player typology of Bartle. Such an approach has been used to classify consumption behavior of players in MMORPG environment.

Pang et al. [105] propose an approach to classify MMOG players according to their relationship network. Their research suggests that since core players can affect other players, game designers and industry should take this in consideration.

Aruan et al. [106] developed a virtual tutor agent (VTA) that is suitable for multiple users, and problem-based learning in cooperative environments inspired by MMOG methods and techniques. Both conceptual issues of learning using interface-supported cooperative environment and technological issues of deploying/dealing with massive users from MMOG perspective were combined together. In addition, some applications and coding have been used to achieve the goal, and the result was acceptable.

Borbora and Srivastava [107] depended on the life-cycle of MMORPG players to model their churn behavior. The goal was to measure and analyze the activity traits of both churners and traditional players. To enhance evoked features, three levels of semantic (engagement, persistence, enthusiasm) have been used. The suggested method was based on labelled clusters and weighted distance between them. The performance of the proposed classifier to predict such patterns was good compared to the use of other classifying models (e.g. SVM, and Naive Bayes). Additionally, they suggested a distance-based classifier called "wClusterDist" using the behavioral profiles that been collected. The suggested classifier results in reasonable performance, but it has not been tested for other different cases.

To reduce the costs of monitoring and analyzing player behavior, Kang et al. [108] proposed an automated system for the analysis of MMOG players' behaviors using trajectory (non-parametric) clustering algorithm with simple data. At first, they classified the data hierarchically, and then used trajectory clustering algorithm to analyze behaviors. The system was tested on world of warcraft (WoW) environment and the results were good in both analyzing player's behavior and creating players' experience insights and profiles automatically.

Ho and Thawonmas [109] proposed a model to convert sequences of MMOG players' actions into sequences of episode. The model test shows that the performance of classifier exceeds the performance of other approaches that work on action or item sequences. However, Matsumoto and Thawonmas [110] used player-action approach with hidden markov model (HMM) as a classification model and the results were acceptable in classifying different player types with common action.

Lotte et al. [95] reviewed a number of most commonly used classification methods (e.g. SVM, MLP, HMM) and compared their performances to find the most proper classification algorithm(s) for brain-computer interface (BCI) using electro-encephalo-graphy (EEG) dataset (i.e. BCI is a communication system, in which no external device activity is required [111]). In other words, a BCI is a system that enables a peripheral to send commands to other electronic device(s) through brain activity [112]. Electro-encephalo-graphy (EEG) can be defined as:

> *"The recording of electrical activity along the scalp. And EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain"* [113].

The results and efficiency of each classifier were analyzed and compared with other classifiers to present a concrete base of knowledge that can be considered when choosing the proper classifier for a specific task. In general, for BCI using EEG dataset, it was found that SVM performs better than other classifiers. However, the performance of MLP was also acceptable for this task, as neural networks are commonly used in BCI research.

2.6 Summary

This chapter explains the tools that are used in this study, and presents some related studies. As MOOCs are new, very few previous studies explored the participants as gamers. Furthermore, so far only a few studies have tried to use machine learning methods to classify MMOG gamers [108, 109]. Additionally, the current exploratory research classifies MOOC base on MMOG gamers' player type, which can be considered as one of the contributions of this study. In the next section, we discuss the proposed methodology that is used to achieve the goals of this research study.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter explains our proposed method to achieve the goals of this study. It details the story of data collection process, and explains the two phases of the proposed method. Phase 1 details the steps for exploring personality types (i.e., using MBTI assessment), and player types (i.e., Bartle's player types). And phase 2 presents the steps of preparing datasets, and basics for training and testing the automated classifier (i.e., using BP algorithm).

3.2 Methodology

The approach used in this study consists of two main phases. In the first phase, we conducted a survey to assess personality types of individuals. The goal was to reveal the personality type of participants using MBTI. Next, the results were used for investigating types of participants based on Bartle's player types. In the second phase, a dataset was produced based on Bartle's player types that were investigated in phase one, and the responses of participants to Bartle's test. This dataset was used to train and test a machine-based BP classifier of player types. Figure 8 illustrates the suggested methodology.

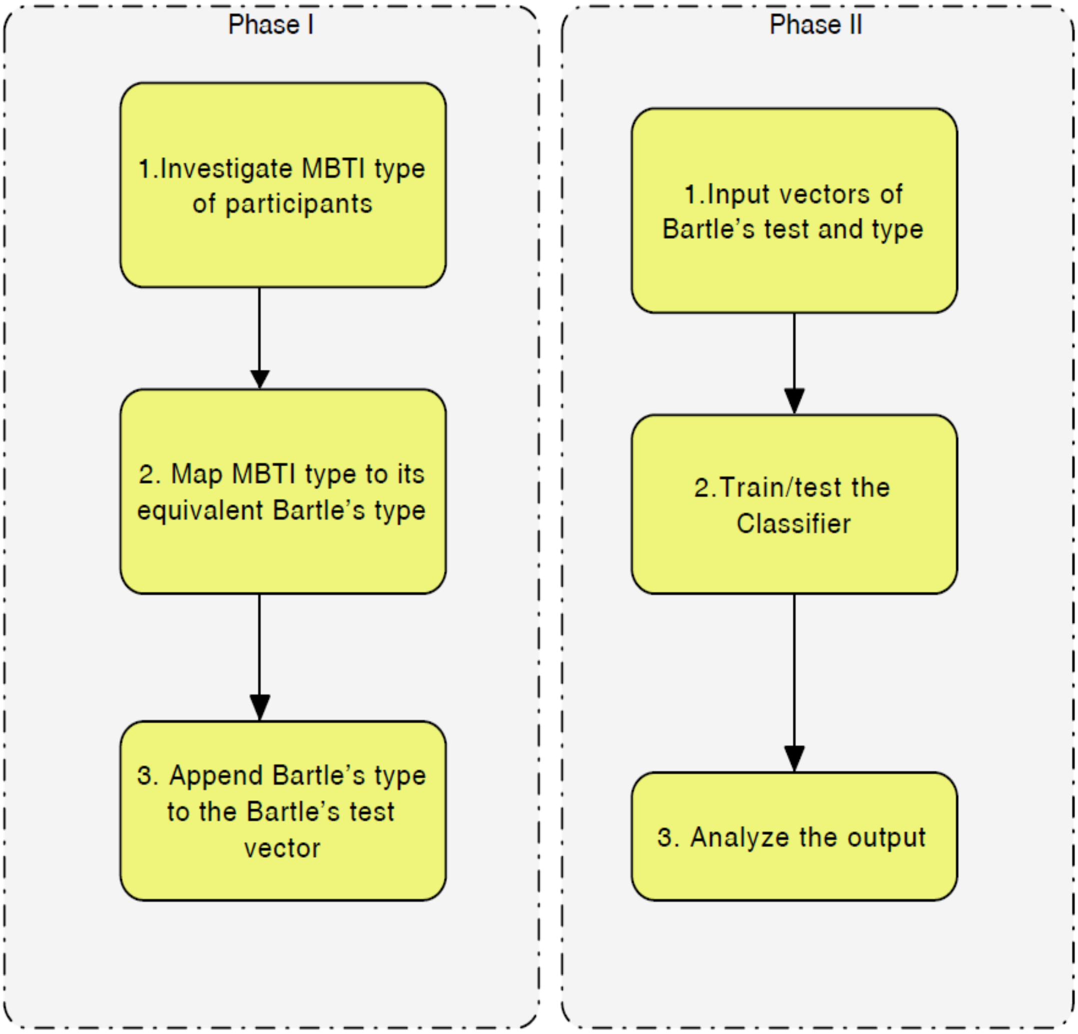

Figure 8 Methodology

The data were collected by means of a questionnaire, which includes 55 questions under 3 categories to explore: (i) demographics of MOOC participants (5 questions), (ii) personality traits using short version of MBTI (20 questions), and (iii) Bartle's player assessment (optional 30 questions). Appendix A explains the purpose of survey, and provides the respondents with some information about answering the questions. Appendix B illustrates the body of survey in details. The survey was created using Google forms, and it was published online for 5 months (From May to September, 2014). To make sure that the responses are reliable to be used as input data, we surveyed only the people who attended at least one MOOC and played at least one MMOG. However, people do not really like to answer surveys. This is the main problem we faced during the data collection process.

3.3 Phases

In this subsection, steps in each phase were discussed in detail.

3.3.1 Phase 1: Exploring player types

1. Investigate the personality type of MBTI assessment for each participant using the four dichotomies that discussed previously [37]. Table 3 illustrates the procedure of evaluating MBTI types.

Put1 point for selecting the first choice, and 2 points for selecting the second choice of any question.			
Sum points for questions (1, 3, 6, 8, and 12).	Sum points for questions (2, 5, 11, 15, and 19).	Sum points for questions (10, 13, 16, 18, and 20).	Sum points for questions (4, 7, 9, 14, and 17).
According the total number of each column above, select the appropriate letter from columns below:			
E If the total points were less than or equal to 7.	S If the total points were less than or equal to 7.	T If the total points were less than or equal to 7.	J If the total points were less than or equal to 7.
I If the total points were greater than or equal to 8.	N If the total points were greater than or equal to 8.	F If the total points were greater than or equal to 8.	P If the total points were greater than or equal to 8.

Table 3 Calculation of MBTI Types

2. Explore Bartle's player type of each participant according to his/her personality type that has been investigated in step 1. The main assumption for this study is that basic psychological models of game playing styles and behaviors cab be explored and unified in one model [114]. Consequently, we used Bart's unified model, which explored the most common gameplay styles and player models (e.g. Bartle's player types, Cailloiss playing styles, and Lazzaros types of fun) and game design models (e.g. Gamist/ Narrativist/

Simulationist (GNS), and MDA framework) and which showed that all those approaches can be considered as one identical model. Furthermore, a linkage was proposed between both Keirsey temperaments (four distinctive patterns concluded out of 16 types of Myers-Briggs model of personalities) [100, 115] and Bartle's player types [114]. Figure 9 shows the mapping of MBTI 16 types (4 types in terms of Keirsey temperaments) to Bartle's types of players using a periodic table form adopted from [45]. Here, Figure 9 presents a linkage between MBTI-Keirsey and Bartle's player types.

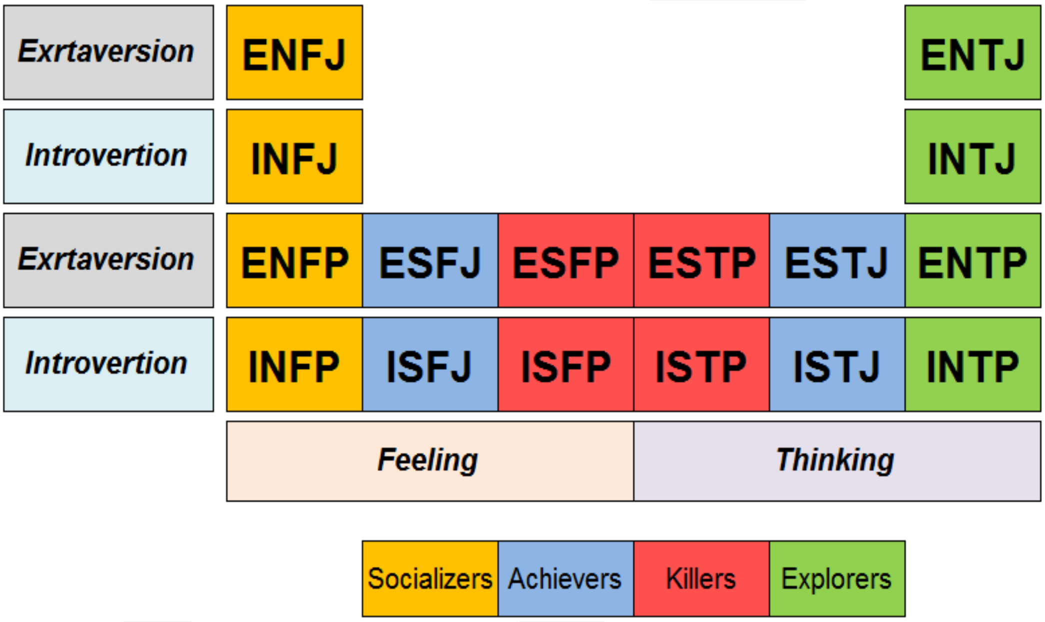

Figure 9 Mapping of MBTI types to Bartle's player types

According to the figure and in terms of Bartle's player types, the blue colored types have been considered as explorers, while green colored types represent achievers; yellow colored types represent socializers; and red colored types represent killers.

3. Attach the Bartle-type that has been explored in step 2 as a class at the end of Bartle's test questions for each participant.

3.3.2 Phase 2: Automated Classifier

In order to 1) cope with problems of missing data, 2) make use of the collected dataset continuously, 3) compare the previous methodology used in the first phase and to the methodology presented by the founders of Bartle's player types test, in classifying players to their Bartle's type, and 4) test whether the machine can learn and classify such patterns, we used one of the most powerful machine learning methods, the BP algorithm [92, 93, 94, 116], as automated classifier.

Specifically, the use of machine learning methods to train and test a proper classifier model in favor of automatical classification of MOOCs participants into their correspondent Bartle's player type will be explored in phase two. Bartle's players' type test questions are optional questions to be answered by survey respondents. By using respondents' answers to Bartle's type of player psychology questions, and player's type obtained from the previous phase, a reliable dataset can be collected. We split the data set into two distinctive sets: a training set (80% of instances), and a testing set (20% of instances).

Furthermore we used artificial neural network (ANN) method to train and test a classifier model towards better understanding and recognition of primitive behavior patterns [117].

The steps of this process were as follows:

1. Pre-processing data and preparing sets: For this level of the study we surveyed a population generally and anonymously, and explored their personality preferences as well as their demographic information and their experience with MOOCs. In addition, we explored the Bartle player types of all participants, even for those who did not answer the optional questions of Bartle's player test. By combining respondents' answers to the Bartle's type of player psychology questions with player's type obtained from the previous phase a testable dataset could be created.

   Pre-processing operations refer to the operations taken to convert, eliminate, organize, and generalize data in order to make it understandable by the classifier and ready to be tested [79]. In this manner, we replaced the text of each reply in the dataset with a given number related to the nature of the reply, according to Bartle's approach and taxonomy. After preparation and pre-processing, the next process was to split the data set into two distinctive sets: a training set (80% of instances), and a testing set (20% of instances). Each vector/instance of sets includes 31 entries (30 entries for Bartle's player test, and one entry to represent the class (player type) of this vector). It is important to split the data carefully, that is, both the training set and the testing set should contain all types (classes).

2. Train and Test the Classifier

   The machine learning artificial neural network (ANN) method, BP, was used to train-test a classifier model towards better understanding and recognition possibilities of behavioral patterns [117]. Different architectures and parameters of BP model were examined to find the most efficient model (under the condition of root mean square error (RE) of the learned BP should be less or equal to 0.2). A BP model consisted of 34 input layer nodes (one node for each Bartle's test question, and 4 extra nodes for MBTI 4 dichotomies) and 4 nodes in output layer (each node represents a single Bartle's player type).

The total number of respondents was 75 (who completed the first two categories; demographics part and personality preferences part of MBTI), and 55 respondents out of 75 respondents answered the third part (Bartle's test part) as well, while 12 respondents answered at least 27 out of 30 Bartle's test questions. The option of skipping questions was available only for the Bartle's test. The completed vectors (N=55) were used as training data set, and the partially completed vectors (N=12) were used for testing the BP classifier.

3.3 Summary

This chapter explains the proposed methodology of this study in detail. It presents the story of data collection process by means of a questionnaire, and the steps followed in this data to achieve the goals of this study. The proposed method consists of 2 general phases: (i) phase 1, in which we explore the personality types and player types of the participants (see research question 1). And (ii) phase 2, in which we apply BP algorithm to classify participants into their equivalent Bartle's player types (see research question 2). Next, we present and discuss the results.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Introduction

Chapter 4 explains the results of our study. It details the collected data in 4 categories: (i) demographics of participants, (ii) their personality types, (iii) their player types, and (iv) result of BP player types classifier with validation in different experiments. Lastly, limitations and threats to validity aspects are illustrated.

4.2 Overview

The total number of respondents was 75 of persons who completed at least the mandatory questions (the first two categories; demographic part and personality preferences part of MBTI), and 67 out of 75 respondents also answered the optional part (the third part which was related to Bartle's player psychology test). The option of skipping questions was available only for the Bartle's test. The processes of designing a survey, collecting data, and response/cooperation of people were some of the difficulties faced in this kind of research, alongside long, unpredictable time consumption, and other challenges such as the honesty of the participants. However, empirical results analyzed, compared, and delivered by dividing them into 4 categories: (i) demographics of participants, (ii) their personality types, (iii) their Bartle's player types, and (iv) the result of the player types automated classifier. This approach to presenting the results provides more details and allows better understanding of the findings.

4.3 Demographics

In this section, demographical aspects of our respondents will be presented. Respondents were asked about their demographics: age, gender, and level of education, along with 2 questions about their experience in MOOCs: number of MOOC(s) taken so far, and whether or not a participant will repeat this experience. Figures 10 through 14 absolutely illustrate the results of demographic information and MOOC experience of participants.

The majority of our participants were males (with percentage of 76%), while 24% of participants were females. In numbers, 57 participants were male, and 18 were female. Figure 10 shows the gender of the participants.

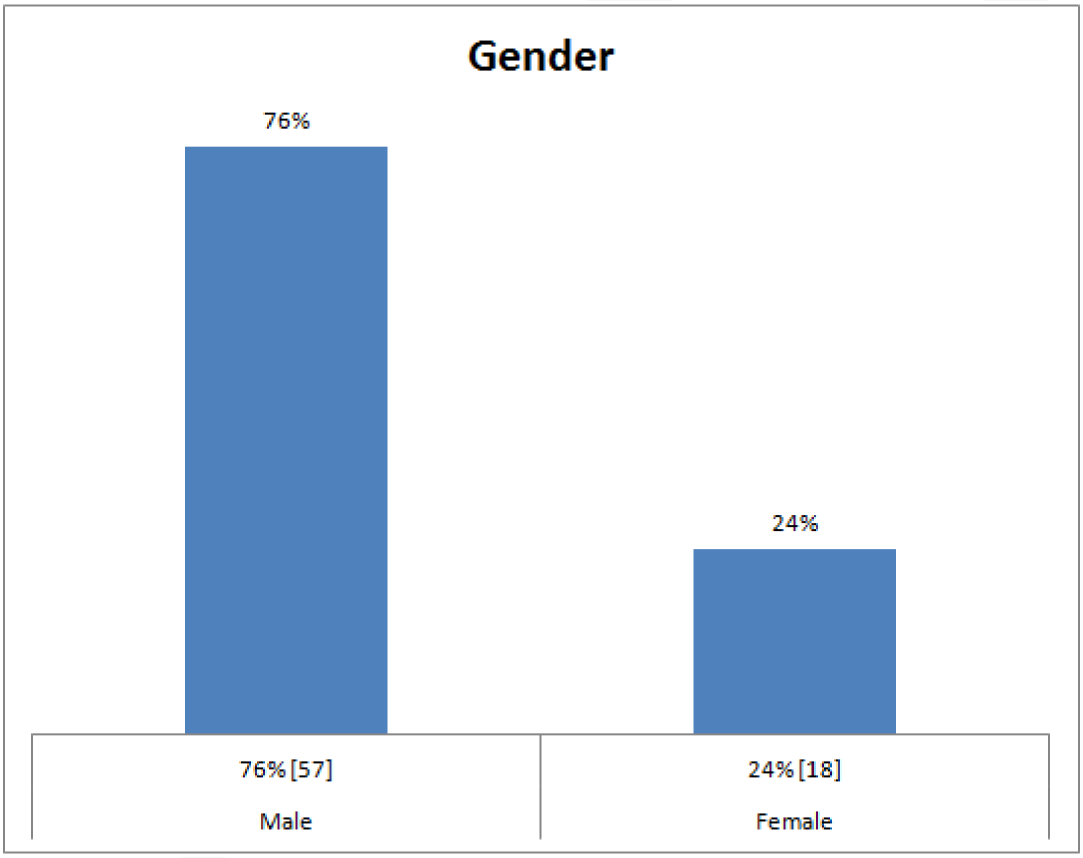

Figure 10 Gender of the participants

Analysis of the age factor of the participants revealed that 60% (45 persons) were within the range of 25 to 34 years old. In both the age group 18 to 24, and 35 to 44, were 19% of the participants (14 persons). 3% (2 persons) of the participants fell into the 45 to 55 age group. This shows that individuals age 25 to 34 are the most interested in attending MOOCs. Moreover, individuals aged 18 to 44 (representing about 98% of the participants) were the age groups most interested in the MOOCs movement. Figure 11 shows the age distribution of the participants.

