UNIVERSITY OF IOANNINA
SCHOOL OF EDUCATION
DEPARTMENT OF PRIMARY EDUCATION

«Using psychophysiological measures to assess learners' cognitive and affective states in a theory-based gamified MOOC»

Angeliki Tsiara

PhD Thesis

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School of Education, University of Ioannina, Greece

<u>Three-member Advisory Committee</u>

1. Anastasios Mikropoulos, Professor, Department of Primary Education, School of Education, University of Ioannina, Greece - supervisor
2. Spyridon Konitsiotis, Associate Professor of Neurology, Medical School, University of Ioannina, Greece
3. Konstantinos Kotsis, Professor, Department of Primary Education, School of Education, University of Ioannina, Greece

<u>Seven-member Examination Committee</u>

1. Anastasios Mikropoulos, Professor, Department of Primary Education, School of Education, University of Ioannina, Greece - supervisor
2. Spyridon Konitsiotis, Associate Professor of Neurology, Medical School, University of Ioannina, Greece
3. Konstantinos Kotsis, Professor, Department of Primary Education, School of Education, University of Ioannina, Greece
4. Julien Mercier, Professor, Département d' éducation et formation spécialisées, Université du Québec à Montréal, Canada
5. Vasilios Komis, Professor, Department of Educational Sciences and Early Childhood Education, University of Patras
6. Demetrios Sampson, Professor, Department of Digital Systems, University of Piraeus
7. Athanasios Tzimogiannis, Professor, Department of Social and Education Policy, University of the Peloponnese

Abstract

Current literature on Massive Open Online Courses (MOOCs) focuses on adopting gamification to address the high dropout rates targeting on enhancing learners' engagement. Recent reviews suggest to go beyond a simple application of game elements and use theory-driven gamification designs for learning scenarios in MOOCs. The present thesis emphasized on the importance of designing gamified learning assessment activities for MOOCs that create smooth learning curves for learners and evaluated their effectiveness by using psychophysiological measures. Our goal was to investigate whether the integration of the game element progression, could affect the learners' cognitive and affective states. The design of the gamified activity was based on Goal-setting Theory and the revised Bloom's Taxonomy. To evaluate the effectiveness of the proposed intervention, we conducted an empirical study, on Coursity MOOC platform, with a sample of 58 participants 19 to 46 years old. We used the technique of electroencephalography (EEG) to objectively evaluate the participants' cognitive and affective state by extracting a set of EEG spectral features. Specifically, we calculated the absolute and relative power values in four frequency bands of EEG signal i.e., theta (θ), alpha (α), beta (β), low beta (low_β), and their ratios i.e., task engagement $\beta/(\alpha+\theta)$, attention ratio θ/low_β, workload θ/α, arousal β/α, and valence $\alpha F4/\beta F4 - \alpha F3/\beta F3$. We also used a questionnaire to study the participants' perceived engagement. Our results showed that the proposed gamified intervention did not have a significant impact on learners' cognitive and affective states. Also, arousal was significantly increased in the task condition for both groups as compared to the baseline values. A significant increase was found in participants' workload for the experimental group between the two conditions. Results regarding the participants' perceived engagement showed no statistically significant differences between the two groups, which confirms the results from the neural data. This study contributes in the field of theory-based gamification design using the goal-setting theory as theoretical framework as it has not exploited in the field of MOOCs. The study provides psychophysiological measures for the evaluation of gamification in a MOOC assessment activity and discusses the potential value of these measures. Finally, we argue that electroencephalography has the potential to inform MOOC designers to design more engaging courses leading to lower dropout rates.

Keywords

Massive Open Online Courses (MOOCs), gamification, electroencephalography (EEG), progression, engagement, learner's cognitive states, spectral analysis

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Chapter 1. Introduction

1.1. Problem Statement

Massive open online courses (MOOCs) are an advanced version of online education that has recently received great attention by higher educational institutes due to their remarkable features. MOOCs are massive, as they have no limit on learners' enrollments, they are open, as anyone may attend them without any constraints, they are online, as their learning material and activities are accessible via the web, and they are courses structured on video lectures and other interactive material. Through MOOCs, learners from all over the world are given the opportunity to access world-class educational resources. In the last decade, the number and the diversity of MOOCs have grown greatly and have gained popularity among learners and educators. Despite their flexibility and convenience over the traditional online learning, MOOCs have to deal with several challenges (Kim et al., 2017).

The most significant challenge of MOOCs, as mentioned in the relevant literature, is the low completion rates. Research studies report that only a small percentage (about 10%) of the enrolled learners complete the course (Feng et al., 2019). As MOOCs are gaining more popularity worldwide, researchers and course developers are striving to find innovative ways to help learners that enroll in MOOCs to persist more (Barak et al, 2016; Chen et al., 2019). Their efforts lie on the fact that high dropout rates result in reduced revenue for the institutes, but more importantly, they are struggled to improve MOOCs' educational effectiveness which is the principal goal for open learning.

Several research studies have suggested models that predict learners' dropout in order to help MOOC developers gain greater understanding of the factors that are affecting learner's persistence in MOOCs. According to Aldowah et al. (2020), learners' academic skills and background knowledge, feedback, course design, social presence, and social support, are factors that have a primary impact on learners' dropout. However, other researchers argue that in order to evaluate the success rate in MOOCs, we should not take into account only the completion rates, but we should also be aware of learners' initial goals and intentions. It should be noted that MOOCs are not traditional online courses as they can afford a massive number of learners, with diverse backgrounds, who may interact with the course in different ways. Some learners may enroll out of curiosity, other learners are interested in attending only a part of the course, while others may complete the course but not apply for a certificate. In every case, to continue with a MOOC, learners should be motivated. Their motives can be either intrinsic or extrinsic. For example, learners who acknowledge that receiving a certificate of completion is important for obtaining employment, are extrinsically motivated. Other learners although may not be motivated enough to complete the course. Therefore, MOOC designers should use innovative features in their course design to provide (intrinsic or extrinsic) incentives to learners and keep them engaged during the course. Antonaci et al. (2019) argue that in order to increase completion rates, MOOC designers should enable learners to plan their objectives within the course while offering engaging learning activities.

Engagement has a significant role in the design of contents and services. However, there are challenges regarding its conceptualization and measurement. The term "engagement" is used to describe the simultaneous experience of concentration, interest and enjoyment in a certain activity (Shernoff, 2013). Engagement is identified by researchers as a multidimensional construct with cognitive, behavioral, and emotional aspects. Cognitive engagement refers to an individual's willingness to exert the necessary effort to comprehend complex ideas and master difficult skills (Fredricks, Blumenfeld, & Paris, 2004). Emotional engagement is defined as learners' emotional reactions towards co-learners, instructors, or subject areas. Behavioral engagement refers to learner's observable actions related to participation. Researchers should acknowledge that it is difficult to study only one dimension of engagement, as all three dimensions occur simultaneously and affect its measurement.

To evaluate learners' engagement, researchers should define engagement before selecting the method for its measurement. Their definition should drive the choice of appropriate measures. Researchers should also define the context and the level in which engagement is being measured. For example, we can measure learners' engagement in microlevel, e.g., in a specific task, or we can measure it in macrolevel i.e., evaluate the engagement of a group of learners' e.g., in a course, class, etc. Task engagement is described as an effortful commitment to task goals (Matthews et al., 2002; Fairclough, Ewing & Roberts, 2009). It is a multidimensional concept that involves cognition, motivation, and affect.

Engagement in learning is typically assessed with surveys that are administered to learners after learning has completed. These questionnaires do not assess learner's engagement during the learning process, and it is not clear whether they are reliable for measuring learners' engagement (Trowler & Trowler, 2010). This stands true for MOOCs as well. Other research studies on engagement primarily focus on examining behavioral engagement based on MOOC learners' observable actions (Li & Baker, 2016).

Several physiological measures such as heart rate variability, oculomotor activity, galvanic skin response, etc., have been proposed to measure engagement (Chaouachi et al., 2010; Nacke & Lindley, 2008). Among them, the electroencephalogram (EEG) is the only physiological signal that can reliably detect changes in learners' cognitive and affective states in real-time with high precision. Therefore, EEG provides an unobtrusive method to assess learners' engagement. However, it is generally accepted that a single method poses another challenge in the measurement of engagement. Ideally, researchers should use a combination of different methods and instruments to better approximate engagement (Park, Liu, Yi & Santhanam, 2019). Task engagement is measured using EEG either to monitor and evaluate learners' cognitive state or to provide input data in real-time adaptive systems (such as intelligent tutoring systems, games, etc.). MOOCs can take advantage of the technological advancement of neurophysiological sensors to inform the design of MOOCs or to provide learners with a personalized experience.

Gamification, which is the process of using game thinking and game mechanics in non-game scenarios, is often suggested as a strategy that has the potential to engage individuals in various settings. Gamification combines elements that promote both aspects of motivation i.e., the intrinsic and the extrinsic motivation. It uses rewards such as points, badges, levels, etc. (extrinsic), while trying to raise emotions of mastery, self-efficacy, satisfaction, and autonomy (intrinsic).

In MOOCs, although the implementation of gamification has not been studied extensively, it is considered to be a successful strategy to engage and facilitate MOOC learners to attain their goals within the course (Antonaci, Klemke & Specht, 2019; Rincón-Flores, Ramírez Montoya & Mena, 2019). It should be noted that, gamification design is a process that depends on the problem to be solved, the effect to be generated, the context, and the audience (Antonaci, Klemke & Specht, 2019). Additionally, recent studies suggest going beyond the simple applications of external rewards such as points, badges, leaderboards, etc., and exploit theory-based gamification designs that provide a better match between gamification affordances and existing problems (Nacke & Deterding, 2017; Park et al., 2019, Rapp et al., 2019). Several theories of motivation have been suggested as the basis for gamification design methodologies. The Self-Determination Theory proposed by Deci & Ryan (2000) and the Flow Theory proposed by Csikszentmihalyi (1975) are the most referenced theories on gamification. The former highlights the importance of satisfying three human psychological needs, autonomy, competence, and relatedness, to increase motivation, while the latter suggest that the optimal state of intrinsic motivation is caused by providing challenges (tasks) that are in balance with the individual's skills.

MOOC platforms technologically provide features that can be considered as game elements, e.g., the narrative of the video lectures, the challenges of the assignments, the score (or grade) of the assignments (usually quizzes with multiple choice questions), the potential to have timed assignments and graded/ungraded assignments, the automated performance feedback, learners' potential to view their learning progress (grades) on their individual progress page, etc. Although technology allows the integration of game elements such as points, scores, leaderboards, levels, avatars, etc., the way these elements are selected, designed and embedded in a MOOC learning environment, depends on the choices of the MOOC designer. According to Ortega-Arranz et al. (2017), although some educational platforms have gamification capabilities, the effects of gamification in real MOOC contexts have not been thoroughly explored. Also, the authors argue that the most frequently used game elements in MOOCs are related to external rewards such as points, badges, and leaderboards (PBL), as it is shown by other reviews on gamification (Antonaci, Klemke & Specht, 2019; Dichev & Dicheva, 2017; Dicheva et al., 2015).

Several frameworks have been proposed for incorporating game elements into non-game environments. The framework of Werbach & Hunter (2012) is usually mentioned in gamification studies. This framework organizes game elements into dynamics, mechanics, and components. The elements can be used separately or in combination, depending on the goal to be achieved. Dynamics are the most abstract elements and they are used to define the context in which gamification is applied. Dynamics comprises of five elements, progression (i.e., the player's growth and development in the game), emotions (e.g., competitiveness, curiosity, frustration), constraints (i.e., limitations), narrative (i.e., a progressive storyline), and relationships (i.e., social interactions). Each dynamic connects players' actions with the goal in the game. Mechanics are the processes that are implemented according to the dynamics, to encourage individuals to engage in a gamified setting such as challenges, rewards, feedback, competition, etc. Components are the implemented form of dynamics and mechanics, such as levels, points, leaderboards, badges, etc. Despite the elements and the frameworks that are used, research studies have showed that gamification increases the completion rates in MOOCs. Usually, researchers use subjective measures, such as self-reported questionnaires to assess cognitive or behavioral engagement in gamified interventions in MOOCs (Deng, Benckendorff & Gannaway, 2020). However, other researchers suggest that gamification should be assessed using objective measures to state its effectiveness (Rincón-Flores, Ramírez Montoya & Mena, 2019).

1.2. Research goal of the thesis

The present thesis suggests a gameful design method for MOOCs and aims to investigate empirically the effect of a proposed gamified intervention on learners' cognitive states, mainly in terms of task engagement. The proposed design method uses the Goal-setting Theory (Latham & Locke, 1991) as a theoretical background for the design and the implementation of a game element, namely progression. The proposed design method concerns the implementation of the progression element in MOOC assessment activities (with multiple-choice questions) and seeks to enhance learners' task engagement in these activities. Progression is a game element that (is included in the category of dynamics based on Werbach & Hunter's model) and describes players' development and growth in the game by continuously increasing their skills. Progression is also recognized in pedagogy as scaffolded instruction. This element is selected as learners' skill level has been found to have a significant impact on learners' retention in MOOCs. The proposed gameful design method attempts to create a smooth learning curve that allow individuals to acquire the necessary skills as to move forward.

Goal-setting theory has been used mainly in work-related tasks to explain how to motivate individuals to perform better by setting goals. Interventions based on this theory are considered to be effective across various tasks (Latham & Locke, 1991). Gamification is also a goal-oriented activity. However, very few research studies so far have explored the use of goal-setting theory to inform a gameful design method. Most of these studies use the goal-setting theory to describe a specific game element (e.g., badges, leaderboards, levels, rewards, progress bars). In this thesis we combine the two practices to inform the design of the element of progression and to implement gamified MOOC assessment activities.

EEG studies on MOOCs provide guidelines on how to improve the design of the learning content that is delivered through a MOOC mainly for the video lectures and other hardware choices (Díaz, Ramírez & Hernández-Leo, 2015; Moldovan, Ghergulescu & Muntean, 2017; Wang, Chen & Wu, 2015). The present thesis exploits the technological affordances of an OpenEdX MOOC platform (named Coursity) to implement a gamified MOOC assessment activity that integrates the element of progression. The procedure of designing the element of progression for a MOOC assignment is based on the basic principles of goal-setting theory and Bloom's taxonomy. Using the technique of electroencephalography (EEG), we extracted power spectral features to study participants' cognitive and affective states while interacting with a gamified theory-based assessment activity. The present thesis follows a multi-method approach by comparing participants' task engagement as calculated from their neural data with the perceived self-reported engagement.

1.3. Contribution of the thesis

The present thesis introduces the goal-setting theory in MOOCs. It investigates the potential value of goal-setting theory as the theoretical framework for the design and the implementation of the game element progression in MOOC assessment activities and evaluates its effectiveness to enhance learners' engagement and improve their learning experience. Specifically, this thesis contributes to the understanding on how gamification can be implemented in MOOC assessment activities to produce smooth learning curves that help learners persist more and engage in the learning through MOOCs.

Moreover, this work suggests the use of EEG as a method to evaluate gameful interventions in MOOCs and provides information about the potential value of neural data in evaluating learners' cognitive states in terms of engagement. Specifically, this thesis follows a multi-method approach to evaluate learner's engagement by comparing neural and subjective (self-reported) measures.

Finally, this work helps to address the current shortage of research in the area of gamification in MOOCs (as most research studies involve external rewards such as points, badges, etc.) and propose an objective evaluation of the gamified intervention.

1.4. Thesis outline

The present thesis is divided into nine (9) chapters. A brief description of the chapters follows.

In Chapter 1 the subject of this thesis was introduced. The problem that this work addresses, the research goal, and the contribution of this work are presented. The limitations of the study are also discussed.

In Chapter 2 some of the key concepts related to online learning, Open Educational Resources and Massive Open Online Courses (MOOCs) are described. A brief historical review of MOOCs' growth is also presented. Also, the most widely used types of MOOCs i.e., xMOOCs and cMOOCs, are described, while other types that have been referenced are presented briefly. The most popular MOOC providers in national and international level are presented, while the basic characteristics of MOOC learners, courses and MOOC platforms are also discussed. Furthermore, the main challenges that MOOC encounter regarding their design and management, emphasizing in the factors that affect learners' dropout in MOOCs are presented. Finally, the basic elements of a MOOC, such as video lectures, learners' assessments, discussion forum and progress page are described, while the core pedagogical aspects of MOOCs are also presented.

In Chapter 3 basic concepts on motivational design are defined and some of the most popular theories of motivation are described. Key concepts on gamification are identified while the most widely used gamification frameworks and game elements are presented. Finally, the most frequently used in MOOCs game elements are presented.

In Chapter 4 the human nervous system and the most popular brain imaging technique i.e., the electroencephalogram (EEG) is described. The EEG is the technique that is used in this thesis to record the brain activity of the participants. The frequency bands of the EEG are presented as well as the method of power spectral analysis that is used for the quantification of the EEG, specifically the Welch method. Also, the most widely referenced event-related potentials (ERPs) and process of the (de-) synchronization of alpha and theta bands are briefly discussed. Finally, the advantages and disadvantages of the EEG are presented.

In Chapter 5 neural measures that are commonly used in EEG studies and the cognitive processes that are related to them are presented. The term engagement as well as its dimensions are defined. Other measures related to engagement such as attention, workload as well as to emotional states are also described. Finally, studies relevant to the neurophysiological measures that are used for assessing learners' cognitive and affective state in MOOCs are presented.

In Chapter 6 a detailed description of the research methodology, the research questions that are addressed, and the data that are collected are presented.

In Chapter 7 the results of this thesis are presented in terms of statistical analysis and short comments on the results.

In Chapter 8 the discussion and conclusions the emerged from the results of this work are presented, as well as assumptions, considerations, and points that need further investigation. Also, some recommendations for future works are given.

The present thesis is completed with the references and the Appendices I and II. In Appendix I the multiple-choice questions that consisted the MOOC assessment that was used in the experimental procedure is presented in Greek, while in Appendix II the self-reported engagement questionnaire that was administer to the participants is presented in Greek.

Note: This thesis has been checked for plagiarism with turnitin.

Chapter 2. Massive Open Online Courses - MOOCs

2.1. Introduction to Massive Open Online Courses

Massive Open Online Courses (MOOCs) is an advanced form of online education with innovative features that was developed to support open learning on a large scale. MOOCs in less than ten years, became the most prominent trend by allowing free participation for millions of learners who want to acquire professional knowledge and skills, anytime and anywhere.

Many universities, mainly in the USA and some of them in Europe, are collaborating with MOOC platforms to provide online highly interactive online courses. MOOCs are created to engage learners who must self-determine their involvement in the course according to their background knowledge, skill level, interests, and objectives.

Nowadays, MOOCs come in various formats and cover a broad range of topics. Most of them are delivered on a pre-defined schedule that is set by the course team. In those courses, learners sign up for a course which begins on a given date and usually has a duration of 4-10 weeks. The content is made available per week, with learners working approximately 2-10 hours a week in their own time and pace. Other courses give learners the opportunity to participate in a more flexible way adjusting the schedule according to their convenience. These courses are called self-paced. We should note that, most online participation in MOOCs is asynchronous.

Common activities in MOOCs involve watching video-lectures (i.e., videos broken into small chunks of approximately 10 minutes), reading articles or other recommended materials, submitting assignments, etc. Additionally, MOOCs provide discussion forums that enable learners' interaction with their co-learners and with the course staff (Agrawal et al., 2015). Learners who successfully complete a course can receive a certificate of completion.

Taking the above into account, it is considered that MOOCs can provide an alternative to traditional classroom education or used in combination e.g., in flipped classrooms.

2.1.1. Open education

Open education refers to the resources, the tools and the practices that apply a framework of open sharing, to enhance the access to educational material as well as to improve learning effectiveness. Wiley (2007) has proposed a 4Rs framework to describe the permissions on the use of Open Educational Resources (OER): Reuse (i.e., to use the resource as you found it), Revise (i.e., to alter the resource to meet your needs), Remix (i.e., to combine resources to meet your needs), and Redistribute (i.e., to share resources with others). More recently, the author added another R to this framework, Retain, to describe the right to create, own and manage a resource (Wiley, 2014). Atkins, Brown & Hammond (2007) argue that OER are resources that publicly available and they are released under a license of intellectual property that allows their free use (but not necessarily their commercial use). OERs include courses, materials, software, techniques and any other tool that supports the access to knowledge.

In the last ten years, there is a shift of attention from Open Educational Resources (OER) to Open Educational Practices (OEP). According to Ehlers & Conole (2010), OER focuses on contents and resources' availability and accessibility, while OEP represents the framework that helps to develop the educational environment in which OER can be created and used. Weller et al. (2018) reports several principles that are associated to OEP, such as open access, freedom to reuse, free of cost, easy to use, digital and networked content, ethical issues, and openness as a model. The authors proposed three main antecedents of the open education movement, web 2.0 culture, open-source software, and open universities. However, research on open education evolves continuously.

Recently, the term "open education" is used to describe Massive Open Online Courses (MOOCs), as this initiative provides opportunities for opening up education, supporting social inclusion and widening participation (Conole, 2012). Although, MOOCs do not always meet Wiley's 5Rs framework. Yuan & Powell (2013) stated that the development of MOOCs has its roots in the ideal that knowledge should be shared freely and without constraints such as geographical, economic, etc.

2.1.2. The key features of MOOCs

MOOCs have two core features, "openness" i.e., access to anyone and from anywhere with internet connection (Conole, 2015; Levy, 2011; Pappano, 2012) and "scalability", in terms that courses are designed to support millions of participants (Conole, 2015; Hollands & Tirthali, 2014). Baturay (2015) adds two other characteristics, namely participation and distribution. MOOCs offer free and open participation to anyone who with an Internet connection and the learning content that is generated through these courses, either by the instructors or the learners, is made available to anyone. Any knowledge is distributed across the network of the participants and although, the participation is voluntary, the learning in a MOOC is enhanced by the participation of the learners. Cormier (2010) defines MOOC as being open, participatory, distributed and supporting lifelong network learning. The term MOOC can be analyzed as following:

“Massive” refers to the capacity of MOOCs to accommodate thousands of learners. This capacity reflects both the advancements in Information and Communication Technology (ICT), i.e., software services to store and remotely access the educational content, secure registration and identification of learners, as well as, the advances in pedagogy and educational technology of online and distance learning, such as connectivism, e-learning, learning management systems (LMS), computer-based education and training (CBT), etc.

“Open” has several different meanings. “Open” may refer to the access in a MOOC as it is open to all, without restrictions on age or other individual differences, prior learning, qualifications etc. It may also refer to the scheduling, as learners may take the course at any time. Moreover, open may refer to open standards and formats for storing and sharing learning resources, or even to education, as it provides practices that increase access to formal education for learner who deal with physical, cognitive, geographical or other barriers in order to participate in educational institutions. Finally, open may refer to the assessment, as the learners have the opportunity to choose whether to have their work assessed or not, by applying an “on-demand accreditation”. Yuan and Powell (2013) add another aspect of openness by considering the curriculum that is created from learners by attending a MOOC.

“Online” defines that MOOCs are online courses, regardless of their relationship to classroom-based courses. In MOOCs, online participation is mostly asynchronous i.e., learners at their own time and pace can access the content and complete the course activities. Being online and open, MOOCs can also be used as OERs, as a part of a traditional classroom course in order to transform it into a blended learning course. An adaptation of this model is a “flipped classroom” (Baker, 2000; Forsey, Low & Glance, 2013), in which students, study at home through a MOOC and lessons in the classroom are used to explain issues and handle difficulties that arise from homework.

“Course” refers to a systematic sequence of learning activities that need to be designed, developed, evaluated and revised, particularly when they are open to massive numbers of learners of diverse skills and backgrounds. In a MOOC the learning content is organized according to a pedagogical concept, the development of knowledge follows certain predefined learning objectives, design elements such as course schedule, learning content, submission deadlines, social learning interaction etc. must also be defined.

2.1.3. History of MOOCs

Distance education has started many years ago with correspondence courses that were delivering the educational material to learners and the submission of learners' assignments were completed via postal services (Casey, 2008). The development of home computing and mobile internet allowed academics to share digital educational content. The sharing of open educational resources has gained great interest from higher education institutes (Adams et al., 2013). OpenCourseWare (OCW) was released in 2001 by the Massachusetts Institute of Technology (MIT) aiming at publishing educational material from its courses, with licenses allowing the use, the modification and the redistribution of the material. Afterwards, many well-established universities have joined this movement. OER allowed learners to access the educational material and learn from it, while teachers could use the OER as part of their lessons. It should be noted that, some of these OER were created to be a part of larger educational experiences within specific educational contexts. Therefore, learners who attempted to learn directly from this material, they did not how to make the most of it and they were getting frustrated about its value (Liyanagunawardena, Adams & Williams, 2013).

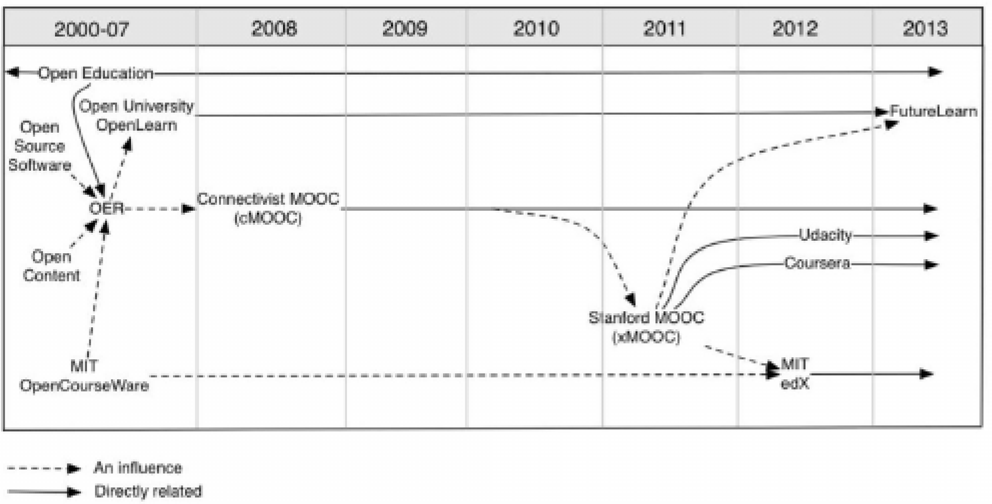


Figure 2.1. Timeline of MOOCs (Yuan, Powell, & CETIS, 2013)

MOOCs combine e-learning and open education opportunities as they provide unrestricted access to large number of learners via the web. The term MOOC was introduced by Cormier and Alexander in (Siemens, 2012). Although, the first online course with massive participation was the "Connectivism and Connective Knowledge" offered by George Siemens and Stephen Downes to more than 2000 students from the University of Manitoba and the general public (Daniel, 2012; deWaard, 2011). This course uses the principles of connectivism (Siemens, 2005) and it is still offered to anyone for credit.

In 2011, MOOCs took another direction with the course "Introduction to Artificial Intelligence", offered by Sebastian Thrun from the Stanford University and Peter Norvig, then Director at Google (Figure 2.1). The course team that created this MOOC, developed the for-profit company Udacity. Udacity offers courses for free while giving learners the option to pay for certification. Udacity activities were recently expanded in matching students who are qualified with partner companies to provide employment. Coursera is also a for-profit company that collaborates with leading universities to offer MOOCs in a broad range of topics. The pedagogical approach of Coursera includes peer assessment and mastery learning. Peer assessment is used in cases that automated assessment cannot be applied. MIT that has long history in open online courses through OpenCourseWare, started offering MOOCs through MITx. The first MOOC was offered by MITx in 2012 and was about Circuits and Electronics. This course had about 150,000 enrolled learners. In 2012, MIT and Harvard have created edX, a nonprofit organization that was dedicated to offer MOOCs. This learning innovation continues to grow and gain popularity.

2.2. Types of MOOCs

2.2.1. xMOOCs and cMOOCs

As MOOCs have grown in popularity, researchers started to suggest several schemes for their classification. Rodriguez (2012) defines two categories of MOOCs, connectivist MOOCs (cMOOCs) and AI-Stanford like courses. The author argues that cMOOCs have a social approach for learning while courses similar to AI-Stanford are based on an individualist learning approach. For Daniel (2012) two MOOCs categories have emerged: xMOOCs and cMOOCs. Daniel does not give a definition for xMOOCs, so we cannot argue that Rodriguez (2012) and Daniel (2012) are categorizing MOOCs in a similar way using different labels for "AI-Stanford like courses" and "xMOOCs".

Table 2.1. MOOCs in terms of components

cMOOCs	MOOCs	xMOOCs
Connectivity	Massive	Scalability
Access and license	Open	Access but not license
Networked learning	Online	Individual learning
Develop shared practices and knowledge	Course	Acquire knowledge and skills

Based on the relevant literature, in xMOOCs the lesson is organized with pre-recorded video lectures, auto-graded assessments, slide presentations, and online notes. xMOOCs resemble the traditional way of a course in a classroom where the instructor has a central role. On the contrary, in cMOOCs learners learn by communicating and collaborating with each other and with their instructor. Learners and instructors collaborate to create the educational material and the assignments of the course. Learners in a cMOOC use blogs, social media, videoconferencing and e-communities to communication and collaborate. Learners in xMOOCs use the forum to address questions mainly to the instructor and less to their co-learners. Table 2.1 gives an overview of xMOOCs and cMOOCs regarding the components of the term Massive Open Online Course (Yuan & Powell, 2013).

The most important difference between the two pedagogical models is related to the group that develops the courses. A cMOOC is created by a group of academics while a xMOOC, is created by one or more higher education institutions and, usually, a for-profit company. Platforms like Coursera, edX, and Udacity offer xMOOCs.

According to Siemens (2013) apart from xMOOCs and cMOOCs, there is another category, the quasi-MOOCs. Quasi-MOOCs comprises of e-tutorials serving as OER. Technically, they are not courses but are intended to support learning tasks consisting of asynchronous learning resources. Thus, quasi-MOOCs do not provide the core features of cMOOC or xMOOCs i.e., social interaction and automated grading. In Table 2.2 the main differences cMOOCs and xMOOCs are presented (Admiraal, Huisman & Pilli, 2015).

2.2.2. Other categories and taxonomies of MOOCs

There are also researchers that have developed several other MOOC types. Lane (2012) organizes MOOCs according to the following elements: network, content and task, as Network MOOCs, Content MOOCs and Task MOOCs. Network MOOCs are similar to cMOOCs, they focus on the relationships among the learners. Content MOOCs are similar to xMOOCs having as a priority the acquisition of the content. Assessments with multiple choice questions or peer assessments are used due to the massive number of learners that participate in this type of courses. Finally, task MOOCs focus on problem-based learning. A task-based MOOC focuses on skill acquisition by performing activities. In this type of MOOC, the creation of learners' communities is important for sharing knowledge and to providing support.

Table 2.2. Differences between xMOOCs and cMOOCs

Basic Features	**xMOOCs**	**cMOOCs**
Learning theories	Cognitive/ Behaviorist	Networking/ Connectivist
Teaching approach	Objective-oriented	Construction-oriented
Learning approach	Information transferring	Knowledge sharing
Interaction	Interaction is limited. It is mostly focused on learner-content interaction	Interactions between learners, learner-content and learner-instructor interaction
Student role	Receivers of the content, the instruction is mainly based in video lectures, submits assignments	Creators of the learning content, contributors through discussion forms etc.
Teacher role	The instructor creates the content, assignments, quizzes and delivers the course	Co-learners, create the content and define the goals, collaborating with their peers
Content	Fixed syllabus	Individual syllabus
Assessment	Multiple-choice questions, assignments with automated grading, peer-assessments	Informal assessment and feedback from knowledgeable learners
Teaching materials	Video-lectures, text-based notes, slides, assignments, online resources and online articles	Social media, wikis, learning management systems (e.g., Moodle), Student-created material
	Centralized repository	Distributed knowledge
Providers	Created by universities or organisations	Created by academics

Clack (2013) presented a taxonomy focusing on the delivery methods of the MOOCs, classifying them in eight (8) non-mutually exclusive categories (meaning that the same course might belong to one or many of these categories): Transfer MOOCs (classroom courses are transferred into MOOCs), Made MOOCs (developed by scratch as MOOC), Synch MOOCs (with fixed schedule), Asynch MOOCs (with more flexible schedule), Adaptive MOOCs (provide personalized learning experiences through dynamic assessments), Group MOOCs (small groups of learners who collaborate), Connectionist MOOCs (connection with peers through networks) and Mini MOOCs (smaller in duration).

As MOOCs are still evolving, instructors are experimenting to improve learning outcomes and enhance learners' experience. In this direction, researchers have defined several types of MOOCs. Although various taxonomies have been proposed, classifying a MOOC into one category does not exclude it from the others. Table 2.3 briefly describes the types of MOOCs that are found in the literature (Economides & Perifanou, 2018; Sanchez-Gordon & Luján-Mora, 2014; Pilli & Admiraal, 2016).

Table 2.3. MOOC types

MOOC type	Description
BOOC (Big Open Online Course)	Provides distributed learning and personalized feedback for a small number of learners. Provided more interaction than ordinary MOOCs while learners are typically less than 500.
COOC (Community Open Online Course)	Small scale and non-profit course. Community decides the content of specific subjects and develops its own way of learning. These courses are based on contributions from informal instructors.
SPOC (Self-Paced Online Course)	Without any restriction learners can enroll in the course and complete the course at their own convinience.
POOC (Personalized Open Online Course)	Defines a personalized learning path according to the learner's profile. Learning material and assessments can be formulated along with the participants' characteristics. Technology is used to analyze learner's learning profile.
DOCC (Distributed Open Online Course)	Recognizes that knowledge is distributed among participants situated in diverse institutional contexts, who embody diverse identities (as teachers, as students, etc.).
MOOR (Massive Open Online Research)	Gives emphasis on research that allows students to work together to improve learning outcomes. These courses give learners the opportunity to collaborate on research projects under the guidance of experts (Hosler, 2014).
SMOC (Synchronous Massive Online Course)	Live lectures are broadcasted and learners are encouraged to interact with instructors and their peers through chat rooms.
sPOC (Small Private Online Course)	A limited number of online learners are allowed. Involves a more customized experience such as custom-designed for corporate clients.
aMOOC (Adaptive MOOC)	Adapts the materials and feedback to learners' preferences.
MOOL (Massive Open Online Laboratories)	Cost efficient experimentations are conducted by students at their own place and time.
POOC (Participatory Open Online Course)	Learners are expected to participate actively by creating and sharing knowledge.
mMOOC (Mechanical MOOC)	"Mechanical" there is not an instructor to guide the course. It focuses on peer-learning.
pMOOC (Project-based MOOC)	It follows a collaborative project-based pedagogy.
iMOOC (Innovative MOOC)	It follows a pedagogical model that focuses in innovation and individual responsibility.

Conole (2014) proposes a categorization based on the following dimensions: the scale of participation, the degree of openness, the use of multimedia, communication, the extent of collaboration, the type of learner pathway, the level of quality assurance, the degree to which reflection is encouraged, the type of assessment, autonomy and diversity. To examine the efficacy of the proposed classification scheme, Conole evaluated the degree to which five MOOCs (that comprised her study sample) satisfied each dimension in order to illustrate the goodness of fit. The work of Conole also provides an example of how to design a MOOC using the proposed dimensions. In a later study, Pilli & Admiraal (2016) suggested a categorization of MOOCs considering the dimensions of Massiveness and Openness. The authors described the following categories: small scale and more open, small scale and less open, large scale and more open, and large scale and less open. Finally, Mohamed & Hammond (2017), examined ten MOOCs by considering three aspects: pedagogy, content and assessment.

2.3. MOOC affordances

There several opinions about what is a MOOC and what a MOOC should offer to learners. MOOCs are designed to have certain features that make learning engaging and therefore effective. Apart from the obvious features described by their name, MOOCs provide personalized learning by allowing learning to be broken into smaller modules and allowing learners to select the learning unit that they will attend based on their prior knowledge and skills. Also, MOOCs have the power to ensure that every learner engages with the learning material. This is achieved through learner's interaction with the course material as well as through the learner's interaction with the instructors and their peers. The element of peer learning forms a global community where learners learn from their peers around the globe. This learning community gives learners access to a group of people who shares a common educational endeavor. Also, MOOCs enable learners to create and share content through their personal contributions.

Economides & Perifanou (2018) proposed a model regarding the affordances of MOOCs consisting of eight (8) items: Massiveness, Openness, Interaction, Personalization, Autonomy, Support, Mobility, Accreditation. This model helps to classify a MOOC across a space of certain affordances. MOOCs can provide (or not) each of the affordances at a certain level. Table 2.4 presents MOOC affordances model.

MOOC affordances depend in a great extent on the technology of the MOOC platform, however, even if technology offers all the above characteristics, a MOOC designer or instructor can decide to use all or some of them and to what extent. For example, cMOOCs that are grounded in connectivism, utilize the affordances of networked online technology, where learners have a central role in activity design and self-organized learning (Yousef et al., 2014). In a cMOOC, learners decide their own objectives they collaboratively build their knowledge. Course contents are located in multiple resources within the web such as Learning Management System, social media, email, blogs, etc., unlike the traditional management systems. On the other hand, xMOOCs use a transmission model of instruction. Course content is delivered through video lectures, multiple choices quizzes, assignment submission and discussion forums. Openness is also defined differently in cMOOCs and xMOOCs. cMOOCs are open regarding content's copyright, curriculum design and delivery methods, while in xMOOCs openness is limited in the use of the content but is open in accessibility to anyone.