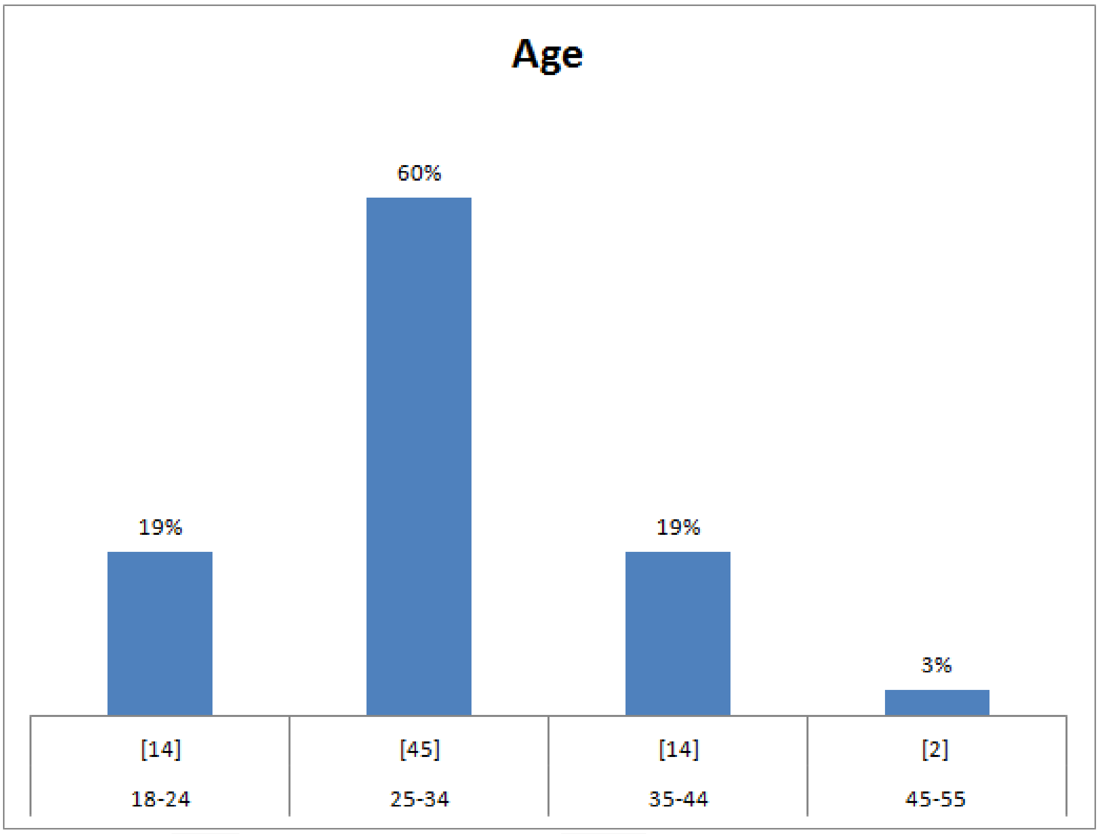

Figure 11 Age of the participants

Figure 12 shows education level of respondents. Of the participants 45% (34 persons) have a Bachelor degree, 44% (33 persons) have a Master degree, 5% (4 persons) have a high school degree, and 4% (3 persons) have a doctoral degree. The other education category represented about 1% (1 person). It is clear that individuals with Bachelor and Master degrees represent about 90% of individuals, which means they are the most interested ones about MOOCs.

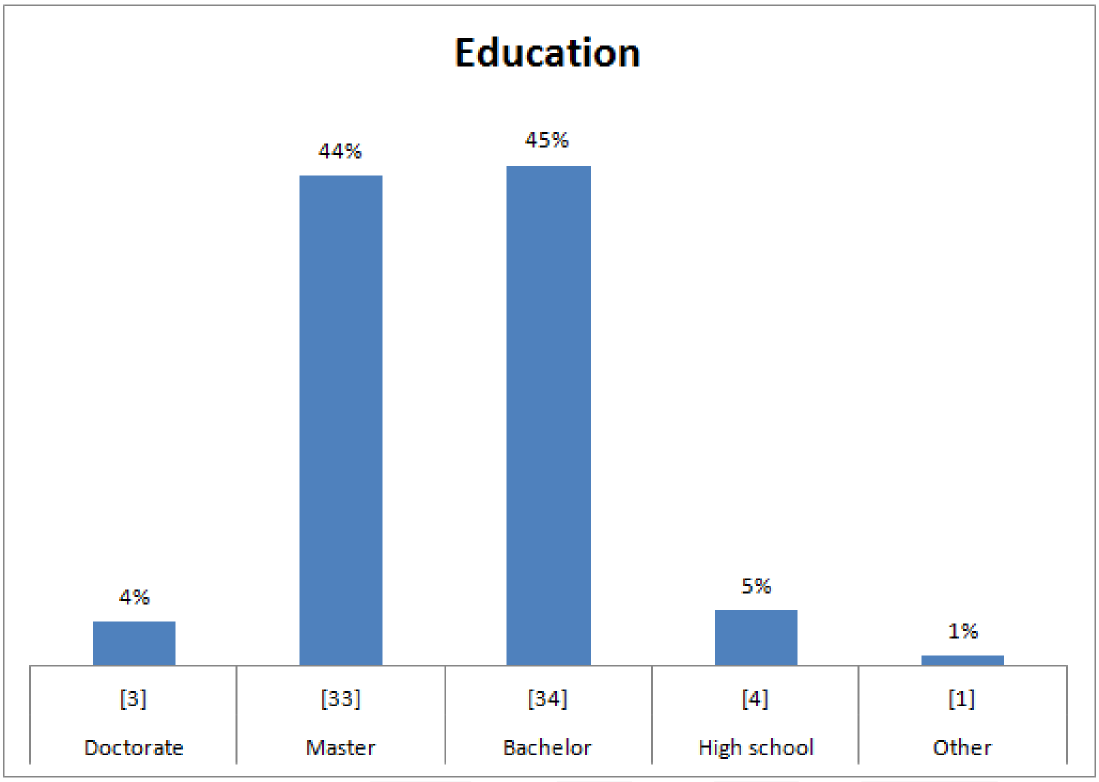

Figure 12 Participants' level of education

Figure 13 shows participants' previous experience with MOOCs. It is seen that 69% (52 persons) of the participants attended 1 MOOC, 13% (10 persons) attended 2 to 3 MOOCs, 9% (7 persons) attended 4 to 6 MOOCs, and 8% (6 persons) attended more than 6 MOOCs.

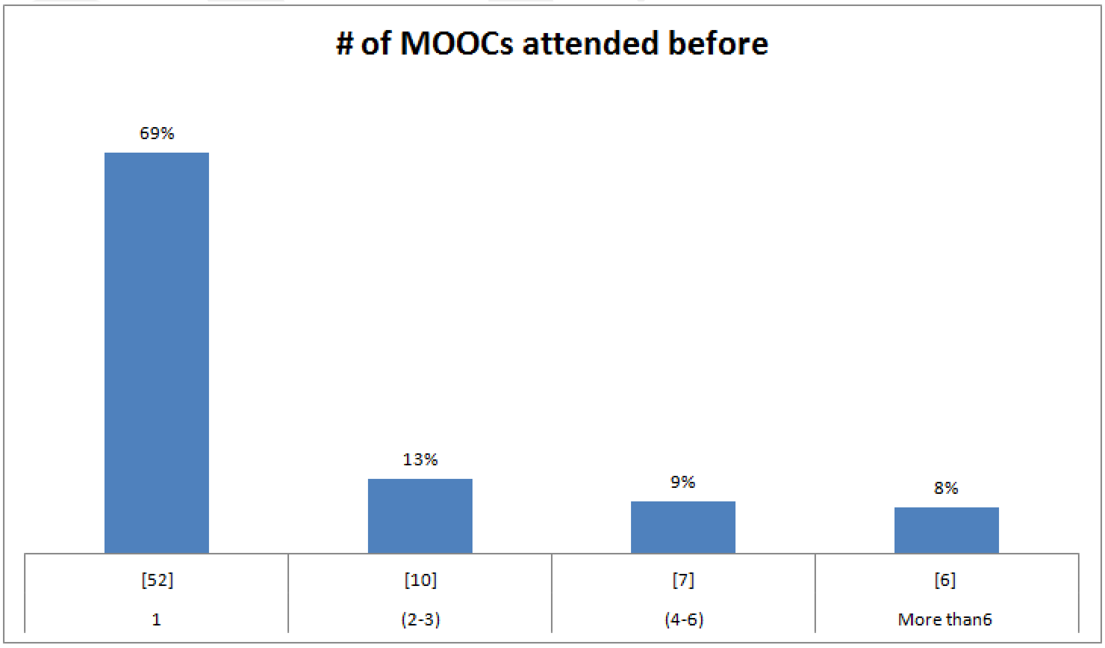

Figure 13 Number of MOOCs attended

Will you attend more MOOC(s)? This was question number 5 of the sur vey, and can be considered a question that illustrates our participants' opinion about their experience with MOOCs, their needs, motivations and engagement. Of the participants 55% (41 persons) answered Yes, and 45% (34 persons) No. Figure 14 shows participants' willingness to taking MOOCs in the future.

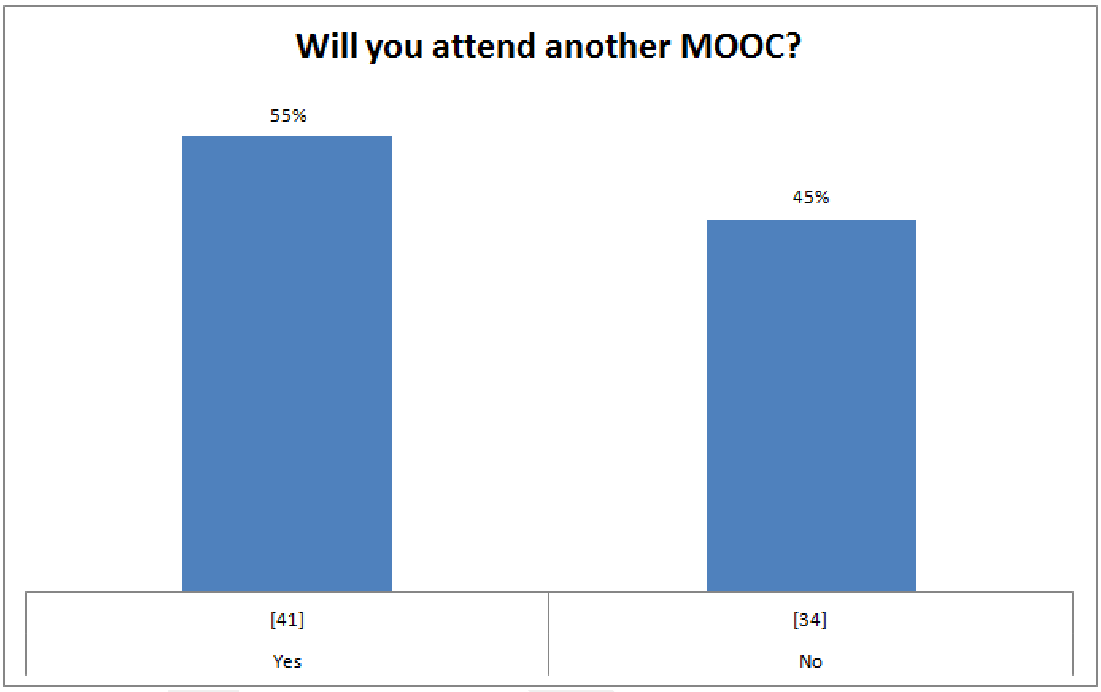

Figure 14 Attend more MOOCs responses

Appendix C illustrates the demographic information of respondents in details.

4.4 Personality Preferences

Personality preferences were explored with the MBTI tool. The results of matching participants with their personality types, along with percentages and number of individuals for each type are shown in Figure 15 using the periodic table approach (also see figure 9).

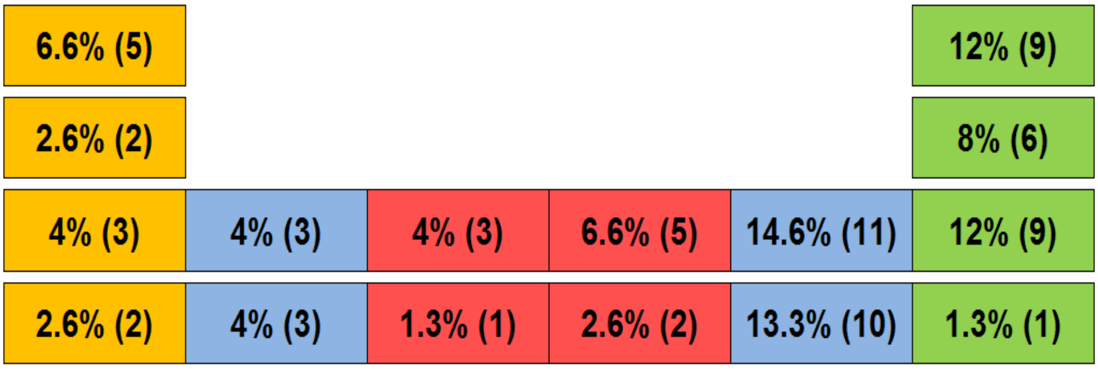

Figure 15 Distribution of participants into their MBTI types

In addition, as seen in Figure 15 above, a general view of participants' preferences can be derived. Table 4 illustrates the general preferences of participants.

Participants	E/I		S/N		T/F		J/P	
All	64%	36%	51%	49%	70%	30%	65%	35%

Table 4 Distribution of Participant's Preferences over 4-dichotomies

Furthermore, for better analysis and understanding of Table 4 above, a radar chart[8] [118] might be a suitable method here (representing MBTI dichotomies as polar coordinates to visualize them in a form of radar chart is proposed by [45], which contains more information about this model). Figure 16 shows a radar chart of Table 4 above. It clearly reveals the general directions among the preferences of the participants.

[8] A radar is a graphical method used to represent multiple variables of data in 2 dimensional polar space. So, it represents variables together for clearer analysis and comparison of these variables.

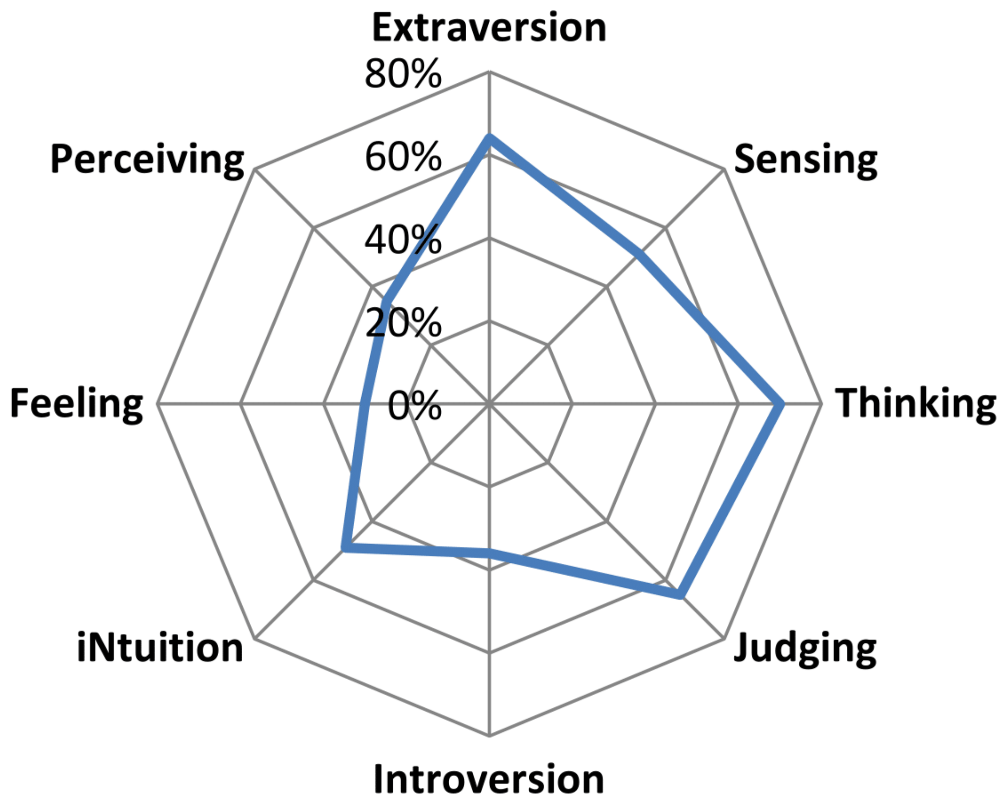

Figure 16 Radar graph of participants' preferences

The radar graph in Figure 16 illustrates that the general directions of our participants' preferences went more toward extraversion, sensing, thinking, and judging rather than introversion, intuition, feeling, and perceiving, respectively. However, the percentages of sensing/intuition preferences were close to each other, which means bringing achievements is done by sensing efforts (51% of the participants) and by intuition efforts at the second stage (49% of the participants). In addition, it is noticeable that the thinking preference was the dominating function among the participants. Furthermore, judging preference was higher than perceiving, which reveals that the participants prefer to use planned methodologies rather than using light practice techniques.

Appendix D illustrates participants' responses to personality preferences questions (i.e., the MBTI assessment) in detail (also see table 3). Appendix G shows participants' personality types.

4.4.1 Personality and demographics

Correlating participants' demographics results with their personality preferences that were extracted using MBTI instrument was very helpful in better understanding the participants. Here, the correlations between both demographic information and personality preferences derived from the MBTI will be presented.

Firstly, gender information versus personality preferences were investigated, the results of which are shown in Table 5.

Gender	E/I		S/N		T/F		J/P	
Male	60%	40%	54%	46%	81%	19%	63%	37%
Female	78%	22%	39%	61%	39%	61%	72%	28%

Table 5 Gender versus Personality Preferences

In addition, the radar graph for gender versus personality preferences distribution is shown in Figure 17 below:

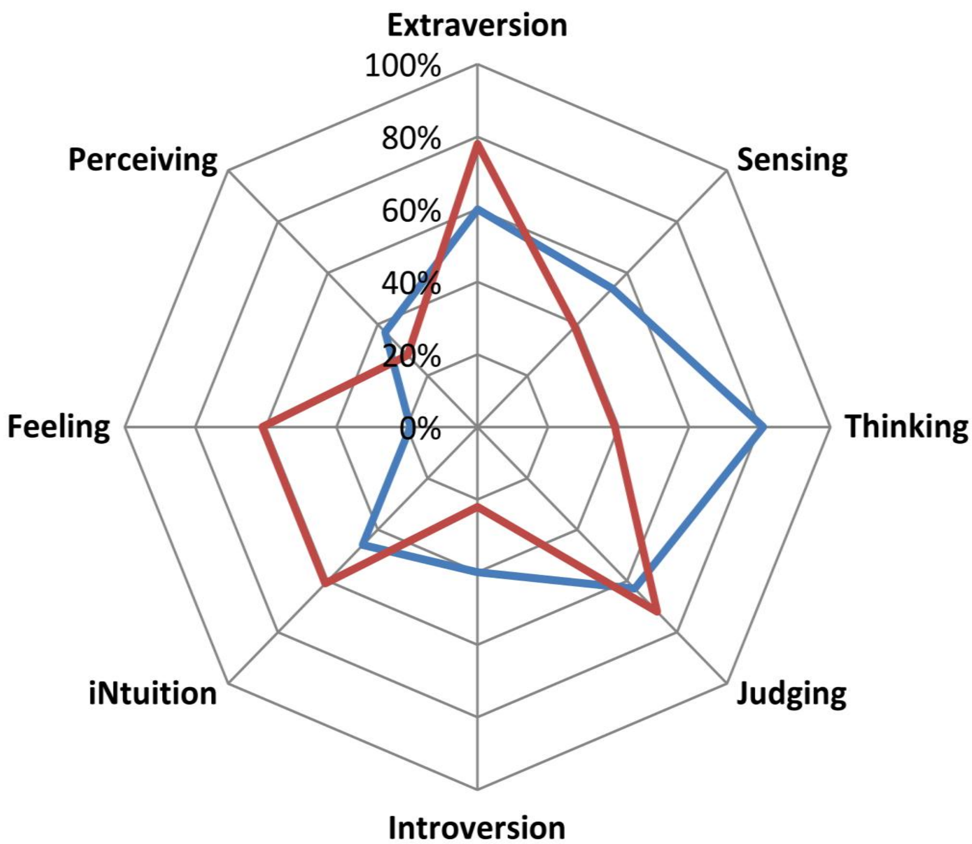

Figure 17 Participants' preferences radar graph over gender

Figure 17 above illustrates that male participants' preferences were extraversion, sensing, thinking, and judging rather than introversion, intuition, feeling, and perceiving, respectively. In addition, the thinking preference was the dominant preference. On the other hand, female participants' preferences were extraversion, intuition, feeling, and judging above introversion, sensing, thinking, and perceiving, respectively. Furthermore, extraversion and judging were the dominant preferences of the female participants.

Secondly, correlation between age and personality preferences was investigated. The correlation between age and personality preferences is presented in Table 6.

Age	E/I		S/N		T/F		J/P	
18-24	72%	28%	57%	43%	50%	50%	57%	43%
25-34	58%	42%	43%	57%	76%	24%	69%	31%
35-44	71%	29%	36%	64%	79%	21%	64%	36%
45-55	100%	0%	50%	50%	50%	50%	50%	50%

Table 6 Age versus Personality Preferences

The radar graph of Table 6 is shown in Figure 18.

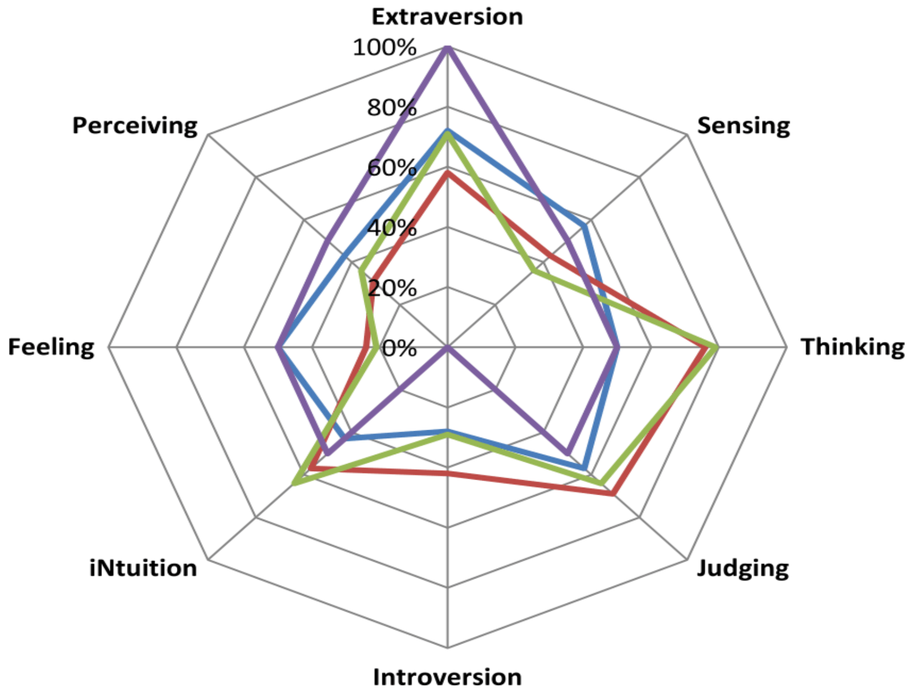

Figure 18 Radar graph of participants' preferences over age

The radar chart in Figure 18 above shows that the participants' preferences over all age groups were extraversion, intuition, thinking, and judging above introversion, sensing, feeling, and perceiving dichotomies, respectively. In addition, thinking preference was the dominant dichotomy for all age categories. Specifically, the preferences of participants from age category (18-24 year old) were: extraversion, sensing, thinking or feeling dichotomy result was equal, and judging. The preferences of participants from age category (25-34) were: extraversion, intuition, thinking, and judging, while the preferences of participants from age category (35-44) were: extraversion, intuition, thinking, and judging. However, the preferences of participants from age category (45-55) were equal (except for E/I dichotomy, they are all with extraversion preference).

Thirdly, education level of the participants versus personality preferences were investigated, the results of which are shown in Table 7.

Education	E/I		S/N		T/F		J/P	
High Sch.	50%	50%	50%	50%	75%	25%	75%	25%
Bachelor	65%	35%	44%	66%	68%	32%	65%	35%
Masters	61%	39%	55%	45%	73%	27%	67%	33%
PH.D	100%	0%	67%	33%	100%	0%	67%	33%
Other	100%	0%	100%	0%	0%	100%	0%	100%

Table 7 Education Level versus Personality Preferences

The radar graph of Table 7 is shown in Figure 19 below:

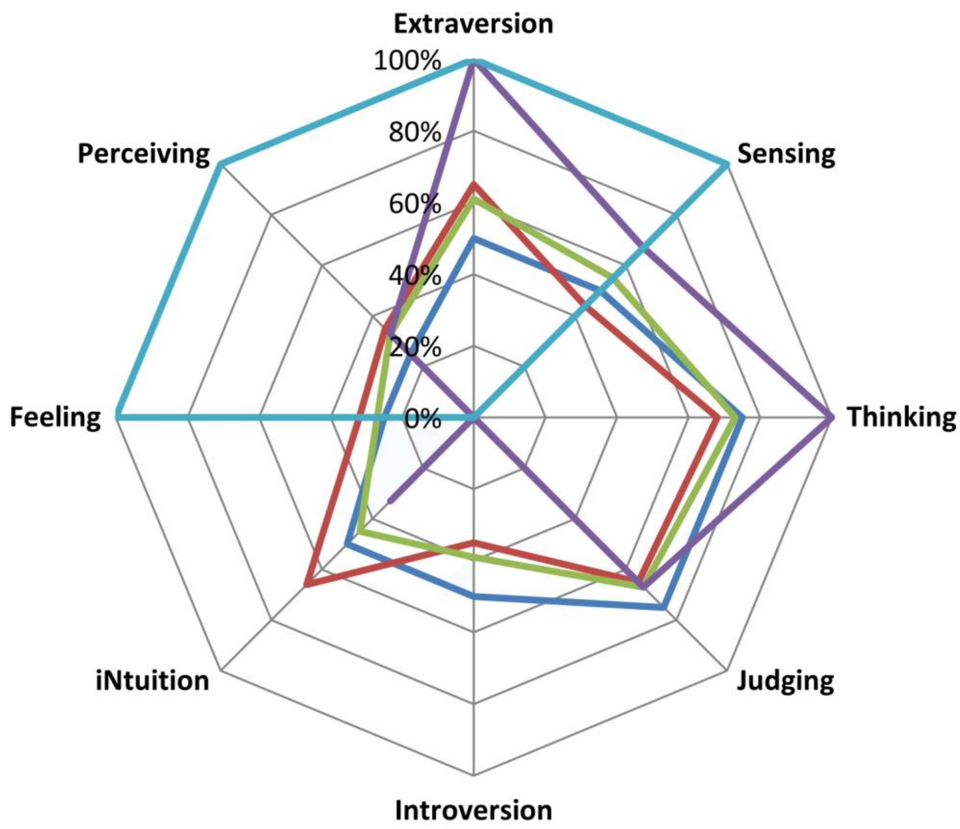

Figure 19 Radar graph of participants' preferences over education

Figure 19 above illustrates that the general dichotomies of participants were: extraversion, sensing, thinking, and judging above introversion, intuition, feeling, and perceiving, respectively. In addition, the thinking preference was the dominant dichotomy.

Fourthly, the number of MOOCs attended before by participants was analyzed in relation to personality preferences. The results are illustrated in Table 8.

No. of MOOCs	E/I		S/N		T/F		J/P	
1	67%	33%	46%	54%	67%	33%	63%	37%
2-3	60%	40%	60%	40%	100%	0%	80%	20%
4-6	43%	57%	71%	29%	43%	57%	57%	43%
More	67%	33%	50%	50%	83%	17%	67%	33%

Table 8 Experience in MOOCs versus Personality Preferences

Figure 20 shows the radar graph of Table 8.

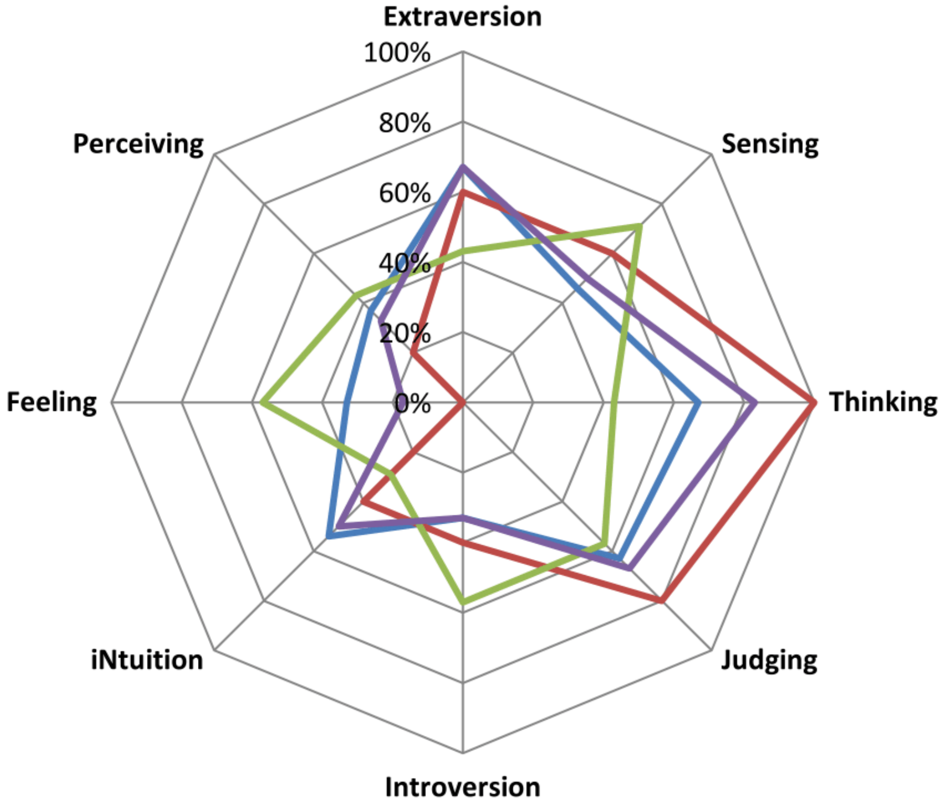

Figure 20 Radar graph of participants' preferences over MOOCs experience

However, Figure 20 above illustrates that the general dichotomies of participants were extraversion, sensing, thinking, and judging above introversion, intuition, feeling, and perceiving, respectively. In addition, judging preference was the dominant dichotomy.

Fifthly, participants were asked if they were motivated to attend other MOOCs. This information was correlated with personality preferences. The results are illustrated in Table 9 below.

Attend more?	E/I		S/N		T/F		J/P	
No	70%	30%	59%	41%	70%	30%	62%	38%
Yes	59%	41%	46%	54%	71%	29%	68%	32%

Table 9 Attending Other MOOCs versus Personality Preferences

Figure 21 below shows the radar graph of Table 9.

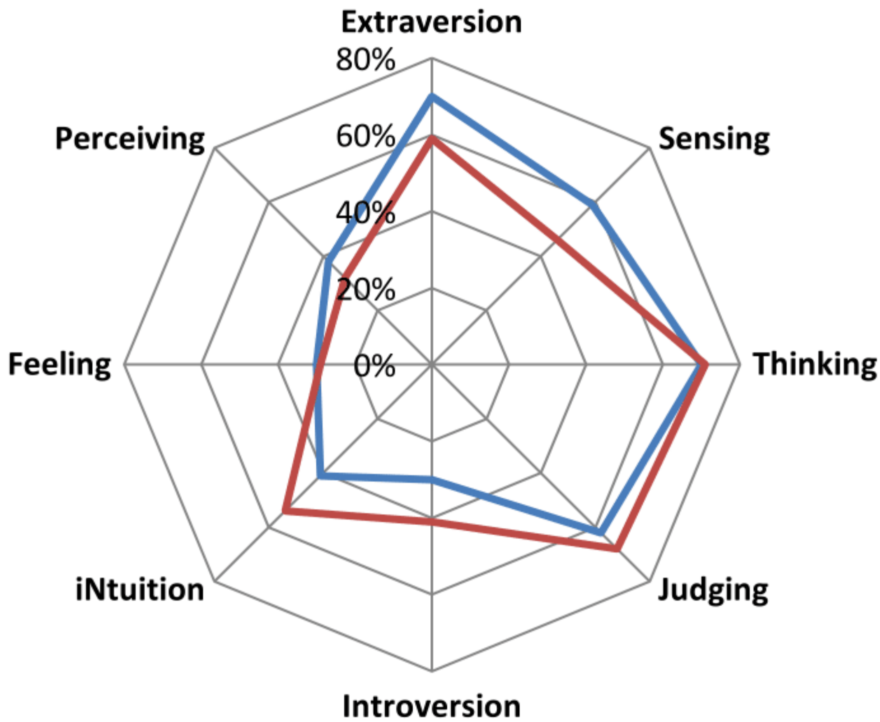

Figure 21 Radar graph of participants' preferences over MOOCs attending

Figure 21 above illustrates that the general dichotomies of participants were: extraversion, sensing, thinking, and judging above introversion, intuition, feeling, and perceiving, respectively. In addition, thinking preference was the dominant dichotomy. The personality preferences of participants who decided not to attend other MOOCs were extraversion, sensing, thinking, and judging. On the other hand, personality preferences of participants who decided to attend more MOOCs in the (foreseen) future were extraversion, intuition, thinking, and judging.

4.5 Bartle's Player Types

In phase 1 of the presented methodology, exploration of Bartle's game player types was achieved. Figure 22 shows the distribution of participants in percentages and numbers into their corresponding Bartle's player types, using the periodic table approach.

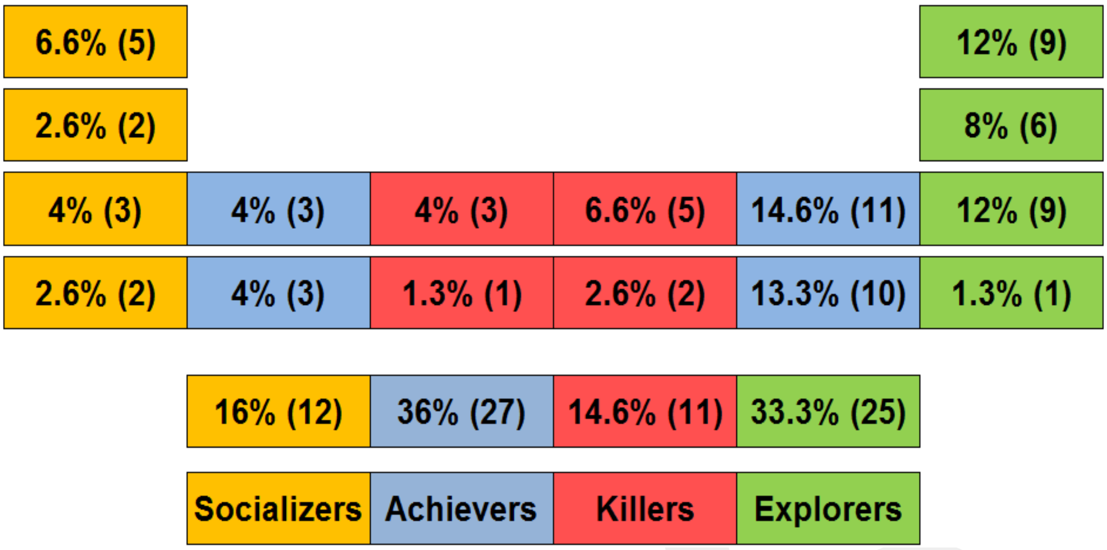

Figure 22 Bartle's player types by means of MBTI representation

Figure 22 above illustrates that achievers were the highest in number with percentage of 36% of our population, followed by explorers with a percentage of 33.3%. Socializers formed 16% of the population, and killers 14.6% of the population.

Appendix E illustrates the responses to Bartle's player types test in details. Also see appendix F, which illustrates the personality preferences and Bartle's player types.

4.5.1 Bartle's player types and Demographics

Correlating Bartle's player types' results with demographics information provided a detailed understanding about participants.

Figure 23 shows the gender of participants mapped onto their correspondent player types of Bartle. It shows that the Bartle's player type for the majority of male participants was achiever, while it was socializer for female participants.

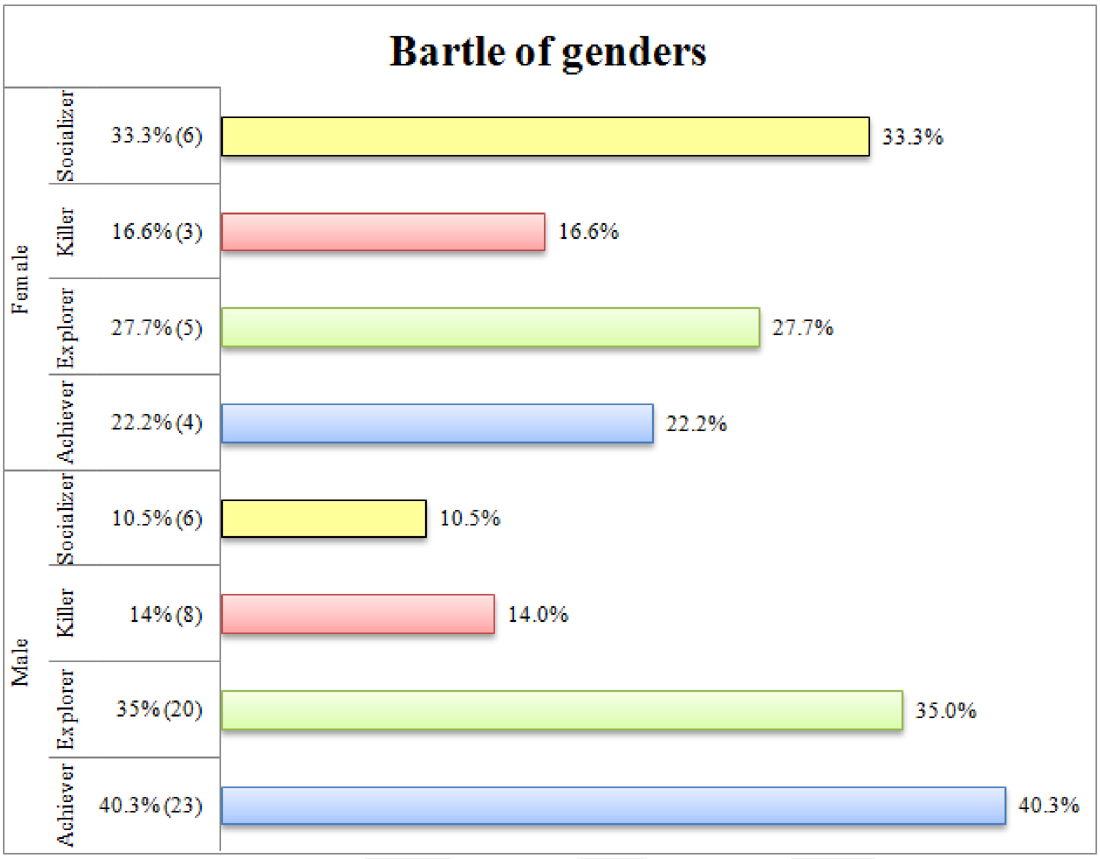

Figure 23 Bartle's player types versus participants' gender

In relation to the age factor of our participants, correspondent Bartle's player types were also mapped. Figure 24 shows the correlation between participants' age and their Bartle's player types.

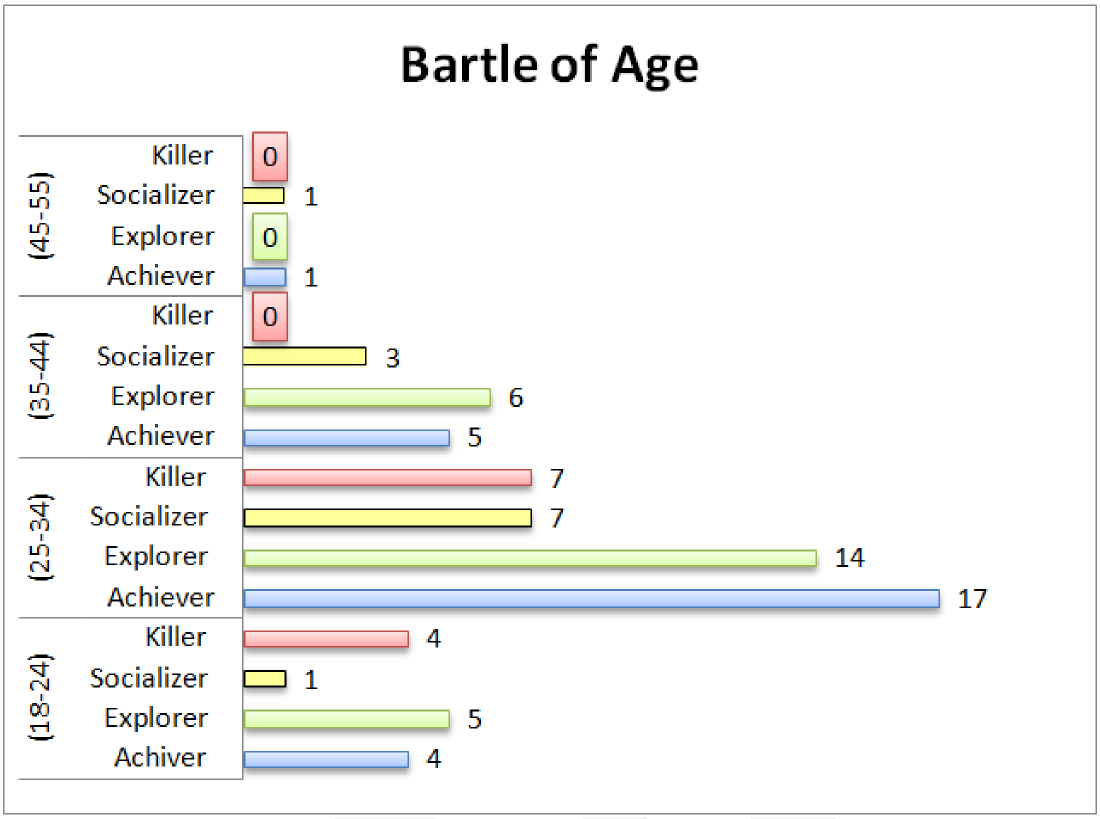

Figure 24 Bartle's player types versus participants' age

The result of mapping participants' education level with their Bartle's player types was also explored (as shown in figure 25). Participants with Bachelor or Masters degrees constitute the largest group of individuals interested and concerned with MOOCs. In addition, the majority of participants with Masters degree were achievers, followed by explorers. In contrast, explorers were the main type among participants with Bachelor degree, followed by achievers.