Table 2.4. MOOC affordances based on Economides & Perifanou (2018)

Affordance	**Description**
Massiveness	the upper limit of learners that can enroll in a MOOC.
Openness	the degree to which a MOOC provides free access, interaction, use and sharing of resources, knowledge, competences, collaborations without restrictions.
Interaction	the degree and quality to which a learner can communicate, collaborate, and interact with their co-learners, tutors, virtual agents, etc. using a range of tools.
Personalization	the degree and quality to which MOOC's components i.e., schedule, interface, learning path, content, etc., could be adapted to learners' characteristics (e.g., interests, skill level, etc.) as well as to learners' devices' characteristics.
Autonomy	the degree and quality to which a participant could efficiently control the interface of the learning environment, the schedule of the course, the learning path, the course contents, resources etc.
Support & Scaffolding	the degree and quality to which a learner could receive effective and on-time educational, technical and administrative support.
Mobility & Ubiquity	the degree and quality to which a learner could be able to connect to the MOOC easily and efficiently, anytime and anywhere.
Assessment & Certification	degree and quality to which a participant could receive a valuable, credible, and reputable Certification after submitting Assessments that are of high validity and reliability.

2.4. The context of MOOCs

2.4.1. MOOC providers and aggregators

A MOOC provider is usually for-profit companies that collaborates with universities, academics or individual instructors to create online courses and make them available to learners. Most providers offer additional services, such as marketing, technical support, certification, etc. MOOC providers are funded by venture capitals, government or private sector. Coursera, edX, Udacity, Udemy and NovoEd (US), MiriadaX and OpenMOOC (Spain), FutureLearn (UK), iversity and openHPI (Germany), OpenLearning and Open2Study (Australia), France Université Numerique (France), XuetangX and EWANT (China), Schoo (Japan), and Swayam (India) are some examples. Learning Management System companies (e.g., Moodle), Open Education Resource companies (such as Khan Academy) have followed the example of MOOC delivery. Lately, the social media company LinkedIn started to offer MOOCs (LinkedIn learning) from top universities and colleges with subjects relevant to professional development. Coursera is probably the largest MOOC provider, but its audience is constantly reduced as new providers are emerging (dela Cruz, 2015).

Coursera is probably the largest MOOC provider. It is a for-profit company which started as spin-off company of Stanford University. The company was founded by venture capitalists. Coursera is a collaborative effort of universities and organizations such as the Princeton University, the Stanford University, the University of Pennsylvania, etc. Coursera partners with educational institutions, government entities, and businesses from all over the world but it also collaborates with organizations in Europe, China, Korea, Russia, and Mexico, etc. Coursera has started offering a Career Service to companies, introducing their learners to potential employers.

edX is an open-source MOOC platform launched by the Massachusetts Institute of Technology and Harvard University. EdX is a non-profit company that started as a collaborative effort of the two Universities having as a goal to use the platform for research, and to investigate alternative models for education. It uses the OpenedX platform, an open-source course management system. According to Liyanagunawardena et al. (2019), edX provides courses of the following subject areas: Business Management, Data Analysis, Computer Science, Education, Economics, Biology, Engineering, Humanities, etc. Moreover, edX offers a number of different types of certificate programs such as MicroMasters (a series of Masters' level courses which can be used to form a Masters' degree), XSeries (courses that aim to provide a deeper understanding on key subjects), Professional Certificate (courses on specialist training) and Professional Education. Google has partnered with edX, to develop the mooc.org, a Do-It-Yourself course creation site that allows teachers to create their own courses.

Udacity is a for-profit start-up, founded by the professors Sebastian Thrun, David Stavens and Mike Sokolsky, from the Stanford University. Udacity started after the success of Thrun's course "Introduction to AI", with more than $20 million in investments from venture capitalists. Initially, Udacity offered university-style courses while now it focuses on vocational courses. It also offers "nanodegrees" for a fee for learners who want to develop new skills in areas such as mobile app development or earn certificates of completion. Udacity has partnered with Pearson VUE to provide proctored exams.

Udemy is a MOOC provider that allows anyone to create or attend a course. It was founded in 2010 by Eren Bali, Oktay Caglar and Gagan Biyani by using venture capital. Udemy hosts the courses under a revenue-sharing agreement. Udemy is more oriented toward professionals' skills than higher education studies.

Khan Academy was founded by Salman Khan in 2008. It is an adaptive learning platform/provider that offers focused education programs and skills-development courses. Is a non-profit organization with funding from the Bill & Melinda Gates Foundation and Google. While not strictly a MOOC provider, Khan Academy is an established organization that offers massively online material as Open Education Resources. It offers video lectures in academic subjects with auto-graded assignments and continuous assessment. Other such examples are Saylor.org and P2PU.

P2P University started in 2009 with funding from the Shuttleworth Foundation and the Hewlett Foundation. Although, P2PU provides some MOOC' features, it focuses more on a community-centered approach. This means that anyone from the community can teach or learn.

The Saylor.org is a platform that was created by the Saylor Foundation to offer certificates of successful completion of online classes.

Several MOOC platforms have recently developed in Europe.

FutureLearn was founded in 2012 by a consortium of UK universities as an effort to provide the opportunity to British higher institutions to get involved with MOOCs. Futurelearn aims not only to increase access to higher education by delivering high quality open learning, but also to redesign the learning experience combining online with mobile technology and social media. Initially the company was collaborating only with UK institutions, however Futurelearn currently has expanded globally and offers courses from partner institutions in many countries e.g., Norway and Australia. FutureLearn has also partnered with non-university institutions, such as the British Museum, the British Council, etc.

iMooX launched in 2014 in Austria. It was funded by the University of Graz and Graz University of Technology with the goal to offer online courses to the public. Now, more than fifteen universities and federal ministries of German speaking countries are associate partners of iMooX. It provides Open Educational Resources explicitly. All learning objects hold creative commons license. Moreover, in iMooX courses after their end, are not delete or hide from enrolled learners' account. Courses are also available for self-paced learning (Kopp & Ebner, 2015).

FUN launched in France in 2013 using the OpenEdX platform.

Miríada X launched in 2013 in Spain. It is the leading MOOC provider for the Spanish speaking people that has expanded globally into wider markets such as the Latin American market. The courses are offered in Spanish and English.

Alison is a for-profit company and one of the most popular e-learning providers in the world that was founded in Ireland in 2007, to provide distance learning in many fields. It is a UNESCO award-winning platform that focuses on topics relevant to workplace readiness such as business and enterprise skills, IT skills, etc.

iversity was established in Germany in 2011 to develop initially a cross-university platform for distance education. The platform was re-launched in 2013 as a MOOC platform having as a goal to make education gain a more digital approach.

In Greece, there are two MOOC platforms both build on edX's open-source learning platform (OpenedX), namely Coursity and Mathesis.

Coursity is a start-up company that was established in Greece in February 2017 to create and host of online courses, according to the standards of MOOCs. Coursity has developed a dual partnership with Greek Universities to create high quality courses. The instructors are well-known Professors of Greek Universities while the approval and certification process are controlled and permeated by the Lifelong Learning Centers of Greek Public Universities. Coursity is currently the only for-profit company in Greece that has a platform (based on OpenedX technology) with features that makes it the most innovative and advanced in terms of learning technologies and software technologies for MOOCs. The platform is currently hosting courses with a length of two months or annual courses. The bimester courses can be attended by anyone who is interested in free, with full access to the educational material and full teaching and technical support. The learners who successfully complete the course and wish to receive a certificate of completion are required to pay an affordable fee. The annual courses are specialized training programs and are offered only as verified courses, i.e., free attendance is not offered. In these courses, the enrolled learners are less than at the bimester courses (approximately 600-700 participants), thus providing the chance for more intensive interaction between the learners and between the learners and the instructors. Coursity has at the moment 15 courses about Special Education and Learning disabilities, Statistics, Programming and Intercultural Education. In Coursity almost all the courses offer subtitles in Greek in order the help people with hearing disabilities to attend the courses. Recently, Coursity has been upgraded into a multilanguage platform targeting at hosting courses in English language as well.

Mathesis was founded in 2015 in Greece as a special section of the University Publications of Crete. Its purpose was to create and offer online courses for free. The courses are open to students, scientists and everyone who is interested in joining these courses. Courses have a duration of about 4-6 weeks and their successful completion leads to a certificate of attendance by paying an affordable fee, only for those who apply for a certificate. Mathesis has at the moment approximately 40 courses about history, physics, math, ancient Greek civilization, philosophy and computer science.

In addition to MOOC providers, learners who are interested in attending MOOCs in their field of interest can search for courses through aggregators such as my-mooc.com and mooc-list.com. The aggregators are offering MOOCs from different providers from all over the world. There is a search function with courses organized into categories according to the providers, subjects, start dates, etc. The mooc-list.com declares to offer a complete list of all available MOOCs by category, organization, etc. Another popular aggregator is Class Central. It is a multiplatform register of MOOCs. It also provides reports with trends and news about MOOCs.

2.4.2. Higher-education institutions and organisations

In the last ten years there has been a rise in the number of institutions that collaborate with providers to offer MOOCs. MOOCs are thought to expand the access to education and extend an institution's reputation not only nationally but also globally. MOOCs have the potential to address important issues of higher education such as budget constraints by offering inexpensive, low-risk experiments. Hollands & Tirthali (2013) conducted a study from the perspective of institutions. Their study was based on interviews with people (researchers, administrators, etc.) working on MOOCs from more than 60 institutions. The authors reported that institutions offer MOOCs for the following reasons, to extend learners' access to knowledge, to build or maintain the institution's brand name, to increase revenue, to enhance educational outcomes, and for conducting research on instruction and learning. Higher-education institutions are collaborating with MOOC providers to offer open courses.

2.4.3. Courses

Since the appearance of MOOCs in 2012, the number of available courses has increased rapidly. Additionally, the course formats and the modes of course delivery, are keep evolving. The most used formats are two: the instructor-paced and the self-paced format. Pacing defines the way that a course team run a course and whether learners need to complete the course materials on a set schedule. In both formats, MOOCs are being implemented mostly based on asynchronous online learning combined with interactive multimedia.

Instructor-paced vs self-paced courses

Instructor-paced courses have a fixed schedule. The course team sets specific due dates for assignments and learners must complete the course within a defined period of time. Course materials become available as the course progresses at specific dates. On the Course page, indicators show whether learners have a graded assignment and the due date for the assignment. Usually, in the instructor-paced courses, certificates are generated within two weeks of the end of the course.

Self-paced courses do not have a fixed schedule. Course materials are available from the beginning of the course and assessments do not have a due date. The course shows marks for assignments that are graded. However, learners can complete the assignments at their own convenience. The only requirement for successful completion is to submit all assignments before the end of the course. In self-paced courses, the course team generates certificates on a schedule, such as once a month. The certificate generation schedule varies by course.

Self-paced formats may have several variations. Usually, these courses have a longer duration. Course contents and assignments are available from the beginning of the course and there is only one due date for all assignments at the end of the course, allowing learners to study anytime they want. Therefore, self-paced MOOCs are very close to the characteristics of open educational resources (OERs). However, in contrast to OERs, self-paced MOOCs are formed on an idea of a classroom lesson, where students drop in and drop out of the course, they interact with their peers and receive support from staff members.

The way in which self-paced MOOCs are delivered is attractive to both learners and instructors. From a learners' perspective, the self-paced courses offer more flexibility since learners are not bound to deadlines. Recent studies have showed that learners from less developed countries are often less successful in MOOCs (Hennis et al., 2016; Kizilcec, Perez-Sanagustín & Maldonado, 2017). This may be explained by the fact that they have fewer opportunities due to lack of resources such as internet connection. Moreover, the format of self-paced courses seems beneficial for all learners as the main challenge for completing a MOOC is the lack of time (Kizilcec & Halawa, 2015; Yeomans & Reich, 2017).

For the instructors, it may be easier to run a course one time in a self-paced format than several times in an instructor-paced format. Rhode (2009) argue that learners consider interactions as one of the most essential aspects of their learning experience, although they accept the fact that in a self-paced course interactions are difficult. Organizations may benefit from self-paced courses in several ways. Self-paced courses can provide higher revenues as they can attract more learners, can be easily available regularly, and costs that are required for each run can be lower. Moreover, they can support the ambition of the organizations of opening up education.

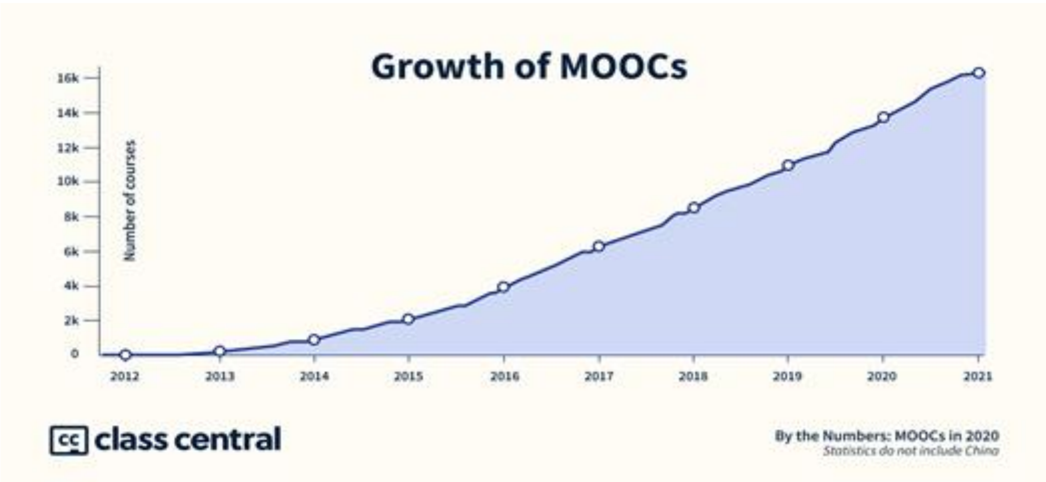


Figure 2.2. Growth of MOOC courses

Course domains distribution

In the first years of MOOCs the disciplines were limited to those that could be assessed with quantitative assessments, such as engineering, computer science and math. Nowadays, MOOC platforms support several assessment methods (e.g., peer-assessment), thus, these courses are applicable to all disciplines. Figure 2.2. shows the growth of MOOCs through the years.

The subjects of MOOCs have remained quite similar in the last two years. Approximately, forty percent of the MOOCs are relevant to the subjects that are the easiest to generate revenue. Other significant subjects are Social Sciences, Science and Humanities. Figure 2.3. presents the course distribution by subject.

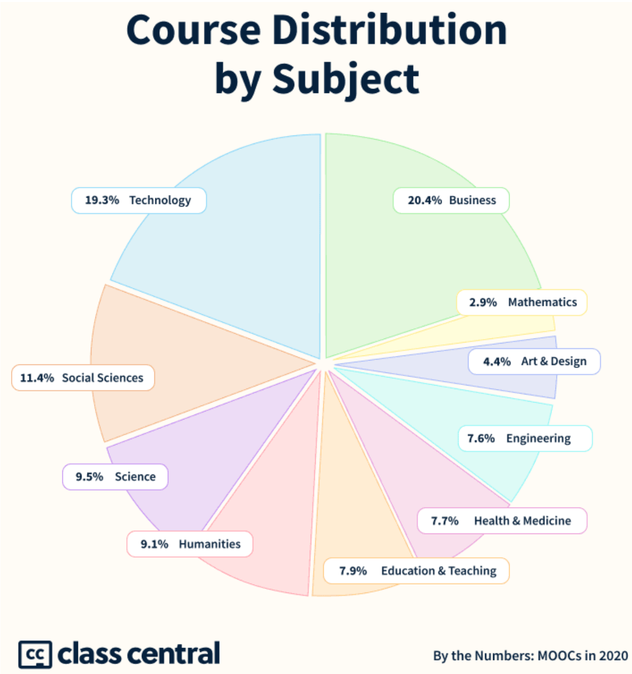


Figure 2.3. Course distribution by subject (from classcentral.com)

Types of enrollments in MOOCs

Learners usually have two options when enrolling on a MOOC course: the audit (free) or verified (paid) track.

The verified track gives learners unlimited access to course materials, including graded assignments, until the end of the course. MOOC learners still have access to the material after the end of the course but they cannot submit their assignments or apply for a certificate of completion. Learners who select the verified track pay a fee and they receive a certificate upon successful completion.

The audit track gives learners access to all course materials, except graded assignments, and they cannot receive a certificate of completion. Learners are given access to the free content of the expected course length that is shown on the course "About" page. They can access the course from the course start day until the day it ends. After this duration, learners are no longer able to access the course material. If learners are enrolled in the audit track and decide that they do want to receive a certificate of completion, they can pay to change to the verified track. This is possible until the upgrade deadline that it is set by the course team. Learner in order to earn the certificate must take the graded assignments that are required.

2.4.4. Platforms

In recent years, MOOC platforms have had a considerable growth due to the shifting from traditional classroom activities to virtual activities. A MOOC platform is not only providing courses to learners but also all the associated services. It is either based on a web site (as in case of a xMOOC) or it can be distributed among several sites (as in case of a cMOOC). MOOC platforms provide the place where instructors can host their courses and manage the learning process. Anyone who wants to deliver a MOOC, an institution, or an individual instructor, should consider and select a suitable platform based on their needs and the technological capabilities.

MOOC platform is a web-based software that it can be open source (edX), proprietary such as Coursera, or built on an LMS such as MOODLE. The platform can be hosted by the provider (Software as a Service-SaaS or Platform as a Service-PaaS) or can be self-hosted by the institution. MOOC platforms are more than an LMS (that is primarily used for management tasks, such as students' registration, contents' hosting, hosting of discussion forums etc.). They provide innovative assessment features and communication tools.

An open-source platform is a software whose source code is available to the public. Developers are allowed to deploy, modify and distribute this software with no cost. One such example is OpenedX, the open-source platform offered by edX. OpenedX, is a full-featured LMS and authoring tool, specifically dedicated for building MOOCs. It is a flexible and robust course-management platform that has the ability to accommodate thousands of users (over 100000 enrollments). Moreover, the edX's software allows course developers to create courses via a graphical user interface. Several MOOC platforms are developed on OpenedX software, such as Edraak (Arab), XuetangX (China), France Université Numérique (France) and Coursity (Greece).

2.4.5. Learners

There is a wide range of MOOC learners, as MOOCs concern from high school students to retired people. In their majority, MOOC learners hold a college degree (Despujol et al., 2014; Ding et al., 2014) and they are employed (Dillahunt, Wang & Teasley, 2014). Christensen et al. (2013) mentioned that a percentage of 83% of MOOC learners hold a post-secondary degree, about 80% of learners hold a Bachelor's degree or higher, and almost 45% stated having a degree beyond Bachelor. Regarding the gender, males often constitute the majority of learners in a MOOC (Davis et al., 2014). Macleod et al. (2014) argue that the gender is associated with the topic of the course that learners enroll. The authors also argue that the differences in traditional education courses are replicated in

MOOCs (Macleod et al., 2014). Based on Park & Choi (2009) learners' characteristics (e.g., gender) do not affect their performance in online courses, while other factors such as family, or financial support have a significant impact on learners' persistence.

According to Kizicec & Schneider (2015), the main reasons that learners enroll in a MOOC include learner's general interest, academic relevance and social engagement. Koller et al. (2013) indicated three categories of learners in MOOCs: passive participants (watching/ reading the educational content), active participants (completers) and community contributors (posting in discussion forums). A positive relationship between learners' motivation, performance and participation has been reported (De Barba, Kennedy & Ainley, 2016). McAuley et al. (2010) argued that learners determine their own levels of participation, based on their background knowledge, skill level, learning goals, and interests.

Kizelec et al. (2013) conducted a research study on the disengagement of learners from MOOCs. Authors traced four clusters of learners that exhibited the same traits across different courses, and they were able to identify these patterns by tracking and clustering the engagement of learners in three different courses, with different difficulty level. The clusters that have been identified are the following:

- Auditing learners i.e., the learners who watch all the video-lectures but attempt only a few assessments.
- Completing learners i.e., the learners who submit most of the assessments.
- Disengaging learners i.e., the learners who submit assignments at the beginning of the course but then rarely. They are only watching the video-lectures or disappear completely from the course.
- Sampling learners i.e., the learners who explore the course by watching only a few videos-lectures.

Authors also argue that "completing" learners are most satisfied with their learning experience and they tend to interact more through forum discussions.

Researchers have already presumed several reasons that could explain the large dropout rates in MOOCs. The first barrier that MOOC learners encounter concerns the cost. MOOCs are free (at least for attending the course), so many people enroll just out of curiosity in order to check the new courses. Since learners do not invest on the course either psychologically or financially (i.e., they do not have an intrinsic or extrinsic motivation), it is easy to become disengaged. Another reason that concerns learners' extrinsic motivations is that, since most learners will not earn a validated certificate or credits, they are less focused on the course requirements i.e., to complete the assignments and finish the course. Though, if the content is too hard to understand, their interest declines. A third reason concerns the scope of learners' interest. Some learners are interested only in one specific learning section of the course. They enroll to have access to the video lectures, the rest of the educational materials and the discussion forums, without having the intention to finish the course. Finally, the lack of physical interaction creates an absence of engagement which inevitably leads to dropouts. Yuan & Powell (2013) argue that MOOCs also demand from participants to have a certain level of digital literacy to be able to learn, which probably raises concerns on the equality of access.

2.5. Possibilities and barriers of MOOCs

2.5.1. Strength and challenges of MOOCs

MOOCs, as a new initiative in the field of distance learning, have some strengths and limitations. According to Fasihuddin, Skinner & Athauda (2013), the strength points concern the way MOOCs are structured and offered to learners as well as the level of knowledge and skills that they provide. Specifically, MOOCs are mostly university level courses that cover a wide range of academic fields, offered online without any restriction to anyone who is interested. Also, MOOCs are learner-centered courses, which means that learners can adjust learning at their own pace and time. This is very important aspect of MOOCs as it provides learners the opportunity to keep their cognitive ability in the highest level. Moreover, in MOOCs learners have access to the learning resources of the course (i.e., video-lectures and other materials) continuously until they cover their learning needs. The authors also mention some limitations of MOOCs that may affect their efficacy. For example, in MOOCs, although learners are allowed to learn at their own pace, there are some deadlines in the submitting assignments. These deadlines can be an obstacle for learners in completing the course. Furthermore, in a MOOC, the content that can be delivered in a certain format mainly with video-lectures, however, there are some fields, such as humanities, where the teaching approach is based on discussion and dialogue. Thus, in order to offer such courses as MOOCs is must be further researched. One major limitation of MOOCs is that they deliver the learning materials using traditional approaches such as video-lectures. Therefore, they are not covering learner's variable needs. Finally, in MOOCs, the possibility that a learner can create multiple accounts in order to earn a certification of completion, as well as the difficulty for learner's identity authentication and are considered to be the most important limitations.

Based on the relevant literature, MOOCs have to deal with several challenges regarding their design and management (Bezerra & da Silva, 2015). The main issues that are mentioned in the research studies concern their business model, their pedagogical model, the high dropout rates, certification and quality issues.

Business model: The model that MOOCs follow is not a new one. Dellarocas & Van Alstyne (2013) argue that MOOCs have adopted the business model of well-known technology companies that offer a basic service to their customers for free and then they charge for extra services. Even though MOOCs are free for enrolling in a course and for providing access to course contents, some institutions charge for issuing certificates of completion. This initiative could have the potential to generate a sustainable business model, considering the large number of learners. Nevertheless, only a small number of educational institutions receive funds for the development of a MOOC platform, for content production and distribution, that has the potential to result in the creation of for-profit companies.

Low completion rate: Dropout in MOOCs is generally high, sometimes reaching 90% (Morris, 2013). According to Jordan (2014), the completion rate is related to the number of people who receive a certificate. However, in MOOCs, dropout should not be compared to that of traditional distance learning because in MOOCs learners do not pay fees. Khalil & Ebner (2014) investigated the factors that lead learners to dropout of MOOCs, including lack of the necessary knowledge and skills, lack of time, lack of learners' motivation, lack of learners' interactions with the peers and instructors, and hidden costs. More information on factors that predict learners' dropout in a MOOC is given at the next section.

Certification: MOOCs are mainly adaptations of face-to-face courses that are offered in higher education institutions. Thus, giving a full course with the certification for free would generate questions if the face-to-face course requires a fee. Another important aspect of MOOCs certification would be to investigate how employers assess such certificates.

Pedagogical model: The most accepted categorization regarding MOOCs pedagogical model, divides them into cMOOCs and xMOOCs. cMOOCs aim to create knowledge through the interaction between the learners. In cMOOCs, learners are encouraged to reflect on their learning while in xMOOCs learners are mainly focusing in comprehending the learning material. cMOOCs follow the principles of connectivism whereas xMOOCs are based on behaviorism. Despite the benefits that cMOOCs offer, xMOOC are more popular and they are being adopted by the platforms such as edX and Coursera.

Quality: The concern with MOOCs quality is closely related to the high dropout rates (Rosewell & Jensen, 2014). The authors argue that MOOCs should follow the quality principles that are applied in traditional courses. This is explained by the fact that MOOCs mainly derive from undergraduate courses and they are created by the same faculty, with approximately the same educational material. It should be taken into account that this material is adapted to the new environment, thus it is important to be evaluated with the issues involving the quality assurance of MOOCs (Read & Rodrigo, 2014; Rosewell & Jensen, 2014).

Validation and plagiarism: A great problem for MOOCs is to ensure that the submitted material from learners are original. According to Cooper & Sahami (2013), Coursera is working to develop a software for plagiarism detection. Udacity and edX have formed a partnership with Pearson VUE, an innovative computer-based testing solution to validate the exams in a supervised form. Although, this practice generates costs to students.

2.5.2. The problem of dropout - factors affecting learner's attrition in MOOCs

The high dropout rate in MOOC courses is a major concern in the higher educational institutes and has led many researchers to investigate the reasons behind this issue. Several models have been proposed to help MOOC designers and developers gain a better understanding and predict learner's dropout (Nagrecha et al. 2017). Although many of the factors that influence learners' retention in a MOOC are beyond the control of the institutes, there are also other factors that are related to learners' characteristics and course design issues that should be considered by MOOC designers when creating course material in order to enhance the efficiency of MOOCs, improve learners' learning experience and increase learners' engagement.

Previous studies attributed the low completion rates in MOOCs to factors such as the large amount of information, the lack of learners' motivation and the limited feedback (Li & Moore, 2018). Other studies, emphasized to certain social factors such as interaction with peers and instructors, learners' characteristics (Khalil & Ebner, 2014; Shapiro et al., 2017), course design issues (Shawky & Badawi, 2019) and social and environmental factors (Ma & Lee, 2019). Specifically, Park & Choi (2009) emphasize in the importance to design MOOCs that satisfy learners' needs, keep them motivated, socially connected, and provide scenarios that apply to their everyday lives in order to improve the dropout rates. Khalil & Ebner (2014) listed the reasons for learners' dropout of MOOCs including the lack of time, learners' prior knowledge and skills, the lack of motivation, feelings of isolation that distant learners experience during the course, and also the hidden costs of MOOCs.

In the same direction, Zheng et al. (2015) argued that factors related to time, motivation, interaction, course content, workload and communication significantly influence learners' dropout from MOOCs. Other researchers have reported that social factors such as interaction and communication along with family and university support can predict dropout in online environments (Rostaminezhad et al., 2013; Yang et al., 2013). According to Itani et al. (2018) dropout rates are mostly affected by personal circumstances such as the lack of time, the lack of prior experience, family issues, etc. Oakley, Poole & Nestor (2016) argue that learners are motivated to persist in MOOCs that have "stickiness" factors, such as clear instructions, content that is relevant to their interests, an engaging instructor, and a manageable schedule.

The recent review of Aldowah et al. (2020) summarizes the factors that affect MOOC learners' dropout. The factors they identified can be classified in four categories: personal factors, social factors, course factors and academic factors. Personal factors such as prior academic skills, students' background knowledge and skill level, as well as prior experience in online courses are related to learners' dropout. Henderikx et al. (2017) argue that personal differences may play a significant role in understanding the problem of dropout in MOOCs, as compared to course design issues, while Yamba-Yugsi & Lujan-Mora (2017) reported, learner's prior experience in MOOC courses and the level of satisfaction from learner's interaction with the platform as core factors. For Kizilcec & Schneider (2015), learners' motivational goals may predict different behavioral patterns among students in the MOOC environment. Park (2007) have stressed that the lack of social support in terms of encouraging learners to continue in the course, might lead to dropout from the MOOC.

On the other hand, factors that are related to course design issues have also been reported as key determinants that lead MOOC learner's dropout. Specifically, Itani et al. (2018) found that factors, such as course design, time, and course difficulty, are critical, while Yousef et al. (2014) argued that feedback, course design and content quality contribute to learners' completion of MOOCs. Jordan (2015) examined the factors the affect the completion rate in 221 MOOCs and found that time in terms of course length, course design, feedback, and the level of commitment, are the core indicators of MOOC learners' dropout. Moreover, academic factors such as feedback and motivation are linked with learners' completion in MOOCs. Barak et al. (2016) argues that considering the importance of motivational differences between learners, the learning process may contribute positively to learners' motivation to complete the MOOC.

To conclude, Aldowah et al. (2020) identified six factors that influence learners' dropout in MOOCs in a direct way. These factors are academic skills, prior experience, course design, feedback, social presence and social support. Moreover, the authors identified factors that have a secondary role in learners' dropout in MOOCs such as interaction, course difficulty and time, commitment, motivation, and individual issues e.g., family or work circumstances.

Although, MOOC dropout rate is an issue that needs further exploration, there are few researchers who argue that the high dropout rate in MOOCs is somehow associated with the learners' low level of commitment to the MOOCs as a result of no or low entry cost and that high dropout rate should be thought as an inevitable consequence of any open online learning activity (Chen, 2014; McAuley et al., 2010). Nevertheless, MOOC designers and developers should take into account the relevant literature to create effective learning environments and provide the necessary means for MOOC learners to achieve their goals.

2.6. Basic elements of a MOOC

A MOOC is usually shaped in three main sections: the course page, the discussion forum page and the progress page. Through MOOC's home page, learners can enroll to the MOOC and enter to the course. The home page has information about the instructors, the learning sections, the duration of the course, assessment activities, costs, etc.

Figure 2.4. A common course structure on edX platform

The course page appears when a learner enrolls in a course. In this section learners can view course announcements and updates and can access the learning material as well as the deadlines for the assessment activities.

The educational content in MOOCs is usually segmented into sections. Each week participants gain access to new content and each section contains the materials that a learner should go through in a week. The content of each week is divided in subsections, relevant to the topics covered during the week. Course structure is further separated into smaller parts (learning units). Each unit in user interface is a single page with a piece of content. To add content in each unit, one or more components can be used (usually contains video lectures and quizzes). Figure 2.4. presents a common MOOC content structure.

2.6.1. Video lectures

There are several ways to produce video lectures for MOOCs. The selected method usually depends on the nature of the course and instructors' preferences. Schmidt & McCormick (2013) have divided those methods into the following types: instructor lecturing by "voice over" using presentation slides, instructors recording themselves in an office setting, recording live lectures in a classroom, recording video lectures in studios, instructor demonstrating a concept, instructor drawing freehand on a digital tablet. Different formats of video lectures have a different impact on the learning process (Chen & Wu, 2015). Researchers argue that the formatting of the video lectures has an impact on learners' engagement and attention (Guo, 2014).

Video lectures are considered to be the most important component in MOOCs as learners spent most of their time watching video lectures (Breslow et al., 2013). Therefore, creating effective video lectures is a challenge for researchers. Instructors have to apply new structures to their courses and acquire new skills as a MOOC structure differs from the traditional way of delivering courses. Recording live lectures in a classroom is a commonly used method to create video lectures for MOOCs. Chen & Wu (2015) refer to this type of video-lectures as lecture captures. These lecture captures provide learners with the sense of being in the classroom.

Institutions or MOOC providers are equipped with recording studios to produce of video lectures for learning (Cheng et al., 2018). These video lectures are designed and formatted to be used for MOOCs. Learners prefer these type of video lectures as they find them more engaging for learning. However, lecturers find it difficult to give lectures without audience. Another issue is that they cannot receive instant feedback from the students about their understanding. Finally, the cost for producing a video lectures in a studio is high, regarding the appropriate equipment, the maintenance fees, and the technical team that is required.

A more widely used method is the recordings of the video lectures by the instructors themselves, using screen recording tools. Researchers argue that learners are more engaged with these video lectures as they are produced with a more personal impression (Guo et al., 2014).

Researchers agree that the duration of the video lectures should not be long, less than 15min (Osborn, 2010; Schmidt & McCormick, 2013), while others that the duration should be shorter than 6min, as learners are more engaged with shorter video lectures (Guo et al., 2014). Another important feature of the video lecture production process for MOOCs is the enrichment of the video lectures with interactive activities. These activities help the instructors to understand learners' progress by providing feedback on specific parts of the lecture. Thus, instructors can further improve on their presentation methods and materials. Interaction activities, such as multiple-choice questions, are usually added within the video lecture during the editing process to increase the learners' engagement (Danielson et al. 2014).

Several types of interactive activities are used in MOOCs e.g., multiple-choice questions, short answer questions, peer assessments, polls, etc. For example, instructors can ask learners' opinion on a specific issue that is related to the lecture topic before the lecture and reveal learners' answers at the end of the lecture (Jemni, Kinshuk & Khribi, 2017). In general, there are two methods to incorporate interactive activities in a MOOC, i.e., after the video lectures and embedded within the video lectures (Figure 2.5). The latter is useful for MOOCs with video lectures of a longer duration (Osborn, 2010). It is suggested these activities to be introduced every 6–9min to sustain learners' engagement (Guo et al. 2014; Guo 2014).

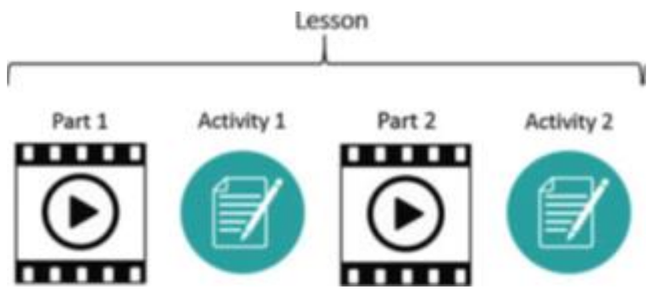


Figure 2.5. Course activities are separated from the video lectures

2.6.2. Learners' assessment

A MOOC is usually separated in several learning units. Each unit comprises of the lecture content, e.g., video lectures, pdf, pptx, followed by various assessment learning activities including quizzes, assignments, homework, final project, etc. MOOC instructors use the video lectures and the quizzes as instructional methods for their course (Yuan, Powell & CETIS, 2013), while the quiz is thought to be the basic method used for assessment by most of the MOOC providers.

Researchers (Anderson et al, 2014; Koller, 2012; Onah, Sinclair & Boyatt, 2014) also argue that the quiz is the basic course activity in MOOCs as it contributes in evaluating a number of factors, such as completion rate (Onah, Sinclair & Boyatt, 2014), engagement (Anderson et al, 2014), usefulness etc. Moreover, the extent in which quizzes are used in MOOCs, forces the providers to work towards the improvement of the quizzes in various ways such as providing better responsive question types.

Quizzes comprise of set of questions of several types i.e., multiple-choice questions, True/False, text or numerical short answers, image-based, activity-based that are delivered with the goal to evaluate learner's performance. The quiz can be evaluated using various assessment methods based on the method selected by the course instructor, such as self-assessment, peer-assessment and most commonly automated assessment.

A MOOC learner has to submit a quiz usually after watching some videos lectures or/and completing some readings. In case that the learners have a prior knowledge, they can submit the assignments before having any course lessons by skipping certain video lectures and jumping directly to a specific assessment, supporting the self-paced style of MOOCs. Learners' answers on the quiz are evaluated according to the assessment method that is used i.e., self-assessment, peer-assessment or automated assessment, and the grading policy that is used by the course. Usually, the answers given by the learners are auto-graded by the system. The system records learner's responses and compares them with the answers stored in the database of the MOOC. Also, in some quizzes, learner has time constraints while attempting a quiz.

To improve the interactivity within the course, quiz questions are embedded within the video lecture that is called in-video or embedded quiz. This embedded quiz enables learners to evaluate their understanding while watching video lectures. Learners can go back to a particular video segment to reinforce their learning. The integration of embedded quiz provides many benefits from the increased interaction between the learner and the course content to the long retention rate (Koller, 2012).

MOOC supports several types of quizzes that satisfy different purposes. Generally, a quiz is used basically for two reasons, to evaluate learner's performance, and for practice purposes to facilitate learners to check their level of understanding. Therefore, quizzes are usually divided into two types, performance-based quizzes that are used to evaluate learners' performance in the form of score, and practice-based quizzes that are used for practice purposes mainly to provide instant feedback to learners. Also, a quiz can be integrated in MOOC courses in two ways, as an independent learning activity, that comprises of several questions with different types, or can be incorporated within the video lecture (embedded or in-video quizzes). The latter type supports limited question types (Chauhan & Goel, 2016).

Quizzes can also be categorized based on the grading practice they apply. Graded quiz provides grades for each response depending on the grading practice that is used. As a learner submits a graded quiz, the grade will be calculated based on the sum of the points that each question gives. The final grade is usually presented as a percentage. On the contrary, non-graded quiz does not provide grades for learner's responses and consequently these quizzes do not affect the final grading of the course. Typically, there is no limitation on the number of the attempts for those quizzes.

The dependency among the above categories is explained as follows, the independent quizzes are used to evaluate performance, while the in-video quiz is used for self-evaluation or practice. Also, independent quizzes can be either graded or non-graded, while in-videos quizzes are usually non-graded. Both types of quizzes provide feedback about learners' performance.

There are three basic assessment methods for computing learners' grades: self-assessment, peer-assessment, and automated assessment. In self-assessment the evaluation is done by the learner using rubrics, in peer-assessment the evaluation is done by co-learner's using rubrics, while in automated assessment, the evaluation is done by a machine learning mechanism. Each of the assessment types serves for a different learning purpose. The simplest assessment method is the automated assessment as it captures learner's responses and compares them with the answers in the database for exact match. A proper combination of all assessment types can assist in creating a better and more engaging learning environment.

2.6.3. Discussion forums

Discussion forums are used in MOOCs to increase learners' engagement and to encourage reflection. Discussion forums in MOOCs provide the space for learners to exchange ideas.

A discussion forum in a MOOC involves making posts, reading posts, commenting on posts, and rating posts. Forum communities in MOOCs are forming spaces where learners can express new ideas and reinforce new thinking.

Recent studies on discussion forums focus on examining learners' activity, the content that is produced by the learners through the forums and the social aspect of learning. Specifically, relevant research studies examine learner-generated content from various perspectives, such as sentiment analysis for dropout prediction (Wen, Yang, & Rose, 2014), identification of linguistic features of learners' posts (Wise, Cui, & Vytasek, 2016), detection and evaluation of learners' cognitive engagement, examination of learner's interactions within the forums to understand the social aspect of learning in MOOCs.

Learning analytics from trace data stored in MOOC discussion forums (e.g., the number of posts) are used to decode learner's engagement (Coetzee, Fox, Hearst, & Hartmann, 2014). Others researchers have examined qualitatively the content of learner contributions in the forum and found significant correlations between learners' level of forum activity and learning outcomes (e.g., Wang, Wen, & Rose, 2016). Although, forum posts have been used to measure of learners' engagement, usually forum threads are dominated by a small number of learners. Completing learners are likely to make more posts than other learners, while those who are not very social or confident about their level of comprehension, are likely not to make any posts.

2.6.4. Progress page

Monitoring the progress of learners in a MOOC and provide individual feedback about grades at each assessment, is impossible considering the large numbers of enrollments and the diversity of the learners. Therefore, MOOC instructors rely on automated mechanisms to assess learner's performance.

MOOCs require learners to be highly self-regulated during learning and to track their progress (i.e., their grades on individual assessment activities as well as their overall course grade) through their individual progress page. This page provides information about the learners' grades in a graphical way as percentages with each column representing the performance on an assessment activity. Moreover, provides a place where learners can take information about their progress and to check whether they meet the criteria to complete the course successfully. Generally, the design of MOOCs is considered to have an impact on learners' progression in different types of activities. Thus, in order for learners to progress in a MOOC, instructors should design the learning material and learning activities in a way to support learners.

2.7. MOOCs pedagogical aspects

Researchers argue that the success of online learning is considered to be closely related to learning design (Conole, 2012). However, there is a lack of research studies on the pedagogical design of MOOCs (Davis et al. 2016; Sergis et al. 2017).

Table 2.5. Pedagogical type decisions (based on Klobas, Mackintosh & Murphy, 2015)

Pedagogical decisions	
Purpose and audience	Course goal. Learning objectives. Level of difficulty.
Course timing, pacing and effort	Start and end dates (can be either open or fixed). Course length. A typical length is about 4-10 weeks. Pace (e.g., student self-paced). Student effort (i.e., the number of hours of student effort to be committed in each period or for each activity needs to be estimated. This is important both for student's planning and for accreditation of MOOCs).
Course structure	Each learning component needs to be pre-designed and pre-packaged following an objectives-based design, defined by what the participants are to learn. Quizzes and assessments also address the learning objectives.
Course content	Multimedia. xMOOC content is typically based on short video-lectures (5–10 min). Intellectual property. Ensure rights are available or obtained, for material developed by others. Design exercises and other active learning activities. Quizzes and self-assessment. Sequencing. Linear, or will learners be permitted to branch to different content or make their own connections. xMOOCs currently offer only linear sequencing.
Designed interaction	Effective interaction in forums requires a design of questions and a structure of discussion categories rather than a laissez-faire approach.
Assessment	What will be assessed and when? Are learners permitted to re-take an assessment? What combination of computer-based assessment, self-assessment and peer-assessment will be used? Is verified identification of learners required for accreditation and is verification online or require physical presence at a testing center?

The technical capacity for infinite enrollments, combined with an openness to acceptance of all learners who register for a MOOC, has important implications for MOOC pedagogy. According to Baturay (2015), the pedagogies relevant for MOOCs are available in the field of distance education. Table 2.5 presents pedagogical type decisions that a MOOC course designer and instructor must take into account.

Chapter 3. Motivational design and gamification in learning

3.1. Motivational design

3.1.1. Introduction to motivation

Motivation is described as an individual's choice to engage in an activity and is related to processes that give energy and direction to peoples' behavior. According to Reeve (2015), motivation is a construct that cannot be measured directly, however, expressions of motivation can be measured through observations of behavioral reactions, physiology, and self-reports. For example, motivation is often measured by the level of effort and persistence that the individual demonstrates in that activity.

Researchers have acknowledged the significant role of motivation in learning and have proposed several theories of motivation. Early motivation theories were based on a behavioristic approach. They have considered as the basis of motivation, elements such as rewards and punishments. Other theories of motivation have been based on individuals' psychological needs and motivational drivers. More recently, researchers have investigated motivation mainly from a social cognitive approach.

Motivational design is described as the process of organizing methods and resources to cause changes in individual's motivation (Keller, 2010). In this direction, game elements have been considered to achieve motivational effects when used in non-game environments or contexts. Gamification, which is the term that is used to describe this use of game elements, can combine the two aspects of motivation. It uses rewards such as levels, points, badges to increase extrinsic motivation while trying to enhance emotions of autonomy, self-efficacy, sense of belonging, etc. According to Keller (2006), motivational design includes rules and principles which guide a longer systematic process. These guidelines should be driven from motivational theories.

Motivation can activate individuals to participate in a learning activity, to complete assignments, to stay focused in an activity, and to continue in an online course. Learners with different level of motivation behave differently towards learning. High motivated learners tend to show more persistence and exploratory learning behaviors. Paas et al. (2005) argue that motivation is an important factor that keeps learners learning, while Hart (2012) found that learners' motivation is an essential factor of persistence in online learning environments. According to Lei (2010), learners' lack of motivation is associated with learners' dropout of learning in online learning environments such as MOOCs. Pittenger & Doering (2010), found that the implementation of motivational design in an online self-paced course increased course completion rate. Therefore, motivation has the potential to decrease attrition rates in courses such as MOOCs.

3.1.2. Theories of motivation

Self-determination theory

The Self-Determination Theory (SDT) concerns three human psychological needs, competence, autonomy, and relatedness (Deci & Ryan, 2000). The theory reports that the fulfillment of these needs can lead to motivation. Autonomy refers to the need for a sense of free choice when participating in a task. For example, in a game, autonomy is achieved when players choose the sequencies of their actions (Ryan, Rigby & Przybylski, 2006). Competence refers to the need to feel effective when participating in an activity or interacting with an environment. During the gameplay, competence is achieved when tasks provide optimal challenges, while the feeling of relatedness is enhanced when players interact with each other. Relatedness expresses the feeling of being connected with peers or of belonging, thus, is related to social interaction.

According to Ryan & Deci (2000), there are two aspects of motivation that control individual's motivation i.e., extrinsic, and intrinsic motivation. Autonomy, competence, and relatedness are the elements that according to SDT facilitate intrinsic motivation. Studies on SDT and education have shown that supporting the intrinsic needs of autonomy, competence, and relatedness enhance learning facilitating a more internalized learning (Ryan, Rigby & Przybylski, 2009). When individuals are intrinsically motivated, it is likely to exhibit higher levels of persistence and engagement.

Based on the literature, game elements can fulfill players needs for autonomy, competence, and relatedness, but they can also have a negative impact on them. For example, according to Liu, Li & Santhanam (2013), competition can affect players' enjoyment in a gameful experience either positively or negatively. The authors also argue that competition can satisfy player's need for competence, while external rewards may undermine players' autonomy. Mutter & Kundisch (2014) also argue that badges and other external rewards harm players' autonomy. Sailer et al. (2017) state that game elements such as leaderboards and badges are related to higher levels of satisfaction of competence while elements such as avatars are related to higher level of relatedness.

Flow theory

Flow theory is the most referenced theory in studies relevant to motivation. Flow is defined as the holistic sensation individuals feel when they act with total involvement (Csikszentmihalyi, 1975). Flow is an optimal state of intrinsic motivation where a person is deeply absorbed in what he/she is doing. This state is characterized by high concentration, a loss of self-awareness, merging of action and consciousness, a sense that one is in full control of one's actions, distortion of temporal experience and experience the activity as being rewarding in itself (i.e., intrinsically rewarding). To experience the flow state, the challenge of the task must be in balance with the individual's skills (Csikszentmihalyi, 1991). According to Nakamura & Csikszentmihalyi (2009), too much challenge causes anxiety while too little challenge causes boredom. Also, the authors argue that flow requires clear and proximal goals, appropriate level of challenges and immediate feedback (Nakamura & Csikszentmihalyi (2009).

Flow is considered to be part of the gaming experience. The game element "challenge" can cause a flow state to players' only when the degree of challenge is in balance with player's skill level. Nevertheless, flow has been proven to be a core experience not only of gameplay but of educational scenarios as well. Nadolski et al. (2008) and Mueller et al., (2011) argue that flow contributes to an optimal learning state.

Goal setting theory

Goal-setting theory describes the way in which goals affect motivation and task performance (Locke & Latham, 2002). According to the authors, goals are objectives that individuals try to attaint while goals affect both motivation and achievement.

The theory is based on the psychological process of *self-regulation* (Latham & Locke, 1991) as it acts as an intermediate process between goal and performance. According to Pintrich & Zusho (2002), the term "self-regulation" refers to the level at which individuals can regulate their thoughts, motivation, and behavior during learning. Self-regulation is associated to monitoring and regulating the learning process, i.e., setting learning goals and choosing strategies to achieve those goals, regulating efforts and resources to exploit external feedback. According to Nicol & Macfarlane-Dick (2006), learners should be aware of the learning goals to self-regulate by comparing their performance against these goals and reduce the discrepancy among them.

Goal-setting theory suggests four mechanism of goals that affect performance and motivation. These mechanisms are described as follows: goals direct individuals' attention in goal-relevant tasks (choice or direction), goals enhance persistence (persistence), goals mobilize individual's effort and energy (effort), goals promote the development and use of goal-oriented strategies (task strategy). Also, it is considered that specific goals are positively related to motivation.

The mechanism of *choice* defines the relationship between goals and performance, as goals direct individual's efforts to goal-oriented task. Based on the mechanism of choice, many gameful design methods provide specific goals to individuals but they also present the next action that must be attained to accomplish the goals. The mechanism of *effort* is associated with an individual choice to act towards the accomplishment of a goal. Latham (2004) argues that the level of individual's effort is proportional to the difficulty of the goal. *Persistence* considers that challenging goals can make individuals to try harder than makes an easy goal. In games, players are encouraged to fail and try again as many times they want, until they acquire the necessary skill to reach their goals (Tondello, Premsukh & Nacke, 2018). Tondello, Premsukh & Nacke (2018) also argue that gameful systems can provide individuals a space for learning and experimentation, which is particularly important when learning concerns the acquisition of new skills or the improvement of current skills. *Task strategy* is another goal mechanism. This is based on the idea that high complexity goals require the ability to use the necessary knowledge and skills, as well as to decide the appropriate strategy.

Apart from the goal mechanism, Locke & Latham (2002, 2013) describe four moderators that are involved in the relationship between goals and performance, namely, ability, task complexity, performance feedback and goal commitment. *Ability* is an important moderator as individuals cannot achieve a goal when they lack the necessary knowledge and skills. The authors argue that performance increases with goal difficulty, however, this relationship fails when goals are perceived unattainable due to their level of difficulty. Moreover, when the *complexity* of a task increases, goal achievement is dependent on individual's ability to develop and apply the appropriate task strategy (Locke & Latham, 2002). For example, in games, challenges are usually separated into smaller ones which are presented with increasing difficulty. In this way players acquire knowledge and skills progressively which lead them to generate a feeling of competence and to pursue more difficult goals. Furthermore, *feedback* is the mechanism that reveals individual's progress in relation to goals. It enables individuals to track their progress towards goal attainment in order to adjust their strategy and effort. Finally, *goal commitment* allows individuals to direct their efforts towards the goals they want to pursue. Tondello, Premsukh & Nacke (2018) argue that goal commitment is supported by goal importance and self-efficacy. The authors mention that it is very important to provide a context for the goals to reinforce their importance and foster individual's commitment. Moreover, self-efficacy has a prominent role in goal-setting theory as it is considered to act as a mediator of goals. Locke & Latham (2013) argue that positive affect can influence self-efficacy and consequently the level of goals that the individual is willing to pursue.

Goal-setting theory considers different types of goals. Locke & Latham (2013) define *outcome* goals, *performance* goals and *process* (*learning*) goals. Outcome goals refer to the accomplishment of a specific result i.e., completing a task. Performance goals refers to an individual's performance standards. Earning a specific number of points or reaching a specific position in a leaderboard are examples of performance goals. Process or learning goals are related to the acquisition of new skills or knowledge. Locke & Latham (2013) argue that in cases that an individual lacks the necessary skills or knowledge to accomplish a challenging goal, it is preferable to set learning goals rather than performance or outcome goals. This is explained by the fact that learning goals or mastery goal are considered to increase individuals' intrinsic motivation. Also, learners who focus on learning goals are usually having a better performance than those who focus on performance goals (Latham & Brown, 2006). Other types of goals in goal-setting theory that are used rarely are stretch goals. Stretch goals are very difficult or even impossible to be attain. For example, some games provide challenges that only the most skilled players can accomplish.

Finally, goal-setting theory defines proximal and distal goals. It is recommended to break distal goals into smaller proximal goals to encourage learning and engage individuals. According to Locke & Latham (2013), proximal goals facilitate the accomplishment of distal goals. For example, in games, completing several levels or challenges might be proximal goals which lead to a distal goal that is completing the game. Goal-setting theory has been used in gamified applications to provide a theory-based explanation about the way goals lead individuals to motivation and task performance. Interventions based on this theory are considered to be effective across various tasks (Latham & Locke, 1991).

ARCS model

The ARCS model is based on the expectancy theory. It claims that individuals are motivated to engage in an activity e.g., to learn, if knowledge that is presented is perceived as valuable i.e., it is considered to satisfy personal needs (value aspect), and if there is a positive prospect for success (expectancy aspect) (Keller, 1987).

Keller (1987) proposed a motivational design model which is defined by four components, Attention, Relevance, Confidence, and Satisfaction (ARCS). *Attention* refers to capturing learners' attention and enhancing their interest and curiosity. This component is separated into the following categories: perceptual arousal i.e., using surprise, novelty or humor to stimulate perceptions, inquiry arousal i.e., offering challenging questions, problems or dilemmas, and variability, i.e., incorporate a variety of resources, presentation modalities and methods for learning. *Relevance* is associated to learners' needs and experiences. Also, it expresses that learners should know how the content relates to their needs. To establish relevance, Keller proposes the three strategies of goal orientation, motive matching, and familiarity. Goal orientation refers to directing learners to useful goals i.e., explain the purpose if the goal, explicitly state their value, and allow learners to select goals. Motive matching is about adapting to learners' preferences, interest, and needs. Familiarity is about using familiar language and relating goals to something familiar such as prior knowledge. *Confidence* aims on creating positive expectations for success. The level of learners' confidence is associated to motivation as well as with the level of effort that individuals are willing to put to achieve a performance objective. Moreover, confidence is based on positive reinforcement for individual's achievements given through timely and relevant feedback. Keller proposes the following strategies to enhance confidence, setting learning requirements i.e., setting clear goals and evaluating criteria, etc., creating success opportunities i.e., provide challenging opportunities for achievement within individuals' available resources and effort, and finally encourage personal control correlating personal responsibility ad effort with success. Personal control is enhanced by providing informative feedback. *Satisfaction* is achieved by building a sense of achievement and reward learning process. Keller suggests three strategies to increase satisfaction, intrinsic reinforcement i.e., encourage intrinsic enjoyment, extrinsic rewards i.e., provide motivational feedback, and equity i.e., maintain consistent equitable evaluative criteria.

According to Keller (1987), motivational strategies have to support instructional goals. The ARCS model uses a systematic design process that consists of four steps, i.e., defining target audiences' motivations, designing motivational strategies, developing the strategies, and evaluating the effects (Keller, 1987).

Bloom taxonomy

A taxonomy of learning activities was proposed by Bloom (1956) to promote higher skills of thinking in education. The taxonomy includes three domains of learning activities: affective, cognitive, and psychomotor. Bloom's cognitive taxonomy describes six consecutive levels referring to cognitive processes, i.e., knowledge, comprehension, application, analysis, synthesis, and evaluation. The taxonomy was revised to be better aligned with the active process of thinking. In this revised taxonomy the names of the categories have changed into verbs while two levels were rearranged. These levels define remembering, understanding, applying, analyzing, evaluating, and creating new knowledge (Anderson & Krathwohl, 2001). Bloom's taxonomy has been used to set goals, to link learning outcomes in digital environments with Bloom's levels, to describe learning outcomes, as well as, as an assessment framework for the learning outcomes of experiential learning (Ben-Zvi, 2010; Legner et al., 2013; Monk & Lycett, 2011). In this work, the revised Bloom's taxonomy was used to develop the learning goals that guided the delineation of levels of our assessment activity.

3.1.3. Implementing game elements in MOOCs

The implementation of game elements into learning management systems is considered as a positive reinforcement strategy to motivate and engage learners. A gamified intervention enhances learner's engagement and self-efficacy, encourages self-regulated learning, and facilitates social and cognitive skills. Several studies have implemented gamification in learning management system to provide personalized experience for learners and prioritize learners' needs. According to Dickey (2005), the main elements of engaging learning are clear goals, reinforcing feedback and increasing challenges.

Learning progression

Learning is an important element in gamification as many design methods suggest that each challenge should increase progressively in order to encourage learners to pursue the goals that are set and to enhance their skills. Gameful design methods should create a smooth learning curve that will allow individuals to practice the needed skills and to acquire the necessary knowledge as the move forward. Progression is recognized in pedagogy, among other things, as scaffolded instruction. Also, learning progression helps learners track the challenges they have completed and plan the next challenges in order to achieve their goals. Progression contributes to increasing learners' self-efficacy within the course. For an effective progression, learners should be able to repeat the same challenges until they master the necessary concepts. In MOOCs, appropriate scaffolding can be provided with the use of levels. As in games, easier levels are presented first, advancing to more complex levels as learners achieve mastery. To enhance engagement, MOOCs should present learners with challenges that match learners' skills and that are a little outside their "comfort area". This means that the desired level of difficulty is at the level at which learners need a moderate support to accomplish the task.

As in games, the necessary assistance can be provided to learners through feedback in order to advance their skills. Effective feedback should always be clear and immediate, and to correspond to learners' actions. Also, feedback can help reinforce motivation.

Formative assessment

Gameful design encourages players to attempt each challenge multiple times by giving them multiple lives. In this way, gamified environments motivate learners to put more effort in pursuing the goals. Sadler (1998) argues that formative assessment describes an assessment that is intended to generate feedback on performance in order to enhance and accelerate learning. It should be noted that, formative assessment focus on learning processes rather than on the result of the assessment as it encourages learners to explore the content. Shute (2008) argues that formative feedback is provided to learners in order to modify their thoughts or behavior about the purpose of improving learning.

Feedback

There are many different types of feedback in learning. Johnson, Bailey & Van Buskirk (2017) have conducted a literature review reporting the feedback types that are presented in the literature on serious games και simulations. The authors argue that the types of feedback are organized into two categories, outcome-based feedback, and process-based feedback. Outcome feedback provides information to learners about their performance and progress, while process feedback directs learners to strategies needed to achieve a goal or an action. Each of these groups are further analyzed into several types of feedback.

Goals, challenges and feedback are the game elements that are suggested by the most gameful design methods (Chou, 2015; Deterding, 2015; Mora et al., 2017, Morschheuser et al. 2017). Several design elements have been employed in gamification to provide feedback such as progress bars (Landers et al., 2015), points, levels, badges, leaderboards, narrative, rewards etc. In a gamified system the feedback mechanisms help learners to progress and to feel that they are responsible for their accomplishments.

Feedback is the information about how learner's current performance relates to goals. The use of feedback in learning is considered a powerful strategy as it helps learners to reduce the discrepancy between current performance and desired performance.

According to Sadler (1989), learners should always know to answer the following questions, what good performance is, how current performance relates to good performance, and how to act to close the gap between current performance and good performance.

Hattie & Timperley (2007) argue that designers should consider three questions regarding the effective feedback (where am I going? how am I going? where to next?). Based on this feedback model, van den Bergh, Ros & Beijaard (2012) stated that the first question relates to the learning goals, the second question addresses the fact that learners need to know how the current performance relates to the learning goals and, the third question refers to the activities that learners need undertake to make progress.

Feedback is thought to have the potential to influence learners' engagement. It is related to greater academic achievement and increased motivation. Nicol & Macfarlane-Dick (2006) suggest seven principles in order to design effective feedback which will facilitate self-regulated learning. Feedback helps learners to understand what good performance is, facilitates the development of reflection in learning i.e., self-assessment, delivers information to learners on their learning, encourages the dialogue around learning, encourages positive motivational beliefs, provides opportunities to close the gap between current and desired performance and provides evaluation to instructors about learning that helps to improve their teaching.

According to Sadler (1989), for learners to attain learning goals, they should understand those goals, assume some ownership and be able to evaluate their progress. To assume some ownership means that there must be an overlap between the goals that are set by the instructors and the goals that learners set.

Gibbs & Simpson (2004) argue that providing timely feedback (regularly and before the final submission of any task), can improve learners self-regulation and their performance. Other strategies to improve the quality of external feedback is to provide corrective advice, to limit the amount of feedback to the necessary, to highlight areas for improvement and to provide online tests so that feedback is available anytime. Feedback strategies that encourage high levels of motivation and self-esteem include automated tests with feedback and opportunities of resubmissions.

3.2. Gamification

3.2.1. Introduction to gamification

Gamification is a framework that guides the integration of game elements and gameful design techniques in non-game context to enhance individuals' engagement and interest. Gamification's definition is usually based on games or their characteristics.

According to Zimmerman & Salen (2003), a game is a system in which players engage in an artificial conflict defined by specific rules that ends in a quantifiable outcome. Koster (2004) includes players' emotional reaction in his definition as it is based on the idea of fun. Koster (2004) argues that "a game is a system in which players engage in an abstract challenge that is defined by rules, interactivity and feedback, that results in a quantifiable outcome while it is often eliciting an emotional reaction". In gamification the aspect of affect is very important as its goal is to drive a behavioral change and a higher engagement. Gamification has an inherent feature from games, namely fun. Fun is one of the reasons that people engage in playing games. Game designers define games as a series of meaningful choices made by the player in pursuit of clear and challenging goals. Several researchers have defined the basic game characteristics. Garris et al. (2002) describe the game characteristics as rules/goals, fantasy, challenge, mystery, control and sensory stimuli. McGonigal (2011) includes, goals, rules, feedback systems and voluntary participation, while Rogers (2017) define game characteristics based on the interactions within a game. The author mentions conflict, challenge, competition, feedback, perception of an event, control, feelings and results of a game.

The term "*gamification*" is described by researchers in different ways. Deterding et al. (2011) describe gamification as the use of game elements in non-game contexts, while Zichermann & Cunningham (2011) describe gamification as the process of using game thinking and game mechanics to engage people. Wu (2011) defines gamification as the use of game elements and techniques in non-game context in order to elicit a game-like player behavior. In another definition, gamification is described as the integration of game elements, mechanics, and frameworks into non-game scenarios or contexts (Sümer & Aydin, 2018).

The concept of gamification is based on marketing efforts, such as memberships rewards and point cards. However, due to growing adoption of mobile technology, game-like elements became an essential part of our daily activities. Gamification has been implemented in several domains, such as trading (Hamari, 2015), marketing (Kim & Ahn, 2017; Yang, Asaad & Dwivedi, 2017), banking (Rodrigues, Oliveira & Costa, 2016), healthcare (Marques et al., 2017; Muangsrinoon & Boonbrahm, 2019). Also, gamification has been applied with the goal to examine whether game elements such as points, levels, leaderboards, etc., can harm motivation (Mekler, 2013).

According to Dicheva et al. (2015), education is a field in which gamification has been applied widely. In education research, several literature reviews have been conducted to describe gamification as the state-of-the-art in education (Dicheva et al., 2015; De Sousa Borges et al., 2014; Caponetto, Earp & Ott, 2014). These reviews report the game elements that are used in educational settings most frequently (Nah et al., 2014), provide an overview of the available gamification design frameworks (Mora et al., 2015) and investigate the effects of gamification on learners in different learning situations e.g., face-to-face and blended learning (De Almeida Souza et al., 2017; Monterrat, Lavoué & George, 2017; Smith, 2017), or in online educational settings (Hamari, Koivisto & Sarsa, 2014; Looyestyn et al., 2017).

Table 3.1. Classification of game elements (reproduced from Deterding et al., 2011)

Level	**Description**	**Example**
Game interface design patterns	Common interaction design components and design solutions for a known problem in a context.	Level, leaderboard, badge
Game design patterns and mechanics	Parts of the game design that concern gameplay and occurring in repeated mode.	Time constraint, turns limited resources,
Game design principles and heuristics	Evaluative guidelines for the design of a problem or the analysis of a design solution.	Clear goals, game styles
Game models	Conceptual models of the game's components or the player's experience.	Game design, fantasy, curiosity, challenge, MDA,
Game design methods	Game design practices.	Playtesting, playcentric design

Well-known examples of gamification include the Foursquare (https://foursquare.com/), the piano staircase in the Odenplan subway station (www.thefuntheory.com/piano-staircase) and the Duolingo application (https://el.duolingo.com/). Foursquare is a social networking platform which has urged its users to "check-in" using gamification techniques. The piano staircase in the Odenplan subway station in Stockholm that was an attempt for citizens to adopt a healthier living by adding game elements to subway stairs. Specifically, the existing stairs were transformed to piano keys that made a relevant sound. Finally, Duolingo is a language-learning platform and application, which provides users provided with instant feedback and experience points as they progress through lessons.

3.2.2. Gamification frameworks, game mechanics and elements

According to Deterding et al. (2011), any element that contributes to the gaming experience is considered to be a game element. A gamified environment is an environment that incorporates games elements. Usually, researchers report in their studies the same game elements, but they categorize them with a different way. This divergence lays on the main dimension on which researchers based their classification. Adams (2009) organizes the game elements into categories based on the aspects of game definition. The author reports the elements of challenging goals (goals, challenges), play (competition, collaboration, feedback), rules (i.e., core mechanics such as levels, luck, risk) and pretended reality (i.e., game world, game aesthetics, story, characters). Deterding et al. (2011) categorize game elements in five game design levels. These elements are on varying regarding the level of abstraction. Table 3.1 presents these levels, starting from the more concrete which corresponds to the game interface design patterns. The levels are defined as follows: interface design patterns, game design patterns and mechanics, design principles heuristics, game models, and game design methods. It is obvious that game mechanics and game design patterns do not define implemented structures, but they can be implemented with several interface elements.

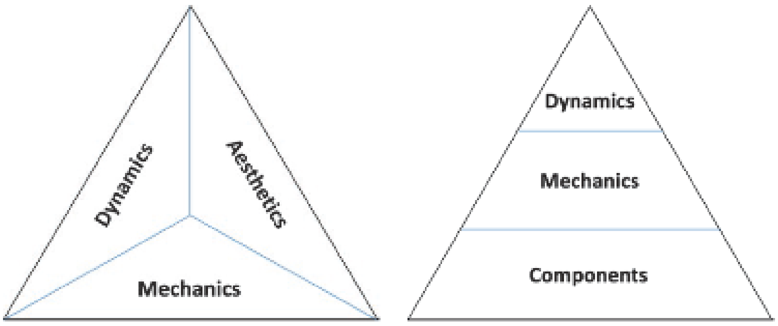


Figure 3.1. MDA framework (left) and Werbach & Hunter's framework (right)

Different frameworks for gamification have been proposed (Kim et al., 2018).

The most frequently leveraged framework of game design is proposed by Hunicke, LeBlanc, Zubek (2004). The authors report a theoretical gamification framework, namely the MDA framework. It should be noted that in Table 4.1 MDA is categorized as a game model. This framework consists of Mechanics, Dynamics and Aesthetics (Figure 3.1). *Mechanics* constitute the functioning components of the game. This means that mechanics include the components that are implemented in a game to guide players' actions and define the behaviors that are allowed. With data and algorithms, mechanics define the behaviors allowed to players and the control mechanisms of the game. *Dynamics* define the interactions with the mechanics, i.e., it is the observable behaviors that players are allowed to perform during the gameplay. For example, forming an alliance is an example of the dynamics of a strategy game. Dynamics determine what a player can do in response to the mechanics of the game. *Aesthetics* describes the emotions that players experience while interacting with the game or with the other players. Aesthetics can be created either from the mechanics or dynamics of the game. Sensation, fantasy, challenge, fellowship, and discovery are examples of aesthetics (Hunicke, LeBlanc & Zubek, 2004).

In another gamification framework Werbach & Hunter (2012) argue that the game elements are organized in a hierarchy (Figure 3.1). The authors organized the elements into dynamics, mechanics and components (Table 3.2).

Table 3.2. Categorization of game elements (Werbach and Hunter, 2012)

Category	**Description**	**Example**
Dynamics	High-level elements that have to be considered but they are not implemented directly.	Progression, emotions, constraints, narrative, relationships
Mechanics	Elements that engage players.	Challenges, feedback, competition, rewards, cooperation
Components	Specific forms of mechanics or dynamics.	Levels, badges, points, avatars

Dynamics refers to the most abstract elements in a game or in a gamified setting. Dynamics comprises of five elements, progression (i.e., the player's growth and development in the game), emotions (e.g., competitiveness, curiosity, frustration), constraints (i.e., limitations), narrative (i.e., a progressive storyline), and relationships (i.e., social interactions). *Mechanics* is the necessary element for the development of dynamics in a game. It is also the element that encourage players to engage in the game. Mechanics is comprised of ten elements, namely, challenges (i.e., tasks that require effort), chance (i.e., elements of randomness), competition (among players or groups), cooperation (players collaborate to attain a common goal), feedback (i.e., information on how the player is doing in the game), resource acquisition (e.g., collectible items), rewards (i.e., benefits that are acquired from an achievement), transactions (i.e., trading between players), turns (i.e., participation of players in a sequential form) and win states (i.e., criteria for winning the game). Finally, *components* are the least abstract game element, and they are considered to be the implemented form of dynamics and mechanics. There are fifteen gamification components: levels (denied steps in player's progression), points (numerical representations of game progression), leaderboards (visual display of player's progression), achievements, badges (visual representations of achievements), avatars (visual representations of a player's character), boss fights (especially hard challenges), combat (a determined battle, typically short-lived), collections (sets of items to accumulate), content unlocking (content available only when player attains a goal), gifting (sharing resources), quests (predetermined challenges with objectives and rewards), social graphs (representation of players' social network within the game), virtual goods (i.e., game assets with virtual or real money value) and teams (groups of players collaborating to achieve a goal)

Bunchball (2016) proposes a framework that consists of only two elements, dynamics and mechanics. The author defines dynamics as the player's experience attained during the game. Dynamics includes reward, achievement, competition, self-expression, altruism, and status. Mechanics is defined as the gamification elements that are essential for providing players a specific experience. Mechanics includes points, challenges, levels, leaderboards, virtual goods, gift and charity.

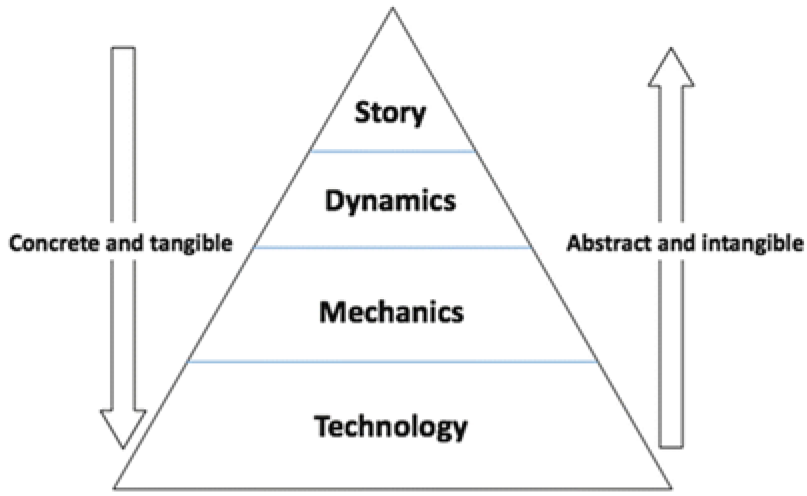


Figure 3.2. The gamification framework proposed by Kim et al. (2018)

Schell (2014) includes the elements of story, mechanism, aesthetics and technology, in his framework. Story is described as a course of events that players experience while playing a game. The story is delivered using aesthetics and technology and can be implemented either in a linear or in a branching structure. The second element, mechanism, defines the rules and the procedures of a game. It describes players' behaviors, rewards, and penalties. The rewards and penalties change the progression of a story. Technology includes materials, hardware and information technologies that are required to create a game. Finally, aesthetics is about the audio and visual elements that affect the appearance of the game and the feel that players perceive within a game.

Kim et al. (2018) proposed an integrative gamification framework based on the previous frameworks (Figure 3.2). Story provides a pivotal process as it comprises of educational objectives and stories related to the objectives. Story integrates various fun aspects in the game. During gameplay, players have a variety of choices that require them to choose one of them to progress in the game. Player's decision will determine in which branch of the story he/she will proceed, even though all players are playing the same game. Dynamics, consists of the twenty playful experiences of PLEX (Playful Experience framework) proposed by Korhonen, Montola & Arrasvunori (2009) namely captivation, competition, fellowship, challenge, completion, control, fantasy, discovery, exploration, simulation, expression, eroticism, sensation, nurture, relaxation, subversion, suffering, sadism, thrill, sympathy.

Dynamics are used to motivate learners to engage in learning. Mechanics is used to implement dynamics. For example, learners receive feedback and rewards through the mechanics i.e., leaderboards, badges, points, etc. Researchers suggest different perspectives on mechanics (Bunchball, 2016; Duggan & Shoup, 2013; Kumar & Herger, 2013; Werbach & Hunter, 2012; Zichermann & Linder, 2013), although, leaderboards, badges, challenges (or quests), levels, points and virtual goods are common mechanics across the different approaches. Technology provides players the means to interact with a game or a gamified setting.

3.2.3. Game mechanic elements

Kim et al. (2018) described several core mechanic elements based on previous studies (Duggan & Shoup, 2013; Kapp, 2012; Kumar & Herger, 2013; Radoff, 2011; Schell, 2014; Zichermann & Linder, 2013). A brief description of these mechanic elements is given in the following subsections.

Rewards

In games or game settings, rewards are usually represented by the following mechanics:

Point: A numerical reward for specific actions. Players can also use points to buy virtual or physical goods. These goods are called redeemable points. Players can share their points with other players. These points are named karma points and they are considered to facilitate altruism between the players.

Level: A part of a game. Players can attain higher levels by completing a specific task. Also, there are systems with a single level or multiple levels. Higher levels require players to complete more difficult tasks than lower levels.

Progression: A way to show player's advancement in a game. Progression is represented by numbers, pie charts, etc.

Badge: A visual achievement note. Players can win badges for completing tasks while badges show to the other players the accomplishments of the player. Some games use badges as leveling system.

Authority: Refers to the ability to control characters, villages or other players, usually after having achieved a specific level.

Virtual Goods: Virtual goods may be clothes, accessories, food, etc. Though the virtual goods players can increase the speed of the game, make the game character stronger or unlock content. Also, the players can sell, purchase or trade these goods.

Physical Goods: Players can achieve the physical goods by an achievement in the game or the use of virtual goods.

Discontinuation: A device to limit the reward according to a specific behavior

Gifting: Refers to giving other players items.

Free Lunch: A reward without player's effort. This mechanism is often used to encourage players to play the game again or in a more regular basis.

Virtual Currency: Currency with a value only within the game. Players purchase items with this currency to improve the speed of game progress. Players can also sell items. A player can gain virtual currency by achieving goals or by paying real money.

Rewards schedule

Rewards schedule defines the algorithms that are used in game settings for rewards. These schedules are the fixed interval reward schedule i.e., rewards are given to players on a specific time schedule. They also are the fixed ratio reward schedule i.e., rewards are given when a player completes a certain number of challenges, or the variable interval reward schedule i.e., rewards are given at irregular time intervals. Finally, schedules are the variable ratio reward schedule, i.e., rewards are provided when a player completes a mission.

Avoidance

Avoidance describes the mechanics that are used to avoid specific behaviors. There are two such mechanics, discouragement, and penalty. Discouragement is a penalty given in order to prevent players to demonstrate a specific behavior, while leaky bucket refers to the fact that players can perform a quest without limitations at the beginning of the game, but limitations are applied over time.