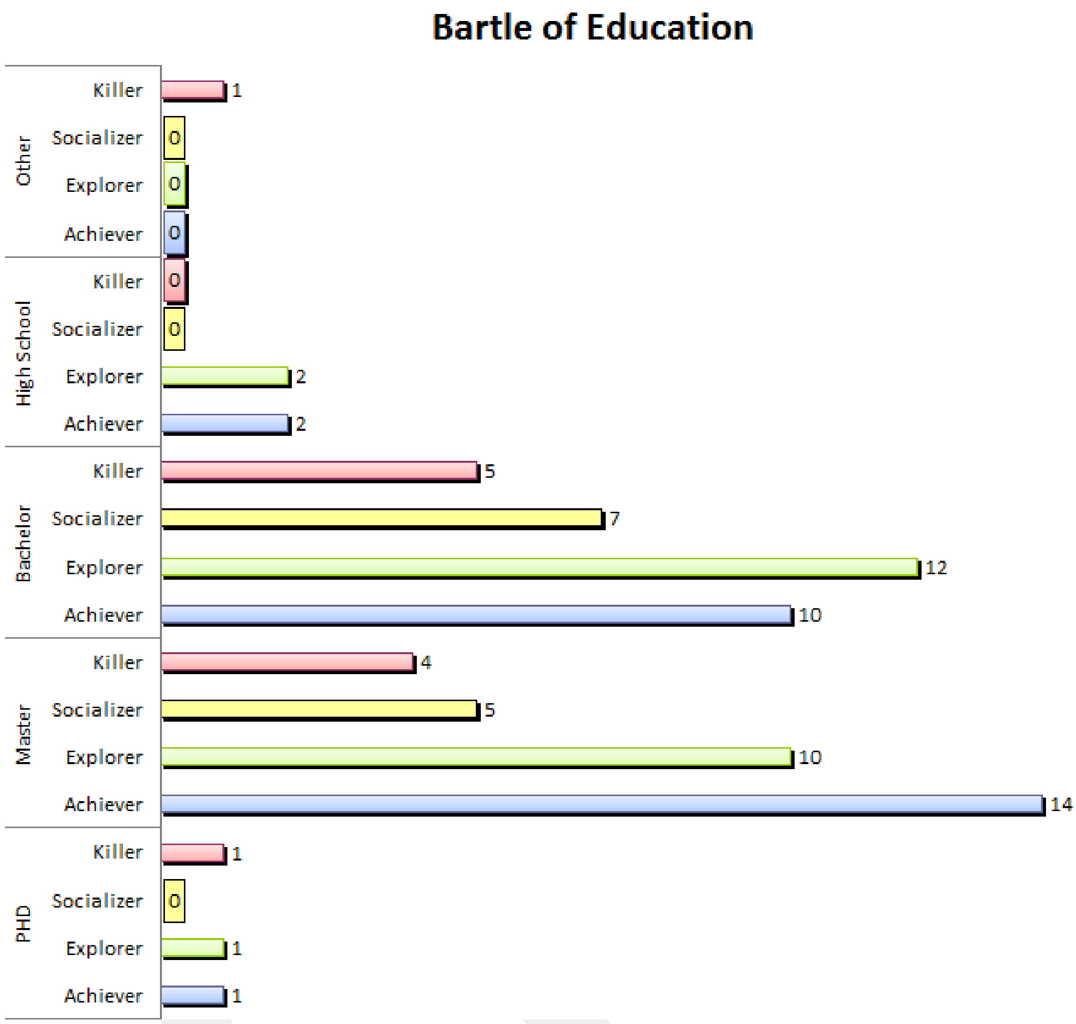

Figure 25 Bartle's player types versus education level

Figures 26 and 27 show the experience of our participants in MOOCs mapped onto their preferences regarding Bartle's player types.

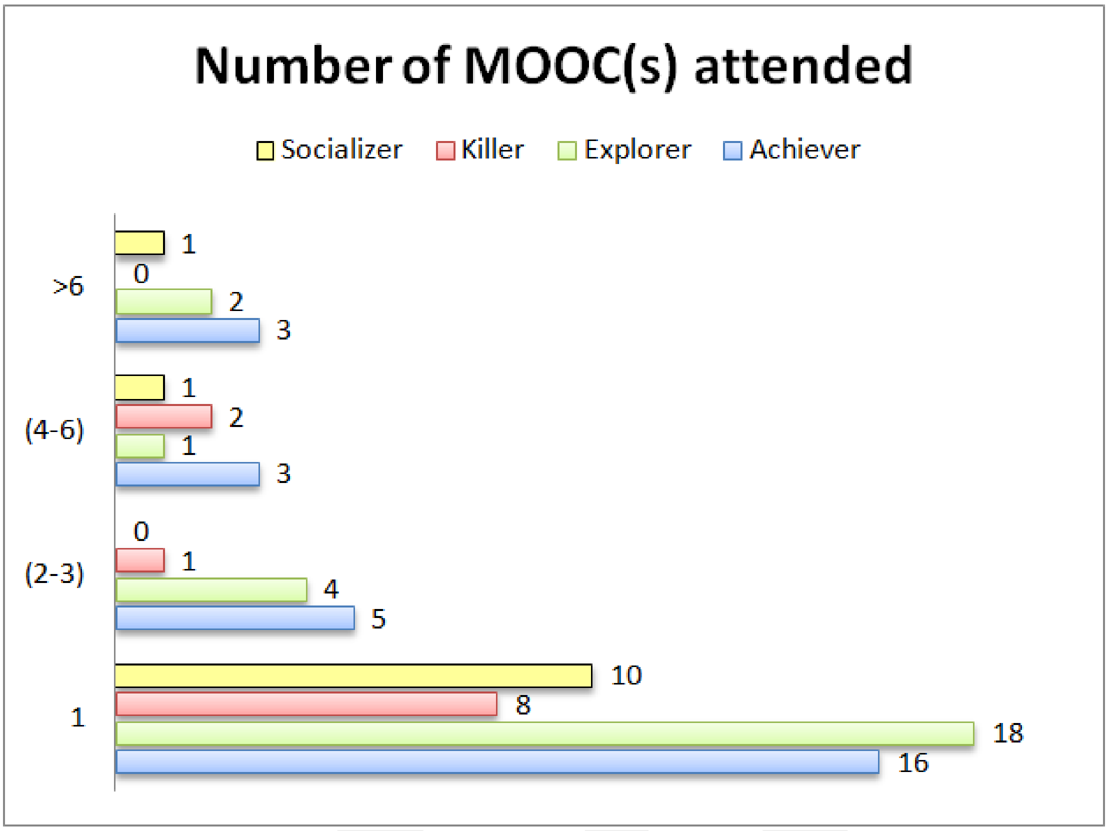

Figure 26 Bartle's player types versus participants' experience in MOOCs

Figure 26 illustrates that explorer was the largest player type group which attended at least one MOOC. Achiever player type made up the largest group which attended 2 to 3 MOOCs. In addition, explorer type of players formed the largest group which attended 4 to 6 MOOCs, and more than 6 MOOCs, respectively.

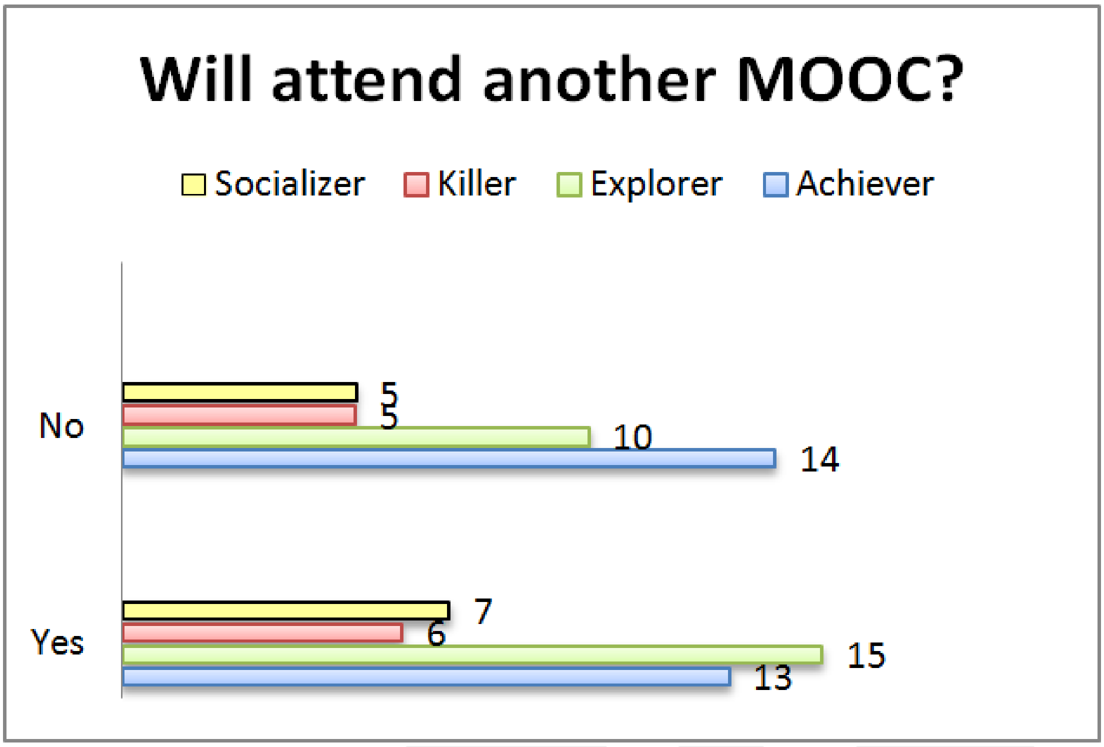

Figure 27 Bartle's player types versus participants' motivation to MOOCs

Figure 27 shows that achiever participants were not very satisfied with their previous experience in MOOCs as the majority do not want to attend other MOOCs again, while explorer participants were willing to repeat this experience.

A link between MBTI-Keirsey and Bartle's player types was explored empirically. The next step was to try to 'check' the possibility of one of the main goals of artificial intelligence, such as programming of behaviors, consciousness, cognition and perception of machines.

4.6 BP Classifier

In phase two, a machine-based classification of players, artificial neural networks (ANN) method was employed. A BP algorithm was used for training and testing processes, after splitting the collected data into two separated sets a training set (with 55 instances) and a testing set (with 12 instances). Each instance consists of 31 entries (30 entries for Bartle's player test, and one additional entry to represent the player's type (class)). Tables 10 and 11 illustrate the number of instances and classes of both training and testing sets, respectively.

Training Set (N=55)		
Bartle's Type	Achiever	19
	Explorer	16
	Socializer	10
	Killer	10

Table 10 Training Set of BP Classifier

Testing Set (N=12)		
Bartle's Type	Achiever	5
	Explorer	4
	Socializer	2
	Killer	1

Table 11 Testing Set of BP Classifier

Performance of the model was 100% for training process, and 91.6% for testing. Table 12 and Table 13 show the model's performance for both training and testing processes, respectively.

Training Process (N=55)	
Correctly Classified	55 (100%)
Incorrectly Classified	0 (0%)
ME	0.01
RE	0.01

Table 12 Training Mode Results from BP Classifier

Testing Process (N=12)	
Correctly Classified	11 (91.66%)
Incorrectly Classified	1 (8.33%)
ME	0.09
RE	0.19

Table 13 Testing Mode Results from BP Classifier

Note that values of the parameters of the classifier producing the nearest convergence were: learning rate=0.1, momentum=0.9, number of epochs=100, Error/Epoch=0.001, and one hidden layer. However, although the performance of classification methods might differ from task to task, in our study it was observed that BP performs better than other methods (i.e. the performance of any machine learning method could be measured by its accuracy[9]) [91]. In specific, in spite of the small dataset used for training and testing processes, the classifier performed adequately and the result was acceptable (91.6%). Additionally, the classifier worked efficiently with incomplete input vectors.

Moreover, this result over performs results obtained from some previous works that tried to classify MMOG players by applying different approaches or other machine learning methods such as decision trees [103, 110]. On the other hand, this result is similar to other results obtained by some previous works that applied BP model as a classiffier for many tasks such as job satisfaction [96, 119].

So far, we explored demographic, personal preferences, and motivation, traits, and behaviors of our participants using MBTI instrument and Bartle's gamer typology. This approach revealed valuable knowledge and findings to be understood and considered about MOOCs audiences in specific, and about personalities, preferences, motivation, engagement level and tools, playing styles, and learning styles, in general. Furthermore, employing machine learning methods to train and test a proper classifier model in favor of automatically classification of MOOCs participants into their correspondent player type of Bartle is successful.

Appendix G illustrates the training set for the classifier in detail. Appendix H illustrates the classifier's testing set in detail, as well.

[9] Means the percentage of classes classified correctly.

4.7 Validation

To validate the result obtained from the BP classifier based on the proposed methodology of this research, and to investigate the best BP classifier model that satisfies the goal of this task, 3 different experiments were suggested and examined:

Experiment 1: checks the ability to predict Bartle's player types by using 30 Bartle's test questions to train/test the model.

Experiment 2: checks the ability to predict Bartle's player types by using both 30 Bartle's test questions and MBTI 4 dichotomies to train/test the model.

Experiment 3: checks the ability to predict Bartle's player types by using both Bartle's test questions and MBTI 4 dichotomies (represented in fractions between [0,1]) to train/test the model.

In order to estimate the performance of BP model, the leave-one-out cross validation (LOOCV) approach was adopted in these 3 experiments. LOOCV is one of the methods used for validating model performance. In this method data is splitted into N samples and perform N rounds of train/test processes (N-1 samples for training and 1 sample for testing). Then, the estimated performance is calculated as the average of testing samples [120, 121]. Figure 1 shows the LOOCV technique.

Figure 28 LOOCV method

4.7.1 Experiments and results

The total number of respondents who answered all the questions is 55 out of 75. To obtain solid results and performances out of these 3 experiments, only the completed vectors of data were used. That is, only 55 vectors were used as dataset for training and testing processes of the suggested 3 experiments. Table 14 illustrates the data set and number of individuals for each player type (N=55).

Bartle's Player Type	Number of players
Achiever	19
Explorer	16
Socializer	10
Killer	10
Sum	55

Table 14 Number of Individuals for each Player Types

In order to conduct the suggested experiments, the dataset was divided into 5 equal samples (folds), with 11 instances each. The details of the experiments and their results are presented below.

4.7.1.1 Experiment 1: using Bartle's test (30 questions)

In this experiment, 30 questions of Bartle's test were used to train BP model in order to classify participants into their equivalent Bartle's player types. Figure 29 shows the classifier model.

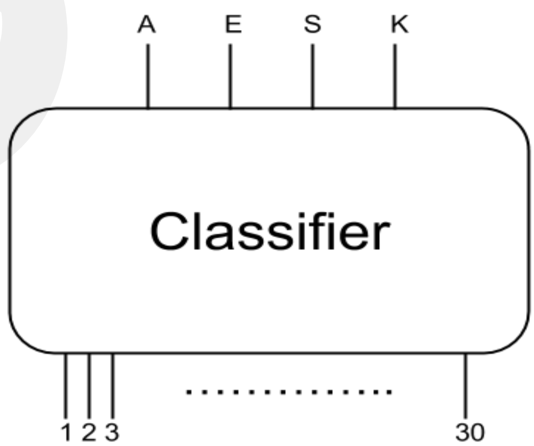

Figure 29 Classifier model 1

LOOCV technique for 5 rounds were performed. The test results and error rates of which are illustrated in Table 15 below:

Round 1		Round 2		Round 3		Round 4		Round 5	
9.09%		27.27%		27.27%		27.27%		27.27%	
ME	RE	ME	RE	ME	RE	ME	RE	ME	RE
0.43	0.62	0.35	0.54	0.38	0.55	0.36	0.54	0.33	0.51

Table 15 LOOCV of Experiment 1

The total result of cross validation for experiment 1 is shown in Table 16 below in the form of a confusion matrix.

A	B	C	D	
7	6	4	2	A=Achiever
6	3	3	4	B= Explorer
5	2	2	1	C=Socializer
2	5	2	1	D=Killer

Table 16 Confusion Matrix of Experiment 1

The average performance and error rate values for this experiment are presented in Table 17:

Performance	ME	RE
23.63%	0.37	0.55

Table 17 Performance of Experiment 1

Table 17 shows that the performance of experiment 1 is poor. Appendix I illustrates the data set for this experiment.

4.7.1.2 Experiment 2: using Bartle's test and MBTI dichotomies (0,1)

In this experiment MBTI dichotomy values were represented in binary (either 0 or 1) form and appended as input nodes along with Bartle's test values. In other words, the model consists of 34 input nodes (30 for Bartle's test and 4 for MBTI dichotomies) and 4 output nodes[10]. Figure 30 shows the classifier model 2.

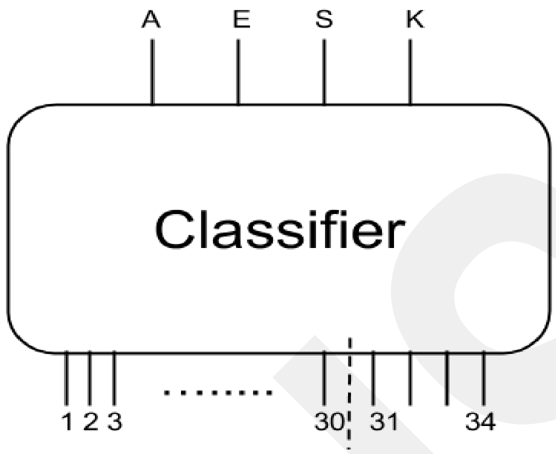

Figure 30 Classifier model 2

The testing results and error rates for each round are listed in Table 18.

Round 1		Round 2		Round 3		Round 4		Round 5	
63.63%		81.81%		81.81%		100%		90.90%	
ME	RE	ME	RE	ME	RE	ME	RE	ME	RE
0.22	0.39	0.09	0.21	0.15	0.29	0.08	0.16	0.14	0.25

Table 18 LOOCV of Experiment 2

The total result of cross validation for experiment 2 is shown in Table 19 in the form of a confusion matrix.

A	B	C	D	
18	0	1	0	A=Achiever
1	15	0	0	B= Explorer
3	0	6	1	C=Socializer
3	0	0	7	D=Killer

Table 19 Confusion Matrix of Experiment 2

[10] In this experiment, we used the same data set that has been used to train the BP classifier in section 4.7 (appendix G illustrates the data set).

The average performance and error rate values for experiment 2 are illustrated in Table 20.

Performance	ME	RE
83.63%	0.13	0.26

Table 20 Performance of Experiment 2

4.7.1.3 Experiment 3: using Bartle's test and MBTI dichotomies [0,1]

In this experiment, the same model used in experiment 2 (see figure 30) was used with some minor changes in input values (i.e., MBTI dichotomy values were represented as fractions between 0 and 1) to be used as input nodes along with Bartle's test values. However, the testing results are as given in Table 21.

Round 1		Round 2		Round 3		Round 4		Round 5	
9.09%		63.63%		36.36%		45.45%		27.27%	
ME	RE	ME	RE	ME	RE	ME	RE	ME	RE
0.40	0.59	0.21	0.38	0.32	0.52	0.29	0.47	0.28	0.46

Table 21 LOOCV of Experiment 3

The total result of the cross validation for experiment 3 is shown in Table 22 below in confusion matrix form.

A	B	C	D	
10	4	4	1	A=Achiever
4	5	3	4	B= Explorer
4	2	2	2	C=Socializer
2	3	2	3	D=Killer

Table 22 Confusion Matrix of Experiment 3

The average values of performance and error rates for experiment 3 are listed in Table 23 below.

Performance	ME	RE
34.56%	0.30	0.48

Table 23 Performance of Experiment 3

However, although the average performance of experiment 3 is higher than that of experiment 1, Table 23 shows that the performance of experiment 3 is non-encouraging. Appendix J illustrates the data set for this experiment.

4.7.2 Results explanation

From the experiments and results obtained it appears that the model used in experiment 2 (with a performance of 83.64 %) is the best model. In other words, combining Bartle's test values with MBTI values is a more powerful approach to predict Bartle's player types using BP algorithm.

In addition, by comparing the results obtained here with MBTI personality types distribution figure used in this work (see figure 9), we might derive Table 24 which matches MBTI types into their correspondent Bartle's player types empirically.

MBTI type	*Bartle type*	*Number of individuals*	*Classifier's result*
	Achiever	8	7
	Explorer	0	0
ISTJ	Socializer	0	1
	Killer	0	0
	Sum	**8**	**8**
	Achiever	3	3
	Explorer	0	0
ISFJ	Socializer	0	0
	Killer	0	0
	Sum	**3**	**3**
	Achiever	0	1
	Explorer	0	0
INFJ	Socializer	2	0
	Killer	0	1
	Sum	**2**	**2**

MBTI type	*Bartle type*	*Number of individuals*	*Classifier's result*
	Achiever	0	1
INTJ	Explorer	5	4
	Socializer	0	0
	Killer	0	0
	Sum	**5**	**5**
	Achiever	0	
	Explorer	0	0
ISTP	Socializer	0	0
	Killer	2	0
	Sum	**2**	**2**
	Achiever	0	1
	Explorer	0	0
ISFP	Socializer	0	0
	Killer	1	0
	Sum	**1**	**1**
	Achiever	0	0
	Explorer	0	0
INFP	Socializer	1	1
	Killer	0	0
	Sum	**1**	**1**
	Achiever	0	0
	Explorer	1	1
INTP	Socializer	0	0
	Killer	0	0
	Sum	**1**	**1**
	Achiever	0	1
ESTP	Explorer	0	0
	Socializer	0	0

	Killer	4	3
	Sum	**4**	**4**

MBTI type	***Bartle type***	***Number of individuals***	***Classifier's result***
ESFP	Achiever	0	1
	Explorer	0	0
	Socializer	0	0
	Killer	3	2
	Sum	**3**	**3**
ENFP	Achiever	0	1
	Explorer	0	0
	Socializer	3	2
	Killer	0	0
	Sum	**3**	**3**
ENTP	Achiever	0	0
	Explorer	5	5
	Socializer	0	0
	Killer	0	0
	Sum	**5**	**5**
ESTJ	Achiever	5	5
	Explorer	0	0
	Socializer	0	0
	Killer	0	0
	Sum	**5**	**5**
ESFJ	Achiever	3	3
	Explorer	0	0
	Socializer	0	0
	Killer	0	0
	Sum	**3**	**3**
ENFJ	Achiever	0	0
	Explorer	0	0
	Socializer	4	4
	Killer	0	0

	Sum	**4**	**4**

MBTI type	*Bartle type*	*Number of individuals*	*Classifier's result*
ENTJ	Achiever	0	0
	Explorer	5	5
	Socializer	0	0
	Killer	0	0
	Sum	**5**	**5**
	TOTAL	**55**	**55**

Table 24 Matching MBTI Types into Bartle's Player Types

The results of table 24 above show that MBTI types with SJ preferences (ISTJ, ISFJ, ESTJ, and ESFJ) specifically correspond to achiever player type in terms of Bartle with a percentage of 94.73%. Similarly, MBTI types with NT preferences (INTP, INTJ, ENTP, and ENTJ) are much closer to be regarded as explorers, in terms of Bartle's player types, with a percentage of 93.75%. Moreover, MBTI types with SP preferences (ISTP, ISFP, ESTP, and ESFP) might be categorized as killers regarding Bartle's taxonomy of player types with a percentage of 70%. Finally, MBTI types with NF preferences (INFJ, INFP, ENFJ, and ENFP) might be classified as socializers according to Bartle's player types with a percentage of 70%. However, the BP model appears to perform highly for classifying achiever and explorer player types while the performance decreases for socializer and killer player types. One of the reasons for this result might be the small number of those patterns in the dataset (10 patterns for each player type). All in all, using MBTI assessment and Bartle's player types test to model a BP player types classifier is possible with overall performance of 83.63% for this case and dataset.