Leaderboard

A board that is presenting the leading players' achievements. There are several types of leaderboards such as, macro leaderboard i.e., a board that presents information of players leading the game (such as names, scores, rankings etc.), micro leaderboard i.e., a board showing information for players leading the game within a certain level, thus encouraging beginners to compete with others players, indirect competition, i.e., competition based on players' relative progression, and direct competition i.e., competition between players.

Status

Status is about avatars, rankings, and social relationship within the game. An avatar visual representation of the player in the game. Sometimes the avatar of a player embeds its characteristics. Players can purchase accessories for their avatar which can also be used to improve the looks or the ability of avatars. Ranking is the result of competing with other players. Ranking is affected not only by players achievements, but also by the achievements of other players. Ranking often used as a criterion for rewards, and finally social network which allows players to view the status of other players.

Quests

A quest describes a specific mission that the player must complete to gain rewards. Quests include unlocking content, e.g., items, characters, missions, scenes, that a player cannot see or use, unless they complete a specific quest or reach a required level or point. Quests may relate to countdown i.e., a given time to complete a quest, lottery i.e., a type of reward that with haphazardness, communal discovery i.e., a quest completed through the collaboration of players and scaffolding i.e., support for the players who need help to complete a quest. There are several ways that scaffolding is implemented, including messages, agents etc.

3.2.4. Goal-setting theory and game elements

Goals are common game elements employed in gamification design. Deterding et al. (2011) argue that gamification as derived from games is a goal-oriented activity. The authors suggest "clear goals" as one of the design elements of gamification. Goal-setting is associated with the most motivating goals. Those goals are just out of the comfortable reach.

In a gamified system, goals can either be explicit such as earning badges, reaching a certain position in a leaderboard, etc., or implicit, presented as outcomes that should be attained. For example, Barata et al. (2017) use challenges as outcome goals in a gamified course. Also, other elements, such as quests and exploratory tasks, are suitable for outcome goals. Gamification is particularly important in increasing an individual's perception of goal importance (Hamari & Koivisto, 2013; Chou, 2015). According to Tondello, Premsukh & Nacke (2018), goals are thought to be motivational affordances. A motivating environment should be built on attainable long-term and short-term goals, provide immediate feedback on learners' performance, and help learners assess their own progress. In the relevant literature goal-setting theory is used with the following ways (Tondello, Premsukh & Nacke, 2018):

- to understand how gamification works (Landers et al., 2015)
- to explain a specific game element (Fanfarelli, Vie, & McDaniel, 2015; Landers, Armstrong & Collmus, 2017; Chernbumroong, Sureephong, & Muangmoon, 2017)
- to serve as a theoretical base of incentives and rewards in gamification (Richter er al., 2015)

Tondello, Premsukh & Nacke (2018) identify the following elements as mechanism for setting goals in gamification: badges (Fanfarelli, Vie, & McDaniel, 2015), leaderboards, levels, progress bars (Landers, Bauer, Callan & Armstrong, 2015), rules, goals, challenges, conflict (Landers, Armstrong, & Collmus, 2017), points, achievements and rewards (Richter, Raban & Rafaeli, 2015). The authors also argue that other elements can also be used to set goals such as, boss battles, collections, exploratory tasks, learning, certificates, quests, unlockable access to advanced features. In a learning environment, learners are motivated to attain a specific goal because goal seeking is considered to be motivating.

3.3. Gamification in MOOCs

3.3.1. Introduction

MOOCs and gamification are two trends in pedagogical design that started almost simultaneously. Gamification is considered to be a successful strategy to engage learners with a potential for online education. Although, there are not yet many research studies concerning the implementation of gamification in MOOCs, gamification is thought to be a successful strategy to increase learners' engagement, along with enabling learners to attain their goals within a MOOC. Current literature focuses on implementing gamification to overcome MOOC drawbacks such as the low completion rates and the lack of learners' engagement.

Ortega-Arranz et al. (2017) argue that even though there are some educational platforms with gamification capabilities, the effects of gamification in MOOC contexts have not been explored thoroughly yet. The authors based on the results of their systematic literature review argue that the most frequently used game elements in MOOCs are points, badges, and leaderboards (PBL). This is confirmed by other reviews on gamification (Dichev & Dicheva, 2017; Dicheva et al., 2015).

Chang & Wei (2016) categorized game elements that are used in MOOCs according to engagement level that cause to learners. The authors suggest that the most engaging gamification mechanics of MOOCs are virtual goods, redeemable points, team leaderboards and badges. According to Ortega-Arranz et al. (2017), some game elements not frequently implemented in small-scale contexts are getting attention in MOOCs, such as duels, ratings, status bars and avatars. Also, there are some other engaging game elements such as virtual goods and memory-game interactions that have not been highly investigated in MOOCs.

There are some game elements that are independent of the learners' performance, such as narrative, while other elements are related to learners' actions in the learning environment. The most frequent actions related to gamification are individual actions e.g., submitting assignments, asking, or answering questions through a forum, voting, getting high scores in quizzes, etc. However, learners can also be involved in interactions with their peer learners, i.e., posting to forums, submitting assignments, and rating their peers' posts and contents.

According to Antonaci, Klemke & Specht (2019), the design and the implementation of gamification are closely related to the audience and the context of application. Thus, in order for gamification to be effective, designers need to be aware of the outcomes that each specific game element could bring in learning, in terms of a certain scenario and audience. Moreover, Dicheva et al. (2015) and Khalil et al. (2018) emphasize on the fact that research should focus more on the empirical study in order to understand how gamification can influence both extrinsic and intrinsic motivation to players.

Finally, Antonaci, Klemke & Specht (2019) argue that the implementation of game elements within MOOC environments has the potential to increase learners' engagement and facilitate learners to attain their goals within the course.

3.3.2. Most frequently used game elements in MOOCs

Antonaci, Klemke & Specht (2019) have conducted a systematic literature review based on empirical studies. The authors provide an overview of the game elements that are most frequently used in online learning environments, including MOOCs and their empirically proven effects on human behaviors. The authors argue that game elements implemented in online learning scenarios are mainly external rewards i.e., points, scores, badges, etc. Twenty-two game elements were found by the authors. These elements are, badges, leaderboards, points (authors refer to points using other terms such as score or ranking), feedback (i.e., information on learners' progress or achievements), which can take several forms and can be delivered as direct or indirect information, e.g., a clue can be considered feedback, challenges (appear in the form of quizzes or problems and they are related to levels or/and to missions), likes and other social features, communication channels (e.g., chats), narratives (a type of stories that is used to pass information and arouse learners' curiosity and interest), levels (related to goals with different degrees of difficulty while in order to move up a level, it is necessary to reach the goals of the current level, progress bars, teams, agent (a virtual character by the system), medal, avatar, trophies, time limit, task, virtual currency, personalizing features, mission, replayability, goal indicators, competition, and win state. Some game elements, such as feedback, can be combined with other elements, such as leaderboards and badges. Furthermore, Antonaci, Klemke & Specht (2019) identify the effects of gamification on learners' behavior within MOOCs. These effects mainly concern learners' performance, engagement, motivation, collaboration, social awareness, and attitude towards gamification.

Rincón-Flores, Ramírez Montoya & Mena (2019) have conducted a systematic mapping about gamification in MOOCs. The authors report that the most frequently used dynamic is the emotional while the second most frequent is the social dynamic. The emotional dynamic is considered to be associated with the use of mechanics such as challenges and rewards, as those mechanics have the potential to generate emotion to participants while trying to solve challenges (i.e., assignments) or gaining recognition about their effort and achievements. Other dynamics used in MOOC scenarios are the narrative and the progression. As far as the mechanics are concerned, the authors report that challenge and rewards were the most frequently used. Other mechanics that are also used in MOOCs are competition, chances, cooperation, and battles. Finally, the most frequently used components are the points, the leaderboards, and the badges. Despite of the use of game elements in MOOCs, Rincón-Flores, Ramírez Montoya & Mena (2019) argue that most research studies show that gamification has increased the completion rates. However, the authors suggest that gamification should be assessed using objective measures in order to declare about its effectiveness. Also, the authors report that the research trend in MOOCs is to improve their didactic design.

Chapter 4. The nervous system and the human brain. Brain imaging techniques

4.1. The nervous system

The nervous system, along with the endocrine system, is responsible for maintaining a stable internal environment (homeostasis) by controlling and coordinating the operations of the other human systems. The human body understands and reacts to environmental changes. These changes are perceived by human as stimuli. Information on these stimuli is collected from the receptors and are transferred to the Central Nervous System (CNS). Then, the central nervous system gives the appropriate instructions to the muscles and the glands. In this way it enables the human body to regulate its functions according to changes in the environment, which is a prerequisite for its survival.

The organs that constitute the nervous system are the brain, the spinal cord and the nerves. The brain with the spinal cord, form the Central Nervous System (CNS), while the nerves, form the Peripheral Nervous System (PNS). We could say that, the CNS is the part of the nervous system located inside the skull and spine, while the PNS is the part outside the skull and spine. The Central Nervous System will be further discussed in this chapter as this dissertation focuses on its association with brain functions.

The CNS of an adult healthy person is bilateral, symmetrical, and is divided into seven main parts: the spinal cord, pons, cerebellum, medulla oblongata, midbrain (or mesencephalon), the diencephalon and the cerebral hemispheres (Figure 4.1).

- *Spinal cord*: It is the lower part of the CNS. It receives and processes sensory information from the skin, the muscles of the limbs and trunk, the joints and the internal organs. It contains motor neurons that control involuntary and reflex movements, and controls many visceral functions. It is divided into cervical, thoracic, lumbar and sacral spinal cord.
- *Medulla oblongata.* It is an extension of the spinal cord. It regulates vital autonomous functions such as digestion, breathing and heart rate. Together with the bridge and the midbrain form a continuous structure called the brain stem.
- *Pons*. It transmits information related to the movement of a person from the cerebral hemispheres to the cerebellum. Along with the medulla oblongata, it regulates the blood pressure and breathing.

- *Midbrain*. It controls many kinesthetic functions, such as eye movements and is responsible for the coordination of visual and auditory reflexes.
- *Cerebellum*. It has an essential role in learning motor skills and modifies the power and range of the motion. Coordinates the movements of the skeletal muscles during movement and the movements related to posture and balance of the body.
- *Diencephalon*. It is located between the hemispheres and the midbrain. It contains two basic structures, the chamber that processes almost all the information transmitted to the cerebral hemispheres by the rest of the central nervous system and the hypothalamus that regulates autonomic, endocrine and visceral functions.
- *Cerebral hemispheres*. The cerebral hemispheres are covered by a layer of tissue called the cerebral cortex. In humans, the cerebral cortex is strongly folded (Figure 3.1). The folds increase the surface area of the cerebral cortex without increasing the total volume of the brain. The cerebral hemispheres consist of the cortex, the underlying white matter, the gray matter, the basal ganglia, the hippocampal formation, and the amygdala. The cerebral hemispheres are separated by a deep slit from the front to the back (called longitudinal fissure) in the left and right hemisphere. The two hemispheres, while they are in their biggest part identical, they generally perform different functions. The larger structure of the cerebral hemispheres, the cerebral cortex, has a central role in all the so-called higher-order brain functions such as memory, attention, perception, thinking, language and consciousness, and is described in more detail in the next section. The basal ganglia are involved in the regulation of the movement and generally in the cognitive function. Hippocampus and amygdala are parts of the coronary system. The hippocampus has an important role in the function of the memory, while the amygdala coordinates the actions of the autonomic and the endocrine systems and is involved in the generation of emotions.

The brain and spinal cord are surrounded externally by bones, the skull and the spine, respectively. The spine forms the spinal canal in which the spinal cord is located. Inside these bones, we find three membranes, the meninges that envelop the brain and spinal cord. The main function of the meninges is to protect the central nervous system. Inside the meninges there is the cerebrospinal fluid.

4.2. The nerve cells (or neurons)

The organs of the nervous system, i.e., the brain, the spinal cord and the nerves are composed of nerve tissue. The cells that compose the nerve tissue are of two types: nerve cells (or neurons) and glial cells. Neurons, which are the structural and functional unit of the nervous system, are capable of responding to specific changes in the environment, such as changes in temperature, pressure, light intensity, pH, etc.

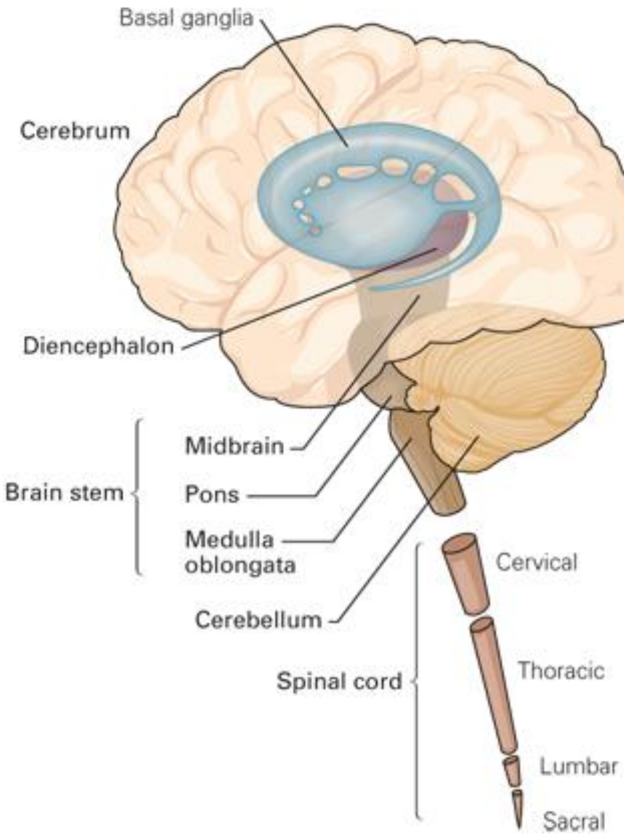


Figure 4.1. Schematic representation of the Central Nervous System (Kandel et al., 2003)

Nerve cells are components and functional units of the nervous system. Therefore, they are a foundation stone for understanding the functioning of the brain. All vertebrate animals, including humans, receive information from their environment through a variety of sensory receptors. From the receptors, information is transmitted to the brain and is transformed by the brain into senses or motion instructions. The complex and particularly useful process is achieved by using only the nerve cells and the connections between them.

A neuron has four defined morphological areas: the cell body, the dendrites, the axon, and the presynaptic terminals (Figure 4.2). The cell body is the center of cell's metabolism. It contains the kernel that is responsible for storing the genetic information. The cell body includes the two types of cellular extensions, the axon and the dendrites.

Dendrites are used as the main system for receiving signals transmitted by other nerve cells. The axon is the main conductor unit of the neuron and can transmit electrical signals in lengths ranging from 0.1mm to 2m. It is divided into several branches for transferring information to different targets. The information is transmitted by chemical or electrical means. The electrical signals passing through the axon are called action potentials and they are short and transient nerve impulses (Kandel et al., 2003).

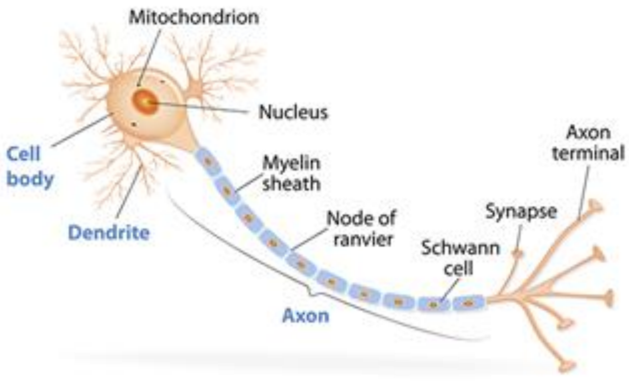


Figure 4.2. Schematic representation of a neuron. The basic parts of the nerve cell (cell body, dendrites, nerve axis) as well as synapses with other (postsynaptic) cells are depicted.

Near its end, the axon comes divided into contact with other neurons. The cell that transmits the signal is called the synaptic cell, and the one that receives the signal is called a postsynaptic cell. The points of this contact are called synaptic terminal buttons or synaptic end bulbs. An important role in the electrical behavior of the neurons is played by the myelin sheath that surrounds and insulates many neurons (mainly the motor and sensory neurons) and which is interrupted at regular intervals by Ranvier nodes.

When the nerve cells are in a state of rest, they are electrically polarized and they maintain a potential difference (difference in voltage) between the inside and outside of the cell membrane on average of 65mV. Since the potential outside the cell is conventionally set to zero, the potential in rest state is negative (-65mV). The potential difference is due to the uneven distribution of the extracellular sodium (Na^+) cations and chlorine (Cl^-) anions inside the cell, as well as potassium (K^+) or other organic anions in combination with the selective permeability of the cell membrane in K^+ and Na^+ ions. This potential difference is called the resting membrane potential.

The most important channels for describing the electrical behavior of the nerve cells are the K^+ and Na^+ channels. Under normal conditions, a membrane protein called a "K^+/ Na^+ pump" or "or sodium–potassium pump", allows ions to move through the cell membrane, thereby altering the electrical balance of the cell relative to its environment.

The neurons have differences regarding their morphology and function, and they are distinguished by their function in aesthetic, motor, and intermediate neurons. The aesthetic neurons transfer information from several parts of the body to the spinal cord and the brain, whereas, the motor neurons transmit messages from the brain and the spinal cord to the executive organs, that respond either with a contraction (muscle) or with a secretion of substances (glands). Moreover, the intermediate, relay, or associative neurons are located exclusively in the brain and the spinal cord and they direct messages coming from the sensory neurons to the appropriate areas of the brain or the spinal cord. They also transfer messages from one area of the brain or the spinal cord to another and ultimately to the pertinent motor neurons.

So, the basic units of the brain, the nerve cells, are simply structured with quite a few elements in common. The brain is capable of producing extremely complex behavior because it contains an astonishingly large number of nerve cells (about 10^{11}) that communicate with each other through specific interconnections. A key finding for the understanding of the brain is that the ability to produce complex behavior does not depend so much on the variety of nerve cells as, on their multitude and the connections between them (Kandel et al., 2003).

The nerve tissue found in the brain and the spinal cord is of two colors: gray and white. The area with the gray color is called a gray matter and the area with the white color is called a white matter. The gray matter is formed by the cell bodies of many nerve cells together, whereas white matter is composed mainly of long-range myelinated axon tracts of these same nerve cells. The color difference arises mainly from the whiteness of myelin. Many axons together have white color since the axons have myelin (that is white), while many nerve cell bodies give a grey (gray) color since the cell body unlike the axons has no myelin. In the brain, the nerve cell bodies are arranged in the periphery, the cortex, and the surface of the brain, while the axons are oriented to the inner part of the brain. The result is that the gray matter is external to the brain, while the white matter is internal. On the contrary, in the spinal cord the cell bodies are central, inside the spinal cord, while their nerve fibers are directed to the periphery of the spinal cord. The long fibers are bundled and transfer information from the brain to the spinal cord and vice versa, as well as between the different levels of the spinal cord. The result is that in the spinal cord the gray matter is inside, while the white is external.

Glial cells are larger in crowd than neurons and they have an auxiliary role. They do not retain other cells, despite the second synthetic part of their name deriving from the Greek word glute (= glue) and they are not necessary for information processing. However, they are thought to be serving the stability and the structural cohesion of the brain and they act as garbage collectors, removing debris after injury or neuronal death. Glial cells have various shapes and specific functions. These auxiliary cells supply the neuron with nutrients and they serve in absorbing and removing junk. The glial cells that surround the axon of most neurons, contribute to its insulation and to the acceleration of the transportation of the nerve impulse.

4.3. The cerebral cortex

The brain is composed of billions of nerve cells, which communicate with each other via an electro-chemical route. Although the brain functions as an autonomous entity, several subsystems can be distinguished.

The human brain can be divided into three main parts: the forebrain, midbrain, and hindbrain (Figure 4.3). The forebrain is the largest part of the brain. It includes the cerebrum, which occupies about two-thirds of the brain's mass and covers most other brain structures. The forebrain is subdivided to the telencephalon and the diencephalon. A prime component of the telencephalon is the cerebral cortex, which is divided into four lobes. The diencephalon is the area of the brain that relays sensory information and connects components of the endocrine system with the nervous system. The diencephalon regulates a number of functions such as autonomic, endocrine, and motor functions. It also plays a major role in sensory perception. Components of the diencephalon include thalamus, hypothalamus and the pineal gland. The midbrain is the area of the brain that connects the forebrain to the hindbrain. The midbrain and hindbrain together compose the brainstem. The brainstem allows the communication between the spinal cord with the cerebrum. Also, it regulates movement and assists in the processing of visual and auditory information. The hindbrain is located at the lower back part of the brain. It includes most of the brainstem and the cerebellum. The brainstem is one of the most important parts of the entire central nervous system, as it connects the brain with the spinal cord and coordinates several vital functions, such as breathing and heartbeat. Hindbrain has three main parts, the pons, the cerebellum, and the medulla oblongata.

The cortex of the cerebral hemispheres is the intense folded surface of the hemispheres. A fold or ridge in the cortex is termed a gyrus and a groove is termed a sulcus. The cerebral cortex is separated into two cortices, by the medial longitudinal fissure that divides the cerebrum into the left and right cerebral hemispheres.

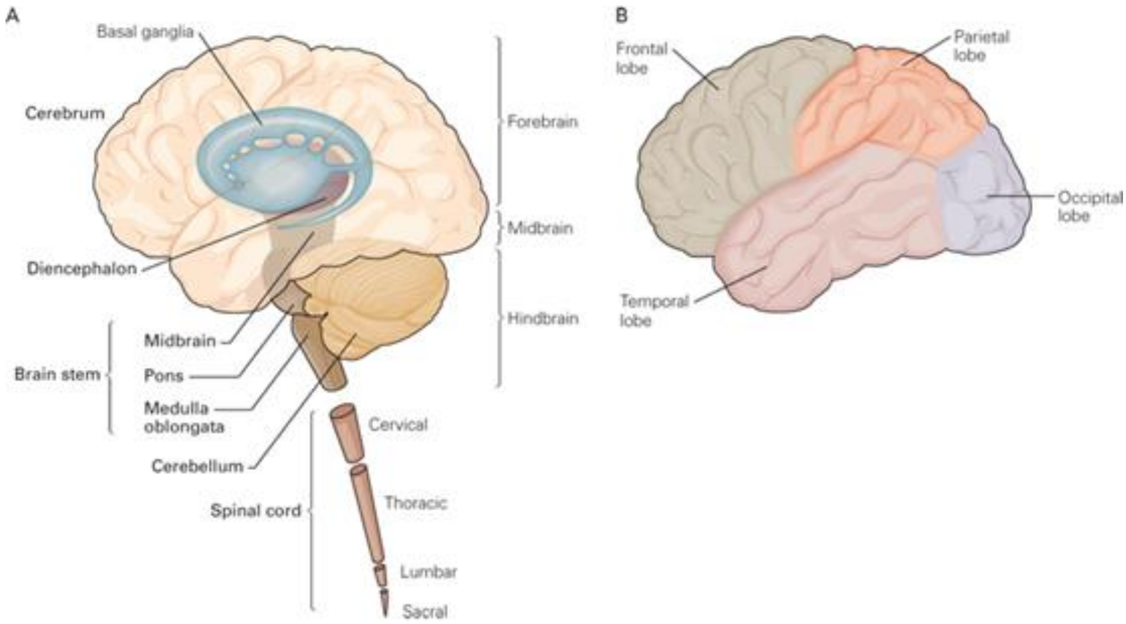


Figure 4.3. The cerebrum and the cerebral cortex

The two hemispheres are joined beneath the cortex by the corpus callosum (mesolobe). The cerebral cortex is the largest area in the central nervous system. It plays a key role in perception, attention, awareness, memory, thought, consciousness, and language. In each of the two hemispheres of the brain, the cortex is divided into four independent lobes: the frontal, the parietal, the temporal, and the occipital (Figure 4.3). The lobes were named after the corresponding skull bones, from which they were covered (Figure 4.4).

- The *frontal lobe* is the anterior part of the cerebral hemispheres to the central fissure that separates it from the parietal lobe. Its anterior lower surface rests on the upper part of the ocular junctions. The lateral sulcus (Sylvius fissure or lateral fissure distinguishes the frontal lobe from the temporal lobe. It has an important role in planning future actions and controlling movements.
- The *parietal lobe* is above the occipital and behind the frontal lobe. The Sylvius fissure separates the parietal lobe from the temporal lobe. It is related to sense of touch and the image of the body.
- The *temporal lobe* is the part of the cerebral hemispheres that lies beneath the Sylvius fissure. The posterior boundary of this lobe is a continuation of the occipital lobe. It is related to the sense of hearing and to some aspects of learning, memory and emotions.
- The *occipital lobe* is the rearmost part of the cerebral hemispheres that it is located above the tentorium cerebelli and in front of the occipital bone. It is the smallest lobe

and it is the center for processing visual stimuli. It includes the large visual area in which information arrives from the eyes, analyzing colors, motion and stereoscopy and finally it is promoted to the association areas.

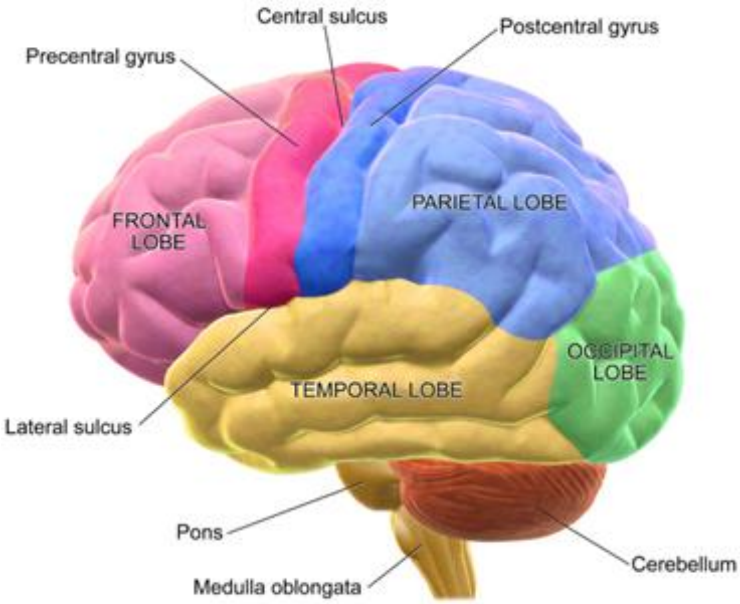


Figure 4.4. Schematic representation of the cerebral lobes and sulci

The hemispheres are connected by a bundle of nerve fibers, called the mesolobe (callosum or corpus callosum). The mesolobe is the great commissure of the cerebral hemispheres that allows the two parts of the brain to communicate and synchronize. The cerebral hemispheric cortex has two important organizational features. First, each hemisphere is related to the sensory and motor functions of the opposite half of the body. A sensory information that enters the spinal cord from the left side of the body is carried to the right side of the nervous system before being transmitted to the cerebral hemisphere. Accordingly, the motor areas in one hemisphere of the brain control the movements of the opposite half of the body. Second, although the hemispheres appear to be alike, they are not perfectly symmetrical in structure, nor equivalent in functioning.

Many areas of the cerebral cortex are related to the processing of aesthetic as well as motor instructions or a combination of them. These areas are classified into primary, secondary, or tertiary (sensory or motor) areas, depending on the level of information that they receive, process and handle. For example, the primary motor cortex processes voluntary movements of the limbs and spine that are projected directly to the spinal cord without the mediation of other neurons, hence its name as the primary. Primary areas are surrounded by secondary and tertiary areas (sensory and motor), which are characterized as upper order areas. They process the information coming from the primary areas and accordingly separate them as sensory or kinetic by re-sending them to the corresponding primary cortex.

The primary as well as higher-order cortical areas are surrounded by three other large cortical areas called association areas. Their main function is to integrate various information for deliberate action and to participate in the control of three main brain functions: perception, motion and motivation. These areas are represented in Figure 4.4.

- *Parietal - temporal - occipital association cortex* is the union of the three lobes and it is associated with higher perceptual functions such as physical sensation, vision and hearing, that is, the primary aesthetic stimuli of the three lobes respectively. This information is combined in the association cortex in order to form complex perceptions.
- The *prefrontal association cortex*, the larger part of the frontal lobe, contributes to the planning of voluntary movements.
- The *limbic association lobe* is associated with emotion, motivation, and memory. It is found in both the parietal, frontal, and temporal lobes.

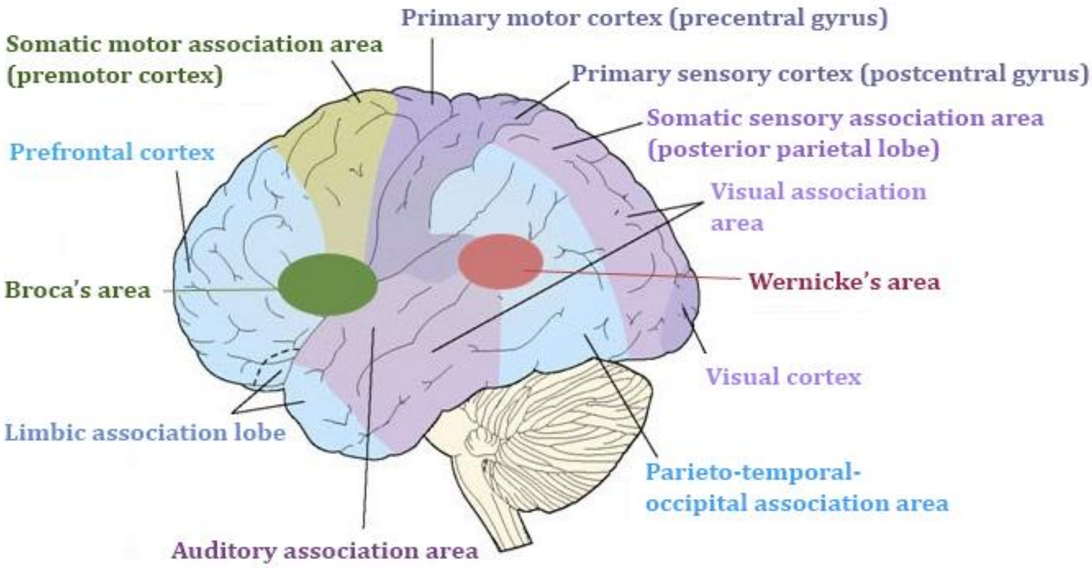


Figure 4.5. Schematic representation of the outer (visible) surface of the left cerebral cortex.

Figure 4.5 illustrates a schematic representation of the outer surface of the human brain. The main areas of the primary motor and sensory cortex, the higher-order motor and sensory cortices, as well as the three association cortices, are shown. The Broca area controls speech production. It is located near the motor area controlling the movements of the mouth and the tongue. The Wernicke area processes auditory information and it has an important role in the understanding of the speech. These two regions communicate with each other through a bundle of axons, the arcuate fasciculus.

4.4. Brain imaging techniques (or neuroimaging methods)

Several non-invasive methods have been developed to record brain activity in healthy subjects. The main methods are the following:

- *Electromagnetic recordings*. There are two techniques for the non-invasive recording of the electrical activity of the brain: *Electroencephalography (EEG)* and *Magnetoencephalography (MEG).* Both techniques are extremely secure for the subject and they have excellent time resolution of milliseconds (ms). Such an analysis allows real-time monitoring of brain activity. However, they have limited spatial resolution as the recording of electrical activity is being made on the outer surface of the scalp.
- *Hemodynamic recordings*. There are two techniques, *Positron emission tomography (PET)* and *Functional Magnetic Resonance Imaging (fMRI)*. The PET records brain activity through the changes in the blood flow and the venous oxygenation level that follows the activation of brain nerve cells. PET records the gamma-ray (γ-radiation) emitted by the decay of the atoms that have initially stimulated by positrons that are released from radioactive elements. Its main disadvantages are the limited ability to repeat recordings on the same subject due to radiation exposure limitations, the low spatial resolution as well as the assumption that the brain should be in static condition for a period of time (60–90sec). The fMRI is based on the ability to bind the signals emitted by the hydrogen atoms that are in the tissues, especially those that are rich in water. When found inside a magnetic field, hydrogen atoms excite. In magnetic resonance imaging, the subject is exposed to a strong magnetic field that it is capable to orient the nuclei in a regular layout by means of a sequence of electromagnetic waves. The main advantage of the method is the very high spatial resolution, while its disadvantages include the need to expose the subject to extremely high magnetic fields and low temporal resolution.

In the next section the Electroencephalogram (EEG) is described in detail as it is the technique that is used to record the electrical activity of subjects in this PhD thesis.

4.5. The electroencephalogram (EEG)

4.5.1. The history of electroencephalogram (EEG)

Electroencephalography (EEG) is the oldest brain imaging technique. The field of electroencephalography has its origin in the discovery of the possibility of recording electrical potentials that are induced by activated nerve cells of the cerebral cortex. The first attempts concerned recording in animals. Since 1791, Galvani had published the idea that the nerve cells contained an intrinsic form of electricity. In 1848, Du Bois-Reymond discovered that the activity of the peripheral nerves was accompanied by measurable changes in the electrical potentials. This prompted the scientific community to investigate the changes in the electrical activity due to the nervous system that would be indicative of its function. In 1875, the English physician Richard Caton published his research on the electrical brain activity of monkeys and rabbits using a galvanometer as a measuring instrument. In 1890, Beck observed the rhythmic electrical activity that was induced in the brain of rabbits and dogs caused by bright visual stimuli. Already in 1877, Catton had shown that there was a relationship between external stimuli and the electrical brain activity of rabbits and monkeys. He even mentioned that it was possible to record weak currents through electrodes placed on the skin surface of their heads.

The first recordings in humans were made in the 1920s by the German physician Hans Berger (1873-1941), who based his research on Caton defining the beginning of the study of brain functions through EEG. Berger recorded electrical potentials from the scalp of patients with cranial injuries and a few years later using more sensitive equipment from healthy individuals. In 1929, Berger published the first electroencephalograms from humans, estimating the frequency of the signal at 10 cycles per second, which he called "alpha waves" from the first letter of the Greek alphabet. Berger's interest was primarily clinical, thus he performed thousands of EEGs in which he observed changes related to sleep, general anesthesia, cranial injuries and epilepsy while failing to detect differences in many other diseases (i.e., schizophrenia, melancholy, etc.). It is noteworthy that Berger's discoveries were ignored by the scientific community for some years because the recorded signals were considered as noise or harmonics due to the heartbeat or epidermal currents.

4.5.2. The Neurophysiology of EEG

Electroencephalography is the electrophysiological imaging technique by which we monitor and record the electrical activity that is produced by the nerve cells of the cerebral cortex (neurons) due to cortical activity. It is noninvasive as the electrodes are being placed over the scalp. EEG records the voltage fluctuations that result from the ionic current within the neurons of the brain. These changing potentials are summed up and transferred to the skull from which they can be recorded (Fisch, 1999; Savoy, 2001; Triantafillou, 1994). Thus, EEG refers to the recording of the spontaneous brain electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp. Electroencephalography is a field that has been heavily criticized particularly regarding key problems during recording as well as the subjective visual interpretation of complex recordings.

The potential differences recorded from specific electrode locations on the skull as they evolve over time, make up the EEG or EEG signal. The EEG signal is a special class of bioelectric signal, i.e., an electrical signal produced by living cell and more specifically, by the cells of the nervous system. The EEG signals that originate by the brain, showing fluctuation over time, are often referred to as "brain waves", although, they are not oscillations in the sense used in wave theory. The production of these brain-derived signals that fluctuate over time is continuous, begins before the birth process, and is interrupted only by death. Another name for the EEG signal is "ongoing or spontaneous" EEG in order to be distinguished from the induced brain waves, such as *evoked potentials*. *Evoked potentials* are called the potential differences that are measured on the skin surface of the scalp, caused in preparation or in response to specific events that occur in the external physical world or take place as a psychological process (Koutsouris, 2003).

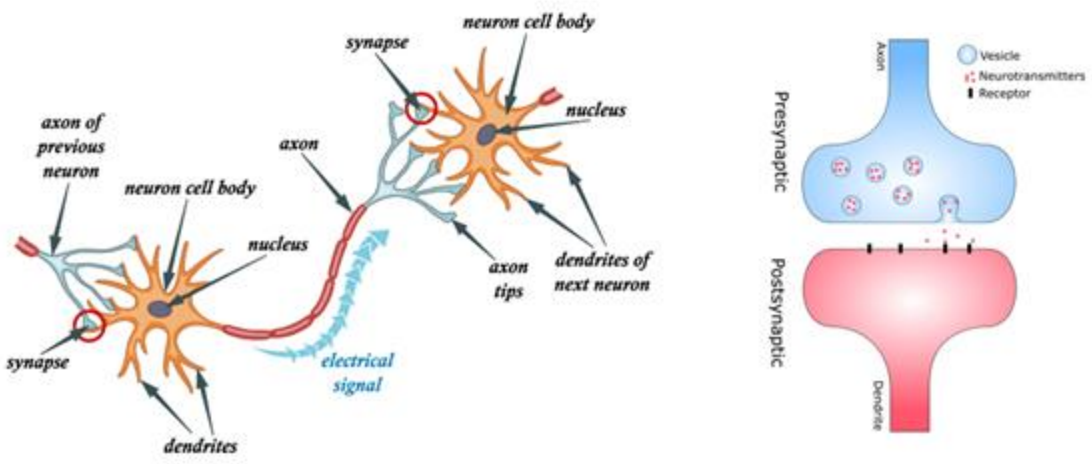


Figure 4.6. The synapse of two neurons (left: https://bcachemistry.wordpress.com/, right: http://openneuronproject.org/synapse/)

A *synapse,* in the human nervous system, is a structure that allows a neuron to pass an electrical or chemical signal to another neuron (Figure 4.6). Synapses are the means that transfer the action from the presynaptic membrane to the postsynaptic membrane, through the very thin cleft that separates them, called the *synaptic gap (or synaptic cleft)*. There are also cases where the synapse is very close to or on the body of a neuron and cases where one synapse involves three neurons at the same time, having two axons tips leading to the same point of a dendrite.