4.8 Limitations

Using personality assessments to investigate people's type of personality does not always yield very accurate results for many reasons, and therefore, they should be regarded as indicators for individuals' preferences and temperaments rather than solid evidence for their exact type [21, 36]. Furthermore, Artificial Neural Networks (ANN) and other similar methods of data mining and pattern recognition have many parameters affecting their performance such as error rate, preparing datasets, size of data, and quality of training and testing sets. Therefore, they do not always provide the optimal results and they should be designed carefully [95]. However, the goal of this study and the method used to achieve it are still reasonable and do not affect the result, as we explored general directions and preferences of a selected population. On the other hand, the automated classifier can classify patterns with 10% missing values in an instance (up to 3 out of 30 questions of Bartle's test can be unanswered).

4.9 Threats to Validity

To administer a valid survey to collect valid and reliable data (as much as possible), we considered some points to reduce threats to validity. However, the pre-assumptions pertinent to this study were as follows:

1. People can be classified by their personalities and preferences into different MBTI types. And MBTI is a legitimized assessment for exploring personality preferences.
2. People can be classified by their playing behaviours and motivation into different playing styles (e.g. Bartle's player type). And Bartle's player type is a legitimized assessment for exploring players' motivation and preferences.
3. Participants played at least one MMOG/MMORPG game during their life time, so they had the experience and knowledge of gaming.
4. Participants had attended at least one MOOC in their life time.
5. Participants were willing to answer the survey honestly and correctly.
6. The education level of each participant was at least high school level.
7. The minimum age to participate was 18 years old.

4.10 Summary

In this chapter the detailed results obtained from our research study were discussed them. Firstly, the demographics of participants (i.e., gender, age, level of education, number of MOOCs attended, and their opinion of attending more MOOCs) were presented. Secondly, the personality types of participants were delineated and correlated with demographics. Thirdly, Bartle's player types of participants were correlated with demographics. Fourthly, the outcomes of player types' classifier were presented and the performance was discussed in comparison with other studies. In addition, limitations and threats to validity were explained. In the next chapter, conclusions and recommendations for future research are presented.

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

5.1 Introduction

The aim of this chapter is to present conclusions from the present study which was designed as an empirical assessment for evaluating the personality types of MOOCs participants using personality tests (MBTI and Bartle's tests) that are conceptually related. Specifically, this study explored and analyzed participants in MOOC from different aspects, objective (e.g. gender, age, etc.) and subjective characteristics (such as personality and player types). In addition, BP-ANN is trained to predict test takers' results with missing data, and to instantly classify the participants in a MOOC into their correspondent player types. Furthermore, a set of suggested future work for this study is presented.

5.2 Conclusions

Returning to the research questions posed at the beginning of this study, it is now possible to state that different player types perform different kind of behaviours depending on their distinctive player profiles. Moreover, BP is adequate method for classifying different profiles into their related MMOG player type (in terms of Bartle's player type).

Despite its exploratory nature, this study offers some insight into MOOCs in general and participants' types in particular. In this study, it was observed that a possible approach to improve MOOCs' design (as they are MMOGs) is to assess the player profiles and keep a balance among the population of distinctive personality types.

This detailed understanding provides concrete ground that can be useful in many aspects:

From the MMOG players' perspective: There is one suitable choice to be recommended in designing MOOCs, regarding the player types of Bartle. Bartle suggested 2 possible ways to deal with different player types of MMOGs regarding interaction between each other type (see page 15) [20, 69], but here it was noticed that the proper approach to design MOOCs (as they are MMOGs/MMORPGs) is to keep a balance among all types: explorers, achievers, socializers, and killers, respectively.

From the game and gamification perspective: Exploring player type and understanding the behaviors of MMOGs' population is helpful in designing more engaging MOOCs. Furthermore, such an understanding can be used for gamification (employing proper game elements) of MOOCs. MOOCs and gamification are now attracting great attention as they can be regarded as significant promising features of our modern society [122]. Future studies on a possible combination of these topics are therefore recommended. This study especially contributed reasonable requirements for gamifying such systems, from understanding and analyzing participants' demographics, personality types and preferences, motivation and playing interests to classifying them in terms of Bartle's player types. Thus, half of the way towards the gamification of MOOCs has been achieved with this research study (i.e. we have empirically explored different targeted audiences' demographics and behaviours, player types, proper tools and game elements to be employed, types of MOOCs to be produced to fulfill the needs of each type, etc.) (See the 6 steps model of gamification in [74]).

From the MOOCs perspective: Although MOOCs have overcome traditional learning problems such as capacity, the problem of lack of attention, and decrease in and loss of motivation still exists (i.e., completion-value is very low compared to the enrollment-value; it is about 10% [123]). This problem can be considered as one of the most important challenges that the MOOCs movement faces. Reviewing 10 most frequently causes of this problem from MOOCs participants' directly [124], it can be seen that major issues can be addressed by applying game design techniques, and therefore using these methodologies in design of MOOCs are vitally important and recommended.

From the machine learning and classification perspective: Machine learning APIs have important functions and uses, many studies and trends are needed to enhance and develop better methods and understanding.

However, important fields and applications like document analysis, sentiment analysis (e.g. for Twitter, Facebook, and other media platforms), gender and age detection, courses/friends recommending, etc., have been researched and now they are available for the public as a cloud service[11].

The importance and contribution of this study is that it presents a machine-learning analyzer and classifier of people according to their profiles, demographics, personalities, and game playing preferences. This goal has been achieved with reasonable results and the method presented can be applied in other fields as well. The second important point of this study is that we tried to apply it on MOOCs attendees for the first time, to explore the behaviors of players in general, and to present innovative tools to design and produce MOOCs as a contribution to MOOCs design trends from both theoretical and practical aspects of game research and development.

5.3 Future Work

The idea of using psychology of fun to correlate education and gaming in favor of trying to learn from games and employing game elements to increase engagement in learning/education process is already implemented. However, such implementations (i.e. educational games, also called serious games) still suffer from problems such as lack of attention and engagement [125]. In this study, we are trying to explore game players, personality types, and demographics of individuals (in specific, participants

[11] For example, see: http://www.datumbox.com/app/webroot/api-sandbox/ and http://textalytics.com/home.

of MOOCs) to reach comprehensive understanding that is useful in many aspects. Consequently, here are some perspectives that are recommended to be further explored in the future:

MMOG perspective: Use the findings of this study as a basis to employ proper mechanics, components, and stronger engagement loops. In addition, different player typologies such as the extended Bartle's player types might be explored (i.e. 8 player types rather than 4), see [21]. Furthermore, gamifying of MOOCs might be explored as a next step of this work.

MOOCs perspective: Use the findings (motivation, preferences, and demographics) here as a basis for the design of more engaging MOOCs and learning platforms.

Machine learning perspective: Employ more complex methods (deep learning methods) for better performance. Actually, MLP method with many hidden layers also known as Deep Neural Network (DNN) with back-propagation technique for learning, is very powerful and successful for deep learning purposes [116, 126]. Additionally, the automatic classifier might be employed as a web-based tool and/or a mobile device application, which could be useful for different purposes (i.e. profile analysis, game recommender, suggesting courses, suggestions of matching individuals as friends or a team, and so on).

Personality perspective: Explore more preferences, demographics, and employ different personality assessments and learning styles. In addition, examine the correlations and relationships between player types on the one hand, and personality preferences and demographics on the other hand.

REFERENCES

1. **Ehlers U. D., (2013),** *"Open Learning Cultures A Guide to Quality, Evaluation and Assessment for Future Learning"*, Springer-Verlag Berlin and Heidelberg GmbH & Company, pp. 1.

2. **Hyman P., (2012),** *"In the Year of Disruptive Education"*, Communications of the ACM, vol. 55, no. 12, pp. 20-22.

3. **Yuan L., Powell S., (2013),** *"MOOCs and Disruptive Innovation: Implications for Higher Education"*, eLearning Papers, Special edition, UK, pp. 60-71.

4. **Mota R., Scott D., (2014),** *"Education for Innovation and Independent Learning"*, Elsevier, Oxford, pp. 65-67.

5. **Severance C., (2012),** *"Teaching the World: Daphne Koller and Coursera"*, IEEE Computer Society, vol. 45, no. 8, pp. 8-9.

6. **Hill P., (2014),** *"Online Educational Delivery Models: A Descriptive View"*, e-Learning Library, In Educause Review 2012, pp. 85-97.

7. **Siemens G., (2012),** *"MOOCs Are Really a Platform"*, Elearnspace, http://www.elearnspace.org/blog/2012/07/25/moocs-are-really-a-platform/, (Data Download Date: 25/7/2014).

8. **Siemens G., (2005),** *"Connectivism: A Learning Theory for the Digital Age"*, International journal of instructional technology and distance learning, vol. 2, no. 1, pp. 3-10.

9. **Kolowich S., (2012),** *"How Will MOOCs Make Money"*, Inside Higher Ed, http://pando.com/2013/08/22/infographic-how-will-the-moocs-make-money/, (Data Download Date: 8/6/2014).

10. **Martin F. G., (2012),** *“Will Massive Open Online Courses Change How We Teach?”*, Communications of the ACM, vol. 55, no. 8, pp. 26-28.

11. **McAuley A., Stewart B., Siemens G., Cormier D., (2010),** *“The MOOC Model for Digital Practice”*, Social Sciences and Humanities Research Council's "Knowledge Synthesis Grants on the Digital Economy ", pp. 3-63.

12. **Downes S., (2010),** *“The Role of the Educator”*, http://www.huffingtonpost.com/stephen-downes/the-role-of-the-educator_b_790937.html, (Data Download Date: 4/15/2014).

13. **Kop R., Fournier H., Mak J. S. F., (2011),** *“A Pedagogy of Abundance or a Pedagogy to Support Human Beings? Participant support on massive open online courses”*, The International Review of Research in Open and Distributed Learning., vol. 12, no. 7, pp. 74-93.

14. **Abuhamdeh S., Csikszentmihalyi M., (2012),** *“The Importance of Challenge for the Enjoyment of Intrinsically Motivated, Goal-Directed Activities”*, Personality and Social Psychology Bulletin, vol. 38, no. 3, pp. 317-330.

15. **Wong M. M., Csikszentmihalyi M., (1991),** *“Motivation and Academic Achievement: The Effects of Personality Traits and the Duality of Experience”*, Journal of Personality, vol. 59, no. 3, pp. 539-574.

16. **Hunicke R., LeBlanc M., Zubek R., (2014),** *“MDA: A Formal Approach to Game Design and Game Research”*, In Proceedings of the AAAI Workshop on Challenges in Game AI, vol. 4, pp. 4-8.

17. **Csikszentmihalyi M., Csikzentmihaly M., (1991),** *“Flow: The Psychology of Optimal Experience”*, Harper Perennial, New York, vol. 41, pp. 4.

18. **Chen J., (2007),** *“Flow in Games (and Everything Else)”*, Communications of the ACM, vol. 50, no. 4, pp. 31-34.

19. **Wohn D. Y., and Lee Y. H., (2013),** *“Players of Facebook Games and How They Play”*, Entertainment Computing, Elsevier, vol. 4, no.3, pp. 171-178.

20. **Bartle R., (1996),** "*Hearts, Clubs, Diamonds, Spades: Players Who Suit MUDs"*, Journal of MUD research, vol. 1, no. 1, pp. 19.

21. **Bartle R. A., (2004),** *"Designing Virtual Worlds"*, New Riders, USA, pp. 125-148.

22. **Taylor T. L., (2009),** *"Play Between Worlds: Exploring Online Game Culture"*, MIT Press, pp. 22.

23. **Wohn D. Y., Lampe C., Wash R., Ellison N., Vitak J., (2011),** *"The "S" in Social Network Games: Initiating, Maintaining, and Enhancing Relationships"*, In System Sciences (HICSS), 44th Hawaii International Conference, IEEE, pp. 1-10.

24. **Minsky M., (2007),** "*The Emotion Machine: Commonsense Thinking, Artificial Intelligence, and the Future of the Human Mind"*, Simon and Schuster, New York.

25. **Engler B., (2013),** *"Personality Theories"*, Cengage Learning, USA, pp. 2-420

26. **Cherry K., (2010),** *"The Everything Psychology Book: Explore the Human Psyche and Understand Why We Do the Things We Do"*, Everything Books, USA.

27. **Emmons R. A., (1999),** *"The Psychology of Ultimate Concerns: Motivation and Spirituality in Personality"*, Guilford Press, New York.

28. **Church A. T., (2000),** *"Culture and Personality: Toward an Integrated Cultural Trait Psychology"*, Journal of Personality, vol. 68, no. 4, pp. 651-703.

29. **Costa P. T., McCrae R. R., (2008),** *"The Revised Neo Personality Inventory (neo-pi-r)"*, The SAGE handbook of personality theory and assessment, vol. 2, pp. 179-198.

30. **Camara W. J., Nathan J. S., Puente A. E., (2000),** *"Psychological Test Usage: Implications in Professional Psychology"*, Professional Psychology: Research and Practice, vol. 31, no. 2, pp. 141.

31. **Schacter D. L., Gilbert D. T., Wegner D. M., (2009),** *"Introducing Psychology"*, Macmillan, USA.

32. **Jung C. G., (2014),** *"Psychological Types"*, Routledge, New York.

33. **Cohen J. J., (2008),** *"Learning Styles of Myers-Briggs Type Indications"*, Ph.D. thesis, Indiana State University, pp. 18-20.

34. **Quenk N. L., (2000),** *"Essentials of Myers-Briggs Type Indicator Assessment"*, Essentials of Psychological Assessment Series, J. Wiley & Sons, New York, vol. 66, pp. 2-10.

35. **Kroeger O., Thuesen J. M., (2013),** *"Type Talk: The 16 Personality Types That Determine How We Live, Love, and Work"*, Dell Publishing, New York, pp. 8-40.

36. **Myers I. B., McCaulley M. H., Most R., (1985),** *"Manual: A Guide to the Development and Use of the Myers-Briggs Type Indicator"*, Consulting Psychologists Press, Palo Alto, California.

37. **Myers I. B., McCaulley M. H., Quenk N. L., Hammer A. L., (1998),** *"MBTI Manual: A Guide to the Development and Use of the Myers-Briggs Type Indicator"*, Consulting Psychologists Press, Palo Alto, California, vol. 3.

38. **The Myers & Briggs Foundation,** *"MBTI Basics"*, http://www.myersbriggs.org/my-mbti-personality-type/mbti-basics/, (Data Download Date: 10/10/2014).

39. **Bowers K. M., (2002),** *"The Utility of the Myers-Briggs Type Indicator and the Strong Interest Inventory in Predicting Service Community Selection at the United States Naval Academy"*, Naval Postgraduate School Monterey, California, pp. 12.

40. **Madter N., Bower D. A., Aritua B., (2012),** *"Projects and Personalities: A Framework for Individualising Project Management Career Development in the Construction Industry"*, International Journal of Project Management, Elsevier, vol. 30, no. 3, pp. 273-281.

41. **Su-li Z., Ke-fan X., (2010),** *"Research on Entrepreneurial Team Members' Personality Traits Influence on Group Risk Decision-Making"*, In Management Science and Engineering (ICMSE), 2010 International Conference, IEEE, pp. 937-942.

42. **House R. J., Howell J. M., (1992),** *"Personality and Charismatic Leadership"*, The Leadership Quarterly, Elsevier, vol. 3, no. 2, pp. 81-108.

43. **Catherine B. C., Wheeler D. D., (1994),** *"The Myers-Briggs Personality Type and Its Relationship to Computer Programming"*, Journal of Research on Computing in Education, vol. 26, no. 3, pp. 358-370.

44. **Bowen P. L., Ferguson C. B., Lehmann T. H., Rohde F. H., (2003),** *"Cognitive Style Factors Affecting Database Query Performance"*, International Journal of Accounting Information Systems, Elsevier, vol. 4, no. 4, pp. 251-273.

45. **Yilmaz M., (2013),** *"A Software Process Engineering Approach to Understanding Software Productivity and Team Personality Characteristics: An Empirical Investigation"*, Ph.D. thesis, Dublin City University, pp. 113-165.

46. **Capretz L. F., Ahmed F., (2010),** *"Making Sense of Software Development and Personality Types"*, IT professional, IEEE, vol. 12, no. 1, pp. 6-13.

47. **Baab R. L. M., (1999),** *"Embracing Midlife: Congregations as Support Systems"*, Rowman & Littlefield Publishers.

48. **Pearman R. R., (1999),** "*Introduction to Type and Emotional Intelligence"*, Consulting Psychologists Press.

49. **Davis S. O., Handschin B., (1998),** *"Reinventing Yourself: Life Planning After 50: Using the Strong and the MBTI"*, Consulting Psychologists Press.

50. **Ancowitz N., (2010),** *"Self-promotion for Introverts: The Quiet Guide to Getting Ahead"*, McGraw-Hill.

51. **Wyman P., (2001),** *"Three Keys to Self-Understanding: An Innovative and Effective Combination of the Myers-Briggs Type Indicator, the Enneagram, and Inner-Child Healing"*, Center for Applications of Psychological Type.

52. **Johnson R., Johndon R., (1995),** *“Your Personality and the Spiritual Life”*, Monarch Crowbridge.

53. **Kroeger O., Thuesen J. M., (1994),** *“16 Ways to Love Your Lover: Understanding the 16 Personality Types So You Can Create a Love That Lasts Forever”*, Delacorte Press.

54. **Myers I. B., Myers P. B., (2010),** *“Gifts Differing: Understanding Personality Type”*, Nicholas Brealey Publishing.

55. **Laney M. O., (2005),** *“The Hidden Gifts of the Introverted Child: Helping Your Child Thrive in an Extroverted World”*, Workman Publishing.

56. **Pearman R. R., Albritton S. C., (2010),** *“I'm Not Crazy, I'm Just Not You: The Real Meaning of the 16 Personality Types”*, Nicholas Brealey Publishing.

57. **Tieger P. D., Barron-Tieger B., (2001),** *“Just Your Type: Create the Relationship You've Always Wanted Using the Secrets of Personality Type”*, Hachette UK.

58. **Penley J. P., (2006),** *“MotherStyles: Using Personality Type to Discover Your Parenting Strengths”*, Da Capo Press.

59. **Provost J. A., Anchors S., (2003),** *“Using the MBTI Instrument in Colleges and Universities”*, Center for Applications of Psychological Type.

60. **Kise J. A., (2006),** *“Differentiated Coaching: A Framework for Helping Teachers Change”*, Sage, Corwin Press.

61. **Kise J. A., (2007),** *“Differentiation through Personality Types: A Framework for Instruction, Assessment, and Classroom Management”*, Corwin Press.

62. **Murphy E., (2008),** *“The Chemistry of Personality: A Guide to Teacher-Student Interaction in the Classroom”*, Center for Applications of Psychological Type.

63. **Dunning D., (2008),** *“Introduction to Type and Learning”*, Consulting Psychologists Press.

64. **DiTiberio J. K., Hammer A. L., (1993),** *"Introduction to Type in College"*, Consulting Psychologists Press, California.

65. **Lawrence G. D., (1997),** *"Looking at Type and Learning Styles"*, Center for Applications of Psychological Type, Incorporated, Florida.

66. **Pratten R., (2011),** *"Getting Started in Transmedia Storytelling: A Practical Guide for Beginners"*, CreateSpace, pp. 25-27.

67. **Lazzaro N., (2004),** *"Why We Play Games: Four Keys to More Emotion Without Story"*, In Game Developers Conference, pp. 1-8.

68. **Yee N., (2006),** *"Motivations for Play in Online Games"*, CyberPsychology & Behaviour, vol. 9, no. 6, pp. 772-775.

69. **Hong K. J., (2012),** *"What's the Big Deal About Bartle's Player Types?"*, http://gamifyforthewin.com/2012/08/whats-the-big-deal-about-bartles-player-types/, (Data Download Date: 7/10/2014).

70. **Tuunanen J., Hamari J., (2012),** *"Meta-Synthesis of Player Typologies"*, In Proceedings of Nordic Digra 2012 Conference: Games in Culture and Society, Tampere, Finland, pp. 1-14.

71. **Zichermann G., Cunningham C., (2011),** *"Gamification by Design: Implementing Game Mechanics in Web and Mobile Apps"*, O'Reilly Media, Incorporation.

72. **Huotari K., Hamari J., (2011),** *"Gamification from the Perspective of Service Marketing"*, In Proc. CHI 2011 Workshop Gamification, Canada, pp. 1-5.

73. **Huang W. H. Y., Soman D., (2013),** *"Gamification of Education"*, Tech. rep., Research Report Series: Behavioural Economics in Action, pp. 1-29.

74. **Lee J. J., Hammer J., (2011),** *"Gamification in Education: What, How, Why Bother?"*, Academic Exchange Quarterly, vol. 15, no.2, pp. 146.

75. **Andreasen E., Downey B., (2001),** *"The MUD Personality Test"*, The Mud Companion, vol. 1, pp. 33-35.

76. **Bartle Test of Gamer Psychology, (2000)**, Tech. report, http://www.gamerdna.com/quizzes/bartle-test-of-gamerpsychology, (Data Download Date: 8/3/2014).

77. **Mulligan J, Patrovsky B., (2003),** *"Developing Online Games: An Insider's Guide"*, New Riders, pp. 389.

78. **Michalski R. S., Carbonell J. G., Mitchell T. M., (2014),** "*Machine Learning: An Artificial Intelligence Approach*", Morgan Kaufmann, vol. 1.

79. **Bishop C. M., (2006),** *"Pattern Recognition and Machine Learning (Information Science and Statistics) Springer-Verlag, New York"*, Incorporation, Secaucus, New Jersey.

80. **Carpenter G. A., Grossberg S., (1987),** *"A Massively Parallel Architecture for a Self-Organizing Neural Pattern Recognition Machine"*, Computer vision, graphics, and image processing, vol. 37, no. 1, pp. 54-115.

81. **Bradski G., Kaehler A., (2008),** *"Learning OpenCV: Computer Vision with the OpenCV Library"*, "O'Reilly Media, Inc.", California.

82. **Viola P., Jones M., (2001),** *"Rapid Object Detection Using a Boosted Cascade of Simple Features"*, In Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference, IEEE, vol. 1, pp. I-511.

83. **Baldi P., Brunak S., (2001),** *"Bioinformatics: The Machine Learning Approach"*, MIT press.

84. **Tesauro G., (1995),** *"Temporal Difference Learning and TD-Gammon"*, Communications of the ACM, vol. 38, no.3, pp. 58-68.

85. **Quinlan J. R., (1983),** *"Learning Efficient Classification Procedures and Their Application to Chess end Games"*, In Machine learning, Springer, pp. 463-482.

86. **Jurafsky D., Martin J. H., (2000),** *"Speech & Language Processing"*, Pearson Education Internation Edition.

87. **Joachims T., (2002),** *"Learning to Classify Text Using Support Vector Machines: Methods, Theory and Algorithms"*, Kluwer Academic Publishers/ Springer, USA.

88. **Domingos P., (2012),** *"A Few Useful Things to Know About Machine Learning"*, Communications of the ACM, vol. 55, no. 10, pp. 78-87.

89. **Chapelle O., Schölkopf B., Zien A., (2006),** *"Semi-Supervised Learning"*, vol. 2, MIT press Cambridge, London, pp. 1-32.

90. **Sutton R. S., Barto A. G., (1998),** *"Reinforcement Learning: An Introduction"*, MIT press, pp. 3-23.

91. **Ratanamahatana C. A., Lin J., Gunopulos D., Keogh E., Vlachos M., Das G., (2010),** *"Mining Time Series Data"*, In Data Mining and Knowledge Discovery Handbook, Springer, pp. 1049-1077.

92. **Michie D., Spiegelhalter D. J., Taylor C. C., (1994),** *"Machine Learning, Neural and Statistical Classification"*, Citeseer, pp. 1-106.

93. **Hagan M. T., Demuth H. B., Beale M. H., Jesús O. D., (2014),** *"Neural Network Design"*, Martin Hagan, pp. 1-1:11-41.

94. **Bishop C. M., et al., (1995),** *"Neural Networks for Pattern Recognition"*, Clarendon press, Oxford, pp. 116-161.

95. **Lotte F., Congedo M., Lecuyer A., Lamarche F., Arnaldi B., (2007),** *"A Review of Classification Algorithms for EEG-Based Brain-Computer Interfaces"*, Journal of Neural Engineering, vol. 4, no. 2, pp. R1-R24.

96. **Azadeh A., Rouzbahman M., Saberi M., Mohammad Fam I., (2011),** *"An Adaptive Neural Network Algorithm for Assessment and Improvement of Job Satisfaction With Respect to HSE and Ergonomics Program: The case of a gas refinery"*, Journal of Loss Prevention in the Process Industries, vol. 24, no. 4, pp. 361-370.

97. **Novak J., (2011),** "*Game Development Essentials: An Introduction"*, Cengage Learning, New York.

98. **McGonigal J., (2008),** *"Engagement Economy: The Future of Massively Scaled Collaboration and Participation"*, Institute for the Future, California.

99. **Borg M. O., Stranahan H. A., (2002),** *"Personality Type and Student Performance in Upper-Level Economics Courses: The Importance of Race and Gender"*, The Journal of Economic Education, vol. 33, no. 1, pp. 3-14.

100. **Keirsey D, (1998),** *"Please Understand Me II: Temperament, Character, Intelligence"*, Del Mart, Prometheus Nemesis Book Company, pp. 1-350.

101. **Yee N., (2006),** *"The Demographics, Motivations, and Derived Experiences of Users of Massively Multi-User Online Graphical Environments"*, Presence, MIT Press, vol. 15, no. 3, pp. 309-329.

102. **Bellman K., Landauer C., (2000),** *"Playing in the MUD: Virtual Worlds Are Real Places"*, Applied Artificial Intelligence, vol. 14, no. 1, pp. 93-123.

103. **Cowley B., Charles D., Black M., Hickey R., (2013),** *"Real-Time Rule-Based Classification of Player Types in Computer Games"*, User Modeling and User-Adapted Interaction, Springer, vol. 23, no. 5, pp. 489-526.

104. **Drennan P., Keeffe D. A., (2007),** *"Virtual Consumption: Using Player Types to Explore Virtual Consumer Behaviour"*, In Entertainment Computing-ICEC 2007, Springer, pp. 466-469.

105. **Pang S., Chen C., Yang Y., (2009),** *"Classify Players Based on Player Relationship Network in MMOG"*, In Computing, Communication, Control, and Management, CCCM 2009, ISECS International Colloquium, IEEE, vol. 4, pp. 143-146.

106. **Aruan F., Prihatmanto A., Hindersah H., et al., (2012),** "*The Designing and Implementation of a Problem Based Learning in Collaborative Virtual Environments using MMOG technology"*, In System Engineering and Technology (ICSET), 2012 International Conference, IEEE, pp. 1-7.

107. **Borbora Z. H., Srivastava J., (2012),** *"User Behavior Modelling Approach for Churn Prediction in Online Games"*, In Privacy, Security, Risk and Trust (PASSAT), 2012 International Conference on and 2012 International Confernece on Social Computing (SocialCom), IEEE, pp. 51-60.

108. **Kang S. J., Kim Y. B., Park T., Kim C. H., (2013),** *"Automatic Player Behavior Analysis System Using Trajectory Data in a Massive Multiplayer Online Game"*, Multimedia tools and applications, vol. 66, no. 3, pp. 383-404.

109. **Ho J. Y., Thawonmas R., (2004),** *"Episode Detection With Vector Space Model in Agent Behavior Sequences of MMOGs"*, In Proc. Future Business Technology Conference, pp. 47-54.

110. **Matsumoto Y., Thawonmas R., (2004),** *"MMOG Player Classification Using Hidden Markov Models"*, In Entertainment Computing-ICEC 2004, Springer, pp. 429-434.

111. **Wolpaw J. R., Birbaumer N., McFarland D. J., Pfurtscheller G., Vaughan T. M., (2002),** *"Brain-Computer Interfaces for Communication and Control"*, Clinical neurophysiology, Elsevier, vol. 113, no. 6, pp. 767-791.

112. **Vaughan T. M., Heetderks W. J., Trejo L. J., Rymer W. Z., Weinrich M., Moore M. M., Kübler A., Dobkin B. H., Birbaumer N., Donchin E., et al., (2003),** *"Brain-Computer Interface Technology: A Review of the Second International Meeting."*, IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society, vol. 11, no. 2, pp. 94-109.

113. **Niedermeyer E., da Silva F. L., (2005),** *"Electro-Encephalography: Basic Principles, Clinical Applications, and Related Fields"*, Lippincott Williams & Wilkins, Philadelphia, pp. 1-30.

114. **Stewart B., (2011),** *"Personality and Play Styles: A Unified Model"*, Technical report, Gamasutra, http://www.gamasutra.com/view/feature/134842/personality_and_play_styles_a_.php, (Data Download Date: 5/5/2014).

115. **Kennerly E., (2004),** *"Elements of the Psyche: Does Myers-Briggs Trump Bartle?"*, http://www.negamedesign.com/personality.html, (Data Download Date: 15/3/2014).

116. **Deng L., Yu D., (2014),** *"Deep Learning: Methods and Applications"*, Foundations and Trends in Signal Processing. Now Publishers, vol. 7, no. 3-4, pp. 206.

117. **Lehrer J., (2008),** *"Can a Thinking, Remembering, Decision-Making, Biologically Accurate Brain Be Built from a Supercomputer?"*, Seed Magazine, vol. 3, pp. 1-2.

118. **Basu R., (2004),** *"Implementing Quality: A Practical Guide to Tools and Techniques: Enabling the Power of Operational Excellence"*, Cengage Learning EMEA, pp. 1-131.

119. **Garrido C., De Oña R., De Oña J., (2014),** *"Neural Networks for Analyzing Service Quality in Public Transportation"*, Expert Systems with Applications, Elsevier, vol. 41, no. 15, pp. 6830-6838.

120. **Cawley G. C., Talbot, N. L., (2003),** *"Efficient Leave-One-Out Cross-Validation of Kernel Fisher Discriminant Classifiers"*, Pattern Recognition, Elsevier, vol. 36, no. 11, pp. 2585-2592.

121. **Demšar, J., (2006),** *"Statistical Comparisons of Classifiers over Multiple Data Sets*", The Journal of Machine Learning Research, JMLR.org, vol. 7, pp. 1-30.

122. **Streck H., (2014),** *"A Gamified Vision on Modern Society"*, http://www.society30.com/gamified-vision-modern-society/, (Data Download Date: 20/6/2014).

123. **Jordan K., (2013),** *"MOOC Completion Rates: The Data"*, http://www.katyjordan.com/MOOCproject.html, (Data Download Date: 5/4/2014).

124. **Colman D., (2013),** *"MOOC Interrupted: Top 10 Reasons Our Readers Didn't Finish a Massive Open Online Course"*, http://www.openculture.com/2013/04/10_reasons_you_didnt_complete_a_mooc.html, (Data Download Date: 5/4/2014).

125. **Ferro L. S., Walz S. P., Greuter S., (2013),** *"Towards Personalised, Gamified Systems: An Investigation into Game Design, Personality and Player*

Typologies", In Proceedings of the 9th Australasian Conference on Interactive Entertainment: Matters of Life and Death, ACM, pp. 7.

126. **Nielsen M. A., (2015),** *"Neural Networks and Deep Learning"*, Determination Press, http://neuralnetworksanddeeplearning.com/, (Data Download Date: 15/1/2015).

APPENDICES

A. LETTER OF SURVEY

This thesis was based on an online survey that has been asked to be answered anonymously by gamers who also have some experience with MOOCs. The purpose, properties, and basic information about this survey and its creator were introduced at the beginning of it; by presenting the following letter:

A Survey to find the relationship between video game playing styles and personality type in open online courses

I am working on my Masters thesis at the Department of Computer Engineering at Cankaya University in Ankara-Turkey. My work is to investigate and determine what are the distinctive factors and relationship between Massively Multi-player Online Games (MMOGs) playing styles and personality type in education; in order to classify participants into their equivalent game player types. It will be highly appreciated if you can help to improve this study by answering the questionnaire below. Your privacy, name, and other personal information are highly ensured as you will remain anonymous. No third party can reach your answers.

The questionnaire was divided into two parts. All questions in the rst part are required. Questions in the second part are optional. Answering all the required questions, of the rst part, may take about 10 minutes. Answering both parts of the questionnaire, the required part and optional part, may take about 20-30 minutes in total. No writing is needed; questions are easy-to-take multi choice questions so all you are asked to do is to check the box that describes your charac-ter more. There are no wrong answers. Please contact me at: *muthqal@yahoo.com* if you have a question or need additional information.

B. BODY OF SURVEY

Survey of this research was organized and delivered in terms of 3 categories: (1) 5 questions were dedicated to investigate respondents' demographic and experience with MOOCs, (2) 20 questions were deployed as a short MBTI version to analyze preferences of respondents, and (3) 30 optional questions representing Bartle's player psychology test in order to explore player type of our respondents automatically. The survey was designed and published using Google Forms service[12]. Questions were as follows:

PART 1 (All questions in this part are required)

Demographic and basic information about MOOC:

Gender:

- Male.
- Female.

Age:

- Less than 18.
- 18-24.
- 25-34.

[12] https://docs.google.com/forms/d/1FQycBvinWxRHcDRGkwD39dp23YWmijKVq2bhD85Pc/viewform

- 35-44.
- 45-54.
- Older than 55.

Level of Education:

- Doctorate.
- Master.
- Bachelor.
- High school.
- Other.

How many MOOC(s) did you attend?

- Only one.
- 2-3.
- 4-6.
- More than 6.

Will you enroll to another MOOC?

- Yes.
- No.

Please select the answer that describes how you usually feel or act.

1. You are:

- Easy to get to know.
- Hard to get to know.

2. What would you rather teach, if you were a teacher:

- Facts courses.
- Theoretical courses.

3. In usual, you are:

- A social person.
- Rather quiet and reserved.

4. You prefer to:

- Arrange meeting, parties, etc., previously.
- Keep options open.

5. You prefer to be considered as a:

- Practical person.
- Person with vision.

6. During social events and/or situations that many people involve, do you more often:

- Introduce others.
- Get introduced.

7. Following a schedule is:

- Appealing.
- Suffering.

8. Do you:

- Talk easily to almost all people.
- It's hard to talk to people that you don't know and trust, but you may say to specific people or under some conditions.

9. If you are going somewhere, you rather:

- Plan for what to do and when.
- Just go.

Please select the word that appeals to you more. Consider the meaning of the words, not how they look or sound.

10.

- Thinking.
- Feeling.

11.

- Facts.
- Ideas.

12.

- Hearty.
- Quiet.

13.

- Convincing.
- Touching.

14.

- Scheduled.
- Unplanned.

15.

- Statement.
- Concept.

16.

- Analyze.
- Sympathize.

17.

- Systematic.

- Automatic.

18.

- Determined.
- Devoted.

19.

- Concrete.
- Abstract.

20.

- Firm-minded.
- Warm-hearted.

PART 2 (The optional questions: Bartle's player types test)

Keep in mind that the questions below should be answered in the context of how you play your character on MMORPG (Massively Multi-player Online Role Playing Games).

1- Would you rather:

- Become a hero faster than your friends.
- Know more secrets than your friends.

2- On an MMORPG, would you rather be known as (a):

- The person with the best, most unique equipment in the game.
- Someone who can run from any two points in the world, and really knows their way around.

3- Would you rather:

- Know how to get things.
- Know where to find things.

4- On an MMORPG, a new area opens up. Which do you look forward to more?

- Being the first to get the new equipment from the area.
- Exploring the new area, and finding out its history.

5- Do you tend to:

- Know things no one else does.
- Have items no one else does.

6- Is it better to be:

- Loved.
- Feared.

7- Would you rather:

- Show them the sharp blade of your axe.
- Hear what someone has to say.

8- Would you rather:

- Vanquish your enemies.
- Convince your enemies to work for you, not against you.

9- Which would you enjoy more?

- Getting accepted by a guild/clan.
- Winning a duel with another player.

10- Another player has killed you. Do you want to:

- Find out why, and try to convince them not to do it again.
- Plot your revenge.

11- Are you more comfortable, as a player on an MMORPG:

- Talking with friends in a tavern.
- Out hunting orcs by yourself for experience.

12- Which do you enjoy more on an MMORPG?

- Getting the latest gossip.
- Getting a new item.

13- Would you rather be:

- Wealthy.
- Popular.

14- Which do you enjoy more in MMORPG quests?

- Getting the rewards at the end.
- Getting involved in the storyline.

15- Which would you rather be noticed for on an MMORPG?

- Your equipment.

- Your personality.

16- On an MMORPG, would you rather:

- Have a sword twice as powerful as any other in the game.
- Be the most feared person in the game.

17- On an MMORPG, would you be more prone to brag about:

- Your equipment.
- How many other players you've killed.

18- When playing a video game, is it more fun to:

- Have the highest score on the list.
- Beat your best friend one-on-one.

19- Would you rather have:

- Two levels of experience.
- An amulet that increases the damage you do against other players by 10%.

20- Would you rather receive as a quest reward:

- Experience points.
- A wand with 3 charges of a spell that lets you control other players, against their will. (Charm person).

21- Which would you enjoy more as an MMORPG player?

- Making your own maps of the world, and then selling them.

- Running your own tavern.

22- What's more important in an MMORPG to you?

- The number of people.
- The number of areas to explore.

23- You want to fight a really tough dragon. How would you approach this problem?

- Get a big group of players to kill it.
- Try a variety of weapons and magic against it, until you find its weakness.

24- You are being chased by a monster on an MMORPG. Do you:

- Ask a friend for help in killing it.
- Hide somewhere you know the monster won't follow.

25- What's more important to you?

- The uniqueness of the features, and game mechanic.
- The quality of roleplaying in an MMORPG.

26- If you're alone in an area, do you think:

- You'll have to look elsewhere for prey.
- It's safe to explore.

27- You meet a new player. Do you think of him as:

- As potential prey.

- Someone who can appreciate your knowledge of the game.

28- You learn that another player is planning your demise. Do you:

- Go to an area your opponent is unfamiliar with and prepare there.
- Attack him before he attacks you.

29- Would you rather:

- Explore a new area.
- Defeat an enemy.

30- On a MMORPG, would rather join a clan/guild of:

- Scholars.
- Assassins.

C. DEMOGRAPHIC INFORMATION OF RESPONDENTS

	Gender:	Age:	Education	How many MOOC(s) did you attend?	Will you enroll into other MOOC(s):
1	Male	35-44	Bachelor	Only 1	No
2	Male	18-24	Master	Only 1	No
3	Male	45-55	Master	More than 6	No
4	Male	18-24	Bachelor	Only 1	Yes
5	Male	18-24	Bachelor	'2-3	Yes
6	Female	25-34	Master	More than 6	Yes
7	Female	25-34	Bachelor	Only 1	Yes
8	Female	35-44	Master	Only 1	Yes
9	Male	25-34	Doctorate	'2-3	Yes
10	Male	25-34	Master	Only 1	No
11	Female	25-34	Master	Only 1	No
12	Female	18-24	Bachelor	'4-6	Yes
13	Male	25-34	Master	Only 1	No
14	Male	35-44	Master	More than 6	Yes
15	Male	18-24	Bachelor	Only 1	Yes
16	Male	25-34	Master	Only 1	No
17	Male	25-34	Bachelor	Only 1	No
18	Male	25-34	Master	Only 1	No
19	Female	18-24	Other	Only 1	No
20	Male	35-44	Bachelor	Only 1	Yes
21	Female	25-34	Bachelor	Only 1	Yes
22	Female	25-34	Bachelor	Only 1	Yes
23	Male	18-24	Bachelor	Only 1	No
24	Male	25-34	Master	'4-6	Yes
25	Male	25-34	Master	'4-6	Yes
26	Male	25-34	Master	'4-6	Yes
27	Male	35-44	Master	'4-6	Yes
28	Male	25-34	Master	Only 1	No
29	Male	25-34	Master	Only 1	Yes
30	Male	35-44	Master	Only 1	Yes
31	Male	25-34	Master	'2-3	Yes
32	Female	35-44	Doctorate	Only 1	Yes
33	Male	25-34	Doctorate	'4-6	Yes
34	Male	18-24	Bachelor	Only 1	Yes

35	Female	45-55	Bachelor	Only 1	No
36	Male	25-34	Master	Only 1	No
37	Male	25-34	Master	'4-6	Yes
38	Male	25-34	Master	Only 1	No
39	Male	25-34	Master	Only 1	No
40	Male	25-34	Master	Only 1	No
41	Male	35-44	Bachelor	Only 1	Yes
42	Male	25-34	Bachelor	Only 1	Yes
43	Male	25-34	Master	Only 1	No
44	Female	35-44	Bachelor	Only 1	No
45	Male	25-34	Master	Only 1	No
46	Male	25-34	Master	Only 1	Yes
47	Male	18-24	High School	Only 1	Yes
48	Female	25-34	Bachelor	Only 1	No
49	Male	35-44	Master	'2-3	No
50	Male	25-34	Bachelor	Only 1	No
51	Female	35-44	Bachelor	Only 1	Yes
52	Male	18-24	Bachelor	More than 6	Yes
53	Male	25-34	Bachelor	'2-3	Yes
54	Male	25-34	Bachelor	Only 1	Yes
55	Male	25-34	Bachelor	More than 6	Yes
56	Male	25-34	Master	Only 1	Yes
57	Male	18-24	Bachelor	'2-3	Yes
58	Male	25-34	Bachelor	Only 1	No
59	Male	25-34	High School	Only 1	No
60	Male	25-34	Bachelor	'2-3	No
61	Female	25-34	Bachelor	Only 1	Yes
62	Female	25-34	Bachelor	Only 1	Yes
63	Female	35-44	Bachelor	'2-3	No
64	Male	25-34	Master	Only 1	No
65	Male	25-34	Master	'2-3	Yes
66	Male	35-44	Bachelor	Only 1	No
67	Male	18-24	High School	Only 1	No
68	Male	25-34	Bachelor	Only 1	No
69	Male	25-34	Bachelor	Only 1	No
70	Male	25-34	Master	'2-3	Yes
71	Female	18-24	Bachelor	Only 1	Yes
72	Male	35-44	Master	More than 6	Yes
73	Female	18-24	High School	Only 1	No
74	Male	25-34	Master	Only 1	Yes
75	Male	25-34	Bachelor	Only 1	No