Membrane potential (or transmembrane potential) is the difference in electric potential between the interior and the exterior of a nerve cell. Typical values of membrane potential, ranges from 40mV to –80mV. There are two types of transmembrane potentials related to the transmission of signals between neurons.

The *action potentials,* that occur when the neuronal membrane is depolarized in response to a stimulus, i.e., brief reversal of electric polarization of the membrane of a nerve cell or muscle cell, beyond a threshold of 10 mV. This depolarization causes a sequence of events (Figure 4.7), consisting of an instantaneous decrease in membrane permeability to Na+ and K+ ions, which leads to a sudden collapse, inversion, and rapid restoration of the potential.

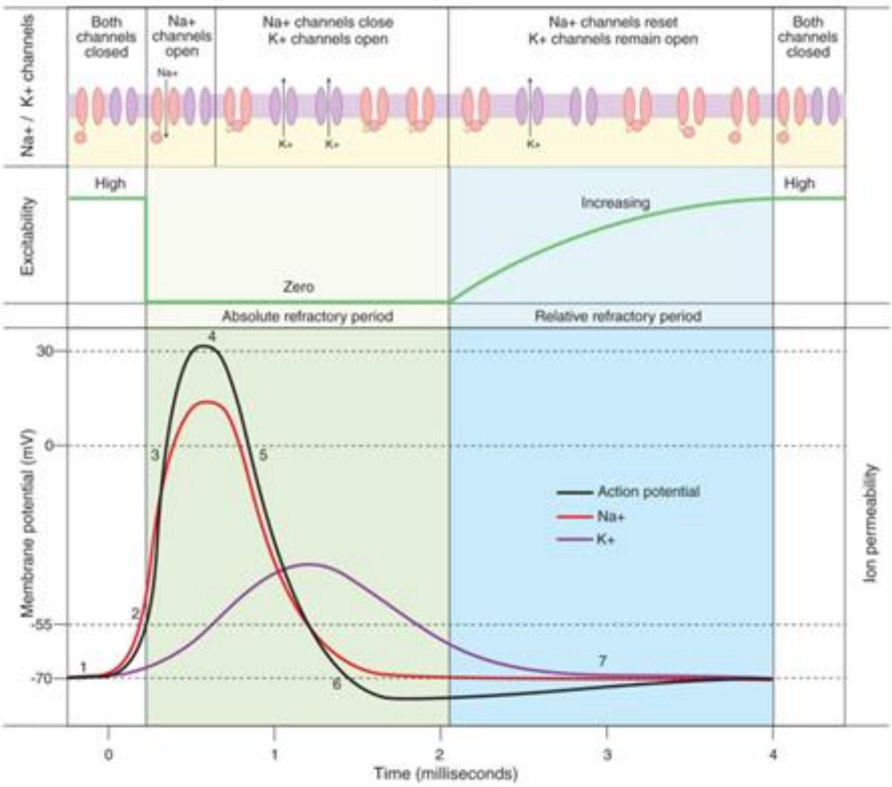


Figure 4.7. Changes in membrane potential and relative membrane permeability to Na+ and K+ during an action potential (http://www.erexam.org). Neurons have a resting potential of about -70mV.

This change in polarity travels throughout the membrane as a wave of excitation and reaching the tips of the dendrites it causes the release of neurotransmitters which in turn cause postsynaptic potentials in neighboring neurons. The action potentials are about 110mV and they last only for 1ms. Action potentials are also known as "nerve impulses" or "spikes", and the temporal sequence of action potentials generated by a neuron is called its "spike train". A neuron that emits an action potential, is often said to "fire". In neurons, action potentials play a primary role in the communication between the cells.

Postsynaptic potentials are changes in the membrane potential of the postsynaptic terminal of a synapse. These potentials are caused by excitation (action potentials) of other neurons reaching the presynaptic area, causing the release of neurotransmitters, which in turn alters the membrane permeability to Na+ and K+ ions in the postsynaptic area interacting with the appropriate receptors. This change in permeability causes a local change in the resting potential or otherwise a postsynaptic potential. The potential difference between the postsynaptic area and the rest of the neuron's membrane generates electrical current that flows through the membrane and changes its potential. A small portion of electric current penetrates through the meninges, the skull and the skin, as they are good conductors of electricity and creates areas with different potentials on the scalp. The potential differences on the scalp that range from 1 to 100μV can be recorded between two electrodes, constituting the electroencephalogram (EEG).

The sum of the electrochemical effects from neuron to neuron, summed up for all areas of the brain, creates the so-called brain function, for which the various processes and manifestations can only partially be detected and studied.

4.5.3. A general description of the electroencephalogram (EEG)

The operation of the electroencephalograph (or EEG system), the device that records the electrical brainwaves via electrodes, is based on the recording of potential differences, which occur on the outer skin surface of the human head as a result of the brain function. There are two modes of recording, monopolar and bipolar recording. A monopolar recording is defined when the recorded signal is calculated as the potential difference between an active electrode and an inactive electrode (reference), while a bipolar recording is defined when the recorded signal is calculated as the potential difference between two active electrodes.

The recorded electrical signals are weak, about 1μV to 100μV. Therefore, there is a need to amplify the signals, as much as possible. A reliable measurement requires an area of at least $6cm^2$-$10cm^2$ of cortex in synchronized activity.

A typical digital EEG system consists of the EEG source, the recording electrodes, the analog amplifiers of the signals that receive and amplify the signals, the digital converters that digitize the signals, as well as the computer that performs the EEG filtering and analysis.

4.5.4. The operation of the EEG system

The first step in the extraction of EEG signals occurs in the electrodes. They convert the Na+ and K+ ion currents from the cerebral cortex to the scalp into electron currents in the cables leading them to subsequent processing steps. Before placing the electrodes, their exact position must have been identified and the area of contact must have been prepared. The skin is cleansed with alcohol or abrasive gel to remove grease, dead sebum or exfoliated cells in order to achieve low contact resistance, below 5KΩ. Various techniques are employed to stabilize the electrode in place, such as the use of adhesive conductive paste, headsets with special positions to stabilize the electrodes, and so on. The electrode comes into direct contact with the subject through the electrolyte that is used. Thus, it is possible for ions to move through the electrode-electrolyte "border" until equilibrium is reached. Insulated cables connect each electrode to the EEG recorder. Cables and especially the electrodes must be made by materials that have low electrical resistance and do not react with the electrolytes used in the conductive creams.

Suitable materials are gold or platinum, silver or silver chloride and tin. A common electrode is made of silver (Ag) and silver chloride (AgCl) and used with an electrolyte mainly containing chlorine (Cl-) anions. Figure 4.8 shows gold-coated electrodes.

Figure 4.8. Gold-coated electrodes

The electrode impedance (z) is measured for each electrode placed on the cap with a device that sends a very weak alternating current through the active electrode to the reference electrode. Impedance is a measure of the impediment to this flow of alternating current, measured in ohms. The values of the impedance in a typical EEG are about 100Ω to 5MΩ. A larger impedance causes significant signal attenuation. Lower impedances are usually due to short circuits that may be caused by the diffusion of the gel between adjacent electrodes or by the subject's sweat or saline that it is sometimes used as an electrolyte. Such phenomena are also limited by the quality of the electrode material, the relatively wide contact surface, and the high input impedance of the amplifiers.

Needle-shaped electrodes with subcutaneous application are rarely used, likewise the nasopharyngeal and wedge electrodes. Often, in typical tests head-mounted electrodes are used consisting of a small silver rod at the end of which is added a pad impregnated with sodium chloride or a conductive cream, which are secured with straps or elastic nets in their locations.

With the advances in integrated electronic systems technologies, a new generation of electrodes has been developed (Figure 4.9). Dry electrodes' surface has an array of spikes that come directly into contact with the scalp. Spikes have been developed in the scale of nanometers, micrometers (MEMS) and millimeters. MEMS dry electrodes have several advantages in comparison with wet electrodes, such as the electrode–skin interface impedance and signal intensity. However, dry electrodes are subject to several challenges since they do not use the conductive gel to penetrate the hair and achieve a good contact with the skin.

Figure 4.9. G.Nautilus dry electrodes

Another type of electrodes are the so-called *active electrodes*. Active electrodes differ from the passive electrodes described above as they do not require skin preparation. They have a built-in preamplifier. This allows the signal to be amplified before additional noise is added between the electrode and the system that would record, process or amplify the signal. Active electrodes greatly reduce EEG preparation time and do not tire the subject. Passive electrodes do not have a pre-amplification module, instead, they simply extend the connection from the conductive material to the equipment for recording, processing or amplifying the signal. Thus, dry and active electrodes seem to be the solution to the disadvantages of wet EEG electrodes. However, these new technologies must be evaluated and validated before use.

A special type of electrodes are intracranial electrodes which are inserted internally into the skull by an invasive method applied to humans, only in pathological conditions. This category will not be further described as it is not used for research purposes.

4.5.5. Electrode positions - The International System 10-20

Various standards have been developed for the placement of the electrodes on a subjects' scalp. The most popular of those standards is the International System 10-20. With this system, the locations of the electrodes on the scalp allow not only a balanced coverage of the entire skull, but also the repeatability of the placement across sessions or subjects. The placement of the electrodes is done by considering the nasal bone at eye level and the occipital bone at the back of the head as the reference points (Figure 4.10).

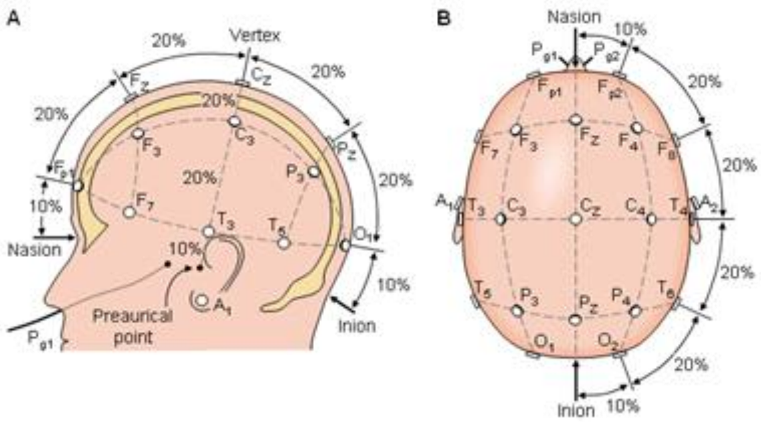


Figure 4.10. The International System 10-20

The semicircle of the skull between the reference points is measured horizontally and vertically. The electrode locations are determined by dividing the two semicircles at 10% and 20% intervals (hence the name of the system) of the measured skull (Teplan, 2002). Three more electrodes are placed on each side at equal distances between those already defined. In this way the locations of the electrodes are adjusted according to the dimensions of the subject's skull.

The electrode locations are named after the cerebral cortex and the area in which they are placed. Their first synthetic consists of the letters: F (Frontal), C (Central), T (Temporal), P (Parietal) and O (Occipital). The second component consists either of an even number (2, 4, 6 etc.), if the electrodes are positioned on the right side of the skull, or of an odd number (1, 3, 5 etc.) if it is placed on the left side. Finally, the letter z refers to the central areas of the skull. For example, electrode named Pz (Figure 4.11) refers to the electrode located on the parietal lobe and the central area of the skull.

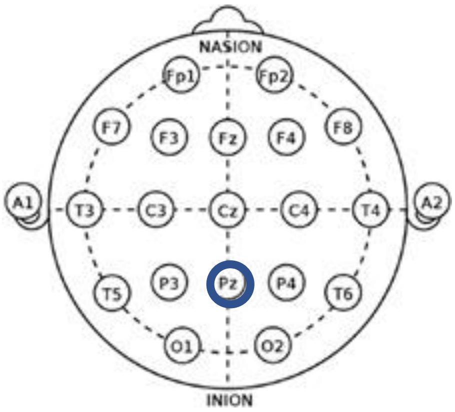


Figure 4.11 The Pz electrode location according to International System 10-20

Some research studies require more detailed EEG recordings. In these cases, extra electrodes can be added using 10% division to fill in the intermediate areas midway between the sites that are defined by the standard 10–20 system. This system is more complicated giving rise to the Modified Combinatorial Nomenclature. The introduction of extra letter codes allows the naming of intermediate electrode sites. These locations are illustrated in Figure 4.12. It is noted that 4 electrodes have a different name than the system 10-20.

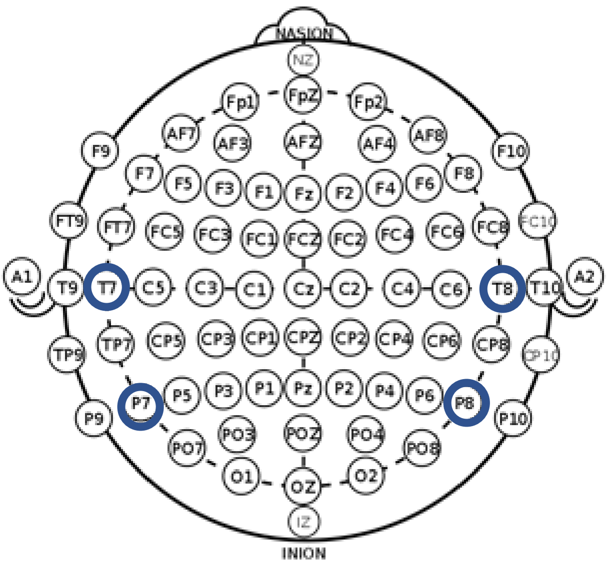


Figure 4.12. The modified combinatorial 10-10 system. In this system four electrodes are renamed regarding the 10–20 system: T3 is T7, T4 is T8, T5 is P7 and T6 is P8 (noted with a blue outline)

The signal recorded at each electrode location occurs as the potential difference between two electrodes at any time. The electrodes that are located above the brain areas that present activity are said to correspond to active sites. On the contrary, electrodes that are placed above areas considered not to be related to brain function are said to correspond to inactive sites e.g., the ear or the two ears connected with a conducted wire, points of the neck, etc. These electrodes are called reference electrodes.

Electrophysiological measurements are contacted following one of the two types of measurement principles, as mentioned above: the bipolar and the unipolar measurement principle. When the recorded signal occurs as the potential difference of two active electrodes, then, according to EEG terminology, we have a *bipolar measurement*. Bipolar measurements for 15 to 30 electrodes are the common methodology in clinical EEG neurological tests as it rejects the parasites that are detect to be common for both two electrodes. However, in psychophysiological research, the recorded signal is usually the difference between the potential of an active electrode and a reference electrode, so we have a *unipolar measurement*. The inactive site is common for all measurements and is considered as the reference electrode which it should not normally be affected by brain currents. In this way, we thus seek to have complete and simultaneous, from all active electrodes, information on any cerebral ion current reaching the outer skin surface of the head.

The differences in potentials (i.e., differences in voltage between two electrodes) that are recorded, are initially driven to the EEG amplifier which also involves filtering devices. At the EEG amplifier, every detected signal is amplified so that it can be easily measured. The amplification factors of about 10^5 are common. The first amplifier stage, the preamplifiers, consists of low noise amplifiers. Specifically, if we intend to measure signals of the order of 1μV, the preamplifier must have an internal noise level of at least one order of magnitude smaller, thus hundreds of nV. In addition, circuits with differential amplifier combinations are used to keep the common mode rejection ratio (CMRR) at 120db. The analog signals are then either driven to a recorder and imprinted on paper, to conventional EEG systems, or, as is used in most advanced systems, via a multiplexer to the analog to digital signal (A/D) converter, where as digital signals are now measured on an electronic voltmeter. Then, a computer receives the digital data, so it is possible to digitally process and display the signal, either during the on-line measurements or at a later time if the signal is stored locally on the computer (offline).

In modern systems, the operation of multiplexing, analog-to-digital conversion and recording, are often performed by data acquisition cards that are installed on the computer, along with the software for card control and digital signal processing.

The computer that presents the stimuli can also control a stimulus device. In this case, clinical and laboratory measurements may be performed, which include controlled trials providing for example specific sounds, words, numbers, images, etc. In this way it is possible to synchronize the presentation of the stimuli with the recording of the potential that arises from the stimulation (see 3.5 Evoked Potentials). It should be noted that for the proper operation of an EEG system, where the recorded signals are in the order of μV, the grounding of all parts of the system should be common so as not to create loops between different groundings which introduce errors.

4.5.6. Artifacts

One of the biggest challenges in recording an EEG signal is to identify and remove artifacts. Artifacts are the electrical potentials that are recorded with the electrodes mounted on the surface of the skull that are not generated by the brain. According to Tzimas (2010) and Bansal & Mahajan (2019), artifacts are divided into two main categories: physiological or biological artifacts and non-physiological or artificial artifacts.

Physiological or biological artifacts (Figure 4.13) are bioelectrical signals that are generated from the subject's body, excluding the brain. The physiological artifacts include the following:

- Ocular artifacts. Eye movements produce potentials recorded mainly by frontal electrodes, although, they can extend to central and parietal electrodes. Special electrodes, placed around the eyes, record the potentials produced by horizontal and vertical eye movements to detect ocular artifacts in the procedure of EEG analysis.
- Muscle artifacts. They can be recognized by their short duration and repeatability. Muscle artifact are considerably reduced during relaxation i.e., if the subject relaxes, opens his/her mouth slightly (because the jaw muscles produce strong muscular artifacts) or changes his/her position to feel more comfortable.
- Movement artifacts. They come from the abrupt movements of the head, the body or the electrodes. Researcher's observation and recording of subjects' movements is important for identifying them and excluding them during the procedure of signal analysis.
- Electrocardiogram (ECG). Artifacts are produced by heart function and are usually recorded by common reference montage, especially when the left ear is used as a reference. The use of both lobes as a common reference have reported a decrease in cardiac potentials. Also, the use of the sternum cervical bipolar as reference reduces such potentials.

- Pulse waves. Artifacts produced by large arterial pulses usually appear in frontal and parietal electrodes.
- Skin potentials. The sweating of the scalp gradually changes the impedance between the scalp and the contact point of the electrodes thus altering the recorded potentials. Skin resistance can change due to sensory stimuli or emotional changes.

Non-physiological (extra-physiological) artifacts result from unsatisfactory technology:

- Electrical interference (known in Greece as the "50Hz artifact"), interference from the wiring of the laboratory devices, buzzers and pacemakers (in clinical cases) and even cables that form loops can cause noise in the EEG. Noise may be caused as well by a malfunction of the recording system itself due to electrode movement, bad installation of the electrodes or the transformers of the recording system etc. Some of these artifacts are easily recognizable and can be removed, while others may be misinterpreted as brain activity.
- Other people's movements in the recording area.
- Artifacts may be also produced by the sampling technique that is used to convert the analog EEG signal to digital. When sampling frequency is low, spectral overlap (or aliasing) can occur.
- Damaged electrodes, non-contact biosensors, movement of reference, etc., produce sharp potential (voltage) variations in EEG signal.

Artifact identification and removal is an important area of research and much progress has been made since digital techniques have been introduced into EEG.

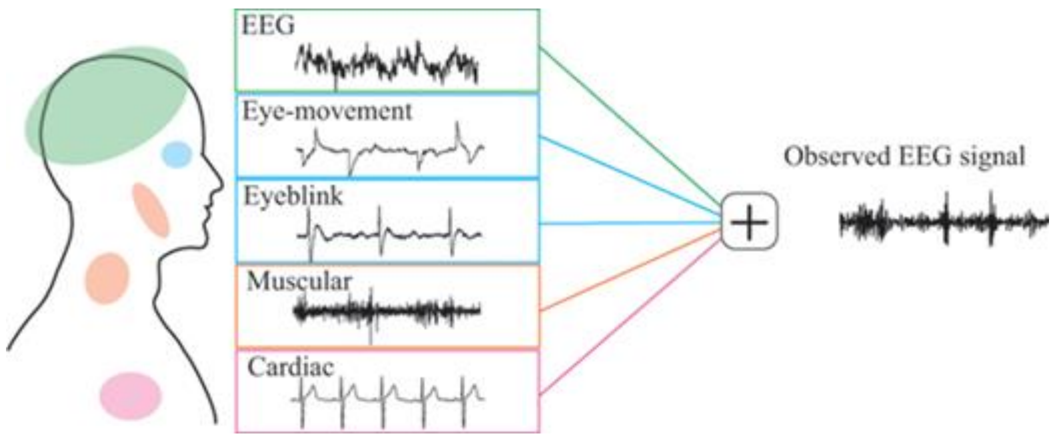


Figure 4.13. Physiological artifacts (from Kanoga & Mitsukura, 2017)

4.5.7. Filtering of EEG signal

During the recording and the offline analysis of the EEG (at the preprocessing or feature extraction phase), filters are used to limit the spectrum of the signal. The selection of the frequency band is based on research's needs. The signal recorded by means of the electrodes is directed to the amplifiers of the system. Amplifiers enhance the potentials that are detected on the surface of the skull to drive them to the digital converter. The amplification factor is 10^6 (conversion from μV to V). After the initial amplification, the signal passes through a series of analog filters to cut off parts of the signal at a very low or a very high frequency. EEG systems typically have three types of analog filters:

- High pass (HP) filters cut off low frequency waves.
- Low pass (LP) filters cut off high frequency waves.

  When both HP and LP filters are applied (band pass filter), the signals with a frequency within the band passes and all other frequencies are blocked.

- Notch filter cuts frequencies at 50Hz or 60Hz to minimize line noise i.e., any noise generated by the power line interference.

Then, the signal is sent to the computer where it is converted from analog to digital, via the Analog to Digital Converter (ADC). This conversion can be viewed as applying a grid on a continuous signal (Figure 4.14).

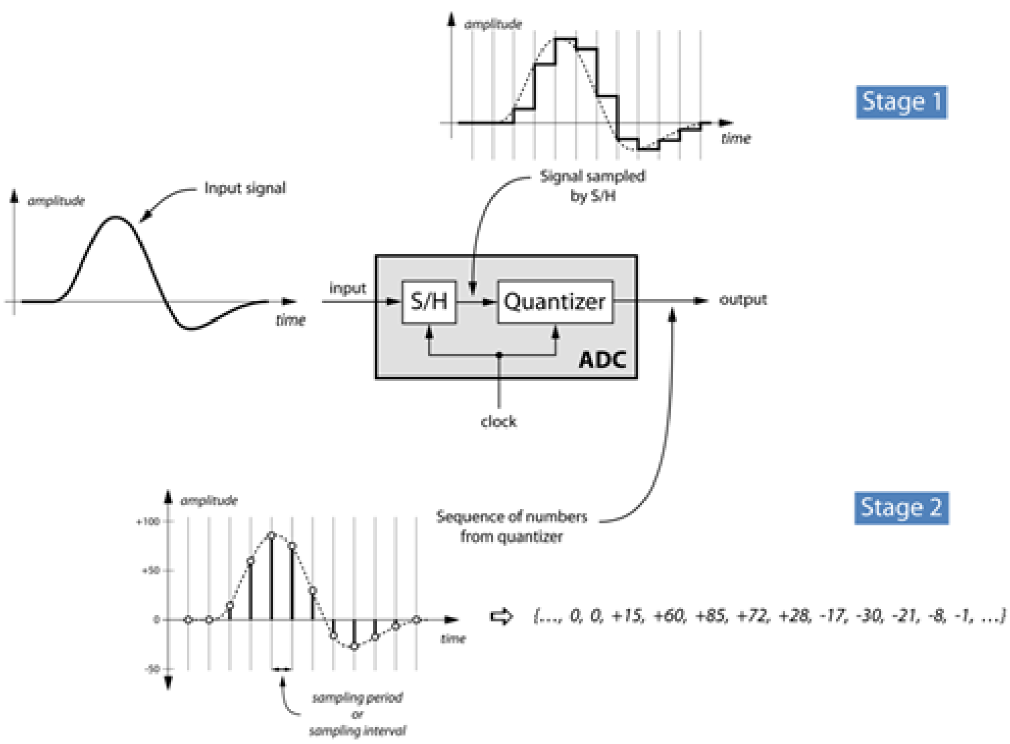


Figure 4.14. Analog-to-digital conversion

The signal becomes discrete in amplitude and time. It should be noted that, the grid must be sufficiently fine and cover the full extent of the signal, to avoid a significant loss of information.

Analog signals are transformed into a voltage that is proportional to the amplitude of that signal. The digital signal consists of a series of discrete data that are separated by equal time intervals (epochs). The process required to convert the voltage recorded by the sensor to its digital equivalent is performed by the ADC through sampling and quantization.

- *Sampling* is performed by the Sample-and-Hold (S/H) which is located directly at the input of the ADC. The S/H briefly opens its aperture window to capture the input voltage on the rising edge of the clock signal, and then closes it to hold its output at the newly acquired level. As shown in Figure 3.13, the signal present at the output of the S/H has a staircase-like appearance. The output level of the S/H is updated on every rising edge of the ADC's clock input.
  The number of digital points per second that are used to represent the analog signal is called *sampling rate (*or *sampling frequency)*. If the sampling rate is 100Hz, then every second of the digitized signal will contain 100 points (samples) (1/100s). When the function domain is time, sampling rates are expressed in samples/sec, and the unit of Nyquist frequency is cycles/sec (hertz). In order to digitize a signal of a given frequency, the sampling rate must be at least twice the frequency of the signal to be analyzed. This sentence is known as Nyquist's first law and the critical sampling rate is referred to as Nyquist rate. In practice it is common for the sampling frequency (usually 256Hz or 512Hz, up to 2048Hz) to be greater than the higher frequency, otherwise the digital signal representation would be far from analog and any interpretation would be particularly difficult. The application of Nyquist's law avoids the phenomenon of spectral overlap (or aliasing) which distorts the EEG signal.
- *Quantization* assigns a numerical value to the voltage present at the output of the S/H. The amplitude of the analog signal is approximated by the discrete levels of the ADC. The number of bits used by the ADC to encode its digitized values. The number of possible different values of the amplitude of the digitized signal is called resolution.

Studying the digital EEG on the computer screen has advantages over the analog EEG since it allows to define the part of the EEG signal or the electrodes that will be represented and processed each time, as well as the ability to apply digital filters. Moreover, an analog recorder system cannot record the small temporal differences (in the order of a ms) between different electrode channels.

Two types of filters commonly used in EEG

Filtering is almost an integral step in the preprocessing of EEG signals as it helps to improve the signal-to-noise ratio (SNR). As mentioned in the previous section, the use of filters is an essential tool for producing interpretable EEG signals. Certain filter settings can be used to accentuate particular types of brain activity. Generally, filters should be used with caution as they can affect the EEG signal in way that range from subtle to dramatic, and they can lead to unintended consequences. The ideal filter design would be the one that removes all the artifacts from the EEG and allows brain activity to pass through without any distortions. Unfortunately, no such filter exists, as all filters remove certain waves based on mathematical rules.

The filters are named after the frequency at which they attenuate the signal. The amount that a filter reduces a given wave is stated in decibels. A bel is defined as the logarithm of the ratio of the powers of two signals and a decibel is 10 times that number.

$$dB = 10 \cdot log\left(\frac{p_1}{p_2}\right)$$

where p_1 and p_2 are the powers of two signals being compared.

The dB unit of a signal is used to describe the change in power rather than the change in amplitude (voltage), however, amplitude measurements are commonly used in EEG. Thus, we should consider the relationship between the power of the signal and its amplitude. The power varies as the square of its amplitude.

$$dB = 10 \cdot log\left(\frac{a_1^2}{a_2^2}\right)$$

where a_1 and a_2 are the powers of two signals being compared. Thus, the equation can be written as:

$$dB = 20 \cdot log\left(\frac{a_1}{a_2}\right)$$

Temporal filtering or frequency filtering concerns to the attenuation of signal components of particular frequencies (bands). A filter can be described as an element in a two-port network with two inputs and two outputs (Widmann, Schröger & Maess, 2015). One electrode and the reference are fed to available inputs, while the output represents the filtered signal of the electrode against the reference. The term impulse response is used to describe filter's response to the input. The frequency response is the Fourier transform of the impulse response which consists of the phase response and the magnitude (i.e., amplitude) response. These responses filter's properties. The transfer function is described by the impulse and the frequency response in the time and frequency domain respectively. They describe the effect of a filter on a signal.

The Fourier transform of the impulse response is used to describe filters' characteristics in the frequency domain. Frequency is usually plotted along the abscissa in Hz, from 0Hz (DC) to sampling rate/2 (Nyquist frequency) or in normalized units (in MATLAB, frequency is normalized to π radians per sample) i.e., one is half the sampling rate. In the *magnitude response*, the amplitude is plotted along the ordinate in linear or logarithmic scale (dB).

Frequency bands in the passband ideally have magnitude values of one, which allows spectral components to pass without changing their amplitudes, while frequencies in the stopband ideally have zero magnitude values. In the *phase response*, phase is plotted in radians or degrees. Negative phase values reflect delayed spectral components. For example, a filter with a linear phase response in the passband has the same delay for all spectral components. This means that the time domain shape of the signal with spectral components within the passband is not changed by filtering. On the contrary, a non-linear phase introduces frequency-dependent delays, which cause changes in the shape of the signal even for spectral components within the passband. The *cutoff frequency* of a filter is defined by the frequency at which the power attenuated by 50% (Figure 4.15). Basically, is the frequency that separates passband from stopband of the filter and always lies within the transition band. This is the value that is most commonly reported when a filter is applied, but it is not enough to characterize the filter. This frequency is also called the "3dB point" of the filter because 50% reduction in power is approximately equal to 3dB (i.e., if p_1 is twice p_2 then 10log (2)≈3). We should have in mind that a reduction in amplitude of 30% corresponds to a 50% reduction in power. The steepness of the roll-off characteristics of a filter is sometimes described in unit of dB per octave. An octave represents a doubling or a halving of the signal frequency. Different definitions of cutoff frequency are used e.g., -3dB cutoff (half-energy) is common for IIR filters, while -6dB cutoff (half-amplitude) is common for FIR filters. These two types of filters are described below in brief.

The *transition band* is the region between the passband and stopband that encloses the cutoff frequency. For most FIR filters the -6dB cutoff frequency is at the center of the transition band. The term roll-off is used to describe the slope of the magnitude response in the transition band. Wide transition bands allow a shallow roll-off, while narrow transition bands lead to a steep roll-off. Filters with steep roll-off can separate the signal from the noise components more efficiently. Moreover, the filter roll-off is a function of the filter order i.e., filter length minus one. Shorter filters with wider transition bands are preferable as sharper and longer filters produce stronger signal distortions. Finally, if the filter's output depends on current and past inputs it is called causal, while. non-causal filters depend on past and future inputs.

Digital filters are implemented as either *Finite Impulse Response filters (FIR) or Infinite Impulse Response (IIR)*. FIR filters have either (anti-)symmetric impulse responses (i.e., linear-phase) or asymmetric impulse responses (i.e., non-linear phase). IIR filters have asymmetric impulse responses and non-linear phase. In EEG, Butterworth is applied widely. Butterworth filters have no passband and stopband ripple and have the shallowest roll-off near the cutoff frequency compared to the other commonly used IIR filters like Chebyshev and elliptic. In electrophysiology, almost exclusively odd length, symmetric FIR filters are applied. For FIR filters, the impulse response has to be windowed by a window function to reduce passband and stopband ripple. The transition bandwidth is a function of filter order and window type. Despite IIR filters often being considered as computationally more efficient, they are recommended only when sharp cutoffs are required. In electrophysiology, throughput is only relevant during recording. In offline analysis, computational time and throughput are not important issues. Thus, for sharp cutoffs and when a causal filter is needed, an IIR filter should be considered. Taken together, FIR filters are stable, have a well-defined passband, and can be converted to minimum-phase.

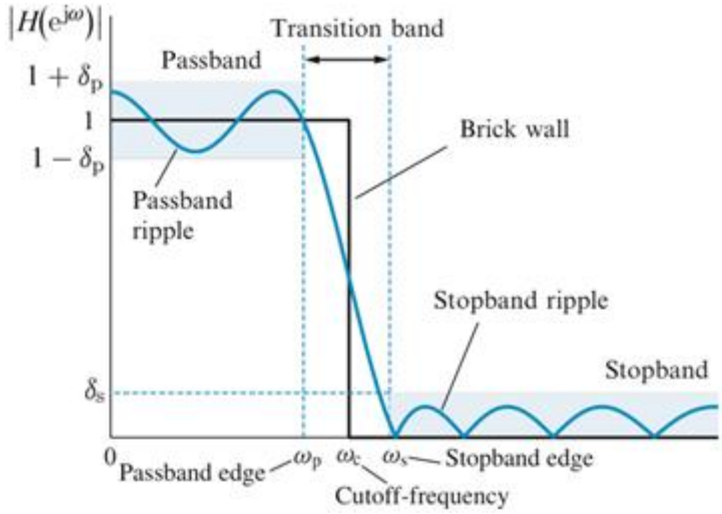


Figure 4.15. Frequency domain response for a low-pass finite impulse response (FIR). The cutoff frequency in the middle of the transition band (ω_c) separates passband and stopband. The deviation from designed passband (one) and stopband magnitude (zero) is described by passband ripple and stopband attenuation. the transition bandwidth is defined by passband and stopband ripple. δp indicates the magnitude of the passband ripple, which equals the maximum deviation from the unity. Passband ripple (1+δp) the maximum amount by which attenuation in the passband may deviate from nominal gain. δs shows the magnitude response of the stopband ripple, which equals the maximum deviation from zero.

4.5.8. Brain rhythms

In healthy individuals, the frequencies and amplitudes of EEG signals varies from one state to another, e.g., between sleep and wakefulness. Brainwaves are actually the result of the brain's electrical activity.

Table 4.4. Description of frequency bands

Freq. band	Description
delta	0.5–4Hz. Delta waves are the slowest but high-amplitude brainwaves. They are mainly related to deep sleep but they could also be present when an individual is in a wakeful state. Rarely, they have been related to some continues attention tasks Frontal waves in adults. Rear waves in children. Delta waves are involved in the formation and consolidation of memory.
theta	4–8Hz. The label “theta” implies its presumed thalamic origin. Theta waves are associated to deep learning and memory, access to unconscious material, creative thinking and deep meditation. Also, they seem to be associated with the level of arousal.
alpha	8-13Hz. Alpha waves are associated to either a relaxed awareness or concentration. They mainly appear over the occipital brain region, having an amplitude normally less than 50μV. Most individuals produce alpha waves when they have their eyes closed. This is why it is assumed to be a waiting or scanning pattern produced by the occipital brain region. It is reduced with the presentation of a visual or auditory stimuli, anxiety or attention. Alpha activity is also related to the ability of recalling memories.
beta	13-30Hz. Beta waves are associated with active attention, active thinking, anxiety and problem solving, and all conscious activities. These waves are produces in normal adults. Beta activity is encountered mainly over the frontal and central regions. Beta waves have small amplitude normally below 30 μV.
gamma	>30 Hz (up to 45 Hz). Gamma waves are mainly found are located in the frontocentral area. They are associated to the concurrent processing of information from different brain areas. They appear mainly during cognitive functions.
μ, mu	Same as alpha frequency. It appears in the central areas in a state of relaxation.

These electrical signals in the brain change when sensory events occur, when there is a demand for attention, and during emotional and cognitive processes. These waves are called "rhythms" and are generally distinguished in slow (less than 7Hz), medium (8-13Hz), fast (14-30Hz) and very fast (30Hz) frequencies. The characteristics of the waves also change with age. Usually, the signals observed in the EEG signal are between 1Hz and 20Hz. Their amplitude is in the order of μV with typical values ranging from 1μV to 100μV for adults. The EEG spectrum is therefore subdivided into frequency bands or rhythms. The rhythms are named after the letters of the Greek alphabet without any order. Twelve letters have been used until today. However, there are slight differences in these frequency regions between researchers, as well as between people due to physiological differences or even from environmental effects on the same person. In 1929, Berger introduced the alpha and beta waves. Later, in 1938, Jasper and Andrews introduced the term “gamma” to describe the waves with a frequency over 30Hz. The delta rhythm was introduced by Walter (1936) to describe all frequencies that are below the alpha frequency range. Walter also designated theta waves as those that have frequencies of 4–7.5Hz. Finally, Wolter and Dovey introduced theta waves in 1944. The most popular EEG signal rates are listed in Table 4.1.

Figure 4.16 shows the main brain rhythms (waves) as time series of potential differences (differences in the voltage between two electrodes).

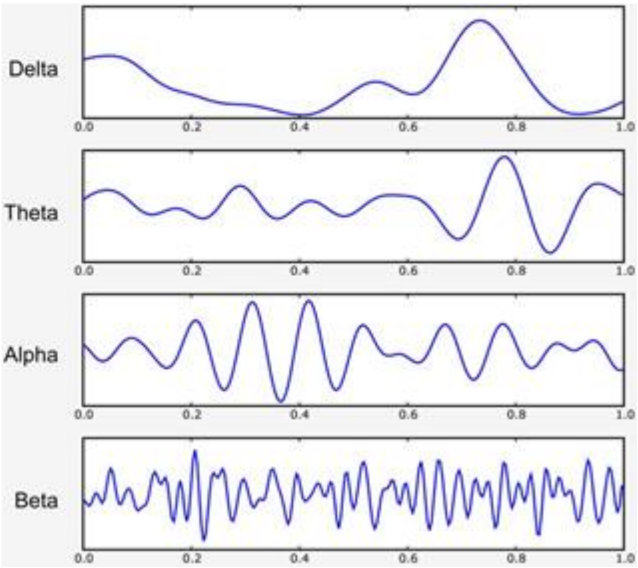


Figure 4.16. Brain rhythms

Frequency is not always a sufficient measure to identify the brain rhythm. The shape, the amplitude, the topology, the skull distribution and the symmetry play an important role as well. In this direction, Klimesch (1999) argues that the use of predefined ranges of the EEG frequency bands is not appropriate because these ranges are affected by individuals’ characteristics such as the age. Specifically, the author suggests the use of peak frequency to define band ranges as it has been proven to provide meaningful and accurate results. Also, we should mention that information about skull distribution and the symmetry provide indications of specific EEG correlates. For example, frontal alpha asymmetry is the most frequently mentioned EEG correlate of valence. Moreover, in adults, two types of theta rhythm have been described. The first type is presented diffused over the skull and is associated with reduced alertness and reduced information processing. The second type, that is called frontal midline θ activity, is spread over the midline of the anterior brain region and is related to selective attention, cognitive effort, and is considered to reflect processes of mental concentration as well as meditative states (Kubota et al., 2001). Finally, beta frequency band appears mainly in the anterior and central regions. Specifically, in the frontal and central brain areas increased beta power can be found during anxious thinking, deep concentration, and problem solving (Malik & Amin, 2017). An augmentation of beta power over the occipito-parietal brain lobe has been associated to a top-down increase of attention (Buschman & Miller, 2007). Therefore, in posterior regions, beta activity is thought to operate like alpha activity.

4.6. Power spectral analysis of EEG

4.6.1 Fourier transform

Spectral analysis is a method widely used for the quantification of the EEG. The power spectral density (or power spectrum) represents the 'frequency content' of the signal, i.e., it shows how the power of the signal is distributed over the frequencies. The most popular method for power spectral analysis is based on the Fourier theorem. According to Fourier theorem, each signal can be analyzed in a sum of simple sine signals with specific frequencies and amplitudes. This means that a signal can be converted from a signal in the time domain to a signal in the frequency domain. Amplitudes corresponding to each frequency of the signal, in the frequency domain, are calculated after the signal has undergone a transformation, called the *Fourier Transform*. The almost invariable used algorithm to compute Fourier transform is the *Fast Fourier Transform (FFT)*. The algorithm calculates, for every frequency bin, a complex number from which we can extract the phase and the amplitude of the signal at each frequency.

If the original signal is denoted by the function x(t), the Fourier transform is denoted by X(f) and is calculated from the mathematical expression:

$$X(f) = \int_{-\infty}^{+\infty} \chi(t) e^{-j2\pi ft} dt$$

where "t" is the time and "f" is the frequency.

Discrete time signals result from sampling of continuous-time analog signals that are converted into digital values. The period between consecutive measurements is specified by the *sampling frequency*. Discrete time signals are not defined between sampling intervals, which means that the highest observable frequency cannot exceed Nyquist limit i.e., half of the sampling frequency. Therefore, for discrete time signals the *Discrete Fourier Transform (DFT)* is used:

$$F\chi(k) = \frac{1}{N} \sum_{n=0}^{N-1} \chi(n) e^{-j\frac{2\pi}{N}kn}$$

where:
N is the number of input samples,
n=0, 1, …, N-1 are time points,
$\chi(n)$ is the signal in the time domain,
k is an integer index and,
$F\chi(k)$ is the vector of DFT samples

For stationary signals where spectral content remains constant over time, Fourier transformation is a good method to calculate the frequency components of the signal. Stationarity basically explains the behavior of a signal in terms of its frequency and time relation. With the *inverse Fourier transformation*, the signal is reversed from the frequency domain into the time domain, in order to reproduce the original signal.

For non-stationary signals where time and frequency are not constant but variable, *Short-time Fourier Transform (STFT)* is usually applied. In this case, the signal is divided into successive segments in which the signal frequencies are considered stationary and Fourier transformation is applied on each segment. The signal is cut into segments using the windowing method.

4.6.2. Window function

In signal processing, a window is a mathematical function which has zero values outside of a specific interval that is to be processed, symmetric around the middle of the interval, having a maximum value in the middle, and tapering away from the middle. For example, a function that has a constant value in a specific interval and a zero value outside this interval, is called a *rectangular window*. When another function e.g., a waveform, is multiplied by a window function, the result will be zero outside the interval and multiple within the interval. That means that what is left is the part where they overlap. This is often called the "view through the window".

The most commonly window functions are:

The rectangular window:

$$w(n) = \begin{cases} 1, -t_1 \leq n \leq t_1 \\ 0, \quad\quad \alpha\lambda\lambda o\acute{\upsilon} \end{cases}$$

Hamming and Hanning window:

$$w(n) = \left\{\alpha + (1-\alpha)cos\left(\frac{2\pi}{N}\right)n\right\}, n = 0,1,\dots,N-1$$

where, N is the length of the filter.

Alpha=0.5 for the Hanning window and alpha=0.54 for the Hamming window.

As mentioned before, when the original signal is distinct, the Discrete Fourier Transform is used. Short-time Fourier transform (STFT) is the method of taking a “window” that slides along the signal and performs the DFT on each segment. The STFT discrete signal is calculated based on the expression:

$$X[n,k] = \sum_{m=0}^{L-1} x[n+m]\, w[m] e^{-j\frac{2\pi}{N}km}$$

where:
n=0, 1, …, N-1: are time points,
x[n], w[n]: are the signal and window sequences respectively,
k: frequency indices,
L: window length.

A disadvantage of the Short Fourier Transform (STFT) method is the fact that windowing is a process of multiplying the signal over time by the window function and therefore, in the frequency domain, the window frequencies appear. Another pitfall of the STFT is that it has a fixed resolution. The width of the window function defines how the signal is represented i.e., it determines whether there is good frequency resolution or good time resolution. A wide window provides a better frequency resolution, while a narrower window provides good time resolution.

4.6.3. Power spectral density

Spectral analysis is divided into two main areas: Fourier transform and power spectral density (PSD). When the data contains no random effects e.g., noise, Fourier transform can be calculated, while PSD is calculated when random effects obscure the desired underlying phenomenon. In the latter case, some sort of averaging or smoothing is employed to see the desired phenomenon,

In case of EEG data, it is common to take the magnitude-squared of the FFT to obtain an estimate of the Power Spectral Density (PSD) that is expressed in μV^2 per Hz. The PSD is a commonly used method for feature extraction. It is a signal processing technique that distributes the signal power over frequency and shows the strength of the energy as function of frequency. It should be noted that, PSD is a good tool for stationary signal processing.

From the power spectrum of a signal, various characteristics of the EEG can be considered. These include the absolute power of frequency bands (absolute band power), the relative power of a frequency band (relative band power), spectral edge frequency, etc. The absolute power of the EEG is considered to reflect not only the amplitude of the signals, but also several other parameters, such as the morphology and electrical conductivity of the skull. With the relative power an attempt is made to dampen the non-cerebral effects by dividing the power of a frequency band by the total power (Abarbanel, 1999).

Usually, the signal is separated in short segments (epochs) when analyzing using FFT. This is done to ensure that these signals segments will be free of artifacts. The length of the segment to be analyzed, is selected based on the following parameters. Firstly, the EEG segment must be small enough for the signal to be thought as stationary. Secondly, the EEG segment must be large enough to achieve the desired level of frequency resolution (i.e., the difference from one frequency to the next). Usually, the power spectrum is analyzed on the basis of broader frequency bands, which represent the sum of power of several smaller frequency bands (bins).

To explain the importance of the frequency resolution, we consider a discrete time signal s (sequence of data values) with N samples:

$s = x[1], x[2], \ldots, x[N]$

Each sample x[n] is indexed by its sample number *n*. The time between two successive samples x[n] and x[n+1] is T sec. The sampling frequency is defined as Fs=1/T samples per sec and the sequence of the data values was a length equal to T_{seq}=T*N sec. The frequency resolution is defined as $F_{res}=Fs/N=Fs/(Fs\times T_{seq})=1/T_{seq}$.

Thus, frequency resolution is the inverse of the segments' length. This frequency is also the frequency increment for the Fourier transform i.e., the maximum difference between two adjacent frequencies to be analyzed. It is calculated as $F_{res}=1/T$, where T is the length of the EEG epoch in sec. For example, if EEG epochs length is 30sec, then F_{res} is equal to 0.033Hz, which is 30 frequency bins per Hertz. If we take 4-second segments, we reduce the frequency resolution to 4 bins per Hz, with every step representing a frequency range of 0.25Hz.

Statistically, estimating a frequency in an EEG epoch has a x^2 distribution with 2 degrees of freedom. The degrees of freedom must increase and the dispersion of estimation must decrease. This is usually done by mediating multiple epochs or by a frequency window.

The transformation of the EEG segments in frequency domain, leads to the mediation of their spectra, creating a new spectrum that is more representative of the activity of the participant's brain. The extraction of the average values has the advantage that reduces the effect of any random activity (generated by brain or not) especially when comparisons are made with other recordings. In a Fourier transform, the larger the epoch we assume, the greater the frequency resolution, while taking short epochs in order to reduce noise, the frequency resolution is quite small.

To obtain the PSD estimation we can use parametric and non-parametric methods. The non-parametric methods are based on the Discrete Fourier Transform (DFT) and they do not assume that data have any structure. The parametric methods assume that data follow a certain model and require a certain amount of past information to calculate PSD. The most common non-parametric methods are the periodogram method which is the squared of the absolute value of DFT and the Welch method which takes advantages from the average of multiple DFT scans. Some examples of parametric methods are the autoregressive model (AR) and the moving-average window model (ARMA).

4.6.4. Welch method

The Welch algorithm (Same et al., 2021; Welch, 1967) is a non-parametric method to estimate PSD. This algorithm makes the frequency spectrum smoother than the raw FFT output. In the Welch algorithm, instead of processing the FFT over the entire signal (on time domain), the signal is separated in windows of the same size. Window size affects the clarity of the PSD by cutting frequencies with periods larger than the window. Windowing is taking a sample of a larger dataset and tapering the signal at the edges of each interval. In this way, the signal is made smoother without sharp transitions that can disturb the frequency spectrum representation. This explains the reason that Welch method is described as a bandpass filter. There are different types of windowing sequence (e.g., Hamming, Hanning, Blackman) that affect the PSD results differently.

The Welch method is based on Bartlett's method. Each window overlaps the adjacent windows by a certain factor, which can be as much as 50% of the window size (Figure 4.17). The overlapping helps to reduce the loss of information because of the tapering and gives a more reliable periodogram. The Fourier transform is calculated on each interval and the value is squared. The average of all periodograms is calculated as PSD estimation. Averaging enhances the SNR and it is optimal for spectrum estimation. The only issue with the Welch algorithm is that the frequency resolution (F_{res}=1/T, T is time in seconds) is reduced compared to the FFT.

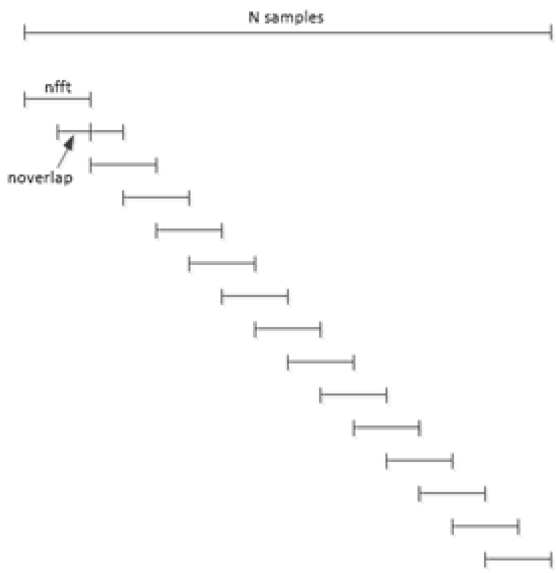


Figure 4.17. In Welch method each window overlaps with the adjacent windows by a factor between 0% and 50%

1. Partition of the data sequence:

The signal s can be separated in K segments with M length (number of samples in each segment) and V overlapping, as following:

1st segment: $s_1 = x[1], x[2], \ldots, x[M]$
2nd segment: $s_2 = x[M - V + 1], x[M - V + 2], \ldots, x[2M - V]$
. . .
Kth segment: $s_K = x[(K - 1)M - (K - 1)V + 1], \ldots, x[KM - (K - 1)V]$
where, $s_i = \{s_i[1], s_i[2], \ldots, s_i[M]\}$ represents the i^{th} segment and K is number of the involved segment in the PSD calculation.

2. For each segment (K=0 to k), a windowed Discrete Fourier transform (DFT) is calculated by the following formula:

$$S_i[v] = \sum_{m=1}^{M} s[m] \cdot w[m] \exp\left(\frac{-2\pi jmv}{N_F}\right), 1 \leq v \leq N_F$$

where w = {w[1], w[2], . . . w[M]} is the windowing vector (or function), N_F is the DFT size, and S_i = {S_i[1], S_i[2], . . . S_i[N_F]} represent the vector of frequency samples of i^{th} input segment.

3. For each segment, periodogram values are calculated as the squared absolute value of the DFT samples:

$$P_i[v] = \frac{1}{C}|S_i[v]|^2, 1 \leq v \leq N_F$$

where C is normalization factor:

$$C = \sum_{m=1}^{M} w^2[m]$$

4. Periodogram values that are calculated from different segments are averaged and the PSD estimate is obtained:

$$PSD[v] = \frac{1}{K}\sum_{i=1}^{K} P_i[v], 1 \leq v \leq N_F$$

We should notice that the number of segments involved in averaging affects the estimated PSD. Using more segments means that the estimation involves more time domain samples and the spectrum that is obtained is smoother as each frequency component is based on more observations. However, to deal with fast variation of frequency, smaller K values are more useful because the averaging over time can filter them (Same et al., 2021).

4.7. Synchronization and desynchronization of alpha and theta rhythm

The alpha rhythm is the dominant frequency band in the EEG signal of the human brain, especially in adults. It appears as a peak in the spectral analysis of the signal. The frequency and the power are two measures closely related. Typically, alpha frequency is defined as the peak in the frequency band corresponding to the alpha rhythm between 7.5-12.5Hz or 8-13Hz. It is important to understand that the alpha rhythm is greatly affected by parameters such as age, possible neurological disorders, memory performance and the demands of the task that a person must perform. Based on the above admission, several researchers argue that the use of fixed frequency bands is not entirely justified. For example, an elderly person with poor memory performance may display at rest a peak at a frequency of 7Hz or less. Thus, if we take for granted that the alpha frequency is the spectral component with the highest power between 7.5Hz and 12.5Hz, we will conclude that the frequency we recorded is the theta and not the alpha.

If the power of the signal near 7Hz is desynchronized (i.e., decreased) during a task, compared to the resting state, we must consider that this peak at 7Hz corresponds to alpha frequency band and not to theta frequency. Alpha and theta frequency bands respond differently and in an exactly opposite way. With the increase of the difficulty of a task, there is a synchronization (i.e., increase) of the theta frequency and a desynchronization (i.e., decrease) of the alpha frequency. Research studies show that the reduction in alpha power due to the suppression of alpha rhythm may be observed primarily when the subjects have their eyes closed. Memory demands related to tasks that require attention and semantic processing, are factors that cause selective suppression of the alpha rhythm in different sub-bands. The result of the visual stimulation caused by the opening-closing of the subject's eyes, corresponds to a special case of sensory-semantic demands of the task. There is a close relationship between sensory and semantic encoding. The encoding of sensory information is always targeting at extracting the meaning of the perceived information which is stored in the semantic long-term memory.

4.8. Evoked potentials

The stimuli or events that every person perceives from the outside environment as well as from the inside of his or her own body can trigger three types of EEG reactions:

- Evoked potentials
- Evoked or induced EEG oscillations
- Synchronization or desynchronization of EEG rhythms i.e., suppression or enhancement of certain EEG rhythms.

Evoked potentials (EPs) are parts of the EEG signal that represent the electrical responses of the cortex to a sensory, cognitive, or emotional event or stimulus. They represent the change in the electrical activity of the brain, which reflects the recognition and, in particular, the response to an external stimulus. Due to their nature, they are observed at specific and distinct intervals of very short duration, in the order of milliseconds (ms).

The potentials are simply measured with electrodes on the skin without exposing the subject to any kind of electromagnetic field, so infants who are very sensitive can also be studied. Moreover, using many electrodes along the entire skull it is possible to examine which part of the brain presents electrical activity.

Evoked potentials may be produced by structures of the central or peripheral nervous system. However, when it comes to evoked potentials, we only consider those that are produced by the nerve cells of the central nervous system. The difference between the continuous EEG and the evoked potentials is that in evoked potentials we are interested in the instantaneous change of the electrical activity of the brain which is caused in response to a cognitive or sensory (visual, auditory, or somatosensory) stimulus.

Evoked potentials consist of a series of positive and negative voltage fluctuations called *components*. Certain parameters describe the evoked potentials. The *latency*, that is the time that elapses from the moment the stimulus is presented to the moment the component (peak) of the potential is displayed. The *amplitude*, which is the maximum deviation from the isoelectric line. The *polarity*, that is the positive or negative of this deviation.

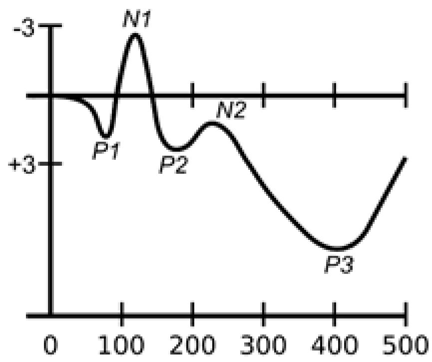


Figure 4.18. The components of the evoked potentials. The horizontal axis shows the time (msec) and the vertical the potential difference (μV)

The amplitude of the evoked potentials is very small compared to the amplitude of the EEG signal. Therefore, it is necessary for the stimulus and measurement to be repeated several times and then to apply techniques of overlapping waveforms, with the most popular technique being the 'averaging' which will be described in detail in section 5.7.1. In this way the automatic activity which generally does not show phase and frequency coincidence (as opposed to the induced dynamics) is greatly degraded due to the averaging, while the signal-to-noise ratio is increased, and the components of the induced potentials are highlighted (Figure 4.18). For example, the P300 is a positive component that appears about 300ms after the stimulus occurs. The P300 is produced when the subject is asked to distinguish between two stimuli (target / non target) that differ in one dimension, e.g., a natural characteristic (Triantafillou, 1994).

4.8.1. The technique of signal averaging

After recording the EEG signal, the technique of signal averaging is usually applied to highlight the ERP components. This technique is an algorithm that calculates the average values for each point on the waveform (based on the sampling rate) on specific EEG segments, as it is based on the hypothesis that ERPs have a stable polarity (positive or negative) and they are closely related to the stimulus, while spontaneous EEG occurs randomly (Luck, 2005).

Depending on the ERP component that it is under study, a short segment on the EEG signal is defined which includes a small region of about 100ms before the onset of the stimulus and a region of about 600ms after the onset of the stimulus. Based on the segments that have resulted from the repetition of the stimulus, the mean value for each point is calculated based on the sampling frequency (Figure 4.19). In this way the averaged final digital signal is obtained. As automatic electrical activity does not have a constant polarity and temporal relevance to the stimulus. After a number of repetitions, it tends to become an isoelectric line. The optimal number of repetitions is determined by the ERP component.

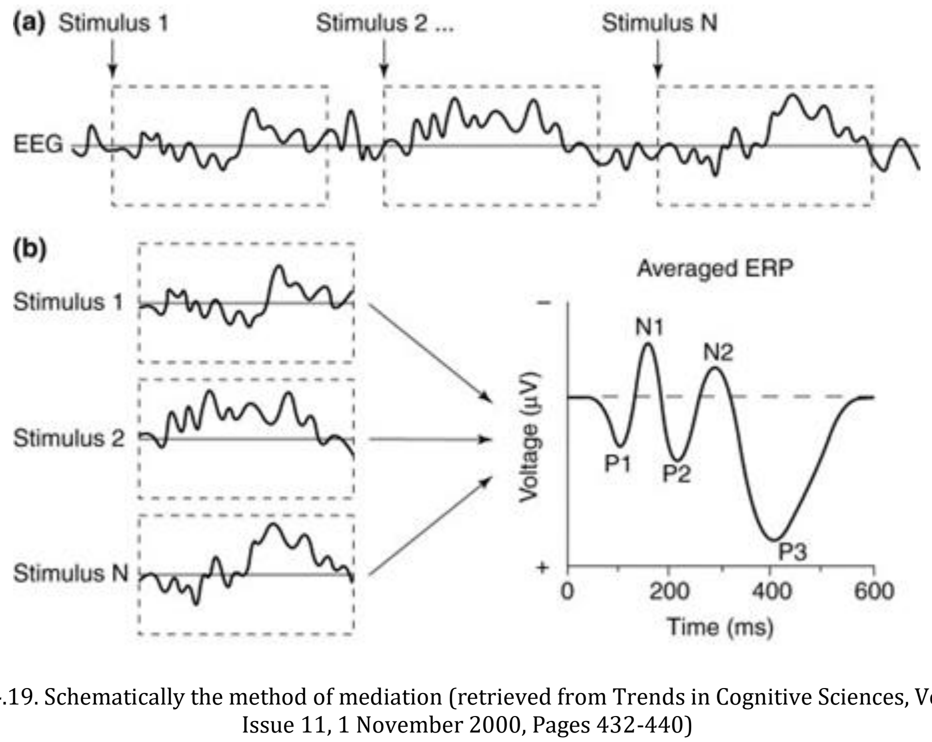


Figure 4.19. Schematically the method of mediation (retrieved from Trends in Cognitive Sciences, Volume 4, Issue 11, 1 November 2000, Pages 432-440)

4.8.2. Exogenous and endogenous evoked potentials

Based on their latent time of onset and other characteristics, the evoked potentials are divided into two categories, exogenous and endogenous. Exogenous evoked potentials (or stimulus-related potentials) are characterized by the following attributes:

- They have a short latency (<= 100ms).
- Their latency and amplitude depend on the physical parameters of the stimulus.
- They are independent of the level of subject's attention.
- They show a relative stability in terms of latency and amplitude, among the normal population but also among the successive measurements on the same subject.

Endogenous potentials are often termed as cognitive or event-related potentials (ERPs). ERPs are related to information processing and differentiation of the stimulus. They are an expression of higher cognitive functions, for this reason they are also called cognitive. They are characterized by the following attributes:

- They have a latency of more than 100ms.
- Their latency and amplitude do not depend on the physical parameters of the stimulus.
- They are elicited when the subject is called upon to distinguish a stimulus (target) from a set of other stimuli (non-targets).
- Their elicitation depends on the subject's selective attention towards the target stimulus.
- It is independent of the type of stimulus (visual, auditory, or somatosensory). They are even elicited as a response to the lack of a stimulus.
- They depend closely on the experimental design.

The most popular ERP components that are often meet in cognitive studies are the N100 (N1), P200 (P2), N200 (N2), P300 (P3) and N400 (N4). In the following sections, the N200 and P300 components are described in detail. Those two components are related to recognition and discrimination processes.

4.8.3. The N100 (N1) and P200 (P2) components

The N100 component is the highest negative peak in the time interval from 70ms to 150ms after the stimulus onset, while the P200 component is the highest positive peak in the interval from 120ms to 250ms after the stimulus onset. The N100 is considered to reflect the degree of attention of the subject, so in cases of distraction it presents a smaller amplitude and a prolonged latency. Current evidence suggests that the N1/P2 component may reflect the sensation-seeking behavior of an individual.

4.8.4. The N200 (N2) component

The N200 component is the highest negative peak in the time interval from 150ms to 350ms after the stimulus onset. It is related with the degree of subject's attention and the difficulty of categorizing the target stimulus. It is recorded in the same areas as the P300 and is often studied together as the N200-P300 complex (Patel & Azzam, 2005). Sometimes the component has two vertices, the N2a, which is considered exogenous and has a parieto-occipital distribution, and the N2b, which appears after the N2a component. The N2b usually gives its maximum value at the Cz electrode location. The time interval between the stimuli changes the latency and amplitude of the component.

4.8.5. The P300 (P3) component

The P300 component is elicited by unpredictable, infrequent task-related stimuli that are presented in a sequence of frequent stimuli i.e., when the subject is called to distinguish between two stimuli (or two categories of stimuli) which differ in one dimension e.g., a natural feature or a semantic feature of them. The elicitation of the component requires the subject's attention, as it is related to the conscious processing of information. The most common experimental design for recording the P300 (as well as other event-related potentials) is the oddball paradigm. According to this design, the subject is asked to distinguish the target stimuli, which are randomly inserted into a sequence of stimuli that are not considered as targets. Non-target stimuli should be ignored by the subject. Considering the averaged signal, the largest positive peak between 250ms and 600ms is called P300.

In terms of its topographic distribution, the P300 component has a parieto-central distribution and is usually displaying its maximum value at the Pz electrode location. Since the initial discovery of the P300, research has shown that the P300 has subcomponents (Luck, 2005; Polich, 2007; Squires, Squires & Hillyard, 1975). The subcomponents are the novelty P3, a.k.a. P3a, and the classic P300, which has since been renamed P3b. The P3a component has a shorter latency and a frontal topographic distribution, the P3b component has a longer latency and parietal distribution. The third component follows the first two components. The P3b is the component that is considered to be related to information processing and requires the subject's attention, which is why it is usually identified by researchers with the P300 component. The brain area that is responsible for producing this potential has not been identified. Most likely, the P300 is a multifocal operating process.

The latency and the amplitude of P300 component change with the age. The elderly usually elicits P300 with a longer latency and a smaller amplitude. Those changes are most likely due to the delay in memory processes. No gender differences are observed in the latency of the P300, while it appears that women have larger amplitude of the component.

It has also been observed that P300 latency and amplitude are related to target stimulus characteristics. The more difficult it is for the subject to distinguish the target stimulus within a non-target sequence, the longer the latent time appears and the smaller the amplitude of the P300 component. In addition, the lower the probability of occurrence of target stimuli, the greater the width of the component. It should be noted that as the parameters of the P300 component vary based on the characteristics of the target stimulus, two consecutive EEG entries in the same subject should be at least 6 months apart to prevent familiarity with the process.

According to Luck (2005) as P300 component depends on the probability of the task-related category of a stimulus, it is necessary that the P300 to be generated after the stimulus has been categorized according to the rules of the specific task. As a result, any manipulation that postpones stimulus categorization increases P300 latency.

Moreover, since the P300 is elicited when a stimulus or an event is subjected to a subject's conscious information processing, it is closely related to decision-making processes. It may also be related to the immediate memory involved in these processes while its latency is directly proportional of the time required to categorize the stimulus.

Finally, two are the main differences between the P300 and N200 components. Firstly, The P300 requires subject's conscious processing of information while for N200 is not necessary. Secondly, the component N200 is elicited when the stimulus differs in one physical property from the preceded stimuli in a sequence, while the release of the P300 component requires the stimulus to be task-related.

4.8.6. The N400 (N4) component

The most studied language-related ERP component is the N400 component. N400 was originally described by Marta Kutas and Steven A. Hillyard in 1980 as a reaction to an unexpected or inappropriate, but syntactically correct word, at the end of a sentence. Initially, the N400 component was described as a negative peak following the stimulus, starting at about 250ms and peaking at about 400ms. Based on the literature, its release time is between 200ms and 600ms (Kutas & Hillyard, 1980). The N400 has been used in research to answer questions about issues such as storing information in the brain (semantic memory) and revealing how the human brain uses auditory language over visual language (Kutas & Federmeier, 2011). The N400 component appears to be generated primarily in the left temporal lobe.

4.9. Advantages and disadvantages of electroencephalography

An obvious advantage of EEG over other brain imaging techniques is that it allows repeated and long-term recordings. At the same time, it is a non-invasive technique, and the subjects are not subjected to strong electrical or magnetic fields or any form of radioactive material and no substances are administered to the subjects during recording.

However, a particularly important advantage of EEG is its excellent temporal resolution, on the order of milliseconds rather than seconds. This is equal to the rate at which the brain functions evolve, which is important for the study of cognitive activities, cases where it is important to detect rapid changes in brain activity. The high availability of EEG systems, the low cost of acquisition and use, as well as the opportunity they provide for recordings outside the laboratory with the use of portable and wireless systems, enhance their usefulness.

Perhaps the most important "problem" in the measurements of brain function with electromagnetic methods is the variability they present. EEG data is largely personalized. They show a differentiation from person to person that in some cases has no known justification. That is why the average values of the quantities calculated in the surveys do not fully correspond to the values that appear in the general population. Differences are also observed between different measurements in the same subject, with, in many cases, no apparent cause, possibly reflecting variability in brain states. This variability is lost with the use of classical averaging techniques. For this reason, analyzing isolated cases have their own value in EEG studies (Krause, 2006).

The ultimate goal of EEG as a method of measuring electrical brain activity is to identify the sources of electrical potential in the skull and to relate them to groups of neurons that produce these potentials inside the brain. A significant limitation in the interpretation of the EEG is posed by the so-called reverse problem. In an EEG recording it is possible to have infinite combinations of sources in the brain that could explain and combine with the recorded signal from the scalp. Therefore, it is theoretically impossible to know the position of the source that produced the signal knowing only the position of the electrode.

In the literature there is a great variability in the study parameters that use EEG measurements, such as the number and location of electrodes, the type of recording (monopolar or bipolar) as well as the choice of reference electrode, the wide variety of signal processing and data extraction methods, the distinction EEG power in absolute and relative, as well as the differences in the determination of the borders of the rhythms.

The most important disadvantages of EEG are mainly the low spatial analysis, the low signal-to-noise ratio, the several types of artifacts, and the great variability of the observations depending on the subject and the process that it is followed.

Chapter 5. Measuring cognition and affect in learning through psychophysiological measures

5.1. EEG as an indicator of cognitive states

Psychophysiological data have been found to provide objective measures of individuals' cognitive state. These measures may include indices for task engagement (Chaouachi et al., 2010; Fairclough et al., 2013; Pope et al.,1995), attention (Chang, Lin & Chen, 2019; Chen & Wu, 2015), cognitive workload (Berka et al., 2007; Kobayashi et al., 2007), confusion (Wang et al., 2013), frustration (Heraz et al., 2007; Kapoor et al., 2007; Moldovan, Ghergulescu & Muntean, 2017), arousal (Bradley & Lang, 2000; Cuthbert et al., 2000; Diaz, Ramirez, Hernandez-Leo, 2015; Xu & Xu, 2019), stress (Fairclough & Venables, 2006) and boredom (Chanel et al., 2008).

Psychophysiological computing has various applications such as adaptive automation, brain-computer interfaces, intelligent tutoring systems, etc. Research on adaptive automation uses users' psychophysiological data to evaluate engagement and cognitive workload and provide assistance when a lack of concentration or an overload because of task difficulty occur. Users' cognitive and emotional state can be also utilized for the design of adaptive systems. Moreover, changes in psychophysiological data can be used as an input to control computer-based systems, such as Brain-Computer Interfaces (BCI).

The most accurate physiological signal for monitoring real-time changes in individual's cognitive state, is the electroencephalogram (EEG). EEG has been also proven to be a reliable predictor of learners' cognitive state while interacting with computer-based learning environments (Khedher, Jraidi & Frasson, 2019; Paradis & Mercier, 2021). Features extracted from spectral powers and ratios of the spectral band powers have been proven to be reliable indicators of cognitive states. The present study uses the spectral power of three frequency bands, namely theta (θ), alpha (α), and beta (β), in order to evaluate learners' cognitive state while taking an assessment activity in a MOOC. Thus, in this chapter we describe features related to these bands.

5.1.1. Theta band θ (4–8Hz): Cognitive workload, concentration

Theta activity at the frontal cortical area has been related to the execution of cognitive processes (Niedermeyer & Lopes da Silva, 2005) as well as with drowsiness and sleep (Takahashi et al., 1997). Schacter (1977) states that during vigilance, two types of θ power have been described in adults. The first type is presented diffused over the skull and is associated with reduced alertness and reduced information processing. The second type, that is called frontal midline θ activity, is spread over the midline of the anterior brain region and is related to selective attention, cognitive effort, and is considered to reflect processes of mental concentration as well as meditative states (Kubota et al., 2001).

In cognitive tasks, theta activity is associated with cognitive workload (i.e., allocation of cognitive resources) and cognitive fatigue (Gevins et al., 1995) as well as with concentration (Yamada, 1998). An increase in frontal theta power is associated to an increase in the level of task difficulty (Antonenko et al., 2010), an increase in cognitive workload (Vidulich & Tsang, 2012; Xie et al., 2016), or the use of higher demands on working memory resources (Gevins & Smith, 2003; Parasuraman & Caggiano, 2002). Generally, frontal theta power increases when a task requires a sustained concentration (Gevins & Smith, 2003). Moreover, an increase in theta power is associated to a lower level of alertness and decreased cognitive vigilance, and is an indicator of lower arousal (Kamzanova, Kustubayeva & Matthews, 2014; Smit et al., 2005). Finally, theta activity has been also linked to emotional arousal and fear conditioning (Knyazev, 2007).

5.1.2. Alpha band α (8–13Hz): Relaxed state, low arousal

Alpha band increases when individuals are in a relaxed state, usually, with their eyes closed. When individuals open their eyes, alpha power has been found to decrease. Therefore, alpha band is closely related to visual attention (Antonenko et al., 2010). When alpha power is increased, the individual is in a state of decreased alertness and cognitive vigilance. This means that the attention resources that are allocated on a task are also decreased (Kamzanova, Kustubayeva & Matthews, 2014; MacLean et al., 2012; Ray & Cole, 1985; Vidulich & Tsang, 2012). Additionally, alpha power is suppressed progressively when task difficulty and cognitive effort are increased (Mazher et al., 2017).

The brain lobes that are mainly related to alpha power changes are, the occipital and parietal lobes (Dasari, Shou & Ding, 2017; Puma et al., 2018). A decrease in the power of a band is called desynchronization, while an increase is called synchronization. It has been found that posterior alpha desynchronization occurs during cognitive tasks (Klimesch, 1999). Moreover, alpha power has been found to be sensitive to workload changes (Puma et al., 2018; Sterman & Mann, 1995) and cognitive fatigue (Borghini et al., 2012). Sterman et al. (1994) have investigated the EEG signals of aircraft pilot in different conditions in an aircraft simulator and reported that an alpha suppression that was associated to increases in cognitive load.

Theta and alpha bands have been shown to reflect cognitive and memory processes. According to Klimesch (1999), these bands have been found to react in opposite ways. Alpha power decreases while theta power increases as an individual is changing from a resting condition to a test condition. Also, an increase in the task demands leads to an augmentation of theta power and a suppression in alpha power. For example, Fairclough & Venables (2004) have shown that an increase in workload on a cognitive task causes an augmentation in theta power along with suppression in alpha power.

Klimesch (1996, 1999) argues theta frequency changes as a function of alpha frequency. Therefore, it is suggested to use alpha frequency band as a common reference to adjust the ranges of the other frequency bands and achieve consistency in the interpretation of the data. Klimesch (1996) gives an example regarding the importance of defining an individual alpha band. He considers an elder adult with a poor memory performance. This individual is expected to show a smaller alpha peak frequency of 7Hz which falls in the range of theta. This is due to the use of predefined ranges of the EEG frequency band. Using peak frequency to define band ranges has been proven to provide meaningful and accurate results.

EEG studies suggest that increases in alpha and theta activity during the vigil indicate a decrease of cortical arousal (Davies & Parasuraman, 1982). Alpha power has been found to be an indicator for a loss in alertness and cognitive fatigue in various settings (Borghini et al., 2012; Craig & Tran, 2012). Gevins & Smith (2003) in studies using multicomponent tasks, reported that workload changes decreased alpha power at parietal sites and increased theta power over the anterior frontal and frontal midline lobes.

Finally, alpha band is separated in two sub-bands. The lower alpha activity is related to stimulus encoding and semantic processing, while the upper alpha activity is related to attention, cognitive processing, and cognitive effort (Jaušovec & Jaušovec, 2000). Upper alpha band is decreased by information processing that requires semantic memory. Lower alpha activity is suppressed as an index of alertness.

5.1.3. Beta band β (13-30Hz): Alertness, anxious thinking

Beta band activity (13–30Hz) is mostly studied with regards to sensorimotor behavior. Beta activity decreases during the preparation or the execution of voluntary movements (Pfurtscheller & Lopes da Silva, 1999). However, Engel & Fries (2010) noted that the changes in beta band during a sensorimotor activity are associated with several types of attention, and it is difficult to separate the processes that are associated to attention from the sensorimotor processes. Beta activity is rarely associated with attention in human studies (Engel & Fries, 2010). On the contrary, alpha activity plays an essential role in the study of visual attention.