D. RESPONSES TO PERSONALITY ASSESSMENT (MBTI)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	1	1	2	1	1	2	1	2	1	1	1	2	1	1	1	1	2	1	1	2
2	1	1	1	1	1	2	1	1	1	2	1	2	2	1	1	1	2	1	2	2
3	2	1	1	1	1	1	1	1	2	1	2	1	1	2	2	1	1	2	1	1
4	2	2	2	2	2	1	1	1	1	2	2	1	2	2	2	2	1	1	1	2
5	1	2	2	1	2	1	1	1	1	1	2	2	2	1	2	1	1	1	1	1
6	1	1	1	2	2	2	1	1	1	2	2	2	1	1	2	1	1	1	1	2
7	1	1	2	1	1	2	1	2	2	2	2	2	2	1	2	2	2	2	2	2
8	1	2	2	2	1	1	1	2	1	1	2	2	1	2	1	1	1	1	2	2
9	1	1	1	2	1	1	1	1	2	1	1	2	1	2	2	1	1	1	2	2
10	1	1	1	1	1	2	1	2	1	1	1	2	2	1	1	1	1	1	2	1
11	1	1	1	1	1	1	2	2	1	2	1	2	1	1	1	1	2	1	2	2
12	1	1	1	2	1	2	2	1	2	2	1	2	2	2	1	1	2	1	2	2
13	1	2	1	2	2	1	1	1	2	2	2	2	2	2	2	1	1	2	2	2
14	2	2	2	2	2	2	2	2	2	2	2	1	2	1	2	1	2	2	2	2
15	1	1	1	2	2	2	1	1	2	1	2	1	2	1	2	1	2	1	1	1
16	2	2	1	1	1	1	1	1	1	1	1	2	2	1	2	1	1	2	1	2
17	2	1	1	1	2	1	1	2	1	1	2	2	1	1	2	1	2	1	2	2
18	1	2	2	2	1	1	1	1	1	1	1	1	2	1	2	1	1	1	2	1
19	1	1	1	2	2	2	1	1	2	2	2	1	2	2	1	2	1	1	1	2
20	1	1	1	2	1	1	1	1	1	1	1	1	1	1	2	1	2	1	1	1
21	1	2	1	1	2	1	1	1	1	2	2	1	1	1	2	2	1	2	2	2
22	1	1	2	1	2	1	1	1	1	2	2	2	2	1	2	1	2	1	2	2
23	1	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2	2	1	2	1
24	2	1	2	1	2	2	1	2	1	1	2	2	1	1	2	1	1	1	1	2
25	1	1	2	2	1	1	1	2	1	1	2	2	2	1	1	1	1	2	1	2
26	1	1	2	2	1	1	1	2	1	1	2	2	2	1	1	1	1	2	1	2
27	1	1	2	2	2	2	1	1	2	2	2	2	2	2	2	1	2	2	2	2
28	2	1	1	2	1	1	1	1	1	1	1	2	2	1	1	1	1	1	1	2
29	1	1	1	2	2	2	1	1	1	1	2	2	1	1	2	1	2	1	2	1
30	2	2	1	2	2	1	1	1	1	1	2	2	1	2	1	1	2	1	1	1
31	1	1	2	1	1	2	1	1	1	1	1	2	1	1	1	1	1	1	2	1
32	1	2	1	1	1	2	1	1	1	1	1	1	2	1	2	1	1	1	2	2
33	1	1	2	1	1	2	1	1	1	1	1	1	1	1	2	1	1	1	1	1
34	2	2	1	2	1	1	1	2	1	1	2	2	2	1	1	1	2	2	2	1

35	1	2	1	1	1	1	2	1	2	2	2	1	2	2	2	2	1	2	1	2
36	1	2	2	2	2	1	2	1	2	1	1	2	1	2	2	2	1	1	2	2
37	1	1	1	2	1	2	2	1	1	1	2	2	1	1	1	1	2	2	2	2
38	1	1	2	1	1	1	1	2	1	1	1	2	1	1	1	1	1	1	2	1
39	1	1	1	2	2	1	2	1	1	1	2	1	1	2	2	2	2	2	2	2
40	1	1	2	1	1	2	1	2	1	1	1	1	1	2	1	1	2	1	2	2
41	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1
42	1	1	2	2	2	1	1	2	1	1	2	2	1	1	2	2	1	1	1	2
43	1	1	2	2	1	1	1	1	1	1	2	1	1	1	2	1	1	2	2	1
44	1	1	1	1	1	1	2	1	1	1	1	1	1	1	2	1	1	1	1	1
45	2	2	1	1	1	2	1	2	2	2	2	1	2	1	2	1	2	1	2	2
46	2	1	1	2	1	1	2	1	2	1	1	2	2	1	2	1	1	1	2	2
47	1	2	2	1	2	2	1	1	2	1	1	2	1	1	1	1	1	1	1	1
48	1	2	1	1	1	1	1	1	1	2	2	2	2	1	2	1	1	2	1	2
49	2	1	1	1	2	1	2	1	2	1	2	2	1	1	1	1	2	1	2	1
50	1	1	1	2	1	1	2	1	1	1	2	2	2	2	2	1	2	1	2	2
51	2	2	1	1	2	1	1	1	2	2	2	1	2	2	2	2	1	2	2	2
52	1	2	2	2	1	2	1	2	1	1	1	2	1	1	1	1	1	1	1	1
53	1	1	2	1	1	2	1	2	1	1	2	2	1	1	2	1	1	1	1	1
54	1	2	2	2	1	2	2	2	2	1	2	2	1	1	2	1	1	1	2	2
55	1	1	1	2	2	1	1	1	2	1	1	1	1	2	2	1	2	1	2	1
56	2	2	1	1	1	2	2	1	2	1	1	1	1	2	2	1	2	2	1	1
57	1	1	2	2	2	1	1	1	1	1	1	2	2	1	2	1	1	1	2	2
58	1	2	2	2	1	1	1	2	2	2	1	1	1	1	1	1	2	1	2	2
59	2	2	2	2	2	1	2	2	1	1	2	2	1	1	1	1	1	1	1	1
60	1	1	2	2	1	2	1	2	1	1	1	2	1	1	2	1	2	1	1	1
61	1	2	1	1	2	2	2	1	2	2	2	1	1	1	2	1	2	1	2	2
62	2	1	2	2	2	2	1	2	1	1	1	1	2	1	1	2	2	2	2	2
63	1	2	1	1	2	1	2	2	1	1	2	2	2	1	2	1	1	1	2	2
64	1	1	2	1	1	2	2	2	2	1	1	2	2	2	1	1	2	1	1	1
65	1	1	1	2	1	2	1	2	1	1	1	2	1	1	1	1	1	1	1	1
66	1	2	1	2	2	2	2	1	2	2	2	1	1	1	2	1	1	1	1	2
67	2	1	1	1	2	2	2	1	2	1	1	1	2	2	2	1	1	1	2	1
68	1	1	1	1	2	1	1	1	1	1	2	2	2	1	1	1	2	2	1	1
69	1	1	1	1	2	1	1	1	1	1	2	2	2	1	1	1	2	2	1	1
70	1	1	1	2	2	1	1	1	1	1	2	2	1	1	1	1	1	1	1	1
71	2	1	2	2	1	2	2	2	2	2	1	2	2	1	2	1	1	2	2	2
72	1	1	1	2	1	1	1	2	2	1	2	2	1	1	1	1	1	2	1	2
73	1	1	1	1	1	2	1	2	1	2	2	1	1	1	1	2	1	2	1	2
74	1	2	1	1	2	2	1	1	1	1	1	1	1	1	2	1	1	1	2	1
75	1	1	2	2	1	2	2	1	2	1	1	2	1	2	1	1	1	2	1	2

E. RESPONSES TO BARTLE'S PLAYER TEST

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	2	2	1	1	1	1	1	1	2	2	2	2	1	1	2		1	1	1	1	1	2	1	2	1		2	2	2	2
2	1	2	1	1	1	1	1	1	1	1	2	2	2	2	1	2	2	2	1	1	1	1	1	1	2	1	2	2	2	1
3	2					1	1	2	1	1	1	1	2	2	2	1	1	1								2	2	1	1	1
4	1	1	1	2	1	1	2	2	1	1	1	2	1	1	2			1	1	2	2	2	1	2	1	2	2	2	1	1
5	1	2	2	2	1	1	2	2	2	2	2	2	2	1	2	2	2	1		1	2	2	1	2	1	1	1		2	2
6																														
7	2	2	2	1	2	1	2	2	2	2	2	2	1	1	1	1	1	1	1	1	2	1	2	1	1	2	1	1	2	2
8	2	1	1	2	1	1	2	2	1	1	1	2	1	1	2	2	1	1	2	1	1	1	1	1	1	2	1	1	1	1
9	1	2	1	2	1	1	1	2	2	1	1	2	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1
10	2	2	2	2	1	1	2	2	1	1	1	2	2	2	2	2	2	2	1	1	2	1	1	1	2	1	2	2	1	2
11	2																									1	1		1	1
12	2	1	2	1	1	1	1	1	2	2	1	2	2	1	2	2	2	1	1	1	1	1	2	2	2	2	1	2	2	2
13	2	2	2	2	1	1	2	2	1	2	2	1	2	2	2	1	2	2	1	2	1	2	2	2	2	2	2	2	1	1
14	2	1	1	2	1	1	2	2	2	1	2	2	1	2	2	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1
15	2	1	1	2	1	1	2	1	1	1	1	2	1	2	1		2	1	1	1	2	1	1	1	2	2	2	1	1	2
16	1	1	1	2	2	1	1	1	2	1	1	1	1	2	2	1	2	2	1	1	2	2	1	2	2	2	2	1	1	2
17	2	1	1	2	1	1	1	2	2	2	2	2	1	1	2	1	2	1	1	1	1	1	1	1	1	1	1	2	2	2
18	1		1	2	2	2	1	1	2	1	2	1	1	2	2	1	2	2	2	2	1	1	1	2	2	2	2	2	1	1
19	2	1	1	1	2	1	1	1	1	2	1	2	1	2	2	1	1	1	1	2	2	2	2	1	1	2	2	1	1	1
20	1	1	1	2	2	1	2	2	2	2	2	2	2	1	2	2	2	1	1	1	2	2	1	1	1	1	1	1	2	2
21	1	1	1	2	2	1	2	1	2	2	2	1	1	2	2	1	1	2	1	2	1	2	2	2	2	2	2	2	2	1
22	2	1	1	2	1	1	2	1	1	2	2	2	1	1	2	1	1	1	1	2	2	2	2	2	1	2	2	2	1	1
23	1	1	1	1	1	1	2	1	1	2	1	2	1	1	1	1	1	2	2	1	1	2	2	1	2	1	1	1	1	1
24	2	2	1	1	1	1	2	1	2	2	1	2	1	2	2	2	2	1	1	2	1	2	1	2	2	2	2	1	1	2

25	1	2	1	1	1	1	2	2	1	2	2	1	1	2	2	1	1	2	2	2	2	1	1	2	1	1	1	2	1	2
26	1	2	1	1	1	1	2	2	1	2	2	1	1	2	2	1	1	2	2	2	2	1	1	2	1	1	1	2	1	2
27	2	1	2	2	1	1	2	2	2	1	2	1	1	1	1	1	1	1	1	1				1	2	1	1	2	1	1
28	1	1	2	1	1	1	2	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	2	1	1	1				1
29	2	1	1	1	1	2	1	2	2	2	2	2	2	1	2	2	2	1	1	1	2	1	1	2	1	2	2	2	1	2
30	2	1	2	2	1	1	1	2	1	1	2	2	2	2	1	1	1	1	1	1	2	2	2	1	2	1	2	1	1	2
31	2	1	2	1	2	1	2	2	2	2	1	2	2	2	2	1	1	1	1	2	2	1	2	1	2	1	1	1	2	1
32	1	1	1	1	1	1	2	2	1	1	2	2	2	1	2	2	1	1	1	1	1	2	1	1	2	2	2	2	2	1
33	1	1	2	2	1	1	2	1	2	1	2	2	1	2	1	2	1	1	1	1	2	2	1	1	1	1	1	2	1	1
34																										1			1	1
35	2	2	1	2	2	1	2	2	1	1	1	2	2	2	2	1	1	1	1	1	2	2	2	2	2	1	2	2	1	1
36	1	1	1	2	1	1	1	2	2	2	1	2	2	2	2	2	2	1	1	1	2	1	2	2	2	2	1	2	2	1
37	1	2	1	1	1	2	1	1	2	2	1	2	1	2	2	1	2	2	1	2	2	1	1	1	2	2	1	2	2	1
38	1	2	1	2		1	2	1	1	1	2	2	2	2	1		1	2	2	1		1	2	1	2	2	2	2	2	2
39	1	2	1	1	1	1	1	2	1	1	1	2	2	2	1	1	2	2	1	1	2	1	1	1	1	2	1	2	1	1
40	1	2	1	2	1	1	2	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
41	1	1		1	2					2		2	2	1	1			1				2	2	2		2		2	2	
42	1	2	2	1	2	2	2	1	1	1	2	2	2	2	2	2	2	1	2	2	2	2	2	2	2	2	2	1	1	2
43	1	2	1	1	1	1	2	2	1	2	1	2	2	1	1	2	1	1	1	1	1	2	2	1	2	1	1	1	1	1
44	2	2	1	1	1	1	1	2	1	1	2	2	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1
45	1	2	1	2	1	1	2	2	1	1	2	2	2	1	2	2	2	1	1	2	2	2	1	1	1	1	2	1	1	2
46	2	1	2		2	1		2	1	1	1	2	2	1	2	2	2	1	2	2	2	1	2	1	2	1	2	1	2	2
47	1	1	1	1	2	1	2	2	1	2	2	2	2	1	2	2	2	1	2	2	2	1	1	2	1	2	1	2	2	1
48	2	2	2	1	1	1	1	1	2	1	1	2	2	1	2	1	1	2	1	2	1	2	2	2	1	2	2	1	1	1
49	2	2	2		1	1	2	1		2	1	1	1		2	1	1	2	1	2	1	1	2	1	2	1	1	1	2	2
50	1	2	2		1	2	2	2		1			1																	
51	2	2	2	2	1	1	2	2	1	1	2	2	1	2	2	1	1	1	1	1	2	2	2	1	2	2	1	1	1	1

52	1	2	1	2	1	1	2	2	2	2	1	2	2	1	2	1	2	1	1	2	1	1	2	1	1	2	2	1	1	1
53	1	1	1	2	1	1	2	2	2	2	2	2	1	2	2	1	2	2	1	1	2	1	2	2	2	1	2	1	2	1
54	2	1	2	1	1	1	2	2	2	2	2	2	2	2	2	2	1	1	1	2	2	2	2	2	2	2	2	1	1	2
55	2	2	1	2	1	2	1	1	1	2	2	1	1	1	2	1	2	2	1	1	1	1	1	1	1	1	1	1	1	2
56	1	1	1	1	2	1	2	2	2	2	1	2	1	2	1	1	1	1	1	2	1	1	1	1	1	2	2	2	1	2
57	1	1	1	1	2	1	1	1	1	2	1	2	2	1	1	1	1	1	2	1	2	1	2	2	1	2	2	2	2	2
58	1	2	1	1	1	1	2	2	1	1	1	1	1	1	2	1	2	1	1	1	2	1	1	1	2	2	1	2	1	1
59	2	2	2	2	1	1	2	1	2	1	2	1	1	2	2	1	1	2	1	1	2	2	2	2	2	2	2	1	1	1
60	2	2	1	2	1	1	2	2	2	2	2	2	2	1	2	2	2	1	1	1	2	1	2	2	1	2	1	2	2	2
61																														
62	2	2	2	2	2	1	2	2	2	1	2	1	1	1	1	2	1	1	2	2	1	1	2	1	2	1	2	2	2	1
63	2	2	1	2	1	1	2	2	1	2	2	2	2	1	2	2	1	1	1	2	2	2	2	2	2	1	1	2	2	1
64	1	1	2	1	2	2	2	1	2	2	2	2	2	2	2	2	2	1	1	1	2	1	1	2	1	2	2	2	2	2
65	1	2	1	1	1	1	2	1	2	2	1	2	1	2	1	1	2	2	2	1	1	1	1	1	1	2	2	2	2	1
66	2	1	2	1	1	1	2	1	2	2	2	2	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	2	1	1
67	1	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	2	1	1	2	1	1	2	1	1	2	1	1	1
68	1	1	1	2		1	2	2	1	2		2	1	2	2	2	2	1	2	2	1	2	1	1	2	2	2	2	2	1
69	1	1	1	2		1	2	2	1	2		2	1	2	2	2	2	1	2	2	1	2	1	1	2	2	2	2	2	1
70	2	2	1	2	2	1	2	2	2	1	1	2	2	1	1	1	1	2	1	2	1	1	1	2	1	2	1	2	1	1
71	2	1	1	1	1	2	1	2	1	2	1	1	1	1	2	2	1	1	2	2	2	2	2	2	1	2	1	1	2	1
72	2	1	1	2	2	1	2	2	2	2	2	2	1	2	2	1	1	1	2	1	1	2	2	1	2	1	2	2	1	1
73	1	2	2	2	1	1	2	2	2	1	1	1	1	2	2	2	1	1	1	1	1	1	2	2	1	1	1	1	1	2
74	2																													
75	2	2	2	2	1	2	1	1	2	2	2	2	1	1	1	2	2	2	2	2	1	2	1	1	2	2	1	2	2	2

F. PERSONALITY PREFRENCES AND BARTLE'S PLAYER TYPES

	MBTI	Keirsey	Bartle
1	ISTJ	SJ	Achiever
2	ESFJ	SJ	Achiever
3	ESTJ	SJ	Achiever
4	ENFJ	NF	Socializer
5	ENTJ	NT	Explorer
6	ENTJ	NT	Explorer
7	INFJ	NF	Socializer
8	INTJ	NT	Explorer
9	ESTP	SP	Killer
10	ISTJ	SJ	Achiever
11	ESTJ	SJ	Achiever
12	ESFP	SP	Killer
13	ENFP	NF	Socializer
14	INFP	NF	Socializer
15	ENTP	NT	Explorer
16	ESFJ	SJ	Achiever
17	INTJ	NT	Explorer
18	ENTJ	NT	Explorer
19	ESFP	SP	Killer
20	ESTJ	SJ	Achiever
21	ENFJ	NF	Socializer
22	ENFJ	NF	Socializer
23	ESFP	SP	Killer
24	INTJ	NT	Explorer
25	ISFJ	SJ	Achiever
26	ISFJ	SJ	Achiever
27	INFP	NF	Socializer
28	ESTJ	SJ	Achiever
29	ENTJ	NT	Explorer
30	ENTP	NT	Explorer
31	ISTJ	SJ	Achiever
32	ENTJ	NT	Explorer
33	ESTJ	SJ	Achiever
34	INTJ	NT	Explorer
35	ENFP	NF	Socializer

36	ENTP	NT	Explorer
37	ESTP	SP	Killer
38	ISTJ	SJ	Achiever
39	ENFP	NF	Socializer
40	ISTJ	SJ	Achiever
41	ESTJ	SJ	Achiever
42	INTJ	NT	Explorer
43	ENTJ	NT	Explorer
44	ESTJ	SJ	Achiever
45	INFJ	NF	Socializer
46	ESTP	SP	Killer
47	ISTJ	SJ	Achiever
48	ENFJ	NF	Socializer
49	ENTP	NT	Explorer
50	ENTP	NT	Explorer
51	ENFJ	NF	Socializer
52	ISTJ	SJ	Achiever
53	ISTJ	SJ	Achiever
54	INTP	NT	Explorer
55	ENTP	NT	Explorer
56	ESTP	SP	Killer
57	ENTJ	NT	Explorer
58	ESTP	SP	Killer
59	INTJ	NT	Explorer
60	ISTJ	SJ	Achiever
61	ENTP	NT	Explorer
62	ISFJ	SJ	Achiever
63	ENTJ	NT	Explorer
64	ISTP	SP	Killer
65	ISTJ	SJ	Achiever
66	ENTP	NT	Explorer
67	ENTP	NT	Explorer
68	ESTJ	SJ	Achiever
69	ESTJ	SJ	Achiever
70	ESTJ	SJ	Achiever
71	ISFP	SP	Killer
72	ESTJ	SJ	Achiever
73	ESFJ	SJ	Achiever
74	ENTJ	NT	Explorer
75	ISTP	SP	Killer