In early studies, it has been found that there is a positive correlation between an augmentation of beta power and the accuracy level in a visual vigilance task, mainly over the occipito-parietal brain lobe (Belyavin & Wright, 1987). This increase has been associated to a top-down increase of attention (Buschman & Miller, 2007). An increase in beta power was also found during stimulus expectancy period (Basile et al., 2007). Townsend & Johnson (1979) have reported that when an increase in beta activity occurs just before the stimulus onset in a task, it could serve as a predictor of performance rate. In the same direction, Hanslmayer et al. (2007) showed that visual stimuli with very short duration were perceived by individuals only when their brain activity in beta band prior to stimulus presentation was high. Also, Gola et al. (2013) and Kamiński et al. (2012) have found that increased alertness, along with faster responses to target stimuli, was associated with a preceded increase in beta power over occipito-parietal brain regions and a decrease of alpha activity over occipital lobe.

In cognitive tasks, beta band is associated with visual attention (Wróbel, 2000) and short-term memory (Palva et al., 2011; Tallon-Baudry et al., 1999). Also, it is considered to reflect an increase in working memory (Spitzer & Haegens, 2017). In general, an increase in beta activity is related to an increase in cognitive workload (Coelli et al., 2015) and concentration (Kakkos et al., 2019). As far as the topology is concerned, an increase in beta activity has been found to be increased over the occipito-parietal area during visual working memory tasks (Mapelli & Özkurt, 2019). In the frontal and central brain areas increased beta power can be found during anxious thinking, deep concentration, and problem solving (Malik & Amin, 2017).

The beta activity is usually divided into three sub-bands. Low beta activity (12–15Hz) or else known as “beta-1” waves, is associated mainly with focused, introverted concentration. Mid-range beta or “beta-2” activity (15–20Hz) is associated with increases in energy and performance. High beta or “beta-3” activity (20–30Hz) is related to significant stress, anxiety, and high arousal.

To examine human cognitive and affective states, apart from the spectral power analysis of the most well-known frequency bands, the use of ratios of multiple frequency bands has been suggested. The use of these ratios is based on the assumption that we can improve the accuracy of the evaluation of cognitive states if we combine the information from multiple frequency bands.

5.2. Engagement

5.2.1. Introduction to engagement

Engagement is described as the simultaneous experience of concentration, interest, and enjoyment for a certain activity (Shernoff, 2013). According to Connell & Wellborn (1991) the term "engagement" reflects the level of behavioral, cognitive, and affective involvement in a certain task. Despite its importance, engagement is considered to be an overgeneralized construct in research studies in the field of education and psychology. Specifically, engagement is used to describe academic performance, students' behavior in the classroom, interaction with instructional materials, instructor's practices, as well as features of learning contexts designed to foster and sustain learning. It should be noted that, engagement is often used interchangeably with other related constructs, e.g., flow and motivation (Christenson, Reschly & Wylie, 2012).

Researchers use engagement to refer to motivational beliefs, self-regulation, behaviors corresponding to cognitive strategies, persistence, as well as affective states. The term "disengagement" refers to a state that is usually related to learner's lack of persistence, lack of perceived value of the task, lack of interest, rare use of effective strategies, negative emotions, and lack of meta-awareness. According to Azevedo (2015), this term is also pervasive and cannot be defined as there is a little agreement on a concrete definition.

Engagement has been associated with positive learning outcomes not only in school education, but also in other educational settings (Fredricks, Blumenfeld, & Paris, 2004). Therefore, educators and policy makers consider engagement as the key to address core problems, such as low performance and low completion rates. Despite its importance in education, there are challenges regarding conceptualization and measurement of engagement.

5.2.2. Defining engagement

The definition of the term *engagement* depends on the theoretical perspective of the researcher and the level at which engagement is being evaluated based on the research context. We can measure a learner's engagement in a specific moment or task, while we can also measure the engagement of a group of learners in a class, course, etc. To measure a learner's engagement, researchers use physiological and psychological measures such as EEG, eye tracking, response time, etc., while researchers mainly use observations and ratings to assess engagement of a group of learners. Engagement in neuroscience research, is usually defined as the level of alertness.

Several aspects of engagement have been described in literature. *Student engagement* is thought to be an important factor that influences not only academic success (Newmann, 1992), but also students' motivation (Shernoff & Hoogstra, 2001), learning outcomes (Klem & Connell, 2004), and academic performance (Shernoff & Hoogstra, 2001).

School engagement is defined as a multidimensional construct with cognitive, affective, and behavioral dimensions (Fredrick, Blumenfeld & Paris, 2004). In brief, cognitive engagement is defined as the willingness to engage in effortful tasks, self-regulation and use of strategy. Emotional engagement is defined as a sense of belonging. Behavioral engagement refers to actions that are related to participation in school activities. Fredrick, Blumenfeld & Paris (2004) as well as Reeve & Tseng (2011) conceptualize engagement as a componential construct with qualitative and categorical dimensions. For example, motivation and self-regulation are two constructs that exist in each dimension of the engagement while, behavioral engagement includes motivational constructs, such as persistence. Lan & Hew (2020) examined engagement in MOOCs in terms of competence, autonomy, and relatedness, using a mixed method.

5.2.3. Engagement dimensions

Most researchers conceptualize engagement as a multidimensional construct consisting of several facets (Anderson et al., 2004; Fredrick, Blumenfeld & Paris, 2004). Fredrick, Blumenfeld & Paris (2004) describe engagement as behavioral, emotional, and cognitive. According to Anderson et al. (2004), engagement consists of four dimensions, namely, behavioral, cognitive, psychological, and academic. According to Bosch (2016), engagement can be defined as affective, behavioral, and cognitive.

Behavioral engagement is related to participation and can be defined as learner's involvement in his/her own learning. According to Christenson & Reschly (2012), behavioral engagement may include classroom attendance, participation in extra-curricular activities, assignments submission, following instructor's dictation and staying focused. To measure behavioral engagement, researchers use indications of effort and persistence, behavioral aspects of attention (e.g., making eye contact), and self-regulating behavior such as seeking out information without instructors' assistance.

Emotional engagement is associated with positive and negative reactions to classmates, teachers (Fredricks, Blumenfeld & Paris, 2004), or to subject areas. Pekrun et al. (2002) define a relationship between engagement and emotions in the Control-Value Theory of Achievement Emotions. According to this theory, Pekrun (2006) suggested a taxonomy that assumes the existence of positive and negative emotions in academic settings, as well as the existence of activating and deactivating emotions. Activating emotions are related to engagement. On the contrary, disactivating emotions may cause learners to disengage with the educational context. It has been shown that both positive and negative emotions can activate learner's attention and engagement mainly when it is compared with neutral emotions. Additionally, research has shown that positive emotions promote engagement more efficiently than negative emotions (Heddy & Sinatra, 2013). Moreover, achievement and emotional engagement have been found to be positively correlated (Pekrun & Linnebrink-Garcia, 2012).

The definition of the emotional dimension of engagement often includes motivational constructs such as perceived value, interest, or relative costs. The perceived value of a task refers to one's belief about the benefits that will acquire out of his/her engagement in a task (Schunk, Meece & Pintrich, 2013). In this direction, Wigfield & Eccles (2000) propose the expectancy theory, which associates the motivation to engage in a task with the expectancy for utility value, interest, achievement, etc. (Eccles, 2005). Relative cost refers to the perceived negative aspects of being engaged in a certain task, while interest is related to intrinsic motivation. All these perceived values operate cumulatively to define the overall value and predict learner's engagement level in a task.

The next two engagement dimensions associate to the emotional dimension. *Psychological engagement* describes a sense of belonging along with the relationships that are developed with their teachers and their peers (Christenson & Anderson, 2002), while *affective engagement* refers to the emotional attitude (Bosch, 2016).

Cognitive engagement is closely related to psychological investment (Wehlage & Smith, 1992). It describes to the willingness to exert the necessary effort in order to comprehend complex ideas, acquire difficult skills (Anderson et al., 2004), use flexible problem-solving strategies, choose challenging tasks and generally to go beyond the requirements of the activity. Conceptualized in this way, cognitive engagement overlaps with behavioral engagement (effort) and emotional engagement (investment). According to Sinatra, Heddy & Lombardi (2015), this overlapping raises an issue about whether the dimensions of engagement could be differentiated effectively.

Despite the definitional issues, cognitive engagement has been positively associated with self-regulation, achievement and self-efficacy. Based on Zimmerman (1990), cognitive engagement can be described in terms of self-regulation and persistence on challenging tasks. Cleary & Zimmerman (2012) argue that self-regulation is associated with the construct of cognitive engagement as, self-regulation is a form of metacognition that is related to the flexible use of problem-solving and effort. Also, high levels of engagement have been found to increase learner's motivation (Guthrie et al., 2004). However, cognitive engagement should not be confused with motivation and self-regulation.

Cognitive engagement has also been found to be a predictor of achievement (Greene, 2015; Greene et al., 2004). Pintrich (2000) argues that achievement goals and cognitive engagement are closely related. More specifically, learners who set mastery (or learning) goals are likely to employ deeper learning strategies than those who set performance-related goals (Anderman & Patrick, 2012). Furthermore, Schunk & Mullen (2012) have found that higher levels of self-efficacy toward a certain activity is related to a higher cognitive engagement, while Anderson et al. (2004) argue that cognitive engagement is related to cognitive processes such as focused attention, memory, creative thinking, etc.

Another dimension is the *academic engagement* which describes to academic identification and participation towards learning, e.g., time on task, etc. (Al-Hendawi, 2012). Finally, Reeves & Tseng (2011) suggest another dimension of engagement, namely *agentic engagement.* Agentic engagement describes students' contribution to the flow of instruction. According to Bandura (2001), students do not only interact, but they also enrich, personalize and modify the flow of the instruction. This contribution is called agency.

To conclude, during learning each dimension of engagement co-occurs with the others. This means that, it is difficult to measure only dimension of engagement as the other dimensions also contribute to this evaluation. According to Sinatra, Heddy & Lombardi (2015), the problem arises when researchers do not take in account that engagement is a multidimensional construct and that is difficult to measure only one component of engagement without considering that other dimensions occur simultaneously and affect its measurement. Thus, the multidimensional approach to define engagement shows how important the different components of engagement are for achieving positive learning outcomes.

5.2.4. Methods for measuring engagement

Several methods are used to measure engagement. Generally, there are two types of data that can be used to measure learners' engagement. Data that are internal to the individual (psychophysiological signals), and data that are external to the individual and can be recorded via observations (facial expressions, speech, actions, etc.). Dewan et al. (2019)

defines a taxonomy of the methods that are used for evaluating engagement. Based on this taxonomy, there are three main categories based on participants' involvement in the engagement detection process, namely manual, automatic, and semi-automatic.

The manual method is divided in two subcategories, self-reporting and observational checklist. Self-reports is the most popular technique through which participants report their cognitive and affective state (i.e., boredom, attention, anxiety, distraction, etc.) through questionnaires. Not all questionnaires evaluate implicitly the level of participants' engagement, in most cases they imply engagement as a descriptive variable using factor analysis (Matthews et al., 2002). Self-reporting is widely used by researchers, as it is easy to administer. There are several questionnaires that have been used to evaluate engagement and related concepts (Appleton et al., 2006; Brockmyer et al., 2009; Whitton, 2007; Deng, Benckendorff & Gannaway, 2020; Lan & Hew, 2018). However, the validity of the data collected through these methods always depend on factors that researchers are not able to control, such as individuals' willingness to state their emotions, whether they can accurately perceive their affective state, etc. Observational checklist is also based on questionnaires filled-in by external observers and not by the participants. Observers evaluate learner's engagement during the task or based on recorded videos (Read, MacFarlane & Casey, 2002; Davies, 2002; Kapoor & Picard, 2005).

The methods that are associated with tracing of engagement are classified in the semi-automatic category. Engagement tracing utilizes elements such as the timing and the accuracy of learners' responses on practicing problems. Many intelligent tutoring systems have used this method (Whitehill et al., 2014).

The automatic category uses features that are extracted from image sensors, physiological and neurophysiological sensors, or by tracing participants activity in a learning environment (time spent on the course, number of forum posts, etc.). These methods do not interrupt learners during the evaluation of engagement. The methods in this category, are divided into three subcategories: computer vision-based, sensor data analysis and log-file analysis depending on the data that the method processes.

Computer vision-based methods measure engagement by identifying cues from facial expressions, gestures, and eye movements that reveal learners' engagement, as is done in a classroom (Hughey, 2002; Jennett et at., 2008; Kappor & Picard, 2005; D'Mello, Craig & Graesser, 2009). The main advantage of these methods is the unobtrusiveness of the evaluation process. These technological advancements can be used in online courses such as MOOCs to provide personalized learning and reduce dropout rates.

Several physiological measures such as EEG, galvanic skin response, heart rate variability, blood pressure, have been used to evaluate engagement (Chaouchi et al., 2010; Fairclough & Venables, 2005; Nacke & Lindley, 2008). Although, these techniques can provide indices to evaluate engagement in real-time with high precision, it is not yet easy to be used in real-life educational contexts.

Log files are also used to evaluate learners' engagement. In online learning environments, learners' actions are stored in log files which can provide useful information for evaluating learner's engagement. Machine learning and data mining techniques can be used to analyze these files (Cocea & Weibelzahl, 2009).

Regardless the method that a researcher uses to measure engagement, there are several concerns that pose challenges in measuring engagement. The first challenge relates to engagement's definition. Researchers should define engagement before they choose a method to measure engagement as the definition should drive their choice of measures. Afterwards, researchers have to define the level of the measurement. This depends on the theoretical framework and the research questions. Learners' characteristics such as age, gender, performance, socioeconomic status, etc. should also be taken into consideration by researchers when measuring engagement levels (Betts et al., 2010).

It is generally accepted that, the single method problem poses another challenge of measuring engagement as each method has strengths and weaknesses. Ideally, researchers should use a combination of different methods and instruments to better approximate engagement. It should be noted that, to measure engagement during learning, researchers should ensure that this is done without disrupting the flow of learning.

5.2.5. Engagement in MOOCs

In MOOCs, studies on engagement primarily focus on examining behavioral engagement based on learners' observable actions (Li & Baker, 2016). However, there is a little consensus on how behavioral engagement can be measured because metrics from the traditional classroom may not be useful for measuring behavioral engagement in MOOCs. In MOOCs, behavioral engagement has been studied either for certain learning tasks such as notetaking or video activity, or for multiple tasks which appear in the relevant literature as patterns of progression, participation patterns and patterns relevant to the use of the course components. Data from learners' clickstream can be extracted from MOOC platforms and used as a metric for evaluating learners' behavioral engagement.

Deng, Benckendorff & Gannaway (2020) have developed and validated a questionnaire for measuring engagement in MOOCs. Kizilcec, Piech & Schneider (2013) examined learners' behavior based on the frequency of watching video-lectures and submitting assignments. The authors identified four distinct learners' engagement patterns, namely disengaging, auditing, sampling, and completing. Other researchers have identified seven patterns of learners' engagement in a MOOC, keen completers, strong starters, samplers, returners, nearly there, late completers, and mid-way dropouts (Ferguson & Clow, 2015). A few studies examined engagement considering not only the behavioral, but also the cognitive and the emotional dimensions (Floratos, Guasch & Espasa, 2015; Hew, 2016).

5.2.6. EEG-based metric for engagement

EEG is a technique that can be used to measure user's engagement during a certain activity. Task engagement is described as an effortful commitment to cognitive (task) goals (Matthews et al., 2002; Fairclough, Ewing & Roberts, 2009). Similarly, it can be described as the energy that is mobilized to achieve cognitive goals (Gaillard, 2001). Task engagement is a multidimensional construct that combines cognition, emotion, and motivation.

Measuring task engagement is important for computing systems that use real-time psychophysiological measurements to monitor individuals' cognitive state (e.g., digital games, adaptive automation systems, intelligent tutoring systems). Unlike Brain-Computer Interface (BCI) systems, the Physiological Computing (PC) paradigm is passive. This means that it requires no additional activity from users and it applies at the meta-level of the human-computer interaction (e.g., to minimize user's negative emotional states). Whereas in BCI systems, the physiological data operate as an input. The cycle that it is created from the mutual exchange of data between the user and the system through which a change on the user's psychophysiological data is automatically transformed into adaptive control of the system, is called *biocybernetic loop* (Pope, Bogart & Bartolome, 1995) (Figure 5.1). This exchange enables the so-called "smart" technology.

Several physiological measures have been used to assess cognitive state e.g., heart rate variability, oculomotor activity, galvanic skin response. However, the EEG can reliably and accurately provide information about the changes in attention, workload, and alertness, in milliseconds (Berka et al., 2007). It has been proven to provide an unobtrusive method to monitor the dynamic fluctuations of cognitive states, e.g., task engagement and cognitive workload.

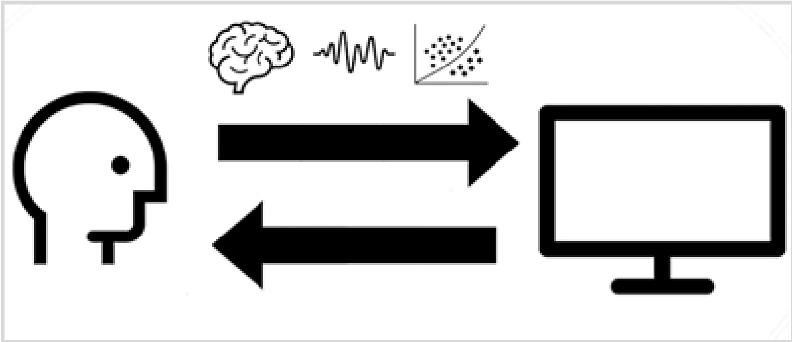


Figure 5.1. The biocybernetic loop

In general, research on EEG-based engagement evaluation primarily focuses on the features that are extracted from power spectral density (PSD) of the frequency bands and their relationship with the construct of cognitive engagement (Berka et al., 2007; Pope, Bogart & Bartolome, 1995; Prinzel et al., 1995). Although engagement is a little ambiguous as a construct, high levels of engagement is associated with a higher level of alertness which enables learners to attend to stimuli that are relevant to the task.

Pope, Bogart & Bartolome (1995) developed at NASA the first adaptive system with the use of an EEG-based task engagement index. The researchers applied the index in a closed-loop system to modulate task allocation. Specifically, the system used a biocybernetic loop by adjusting the level of task automation in a flight control system (manual or automated), in response to the changes on operator's engagement level. The authors reported that the engagement index, beta/(alpha+theta), measured at Cz, P3, Pz, P4 electrode sites, was the most successful from all other candidate indices to sustain operator's engagement over the time. Chandra et al. (2015) used the engagement index to classify workload levels for an automated operating system and found that the index provided more accurate results at different electrode sites (namely at AF3, AF4, F7, F8).

The engagement index was also validated in vigilance tasks. Freeman et al. (1999) extended the research that was conducted by Pope, Bogart & Bartolome (1995) and confirmed the effectiveness of the engagement index in a continuous tracking task. Freeman et al. (2004) and Mikulka et al. (2002) also evaluated engagement index in a biocybernetic, adaptive system. The authors found that better vigilance performance was obtained when negative feedback was given. Also, they argue that there is a need to increase task difficulty when engagement is low to maintain engagement and conversely. Other studies evaluated the success of the index when cognitive engagement was measured by using self-reports and participants' behavioral changes (Prinzel et al., 1995; Freeman et al., 2004).

Researchers have also used the same index to evaluate users' cognitive states in educational settings. Berka et al. (2007) argue that workload and engagement increase during the encoding of learning and during memory test. Szafir & Mutlu (2012) used the index to evaluate participants' attention levels in real-time while interacting with an adaptive robotic agent and adjusted the behavior of the agent for improving the discourse. Additionally, the authors implemented a system that used the EEG-based engagement index to evaluate in real time participants' level of attention to the educational material. The system at the end of the session suggested the optimal review topics (Szafir & Mutlu, 2013). Also, Huang et al. (2014) proposed an EEG-augmented reading system that monitored children's engagement levels in real-time and provided training sessions for improve their engagement in reading. Moreover, Stevens, Galloway & Berka (2007) used the same EEG-based index to relate cognitive changes during problem-solving. Regarding distance education, Booth, Seamens & Narayanan (2018) recorded students EEG data while they were watching online lecture videos and used them to predict engagement rated by human annotators. The authors argue that individual differences in EEG signals demand a more complex index to evaluate engagement in distance learning environments. Eldenfria & Al-Samarraie (2019) developed an online continuous adaptation mechanism to regulate the presentation of learning material based on changes in the learner's aptitude level. The authors reported that this mechanism had a positive impact on learners' levels of concentration and cognitive load which consequently increased their engagement level. They also suggest the use of the proposed mechanism by designers of online courses in order to regulate the presentation of learning contents according to the learners' level of aptitude. Alwedaie et al. (2017) used the task engagement index to capture learners' engagement during the lecture in both real and VR classroom. The researchers found that engagement scores in both classes was approximately the same.

Chaouachi et al. (2010) used the engagement index to confirm that there is a direct impact of learner's affective state on the engagement level. More specifically, the authors found that positive emotions lead to higher levels of engagement, while negative emotions such as frustration and confusion might also elicit high engagement levels.

Khedher, Jraidi & Frasson (2019) investigated whether combining data of two modalities (EEG and data from an eye tracker) have the potential to improve the prediction about students' performance in the context of problem-solving. They confirmed that a prediction model can be built by combining data from two modalities namely fixation duration and cognitive state and suggested the use of a multimodal sensor-based approach to effectively predict learners' performance during their interaction with a learning environment. Also, the study of Nuamah, Seong & Yi (2017) relates to the use of physiological measures from autonomous systems to improve the fit between humans and systems. The researchers examined whether the EEG-based task engagement index could be used as an input to an artificial neural network for the identification and classification of users' cognitive engagement. Authors found that the index can be used to distinguish different cognitive tasks.

McMahan, Parberry & Parsons (2015a) verified the utility of the index for non-vigilance tasks. The authors used three different indices to evaluate players' engagement in gaming modalities with increasing cognitive demands, and found that the ratio of $\beta/(\alpha+\theta)$ (calculated using measurements from all electrode sites) is the best index for assessing the engagement levels of players' while playing video games. In a similar study, McMahan, Parberry & Parsons (2015b) used the task engagement index along with two other indices for arousal and valence and found that the ratio $\beta/(\alpha+\theta)$ can be used to differentiate game events with high intensity from the regular gameplay. Also, the authors reported that engagement and arousal indices can measure immersion levels during game play and could be used to define thresholds that could be used as indicators of players' state of flow.

Kamzanova et al. (2011) evaluated the sensitivity of several EEG indices (lower alpha, upper alpha, frontal theta, EEG-based engagement index, and Task Load Index-TLI θ/α) on the effects relevant to time-on-task and workload changes in a vigilance task. The authors reported that the engagement index failed to show the effects of task period and workload manipulations, while TLI and lower alpha power revealed the effects of both of them. Specifically, lower alpha power was increased and TLI was decreased over successive task periods. Based on the results of their study, the authors propose the TLI as a valid indicator of task engagement. In another work of Kamzanova and her colleagues (Kamzanova, Kustubayeva & Matthews, 2014), examined the validity of five EEG indices as indicators of diagnosing vigilance decrement, at two experiment condition with different levels of workload. Each participant was assigned to one condition, namely cued (lower levels of workload) and uncued (higher levels of workload) to perform a vigilance task. The researchers tested spectral power measures such as lower alpha, upper alpha and frontal theta, as well as ratios from frequency bands such as engagement index and task load index. They suggested that lower-frequency alpha (alpha-1) and TLI can be used to diagnose the loss in operator's alertness on tasks requiring vigilance. Specifically, lower alpha showed a larger temporal change and was suggested to be used as the optimal index for monitor the loss of operator's alertness on task requiring vigilance. Coelli et al. (2015)

also investigated the efficacy of another EEG-based task engagement measure, namely β/α, in monitoring the brain state during a sustained attention test (continuous performance test - CPT) and reported that this index could provide efficient and functional feedback during rehabilitation practice.

To conclude, task engagement can be defined with respect to cognitive activity (mental effort), motivational orientation (approach vs avoidance) and emotional states (positive vs negative valence) (Fairclough et al., 2013). According to Berka et al., (2007), EEG engagement index $\beta/(\alpha+\theta)$ is associated to cognitive processes such as information-gathering and visual scanning. The ratio has been used to evaluate task engagement and alertness (Pope, Bogart & Bartolome, 1995; Freeman et al., 1999; Mikulka et al., 2002), mental attention investment (MacLean et al., 2012), and mental effort (Smit et al., 2005). Finally, other constructs, such as cognitive workload and focused attention, are usually being studied along with engagement, as they are thought to assess engagement indirectly.

5.3. Attention

5.3.1. Introduction to attention

Attention is the cognitive process that describes the direction of cognitive resources toward certain stimuli in the environment. Based on the relevant literature, the process of attention relates to alpha and beta band activity of the human brain. For example, Hanslmayer et al. (2007) found that only the individuals that had a high EEG beta activity prior to the task were able to perceive brief visual stimuli. Also, MacLean et al. (2012) found a relationship between an increase in beta activity and high levels of accuracy in a vigilance task, while increased alpha band power was associated to lower performance. Moreover, many other studies have indicated a relation between alpha activity and attentive behavior (Haenschel et al., 2009; Jokisch & Jensen, 2007; Leiberg et al., 2006; Mathewson et al., 2009, 2010; Ray & Cole, 1985; vanRullen et al., 2011).

5.3.2. Types of attention

Attention is the cognitive process of selectively focusing on a discrete amount of information. There are several definitions of this concept. Attention is described as the allocation of limited cognitive processing resources (Anderson, 2004) or as a process of selecting the information to be processed. Regarding the latter definition, researchers argue that attention is manifested by an attentional bottleneck as the amount of data that the brain can process in each second is limited (Goldstein, 2011).

Visual attention is controlled by cognitive factors, such as prior knowledge, previous experience, goals, etc., as well as by sensory factors that reflect sensory stimulation (Corbetta & Shulman, 2002). Cognitive factors are also called top-down factors, while sensory factors are called bottom-up factors. Other factors, such as novelty and unexpectedness, are also affecting attention and they reflect an interaction between cognitive and sensory effects. The interaction of these factors directs individuals' attention to certain stimuli of the visual environment. For example, it is easier for people to detect an object in their environment when they know in advance something about its features such as its color.

Attention is not unitary but is rather a multidimensional concept with interacting subcomponents. Several processes are related to attention such as alertness, arousal, sustaining attention, and concentration (Parasuraman & Davies, 1984). Sohlberg & Mateer (2001) propose a model for the attention sub-components. This model of attention is based in cognitive theories and can be used as a clinical framework for the evaluation and treatment of attentional impairments. This model divides attention into the following sub-processes:

- Arousal: describes the level of activation and alertness.
- Focused Attention: defines the basic response to external or internal stimuli. The individual rejects irrelevant stimuli while attending to relevant stimuli.
- Sustained attention: describes the individual's ability to attend to a task over a long period of time. It concerns the maintenance of alertness over time in order to detect certain stimuli or stimulus changes.
- Selective attention: individual's ability to attend to a chosen stimulus or while other stimuli are present.
- Alternating attention: describes the ability to control the allocation attention in order to switch between stimuli or tasks.
- Divided attention: describes the ability to simultaneously allocate attentional resources to several cognitive tasks or stimuli.

According to Kamzanova et al. (2014), there is a terminological confusion with the terms used for attention. However, the most studied components are the sustained attention and the selective attention.

Sustained attention

Sustained attention refers to a one's ability to concentrate on a task over a long period of time, even if there are other distracting stimuli present. Sohlberg & Mateer (2001) describe two components of sustained attention, vigilance and working memory. Working memory is associated to cognitive control that is necessary to hold and manipulate information while vigilance is defined as the continual response over time. Therefore, sustained attention is closely related with the process of learning. It should be noted that sustained attention is often used synonymously with vigilance.

Selective attention

Selective attention describes the process in which an individual selectively attends to one stimulus. According to Posner (1975), the term selective attention describes the shift of attention processing to a single source of information. Basar et al. (2001) argue that a significant increase in theta activity, in the frontal and parietal lobes, is related to processes of the selective attention. Grent-'t-Jong et al. (2006) in their study of selective visual-spatial attention of colors with event-related potentials (ERPs), noted that there is a great variability among individuals regarding the changes in the theta rhythm, the variability expanding even in the topological distribution. Moreover, Gruber et al. (1999) they observed a differentiation in gamma rhythm (35–51Hz). The power of the gamma rhythm increased when the subjects noticed a moving visual stimulus in contrast to those who ignored it. The shift of visual-spatial attention to the left or the right visual field was accompanied by a shift in gamma activity to the opposite hemisphere, mainly in parietal-occipital areas. In addition to the expected involvement of parietal-occipital areas, a small increase in gamma power was observed in the frontal areas that was attributed to selective attention function.

Vigilance

Vigilance refers to the state of readiness to detect and respond to stimulus changes (Mackworth, 1957). The time course of vigilance decrement is affected by the cognitive aspects of the stimuli or task characteristics (e.g., modality, intensity, duration, probability) in addition to the motivational values. The loss of vigilance over duration less than one hour has been found in context as vehicle driving and students' attention to lectures (Verster & Roth, 2012; Young, Robinson & Alberts, 2009). For cognitive neuroscientists vigilance is the ability to maintain attention on a task for a period. More specifically, vigilance refers to maintaining attention to discrete sources of stimuli (Kamzanova et al., 2014). For example, performance on a tracking task for a long time would require sustained attention rather than vigilance. Alertness refers to the neurocognitive function that supports vigilance. Moreover, the term "vigilance decrement" refers to the degree to which performance declines over time (Ballard, 1996; Kamzanova et al., 2014).

Finally, it should be noted that EEG-based measures of vigilance have been investigated most frequently in research studies regarding adaptive automation (Freeman et al., 2004). In EEG studies, a decrease in theta power accompanied by an increase in alpha power is related to a state of reduced vigilance.

Arousal

The definition of arousal varies among researchers. Usually, arousal describes a non-specific activation of cerebral cortex. The changes in the arousal are usually assessed from the EDA, while the assessment of sustained attention is usually based on behavioral data regarding performance. As far as the EEG is concerned, the alpha blockade which is related to an increase of faster EEG components such as beta activity, is considered to be the classic marker for general arousal processes (). Alertness overlaps with arousal, but it also includes some cognitive processing while vigilance is conceptually distinct from arousal. In general, researchers recommend different measures or ratios for evaluating attention (Gevins et al., 1997; Matousek & Petersen, 1983).

5.3.3. EEG-based index for measuring attention

The theta/beta ratio (TBR) is considered to be a stable biomarker for attentional control. van Son et al. (2020) define attentional control as the ability to apply top-down controlled attention over bottom-up information processing to support performance in goal-directed tasks. The attentional control can be suppressed by the anxious thoughts which are distracting and can impair working memory (Coy et al. 2011). Lower levels of attentional control are associated with anxiety disorders (Amir et al. 2009). This agrees with the general belief that test anxiety causes divided attention, leading to poorer academic performance (Duty et al. 2016).

This ratio is related to several aspects of attentional control in healthy young adults and decision making (Angelidis et al. 2016; Putman et al. 2010, 2014; van Son et al. 2018). Also, TBR is investigated in studies associated to mind-wandering (van Son et al. 2019), reversal learning (Wischnewski et al. 2016), and reduction of negative emotions (Tortella-Feliu et al. 2014). TBR has been used for monitoring car drivers' cognitive state (Sun et al., 2015) and evaluate distraction from attentive driving (Zhao et al., 2013).

This index is based on the assumption that an increased level of task engagement results to an increase in beta activity and a suppression of theta activity (Gale & Edwards, 1983). Moreover, Derbali & Frasson (2012) argue that TBR correlates with responses to motivational stimuli and affective reactions. The authors argue that TBR is a significant predictor of learners' motivation and can be used to assess motivational strategies. Also, the authors note that, there is a negative relationship between the attention ratio and learner's level of attention. This means that a higher TBR correlates with excessive theta activity and inattentive states.

Theta/beta ratio has been widely used in studies related to clinical disorders such as attention-deficit/hyperactivity disorder (ADHD) (Lansbergen et al., 2011; Arns, Conners, & Kraemer, 2013). An increased TBR ratio is related to shorter reaction time and poorer performance (Loo & Makeig, 2012).

Furthermore, Clark et al. (2019) investigated whether that TBR is an indicator for arousal or a marker for cognitive processing capacity by examining the relationship between the P300 component and the TBR. The authors found a positive correlation between P300 latency and the TBR. Therefore, the authors argue that TBR is an indicator of cognitive processing capacity.

5.4. Cognitive workload

5.4.1. Introduction to cognitive workload

According to Paas et al. (2003), cognitive workload can be defined as a multidimensional construct that represents the load that is imposed on the learners' cognitive system when they perform a certain task. The authors state that cognitive load has a causal and an assessment dimension. The causal dimension reflects the interaction between the task and the learner characteristics while the assessment dimension that reflects the measurable concepts of *cognitive load*, *performance,* and *cognitive effort*. It is argued that cognitive load is an important factor for learning as it can impede performance and learning outcomes (Sweller, 1988; Sweller, Ayres & Kalyuga, 2011).

Cognitive load theory is based on the idea of the limited processing capacity of working (short-term) memory and its interaction with long-term memory (Sweller, 1988; Paas et al., 2003; Sweller, Ayres & Kalyuga, 2011). Thus, cognitive load theory is associated with the design of instructional methods in terms of using the limited working memory efficiently to apply acquired knowledge and skills to new tasks (Castro-Meneses, Kruger & Doherty, 2020).

According to Sweller, Ayres & Kalyuga (2011), cognitive load consists of three different components: the intrinsic load (i.e., the intrinsic nature of the information), the extraneous load (i.e., the way the information is presented) and the germane load (i.e., the cognitive activity required for learning). Moreover, Xie & Salvendy (2000) describe the various ways of considering cognitive load. Instantaneous load describes the changes of cognitive load at each moment while peak load is the maximum value of instantaneous load. Accumulated load measures the total amount of load during the task. Average load is calculated by averaging the instantaneous load. Finally, overall load refers to individual's experience of load. Overall load is measured using the subjective scales of cognitive load, evaluating the intrinsic, extraneous, and germane cognitive load components.

Cognitive workload has been measured mainly by means of subjective scales. Paas (1992) argue that learners can provide a reliable assessment of their cognitive effort. The author proposed a subjective measure consisted of one item on a 9-point Likert scale. This measure has been shown to be sensitive to variations of cognitive load and consistent to performance data. Many studies have used Paas's scale (Antonenko & Niederhauser, 2010; DeLeeuw & Mayer, 2008; Anmarkrud et al., 2019). It should be noted that, subjective scales measure the overall cognitive load (Xie & Salvendy, 2000). Moreover, Leppink & van den Heuvel (2015) propose a 10-item scale for measuring cognitive load. NASA Task Load Index (NASA-TLX) questionnaire is a multidimensional assessment tool for measuring perceived workload and is widely used in the studies on human performance (Hart & Staveland, 1988).

Apart from the subjective measures, physiological measures are also used to measure workload such as heart-rate variability (Paas & Merrienboer, 2004) or via eye tracking (Kruger & Doherty, 2016). EEG due to the high temporal resolution, is considered to be a technique well suited to measure instantaneous and average cognitive load (Castro-Meneses, Kruger & Doherty, 2020; Gevins & Smith, 2003; Xie & Salvendy, 2000).

5.4.2. Defining cognitive load

Cognitive workload describes the reduction of an individual's cognitive resources due to demands that are imposed by a certain task. For example, an increase in task difficulty leads to an increase in workload due to the depletion of available resources (Kamzanova, Kustubayeva & Matthews, 2014). In high cognitive workload and specifically, when workload reaches individual's cognitive capacity, it is expected that individuals will make errors. In addition, low cognitive workload can also lead to human errors due to boredom and consequently possible human distractions.

As humans have a limited amount of cognitive resources, it is important to optimize the allocation of these resources to different tasks in order to have better cognitive results. However, there are many factors affecting the amount of cognitive resources that an individual can dedicate in task, such as demographics (age, gender etc.), affective states (e.g., happy, anxious, sad), previous experience, skills etc.

In the literature, there have been proposed several metrics to measure cognitive workload, both subjective and objective. Subjective metrics are based on questionnaires and interviews. The most popular questionnaire for the self-assessment of an individual's cognitive workload is the NASA Task Load indeX. An overall rating of six dimensions namely, cognitive demand, physical demand, temporal demand, performance, frustration level and effort, is calculated as the average of all six ratings (Hart & Staveland, 1988). One important limitation of the questionnaire is that participants answer the questions after the completion of the task.

Objective measures are based on the physiological, neurophysiological, and behavioral data recorded using different types of sensors and offer a continuous measure of workload in real-time. These measures do not interfere with participants act on the task (Wang et al., 2015). Physiological measures include electrocardiography (ECG), heart rate variability (HRV), pupil dilation, blink frequency and saccades (Tsai et al., 2007) while, neurophysiological measures include electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS). Behavioral measures include keystrokes, mouse tracking and body positioning. Between the three techniques, neurophysiological measures are considered most direct indicators to objectively assess workload (Gevins et al., 1997; Debie et al., 2019; Rojas et al., 2020).

5.4.3. EEG-based metric for cognitive workload

Two components of the EEG have been found to be sensitive to manipulations of task complexity, alpha and theta frequency bands (Gevins & Smith 2003; Klimesch 1999). Researchers have observed that alpha and theta activity is related to task difficulty and cognitive workload in a variety of task demands. As task difficulty increases, theta activity increases (Antonenko & Niederhauser, 2010; Gevins & Smith, 2000), while alpha activity decreases (Antonenko & Niederhauser, 2010; Gevins et al., 1997; Sterman et al., 1993). Some studies show that increases in cognitive workload are associated to increases in alpha power (Jensen et al., 2002; Khader et al., 2010; Klimesch et al. 1999). Several studies have evaluated cognitive load in working-memory tasks (Gevins et al., 1997; Klimesch et al., 1999; Krause et al., 1996). Antonenko & Niederhauser (2010) evaluated participants' workload in the context of instructional design.