G. TRAINING SET OF BP CLASSIFIER

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	Class
1	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	0,	1,	1,	1,	0,	0,	0,	1,	0,	Achiever
2	1,	1,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	1,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	0,	Socializer
3	1,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	Explorer
4	0,	1,	0,	1,	0,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	1,	Killer
5	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	Achiever
6	1,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	1,	1,	Killer
7	1,	1,	1,	1,	0,	0,	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	1,	1,	Socializer
8	1,	0,	0,	1,	0,	0,	1,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	1,	1,	1,	Socializer
9	0,	0,	0,	1,	1,	0,	0,	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	0,	0,	1,	0,	0,	1,	0,	Achiever
10	1,	0,	0,	1,	0,	0,	0,	1,,	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	1,	1,	1,	1,	0,	0,	Explorer
11	1,	0,	0,	0,	1,	0,	0,	0,,	0,	1,	0,	1,	0,	1,	1,	0,	0,	0,	0,	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	0,	0,	1,	1,	Killer
12	0,	0,	0,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	Achiever
13	0,	0,	0,	1,	1,	0,	1,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	1,	0,	Socializer
14	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	1,	1,	0,	0,	1,	0,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	1,	0,	Socializer
15	0,	0,	0,	0,	0,	0,	1,	0,	0,	1,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	0,	0,	0,	0,	0,	0,	0,	1,	1,	Killer
16	1,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	Explorer
17	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	Achiever
18	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	Achiever
19	1,	0,	0,	0,	0,	1,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	0,	0,	1,	0,	1,	1,	1,	0,	1,	0,	1,	0,	0,	Explorer
20	1,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	0,	1,	0,	0,	1,	0,	1,	0,	1,	Explorer
21	1,	0,	1,	0,	1,	0,	1,	1,	1,	1,	0,	1,	1,	1,	1,	0,	0,	0,	0,	1,	1,	0,	1,	0,	1,	0,	0,	0,	1,	0,	1,	0,	0,	0,	Achiever
22	0,	0,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	0,	0,	1,	0,	0,	Explorer
23	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	0,	Achiever
24	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	1,	Socializer
25	0,	0,	0,	1,	0,	0,	0,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	1,	1,	0,	0,	1,	0,	1,	Explorer
26	0,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	0,	0,	1,	Killer
27	0,	1,	0,	0,	0,	0,	0,	1,	0,	0,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	1,	0,	1,	0,	0,	0,	1,	1,	1,	Socializer
28	0,	1,	0,	1,	0,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0,	Achiever
29	0,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	Explorer
30	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	1,	0,	0,	0,	0,	0,	0,	1,	0,	0,	Explorer
31	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	Achiever
32	0,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	0,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	0,	Socializer
33	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	1,	1,	1,	0,	1,	1,	1,	0,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	0,	1,	0,	0,	0,	Achiever
34	1,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0,	1,	1,	0,	Socializer
35	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	1,	0,	Socializer
36	0,	1,	0,	1,	0,	0,	1,	1,	1,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	1,	0,	0,	0,	Achiever
37	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	1,	0,	1,	1,	1,	0,	1,	0,	1,	0,	1,	0,	0,	0,	Achiever
38	1,	0,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	Explorer
39	1,	1,	0,	1,	0,	1,	0,	0,	0,	1,	1,	0,	0,	0,	1,	0,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	1,	0,	1,	Explorer
40	0,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	1,	0,	1,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	0,	0,	0,	1,	Killer
41	0,	0,	0,	0,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	1,	0,	1,	1,	0,	1,	1,	1,	1,	1,	0,	1,	0,	0,	Explorer
42	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	1,	0,	1,	0,	0,	0,	1,	0,	0,	0,	1,	1,	0,	1,	0,	0,	0,	0,	0,	1,	Killer
43	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	1,	0,	0,	Explorer
44	1,	1,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	1,	0,	0,	0,	Achiever
45	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	1,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	0,	1,	0,	1,	0,	Achiever
46	1,	1,	0,	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	Explorer
47	0,	0,	1,	0,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	0,	0,	1,	0,	1,	1,	1,	1,	1,	1,	0,	0,	1,	Killer
48	0,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	1,	0,	0,	0,	Achiever
49	1,	0,	1,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0,	1,	0,	1,	Explorer
50	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	0,	0,	0,	0,	1,	0,	1,	Explorer
51	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	0,	1,	0,	1,	0,	0,	0,	1,	0,	1,	0,	1,	0,	0,	0,	0,	0,	0,	Achiever
52	1,	0,	0,	0,	0,	1,	0,	1,	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	1,	1,	0,	1,	0,	0,	1,	0,	1,	0,	1,	1,	Killer
53	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	0,	0,	0,	0,	0,	Achiever
54	0,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	0,	Achiever
55	1,	1,	1,	1,	0,	1,	0,	0,	1,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	0,	0,	1,	Killer

H. TESTING SET OF BP CLASSIFIER

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	Class
1	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	0,	1,	0.5,	0,	0,	0,	0,	0,	1,	0,	1,	0,	0.5,	1,	1,	1,	1,	1,	0,	0,	0,	Achiever
2	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	0.5,	0.5,	0,	0,	1,	1,	1,	0,	1,	0,	1,	1,	1,	0,	0,	0,	1,	1,	0,	Socializer
3	0,	1,	1,	1,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0.5,	0,	1,	1,	0,	1,	0,	0,	0,	0.5,	1,	1,	0,	1,	0,	0,	Explorer
4	1,	0,	0,	1,	0,	0,	1,	0,	0,	0,	0,	1,	0,	1,	0,	0.5,	1,	0,	0,	0,	1,	0,	0,	0,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	Explorer
5	0,	0.5,	0,	1,	1,	1,	0,	0,	1,	0,	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	0,	0,	0,	1,	0,	0,	Explorer
6	1,	0,	1,	1,	0,	0,	1,	1,	1,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0.5,	0.5,	0.5,	0,	1,	0,	0,	1,	0,	0,	1,	1,	1,	1,	Socializer
7	0,	0,	1,	0,	0,	0,	1,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0.5,	0.5,	0.5,	0,	0,	0,	0,	0,	Achiever
8	0,	1,	0,	1,	0.5,	0,	1,	0,	0,	0,	1,	1,	1,	1,	0,	0.5,	0,	1,	1,	0,	0.5,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	Achiever
9	1,	0,	1,	0.5,	1,	0,	0.5,	1,	0,	0,	0,	1,	1,	0,	1,	1,	1,	0,	1,	1,	1,	0,	1,	0,	1,	0,	1,	0,	1,	1,	0,	0,	0,	1,	Killer
10	1,	1,	1,	0.5,	0,	0,	1,	0,	0.5,	1,	0,	0,	0,	0.5,	1,	0,	0,	1,	0,	1,	0,	0,	1,	0,	1,	0,	0,	0,	1,	1,	0,	1,	0,	1,	Explorer
11	0,	0,	0,	1,	0.5,	0,	1,	1,	0,	1,	0.5,	1,	0,	1,	1,	1,	1,	0,	1,	1,	0,	1,	0,	0,	1,	1,	1,	1,	1,	0,	0,	0,	0,	0,	Achiever
12	0,	0,	0,	1,	0.5,	0,	1,	1,	0,	1,	0.5,	1,	0,	1,	1,	1,	1,	0,	1,	1,	0,	1,	0,	0,	1,	1,	1,	1,	1,	0,	0,	0,	0,	0,	Achiever

I. DATA SET OF EXPERIMENT 1

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	Class
1	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	0,	1,	1,	1,	0,	Achiever
2	1,	1,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	1,	0,	0,	1,	0,	0,	1,	1,	Socializer
3	1,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0,	Explorer
4	0,	1,	0,	1,	0,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0,	Killer
5	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	1,	0,	1,	Achiever
6	1,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	1,	1,	1,	Killer
7	1,	1,	1,	1,	0,	0,	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	Socializer
8	1,	0,	0,	1,	0,	0,	1,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	Socializer
9	0,	0,	0,	1,	1,	0,	0,	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	0,	0,	1,	Achiever
10	1,	0,	0,	1,	0,	0,	0,	1,,	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	1,	1,	Explorer
11	1,	0,	0,	0,	1,	0,	0,	0,,	0,	1,	0,	1,	0,	1,	1,	0,	0,	0,	0,	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	Killer
12	0,	0,	0,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	Achiever
13	0,	0,	0,	1,	1,	0,	1,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	Socializer
14	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	1,	1,	0,	0,	1,	0,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	Socializer
15	0,	0,	0,	0,	0,	0,	1,	0,	0,	1,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	0,	0,	0,	0,	0,	Killer
16	1,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	Explorer
17	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	Achiever
18	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	Achiever
19	1,	0,	0,	0,	0,	1,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	0,	0,	1,	0,	1,	1,	1,	0,	1,	Explorer
20	1,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	0,	1,	0,	0,	1,	Explorer
21	1,	0,	1,	0,	1,	0,	1,	1,	1,	1,	0,	1,	1,	1,	1,	0,	0,	0,	0,	1,	1,	0,	1,	0,	1,	0,	0,	0,	1,	0,	Achiever
22	0,	0,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	0,	Explorer
23	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	Achiever
24	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	1,	0,	0,	Socializer
25	0,	0,	0,	1,	0,	0,	0,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	1,	1,	0,	Explorer
26	0,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	0,	1,	1,	0,	Killer
27	0,	1,	0,	0,	0,	0,	0,	1,	0,	0,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	1,	0,	1,	0,	0,	Socializer
28	0,	1,	0,	1,	0,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	Achiever
29	0,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	Explorer
30	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	1,	0,	0,	0,	0,	0,	Explorer
31	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	Achiever
32	0,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	0,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	1,	0,	0,	1,	Socializer
33	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	1,	1,	1,	0,	1,	1,	1,	0,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	0,	Achiever
34	1,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	Socializer
35	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0,	Socializer
36	0,	1,	0,	1,	0,	0,	1,	1,	1,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	Achiever
37	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	1,	0,	1,	1,	1,	0,	1,	0,	1,	0,	Achiever
38	1,	0,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	Explorer
39	1,	1,	0,	1,	0,	1,	0,	0,	0,	1,	1,	0,	0,	0,	1,	0,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	Explorer
40	0,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	1,	0,	1,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	Killer
41	0,	0,	0,	0,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	1,	0,	1,	1,	0,	1,	1,	1,	1,	1,	Explorer
42	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	1,	0,	1,	0,	0,	0,	1,	0,	0,	0,	1,	1,	0,	1,	0,	0,	Killer
43	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	Explorer
44	1,	1,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	Achiever
45	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	1,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	0,	Achiever
46	1,	1,	0,	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	0,	0,	1,	1,	0,	Explorer
47	0,	0,	1,	0,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	0,	0,	1,	0,	1,	1,	1,	1,	1,	Killer
48	0,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	Achiever
49	1,	0,	1,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0,	Explorer
50	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	0,	0,	0,	Explorer
51	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	0,	1,	0,	1,	0,	0,	0,	1,	0,	1,	0,	1,	0,	0,	Achiever
52	1,	0,	0,	0,	0,	1,	0,	1,	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	1,	1,	0,	1,	0,	0,	1,	0,	Killer
53	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	0,	Achiever
54	0,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	1,	Achiever
55	1,	1,	1,	1,	0,	1,	0,	0,	1,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	0,	0,	1,	1,	0,	1,	1,	1,	Killer

J. DATA SET OF EXPERIMENT 3

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	Class
1	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	0,	1,	1,	1,	0,	0.4,	0.2,	0.6,	0.2,	Achiever
2	1,	1,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	1,	0,	0,	1,	0,	0,	1,	1,	0.8,	0.6,	1,	0.4,	Socializer
3	1,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0.6,	0.6,	0.2,	0.4,	Explorer
4	0,	1,	0,	1,	0,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0.2,	0.4,	0.2,	0.6,	Killer
5	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0.6,	0.2,	0.2,	0,	Achiever
6	1,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	1,	1,	1,	0.4,	0.2,	0.6,	1,	Killer
7	1,	1,	1,	1,	0,	0,	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0.2,	1,	0.8,	0.6,	Socializer
8	1,	0,	0,	1,	0,	0,	1,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0.8,	1,	0.8,	0.8,	Socializer
9	0,	0,	0,	1,	1,	0,	0,	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	0,	0,	1,	0.4,	0.4,	0.6,	0,	Achiever
10	1,	0,	0,	1,	0,	0,	0,	1,,	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	1,	1,	0.6,	0.8,	0.2,	0.2,	Explorer
11	1,	0,	0,	0,	1,	0,	0,	0,,	0,	1,	0,	1,	0,	1,	1,	0,	0,	0,	0,	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	0.2,	0.4,	0.8,	0.6,	Killer
12	0,	0,	0,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	0,	0.2,	0,	0.4,	Achiever
13	0,	0,	0,	1,	1,	0,	1,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	0.8,	0,	Socializer
14	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	1,	1,	0,	0,	1,	0,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0.4,	0.8,	0.6,	0.2,	Socializer
15	0,	0,	0,	0,	0,	0,	1,	0,	0,	1,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	0,	0,	0,	0,	0,	0.2,	0.4,	0.6,	0.6,	Killer
16	1,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	1,	0.6,	0.2,	0,	Explorer
17	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	0.6,	0.2,	0.6,	0.2,	Achiever
18	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	0,	0,	1,	0,	0,	0,	1,	0,	1,	0.6,	0.2,	0.6,	0.2,	Achiever
19	1,	0,	0,	0,	0,	1,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	0,	0,	1,	0,	1,	1,	1,	0,	1,	0.4,	0.8,	0,	0.4,	Explorer
20	1,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	0,	1,	0,	0,	1,	0.4,	0.6,	0,	0.6,	Explorer
21	1,	0,	1,	0,	1,	0,	1,	1,	1,	1,	0,	1,	1,	1,	1,	0,	0,	0,	0,	1,	1,	0,	1,	0,	1,	0,	0,	0,	1,	0,	0.6,	0.2,	0,	0,	Achiever
22	0,	0,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	0,	0.2,	0.6,	0.4,	0,	Explorer
23	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	0.4,	0.2,	0,	0,	Achiever
24	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0.6,	1,	0.6,	Socializer
25	0,	0,	0,	1,	0,	0,	0,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	1,	1,	0,	0.4,	0.8,	0.4,	0.8,	Explorer
26	0,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	0,	1,	1,	0,	0.4,	0.4,	0.4,	0.6,	Killer
27	0,	1,	0,	0,	0,	0,	0,	1,	0,	0,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	1,	0,	1,	0,	0,	0,	0.8,	0.6,	0.8,	Socializer
28	0,	1,	0,	1,	0,	0,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0.6,	0.2,	0.2,	0.4,	Achiever
29	0,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	0.6,	0.6,	0.4,	0.2,	Explorer
30	0,	1,	0,	0,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	0,	1,	0,	0,	0,	0,	0,	1,	1,	0,	1,	0,	0,	0,	0,	0,	0.2,	0.6,	0.2,	0.2,	Explorer
31	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0.2,	0,	0.2,	Achiever
32	0,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	1,	1,	0,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	1,	0,	0,	1,	0.6,	0.8,	0.6,	0.4,	Socializer
33	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	1,	1,	1,	0,	1,	1,	1,	0,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	0,	0.6,	0.4,	0,	0.2,	Achiever
34	1,	1,	1,	0,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0.2,	0.6,	0.8,	0,	Socializer
35	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	1,	0,	0,	0,	0,	0.2,	1,	1,	0.4,	Socializer
36	0,	1,	0,	1,	0,	0,	1,	1,	1,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	1,	0,	0,	0,	0.8,	0.2,	0,	0.2,	Achiever
37	0,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	0,	1,	1,	0,	0,	1,	0,	1,	1,	1,	0,	1,	0,	1,	0,	0.8,	0.4,	0,	0,	Achiever
38	1,	0,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	1,	0.8,	0.8,	0.2,	0.6,	Explorer
39	1,	1,	0,	1,	0,	1,	0,	0,	0,	1,	1,	0,	0,	0,	1,	0,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0.6,	0,	0.8,	Explorer
40	0,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	1,	0,	1,	0,	0,	0,	0,	0,	1,	0,	0,	0,	0,	0,	1,	1,	1,	0,	1,	0.4,	0.4,	0.2,	0.8,	Killer
41	0,	0,	0,	0,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0,	1,	0,	1,	1,	0,	1,	1,	1,	1,	1,	0.4,	0.6,	0.4,	0.2,	Explorer
42	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	1,	0,	1,	0,	0,	0,	1,	0,	0,	0,	1,	1,	0,	1,	0,	0,	0.4,	0.4,	0.4,	0.6,	Killer
43	1,	1,	1,	1,	0,	0,	1,	0,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	0.8,	0.6,	0,	0.4,	Explorer
44	1,	1,	0,	1,	0,	0,	1,	1,	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	1,	1,	0.8,	0.2,	0,	0.4,	Achiever
45	1,	1,	1,	1,	1,	0,	1,	1,	1,	0,	1,	0,	0,	0,	0,	1,	0,	0,	1,	1,	0,	0,	1,	0,	1,	0,	1,	1,	1,	0,	0.8,	0.4,	0.8,	0.4,	Achiever
46	1,	1,	0,	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	0,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	1,	0,	0,	1,	1,	0,	0.4,	1,	0.4,	0.2,	Explorer
47	0,	0,	1,	0,	1,	1,	1,	0,	1,	1,	1,	1,	1,	1,	1,	1,	1,	0,	0,	0,	1,	0,	0,	1,	0,	1,	1,	1,	1,	1,	0.8,	0,	0.2,	0.8,	Killer
48	0,	1,	0,	0,	0,	0,	1,	0,	1,	1,	0,	1,	0,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	1,	1,	0,	0.6,	0,	0,	0.2,	Achiever
49	1,	0,	1,	0,	0,	0,	1,	0,	1,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	0,	1,	0,	0,	0.2,	0.8,	0.4,	0.6,	Explorer
50	0,	0,	1,	1,	0,	0,	1,	1,	0,	1,	0,	0,	1,	1,	0,	0,	1,	1,	0,	0,	1,	0,	0,	1,	0,	0,	1,	0,	0,	0,	0.4,	0.6,	0.2,	0.6,	Explorer
51	1,	1,	0,	1,	1,	0,	1,	1,	1,	0,	0,	1,	1,	0,	0,	0,	0,	1,	0,	1,	0,	0,	0,	1,	0,	1,	0,	1,	0,	0,	0.2,	0.4,	0,	0.2,	Achiever
52	1,	0,	0,	0,	0,	1,	0,	1,	0,	1,	0,	0,	0,	0,	1,	1,	0,	0,	1,	1,	1,	1,	1,	1,	0,	1,	0,	0,	1,	0,	1,	0.4,	0.8,	0.6,	Killer
53	1,	0,	0,	1,	1,	0,	1,	1,	1,	1,	1,	1,	0,	1,	1,	0,	0,	0,	1,	0,	0,	1,	1,	0,	1,	0,	1,	1,	0,	0,	0.4,	0.2,	0.4,	0.4,	Achiever
54	0,	1,	1,	1,	0,	0,	1,	1,	1,	0,	0,	0,	0,	1,	1,	1,	0,	0,	0,	0,	0,	0,	1,	1,	0,	0,	0,	0,	0,	1,	0.4,	0.2,	0.8,	0,	Achiever
55	1,	1,	1,	1,	0,	1,	0,	0,	1,	1,	1,	1,	0,	0,	0,	1,	1,	1,	1,	1,	0,	1,	0,	0,	1,	1,	0,	1,	1,	1,	0.6,	0,	0.4,	0.8,	Killer

K. CURRICULUM VITAE

PERSONAL INFORMATION

Surname, Name: Al-Taei, Ali

Date and Place of Birth: 07 October 1979, France

Marital Status: Single

Phone: +964 7703 911 911

Email: muthqal@yahoo.com

EDUCATION

Degree	Institution	Year of Graduation
M.Sc.	Çankaya University, Computer Engineering	2015
H.D.	University of Technology, Artificial Intelligence, Baghdad	2003
B.Sc.	University of Baghdad, Computer Science, Baghdad	2002
High School	Al-Iraq Al-Jadeed High School, Baghdad	1997

WORK EXPERIENCE

Year	Place	Enrollment
2012- onwards	Dept. of Computer Engineering, Cankaya University, Ankara, Turkey.	M.Sc., Student
2008-2012	College of Managerial Techniques, Ministry of Higher Education and Scientific	Instructor, Computer Lab supervisor, TA, Supervisor of

	Research, Baghdad, Iraq.	Postgraduate Computer Labs, and Registrar of Iraqi Virtual Scientific Library (ivsl.org).
February 2006-November 2006	College of Managerial Techniques, Ministry of Higher Education and Scientific Research, Baghdad, Iraq.	Computer Lab. supervisor, TA, and the Head of Computer Maintenance Unit.
2004-2005	Institute of Medical Techniques, Ministry of Higher Education and Scientific Research, Baghdad, Iraq.	Instructor.
2003-2004	Institute of Medical Techniques, Ministry of Higher Ed-ucation and Scientific Research, Baghdad, Iraq.	Instructor.

FOREIN LANGUAGES

Native Arabic, Advanced English, Intermediate Spanish and Turkish, Beginner French.

THESIS AND PROJECTS

1. Voice Recognition System using Back-Propagation Technique, University of Technology, 2003.

2. Simulation to 8255 PPI, Dept. of Computer Science, University of Baghdad, 2002.

HONOURS AND CERTIFICATES

1. Introduction to Atrificial Intelligence, (aiclass), Statement of accomplishment, 2011.
2. Toefl ITP, 557, 2011.
3. IC3, 2011.

INTERESTS AND SKILLS

- Programming languages: VB, C++, Prolog, Python, and Assembly.
- Topics: Gamers' Psychology, Gamification, Pattern Recognition, Ciphering, Computer Architecture, Automata, Artificial Intelligence, Expert Systems, Neural Network Systems, Genetic Algorithms, and AI Philosophy.

HOBBIES

Movies, Reading, Walking, Writing, Football.