As brain activity changes as a function of the age and individual differences (Klimesch, 1999), it is proposed to study the changes induced by a certain task in the EEG signal, rather than evaluating at the absolute power of frequency bands. A measure for assessing brain activity changes is event-related synchronization (desynchronization). This measure was originally developed to quantify the changes only in the alpha band (Pfurtscheller & Aranibar, 1977). Generally, it represents the change in a band power on a task condition compared to a baseline condition. The baseline condition refers to an interval prior to stimulus with no task demands, while the task condition refers to the interval during the task. The ERD/ERS index is calculated using the formula:

ERS/ERS% = (baseline band power – test band power)/ test band power * 100

Additionally, another EEG-based index for assessing cognitive workload is the theta/alpha ratio (or Task Load Index, TLI). An increase in cognitive load has been consider relating to a decrease in alpha power and an increase in theta power (Stipacek et al., 2003; Käthner et al., 2014). Also, increased levels of fatigue relate to an increase in alpha and theta power (Käthner et al., 2014; Xie et al., 2016). Research has shown that workload changes increased theta power at anterior frontal and frontal midline brain regions and decreased alpha power at parietal regions (Gevins & Smith, 2003; Fairclough & Venables, 2004). We should mention that, EEG indices such as TLI do not discriminate the components of cognitive load (intrinsic load, extrinsic load and germane load) but they evaluate the overall cognitive workload.

Although, many studies have associated high scores of TLI with performance impairment, Kamzanova, Kustubayeva & Matthews (2014) has found that higher TLI is associated with superior performance. Also, TLI increases with working memory load as well as during problem-solving and analytical reasoning. The index is also considered to be reflective of executive functions.

Finally, Fernandez Rojas et al. (2020), propose several of indicators that can be used to objectively assess cognitive workload in a multitasking setting. The authors proposed the evaluation as indicator of workload the θ, α, β band power values as well as of frequency band ratios such as the task engagement index $\beta/(\alpha+\theta)$, the TBR θ/β and the TLI θ/α.

5.5. Affect

5.5.1. Introduction to emotions

Emotion is a psychophysiological process triggered by conscious or unconscious perception of an object or a situation. It is often associated with mood, personality, and motivation. Emotions have a fundamental role in our daily life as they play an important role in human cognition. Human cognition refers to the cognitive process of acquiring knowledge and understanding through thought, experience, and senses. It consists of several processes such as rational decision-making, human perception, human interaction, and human intelligence.

Affective computing is a field that combines technology and emotions into HCI. Affective computing aims to measure individuals' affective responses and to correlate them with their emotions. According to Yadegaridehkordi et al. (2019), emotions can become the driving factor for learning and engagement. Involving an emotion detection capability in online learning environments can expand the use of such educational technologies, and provide personalized instruction (Cabada et al., 2018).

Participant's emotional state can be evaluated by subjective measures (self-reports), physiological signals and external expressions (e.g., audio/visual signals). Many studies on emotion assessment have focused on the analysis of facial expressions and speech. Subjective measures can provide valuable information about participant's emotions, but such measures always confront validity issues. Physiological signals can assist in obtaining accurate and reliable measures of the participants' emotions as they are recorded during the task.

Physiological signals used to measure emotions include the galvanic skin response, which increases linearly with the participant's level of arousal, electromyography, which is correlated with negative emotions, heart rate, which increases with negative emotions and respiration rate as breath becomes irregular with more aroused emotions like anger. Neurophysiological measures are also used to evaluate emotions. Neuroimaging techniques are also used to collect neurophysiological data for evaluating participants' affective state.

Many research studies use physiological signals for emotion recognition (Kim & Andre, 2008; Wang & Gong, 2008; Chanel et al., 2009). Lisetti & Nasoz (2004) used physiological responses to identify emotions in movie scenes. Also, Kierkels et al. (2009) suggested a method for personalized affective tagging of multimedia using physiological signals. Yazdani et al. (2009) suggested a brain-computer interface (BCI) based on P300 component to tag videos with one of Ekman's emotions.

Recent studies have shown that it is possible to use EEG-based emotion recognition in areas such as entertainment, e-learning, e-healthcare applications, etc. As emotion is a complex psychological state that involves three distinct components (i.e., a subjective experience, a physiological response, and a behavioral response), a combination of different measures is often used to evaluate participant's emotional state.

In the literature, there are two different perspectives for the representation of emotions. The first one uses a categorial representation of emotions and indicates that the basic emotions have evolved through natural selection. Plutchik (2001) proposes eight basic emotions: anger, fear, sadness, disgust, surprise, curiosity, acceptance, and joy. According to Plutchik, all the other emotions can be formed by the basic ones. Ekman (1999) suggested a classification based on the relationship between emotions and facial expressions. The second perspective uses a dimensional representation which is based on cognition, specifically on cognitive appraisal. According to Lazarus (1991), cognitive appraisal refers to the evaluation of the significance of an event or a situation for a persons' well-being. This suggests that emotions do not arise automatically but they are elicited by appraisals (people's assessments) of particular events and situations. The emotional reaction is rather influenced by individuals' cognitive processing of those experiences. In this perspective, emotions are organized into three dimensions: arousal, valence and dominance dimensions. Valence ranges from very positive emotions to very negative, while arousal can range from inactive (sleepy, uninterested, bored) to active states (excited). Dominance refers to the degree of control over the emotions (Ekman, 1999; Lang, 1995) and can range from a weak feeling (without control) to an empowered feeling. The model that is most commonly used is the C*ircumplex Model of Affect*. This model defines every emotion using two dimensions, arousal and valence (Posner, Russell & Peterson, 2005).

Emotions are differentiated from similar concepts such as feelings, moods and affects in affective neuroscience. Feelings refer to a subjective representation of emotions, while moods are affective states that last longer and are usually less intense than emotions. The term *affect* is used to define all the aspects of emotion simultaneously. Recent studies have attempted to identify neural markers to understand the nature of emotions (Saarimäki et al., 2016).

EEG signals and emotions are found to be correlated in neuropsychological studies. Alpha asymmetry and changes in alpha power are associated to emotions. A right frontal activation is associated with withdrawal response or negative emotions whereas a relatively greater left frontal activation is associated with an approach response or positive emotions. Therefore, asymmetrical frontal EEG activity may reflect changes on the valence (Chanel et al., 2009; Liu & Sourina, 2011). Beta band is also related to valence (Jatupaiboon, Pan-Ngum & Israsena, 2013).

Alpha asymmetry in prefrontal and parietal lobes and gamma asymmetry in temporal lobe can be used to identify valence, while alpha asymmetry in prefrontal lobe and gamma asymmetry in temporal lobe can be used to identify arousal (Huang et al., 2012). Changes in the gamma band are also related to emotions of happiness and sadness, so is the decrease in the alpha wave in different sides of the temporal lobe. The left lobe is considered to be linked to sadness while the right with happiness. (Li& Lu, 2009; Park et al., 2011). As far as ERP components are concerned, components with short to middle latencies like N100 and P100 as well as N200 and P200 have been associated with valence, whereas the components of middle to long latencies e.g., P300 have been associated with arousal (Kim et al., 2013).

Previous studies suggest that gender affects the processing of emotional stimuli differently. Researchers suggest that men rely on the recall of past emotional experiences to evaluate current emotional experiences, while women seem to engage to the emotional stimuli more readily (Lee et al., 2005). To conclude, the frontal and parietal lobes are the most informative about the affective (emotional) states, while alpha, beta and gamma bands are shown to be the most discriminative.

5.5.2. The circumplex model

The affective (or emotional) state of an individual is defined as a psychological and physiological state in which emotions and behaviors are interrelated and appraised within a certain context (Scherer, 2005). Previous studies (Fredricks, Blumenfeld, & Paris, 2004; Reschly et al., 2008; Pekrun & Linnenbrink-Garcia, 2012) acknowledge the importance of emotions for improving learning and reported that increased positive emotions are closely correlated with higher levels of student engagement. Kahu et al. (2015) argue that understanding the factors that affect emotions and the impact of emotions on learners' engagement, can enable the improvement of course design and support. For example, learners' emotions in online learning environments can be affected by the way learners interpret the learning experience.

Research studies have shown that it is possible to identify EEG correlates of emotional states that are correlated with specific events in computer-based applications such as digital games (Salminen & Ravaja, 2008) or HCI applications in general (Spiridon & Fairclough, 2009). Research studies have used different induction protocols to measure participants' affect, e.g., pictures (Aftanas et al., 2001; Huster et al., 2009; Müller et al., 1999), sentences (Marosi et al., 2002), music (Schmidt & Trainor, 2001), videos (Krause et al., 2000) and recall of emotional events (Chanel et al., 2009; Chanel, Ansari-Asl, & Pun, 2007).

Affect is usually studied within the circumplex model (Russell, 1980). This model defines a two-dimensional emotional space, with an *arousal* and a *valence* orthogonal dimensions. This means that all affective states can be defined in terms of valence and arousal. In the relevant literature, electroencephalogram and other physiological measures have been used to assess brain responses to emotional stimuli in the dimension of valence and arousal. The dimension of dominance is assessed in terms of EEG correlations only in the study of Heraz & Frasson (2007). The authors correlated the continuous EEG measurements with the self-reported valence, arousal and dominance.

Results from research studies have shown that cognitive processes related to emotion recognition are associated with the right hemisphere (right hemisphere theory). Positive and negative emotional states have been associated to regions in the left and right frontal brain areas, respectively. This assumption is called the valence theory (Silberman & Weingartner, 1986). Based on the valence theory, positive emotions are processed in the left frontal brain area, while negative emotions are processed in the right frontal brain area. On the contrary, Davidson (1992) proposes an approach/withdrawal theory in which the two hemispheres are differently activated depending on the motivational direction of the affective state. More specifically, left hemispheric frontal activity is associated with an approach, while right hemispheric activity is associated with a withdrawal. As it is obvious, there is an overlap of the two theories, as most approach-related emotions are related to positive feelings and most withdrawal-related emotions to a negative feeling. Finally, Reuderink, Mühl & Poel (2013) argue that the dimension of dominance enables a differentiation between approach and withdrawal emotions that cannot be differentiated on the two-dimensional space of arousal and valence.

5.5.3. EEG-based indices for measuring emotions

Cortical activation has been shown to be inversely related to alpha activity (Pfurtscheller, 1999). Positive affective information is associated with a decrease of alpha power over the left frontal cortex, while negative affective information is associated with a decrease of alpha power over the right frontal cortex. Therefore, the *frontal alpha asymmetry* is the most frequently mentioned EEG correlates of valence.

Arousal activates the human brain and is associated with a global decrease of alpha activity (Barry et al., 2009). Few researchers studied more localized effects of arousal on alpha band power, reaching to contradictive results. Schmidt & Trainor (2001) found a correlation between the activation of frontal brain area and the perceived arousal of musical excerpts, while Aftanas & Golocheikine (2001) found a deactivation in the frontal brain areas (increased alpha power) associated with increasing arousal. Other EEG correlates have been observed at posterior sites with increasing arousal i.e., an increase of power in the delta band (Klados et al., 2009) and theta band (Aftanas et al., 2002), a decrease of alpha power and an increase in upper gamma power (Aftanas et al., 2004).

Diaz, Ramirez & Hernàdez-Leo (2015) decoded participants' affective states in terms of arousal and valence, using EEG signals recorded while participants were watching educational videos. The authors evaluated the effect of the talking head on cognitive load, emotion and attention by comparing three conditions: taking head, audio only and mixed condition. Arousal and valence were estimated by calculating the ratio of the beta β and alpha α power at four electrode sites in the prefrontal cortex AF3, F3, AF4, F4 (Ramirez & Vamvakousis, 2012; Eldenfria & Al-Samarraie, 2019). The authors used the following formula: Arousal=β/α, or Arousal=(βF3+βF4+βAF3+βAF4)/(αF3+αF4+αAF3+αAF4).

In general, beta brain waves are associated with an alert or excited state of mind, whereas alpha brain waves are more dominant in a relaxed cognitive state. The calculation of the valence was based on the valence theory that was mentioned before i.e., that left frontal brain area inactivation is associated to a withdrawal response and is linked to negative emotions whereas, the right frontal inactivation is associated to an approach response and consequently to positive emotions. Diaz, Ramirez & Hernàdez-Leo (2015) computed valence using the following formula: Valence=αF4/βF3 – αF3/βF4.

Soleymani et al. (2009) computed arousal and valence levels of participants' emotions while they were watching videos using linear regression. Quantized arousal and valence levels for each clip was mapped to emotion labels. Koelstra et al. (2012), used music video clips to elicit different emotions. They proposed a novel semi-automatic stimuli selection method using affective tags which were rated by the participants. The authors reported significant correlates between participants' ratings and EEG data. Specifically for arousal, negative correlations in the theta, alpha, and gamma bands were found. The central alpha power decreased for higher arousal, and generally an inverse relationship between alpha power and the level of arousal was found. Valence showed the strongest correlations in all frequency bands. In theta and alpha band, an increase of valence led to an increase of power. These effects were located over occipital regions which might be indicative of a relative deactivation. For the beta frequency band, authors found a central decrease and an occipital and right temporal increase of power. Increased beta power over right temporal sites has been associated with positive emotional external stimulation.

To evaluate arousal with subjective measures, the Self-Assessment Manikin (SAM) is usually used (Bradley, 1994). SAM is a self-report measure in which participants indicate their emotional state.

Different techniques have been reported in the relevant literature to elicit participants' emotions. When researchers use techniques to evoke emotions, the stimuli are usually taken from popular databases, such as the International Affective Picture System (IAPS) database and the International Affective Digitized Sounds (IADS). Other modalities, such as the recall paradigm and the dyadic interaction, are also used in research studies. Although the images, videos, and audio stimuli has been studied extensively as affective stimuli, olfactory stimuli (Kroupi, Vesin & Ebrahimi, 2016), written words (Briesemeister, Kuchinke & Jacobs, 2014; Mueller & Kuchinke, 2016; Imbir, Spustek & Zygierewicz, 2016), food stimuli (Novosel et al., 2014), and games, have been also used to assess emotional states using physiological signals (Chanel et al., 2011; Spape et al., 2013).

5.5.4. Affective states in MOOCs

MOOC platforms store data that are generated from learners' navigation and interaction during the course. These data can provide the means to detect possible issues and make adjustments to improve learners' learning experience. Affect in MOOCs is receiving an increasing attention because of the importance of emotions in learning. By identifying learners' affective states in a MOOC, we can acknowledge the elements associated to positive and negative valence. The correlation between affect and learning is particularly important as emotions can lead to certain behaviors. For example, negative emotions such as frustration and confusion may affect learners' interest and can be related to learner's dropout. Positive emotions can be associated to increased engagement. Rothkrantz (2017) argues that positive emotions can support the intention of learner to continue in a MOOC. According to Gupta et al. (2016) learners' affective states may indicate learner's involvement and interest, as well as the level of understanding of the educational content.

Different methods have been used to evaluate the affective state of learners in a MOOC. Learning analytics, machine learning, sentiment analysis, physiological signals and self-reports are some examples. Li & Baker (2018) analyzed log data obtained from MOOCs on Coursera to evaluate learners' engagement and its relation to learning outcomes. The authors classified learners in subgroups, namely all-rounders, quiz-takers, auditors, disengagers, and found that an engagement measure may predict achievement for one subgroup but not for another. Guo, Kim & Rubin (2014) analyzed log data of a MOOC on edX platform to examine how video watching behavior correlates to engagement. The authors argue that shorter videos with enthusiastic speakers are more engaging.

Leony et al. (2015) developed mathematical models for evaluating the affective state of MOOC learners to identify frustration, boredom, confusion and happiness. The authors report that frustration was related to the number of learners' attempts to perform the assignments, time spent on the assignment and the level of difficulty, while boredom was calculated based on the time needed to answer a question. To identify confusion, the time and the way learners responded to a question is considered, while for happiness, authors considered gamification elements. Liu et al. (2016) proposed a system for the recognition of affective states in a MOOC. Emotion extraction was based on comments posted on a Chinese MOOC platform.

In machine learning methods data can be of different types (such as text, clicks, time) and can be used as input to algorithms (Support Vector Machine, K-Nearest Neighbors etc.), statistical procedures (regression) and exploratory methods (clustering). These algorithms identify patterns in unlabeled data or try to predict an output variable given a set of mutually exclusive attributes. Yang et al. (2015) proposed a classification model to identify the degree of confusion expressed in discussion forums. Liu et al. (2018), developed a joint probabilistic model that incorporates an emotion lexicon to calculate the emotion-specific topic distribution on forum posts. Chen et al. (2016) created a system to predict personality traits from log data based on Gaussian processes and Random forests.

Sentiment analysis is used to extract subjective information. In MOOCs the main source of data are discussion forums, email and messages exchanged inside the platform or through social media networks. Wang, Hu & Zhou (2018), proposed a model to identify the emotional tendencies of MOOC learners and predict the successful completion of the course.

In general, in MOOCs, it is difficult for instructors to know the true affective states of learners as they are learning in distance. EEG can objectively evaluate learners' affective state and make assessments on the quality of the educational material. If most of the learners maintain a high degree of arousal during the course, then the material is attractive enough to learners, whereas if most students are in a low arousal, then the course materials can be less interesting, and instructors need to redesign the material. Xu & Xu (2019) proposed a prototype system, named Megrez for the detection and adjustment of the arousal level of learners in a MOOC. The authors used the β wave to analyze the arousal of the brain. The brain arousal is fed back to the learners to let them understand their affective state. Additionally, when the brain is in a low awake state, authors proposed a way to stimulate the brain by playing music.

5.6. Neurophysiological measures for assessing learners' cognitive and affective state in MOOCs

Cognitive states, such as attention and memory workload, influence learning outcomes directly, while affective states (e.g., confusion, boredom, etc.) have influence learning indirectly. Unlike classroom education, immediate feedback from the student to instructors is less accessible in Massive Open Online Courses (MOOCs). Physiological signals, e.g., skin conductance, electroencephalogram (EEG), heart rate, facial expressions and eye gaze, are usually used to assess learners' cognitive state.

A selective literature review on the use of neurophysiological measurements in the field of MOOC, from the beginning of MOOCs' research to 2020, focusing mainly on the scientific articles that examine the cognitive or affective states of learners, identified about ten scientific articles. The articles were retrieved from well-known bases such as ScienceDirect, ACM Digital Library, Taylor & Francis, Wiley, IEEE, ERIC, Sage journals, Springer, Scopus, and Google Scholar, using the keywords *MOOC* AND *EEG*. The search concerned articles of scientific journals and international conferences written in English in which the keywords appeared in any field. The search was extended by using the phrases "online course", "e-learning", "online lecture video", "educational video", "video lecture" instead of the word "MOOC" and the words "brainwave" or "electroencephalography" were used instead of "EEG".

Papers that did not have a relevance with the topics or were about people with learning disabilities or other cognitive issues were excluded. Based on the results of this literature review, research on MOOCs that use neurophysiological measurements, aims in improving learner's online learning experience and performance. Articles that were obtained can be separated in three main categories based on their main research purpose:

- articles that use the EEG data to examine weather EEG can provide information about learners' cognitive and emotional state while interacting with the learning content of a MOOC (Chang, Lin & Chen, 2019; Lin & Kao, 2018; Wang et al., 2013; Xu & Xu, 2019).
- articles that use the EEG data to provide guidelines on how to improve the design of the learning content that is delivered through a MOOC (Díaz, Ramírez & Hernández-Leo, 2015; Moldovan, Ghergulescu & Muntean, 2017).
- articles that use the online EEG data to adapt the presentation of the learning content and provide a personalized learning experience (Kavitha, Mohanavalli & Bharathi, 2018; Lin & Chen, 2019; Szafir & Mutlu, 2013).

5.6.1. EEG as a measure for cognitive or affective state evaluation

In a MOOC environment, learners interact with the learning content, the instructor, and their co-learners. The interaction between learners and the instructor is not immediate and there is a lack of immediate feedback as far as learners' affective and cognitive states are concerned. When learning new things, learners might experience emotions such as confusion, frustration, anxiety, fear of failure etc. that negatively impact learning gains and engagement.

Confusion

Wang et al. (2013) examined learner's cognitive state, and more specifically learner's confusion, while watching MOOC clips using a single-channel EEG headset and compared the results with the observations of a human observer. The authors concluded that the proposed classifier had a comparable performance to human observers observing body language in predicting learners' confusion. The authors argue that MOOC providers should supply learners an EEG device to get feedback on students' brain activity or confusion level while they are watching the course materials. The results showed that the classifier has comparable performance to human observers observing body language in predicting students' confusion. Thus, classifier would help instructors improve their video lectures based on the EEG data or the EEG data could be aggregated and augment subjective rating of course materials, to provide a simulation of real-world classroom responses. In this direction, Tahmassebi, Gandomi & Meyer-Baese (2018) proposed an evolutionary framework to enhance the performance of MOOCs using EEG data. A Genetic Programming (GP) function classifier was implemented by the researchers as a multi-objective genetic programming approach based on non-dominated sorting genetic algorithm II (NSGA-II). The proposed framework aimed at detecting the confusion level of students in real time using EEG signals to improve the quality of online education. Based on the classification algorithm accuracy there is a difference in the EEG signals of individuals with confusion vs not-confused individuals.

Liao, Chen & Tai (2019) explored the significance of MOOC-based teaching in comparison with traditional method of teaching by observing changes in brainwaves. Researcher used the fast Fourier transform to find the Power Spectral Density (PSD) values for data analysis. The MindWave mobile brainwave instrument was used to measure changes in brainwaves. EEG data were combined with an unlimited number of instant click ratings that represented users' feelings, in order to verify the subjective assessment results (click ratings) via comparison with the data from brainwaves. The results showed that MOOC-based teaching method can increase the better attention of the participants than the traditional method, while it could also give relaxing learning for the students as it was displayed in their meditation values.

Arousal

During learning, learners might produce positive emotions such as arousal, engagement etc., which enhance the acquisition of the learning content. Xu & Xu (2019) constructed a prototype system called Megrez which detects learner's arousal and adjusts learners' cognitive state, if necessary, by playing the appropriate music in order to improve the arousal. Arousal shows the degree of excitement of human. For the recognition of brain arousal, authors classified EEG signals by frequency and selected β waves for analysis. They argue that the proposed system can only recognize high arousal and low arousal.

Cognitive load

Castro-Meneses, Kruger & Doherty (2020) examined the validity of theta power, as an objective measure of cognitive load in educational video context. The researchers measured the intrinsic cognitive load via a subjective scale and theta activity. The researchers argue that theta power may be used as a valid measure of average cognitive load, emphasizing in the fact that its value lies in the ability to measure online fluctuations of instantaneous cognitive load.

Attention

Chang, Lin & Chen (2019) explored how learners' cognitive styles affect their attention levels and learning effectiveness. Two cognitive styles have been identified to classify individual differences in selective attention, dependent and independent cognitive style. The analysis occurred between the two dimensions of dependent/independent and verbal/imagery (Lee & Hsu, 2004). The authors argue that the attention level and learning effectiveness were positively correlated among learners with the independent verbal type of cognitive style, so these students are the most benefitted from to MOOC teaching methods.

5.6.2. EEG for improving the design of MOOCs

Learners' affective and cognitive state are affected not only by the content of the educational material, but also from the design features that are selected to deliver this content.

Design of video lectures

The talking head is an essential design feature in online lecture video as it produces social presence that enhance learner's engagement. Díaz, Ramírez & Hernández-Leo (2015) examined the effect of talking head in academic videos. Arousal and valence values were calculated from the band power values at four electrode sites of prefrontal cortex. The authors provide guidelines about the design of video lectures. They also suggest that the talking head condition does not improve learning outcomes compared to audio condition. Moreover, Wang, Chen & Wu (2015) investigated the effect of three different video lectures styles, namely lecture capture (or talking head), voice over presentation, and picture-in-picture method, on the sustained attention, emotion, cognitive load, and learning performance of verbalizers and visualizers in an online learning scenario by using participants' brainwave and other metrics. Results showed that learning performance is affected by the type of the lectures.

Design choices for hardware

Moldovan, Ghergulescu & Muntean (2017) investigated the effects of learners' interest, quality of experience and emotional states on learning performance, in a mobile learning scenario, for two different devices i.e., a smartphone and a tablet. Results showed that learning performance and quality of experience were not affected by the type of the device while only engagement was found to be higher on smartphone than tablet. Also, the authors argue that gender has an effect on the mobile learning experience. The results did not show any significant effect of affective states on learning performance.

5.6.3. EEG for adaptive learning

It is argued that assessing learners' cognitive and emotional states during learning in a digital environment makes it possible to provide personalized learning to learners. The goal is to enhance learners' interest and engagement, to make the instruction more efficient and finally to improve the learning experience and students' learning outcomes.

Researchers use not only neurophysiological data, but also facial expressions and other physiological measurements to provide real-time detection of the learners' cognitive and emotional states. Machine learning and deep learning algorithms are considered useful in developing models for predicting the learning behavior.

Szafir & Mutlu (2013) developed a system that monitors learners' attention while they were watching online videos in order to suggest the optimal review topic. EEG data was evaluated along with subjective data from a pre-experiment questionnaire (students' prior knowledge), a recall quiz and a post-experiment questionnaire (self-reported evaluation of participant's experience and demographic information). The results showed that adaptively reviewing content optimizes the time spent on review. In the same direction, Lin & Chen (2019) proposed an attention-based mechanism based on brainwave signals. This mechanism could provide video segments for review based on learners' sustained attention level.

Zhou et al. (2017) proposed a passive Brain-Computer Interaction (BCI) system to continuously monitor learners' cognitive workload using the Emotiv Epoc+ headset in an online digital environment. EEG signals recorded from F3 and F4 electrode sites were used as they are highly related to cognitive workload. Also, theta and alpha activity was used by the system as it is considered to reflect changes in workload. Moreover, Lin & Kao (2018) built a system to evaluate learners' level of understanding during watching videos in online learning contexts based on Cognitive Load Theory. The authors argue that the proposed system can effectively facilitate learners' self-awareness of their learning states and to provide the automatic feedback. The authors also argue that their classifier has high accuracy that MOOC platforms can benefit from in order to detect user's cognitive state and improve learning outcomes and user experience.

Kavitha, Mohanavalli & Bharathi (2018) proposed a hybrid model for predicting learners' cognitive ability in order to make online environments suitable for smart learning. The authors developed a model, to evaluate the several aspects of learning by recording multiple physiological measures such as brain signals, pulse rate, etc., from learners as they were interacting with an online course. The authors suggest that this model could be used to evaluate the overall effectiveness of a course, to design courses for different learning levels and from the learners' perspective to identify one's learning style. The authors also argue that the model could be used in MOOCs, although the experiment did not apply in such setting.

5.7. Research problem

5.7.1. Introduction

The present thesis aims to evaluate the effect of a game element named “progression” on a MOOC assessment activity on learners’ cognitive and affective states. Learners’ cognitive state is assessed mainly in terms of engagement, but other indices such as attention, workload and arousal/valence are evaluated as well. Initially, we propose some guidelines for the design of the “progression” element and its implementation on a MOOC assessment activity. We rely on motivational theories of learning, namely on the goal-setting theory, to draw guidelines for the design of this gamified activity and its implementation on a MOOC platform. Then, we assess the effect of “progression” on participants’ cognitive and affective state, while completing the assessment activity using neurophysiological and subjective measures. The present thesis focuses on the study of measures that are extracted from the power spectrum of participants’ EEG signals.

The general idea of this research lays on the fact that a large number of learners who enroll in a MOOC become disengaged during the course and they dropout of the course. Disengagement is usually related to learners’ negative emotions about their learning (such as confusion, frustration, boredom, etc.), and occurs mainly due to the lack of sufficient interaction. This interaction involves the instructors and the learning materials. MOOC learners and mostly low competent learners feel that they do not have the necessary support to advance their skills. They more importantly feel that the course does not offer the required scaffolding to balance their skills with the challenges that are posed through the assignments as the course progresses. Typically, in MOOC assignments the only feedback that learners receive is related to their performance, i.e., their grade per assignment. Based on the literature, to appeal to the learners’ feelings of competence, several forms of positive feedback should be provided (Deci & Ryan, 2004) such as progress assessments, including leveling system, feedback etc.

The present thesis exploits the technological affordances of an OpenEdX MOOC platform (named Coursity) to implement a gamified MOOC assessment activity that integrates the element of progression. The procedure of designing the element of progression for a MOOC assignment is based on goal-setting theory and Bloom’s taxonomy and is described thoroughly in the following sections.

5.7.2. Research objective

The research objective of the present thesis is to evaluate the cognitive and affective state of participants while interacting with a gamified theory-based MOOC activity. In MOOCs, the multiple-choice problem is the most used learning assessment activity. Using the technique of electroencephalography (EEG) we study participants' cognitive and affective states while completing an assessment task that consists of several multiple-choice problems (quizzes). In the present thesis we focus on the study of three EEG frequency bands (namely theta 4-7Hz, alpha 8-13Hz and beta 13-30Hz), as well as on the EEG-based task engagement index and its proxies, i.e., attention, workload, arousal/valence.

To examine whether gamification in MOOC assignments affects participants' cognitive and affective states, we designed and developed two different assessment activities (modules) that consist of the same multiple-choice questions. The first module has the typical structure that is usually used in MOOC platforms, while the other integrates the element of progression. We name the first module "non-gamified activity" and the second "gamified activity".

5.7.3. Research questions

The research questions that were addressed in the present thesis are the following:

- Does the element of progression affect participants' cognitive state in a MOOC assessment activity?
    - Does the element of progression affect participants' engagement in a MOOC assessment activity?
    - Does the element of progression affect participants' attention in a MOOC assessment activity?
    - Does the element of progression affect participants' cognitive workload in a MOOC assessment activity?
- Does the element of progression affect participants' affectivity in a MOOC assessment activity?
    - Does the element of progression affect participants' arousal in a MOOC assessment activity?
    - Does the element of progression affect participants' valence in a MOOC assessment activity?
- Does participants' cognitive and affective state, while taking a MOOC assessment activity that uses the element of progression, affect their engagement?

    - Does participants' attention, while taking a MOOC assessment activity that uses the element of progression, affect their engagement?
    - Does participants' cognitive workload, while taking a MOOC assessment activity that uses the element of progression, affect their engagement?
    - Does participants' affectivity, while taking a MOOC assessment activity that uses the element of progression, affect their engagement?
- Does the element of progression in a MOOC assessment activity affect participants' perceived learning experience?
    - Does the element of progression in a MOOC assessment activity affect participants' perceived engagement?
    - Does the element of progression in a MOOC assessment activity affect participants' perceived usefulness?
    - Does the element of progression in a MOOC assessment activity affect participants' learning effectiveness?
    - Does the element of progression in a MOOC assessment activity affect participants' cognitive benefits?
    - Does the element of progression in a MOOC assessment activity affect participants' intention to continue?

The ultimate goal of the thesis is to evaluate the effect of the proposed gameful design method on learners' cognitive and affective state and to investigate whether the above-mentioned neural measures could be used to characterize participants' learning experience and serve as a tool to provide useful information for the design of gamified MOOC activities.

Chapter 6. Research methodology

6.1. Sample

The sample of the study consisted of 58 volunteers (24 men and 34 women). The participants were between 19 and 47 years (*M*=34.23, *SD*=7.28). The sample was randomly assigned into two groups, namely Control Group and Experimental Group. The Control Group (Group1) consisted of 16 women and 12 men, while the Experimental Group (Group2) consisted of 18 women and 12 men.

Table 6.1. Sample demographics (N=58)

		Group1 (Control)		Group2 (Experimental)	
Variables	**Classification**	**Frequency**	**Percentage (%)**	**Frequency**	**Percentage (%)**
Gender	Male	12	20.69	12	20.69
	Female	16	27.59	18	31.03
	Total	28	48.28	30	51.72
Age	19-25	3	5.17	6	10.34
	26-35	10	17.24	11	18.97
	36-45	11	18.97	12	20.69
	46 and above	4	6.90	1	1.72
Occupation	Student	1	1.72	3	5.17
	Researcher	3	5.17	5	8.62
	Teacher	12	20.69	10	17.24
	Professor	1	1.72	2	3.45
	Employer/Employee	11	18.97	10	10.24
Education level	Undergraduate	1	1.72	2	3.45
	Bachelor	4	6.90	6	10.34
	Postgraduate	11	18.97	10	17.24
	Master	5	8.62	3	5.17
	PhD student	6	10.34	5	8.62
	Doctoral	1	1.72	4	6.90
Prior experience on Coursity	Yes	10	17.24	12	20.69
	No	18	31.03	18	31.03
Prior experience on online learning	Yes	22	37.93	25	43.10
	No	6	10.34	5	8.62
Prior knowledge on ASD	None	6	10.34	5	8.62
	Poor	11	18.97	8	13.79
	Fair	3	5.17	4	6.90
	Good	4	6.90	10	17.24
	Very good	4	6.90	3	5.17

All participants had normal vision or corrected-to-normal vision. They were right–handed native Greek speakers, without certain diagnosed learning difficulties or mental impairment. They showed no sensory impairments. The participants were informed as not to receive any medication or substances that might affect the operation of their nervous system, and not to consume large quantities of caffeine or alcohol, in the last 24 hours before the experiment. The alpha rhythm of all the participants was checked before the experiment and all participants had a normal alpha rhythm (8–12Hz). The study conformed to the code of ethics of the University of Ioannina. The participants did not receive any compensation for participating, and all of them gave their informed consent. Table 6.1. presents the demographics of the sample for each of the two groups, as frequencies and percentages.

6.2. Gamification design process

The design of gamification is not a linear process. Gamification design is always influenced by several aspects related to psychology, science learning, game design, user's experience design and technology enhanced learning. Thus, gamification design is considered to be relative as it depending on the context, the problem that is to be solved, the effects we want to generate and the target audience (Antonaci et al., 2018). To generate a change in learner's behavior through a gamified activity, all these aspects should be taken into account in the process of the design. In the present thesis the design process was based on the general rules of gamification design cycle proposed by Antonaci et al. (2018). We have followed this process as the authors have validated it in a MOOC scenario.

The gamification design process consists of the following phases (Figure 6.1):

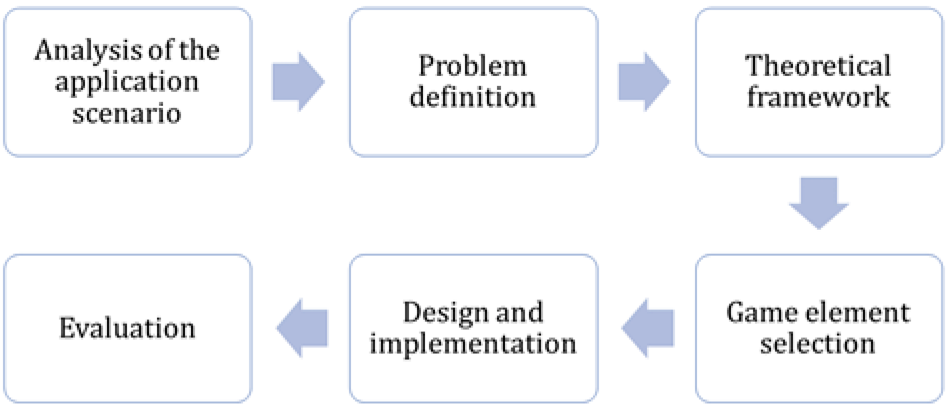


Figure 6.1. Gamification design process

1st phase: Analysis of the application scenario

In this work, gamification is implemented on an online learning environment, namely a MOOC assessment activity. As far as we know, it is the first time that such an intervention is implemented on a MOOC platform. The course, as well as the learning activity that was gamified, is about Special Education and Autism Spectrum Disorder (ASD). The course is offered via a MOOC platform (named Coursity), mainly to educators, adult women, and men, of all ages. The overall goal of the course was to provide the basic knowledge about the characteristics of people with ASD and the necessary skills to handle issues that people with ASD confront daily. This MOOC was selected in our application scenario, as participation in courses with similar topics concerns many people in Greece due to its direct connection to employment.

2nd phase: Problem definition

MOOCs have massive enrollments, but a great number of the enrolled learners quit their attendance before the end of the course. Based on the literature (which is described in Chapter 2), there are many factors that lead MOOC learners to dropout. A factor that significantly affects the attrition rate in MOOCs, is learners' disengagement. The term "disengagement" refers to learners' lack of interest and task value. It is related to learners' negative emotions that originate from the lack of self-efficacy or the lack of goal orientation.

The present thesis proposes the implementation of gamification in MOOC assessment activities, as gamification is thought to raise emotions such as mastery, satisfaction, self-efficacy etc. and to enhance engagement through goal commitment. Particularly, we examined in a micro level (i.e., group level) whether the implementation of gamification in a MOOC assessment activity can positively affect learners' engagement.

To assess learners' task engagement, we used a multi-method approach by combining objective and subjective measures. EEG sensors can provide accurate and valid information about learners' mental engagement, while the perceived engagement level can be obtained with the use of a self-reporting questionnaire.

3rd phase: Theoretical framework

Several motivational theories have been adopted for the design of gamification in various settings. In the present thesis, based on the problem that has been set (i.e., high dropout rate) and the application scenario (i.e., gamification in MOOC assessment activities), we used the goal-setting theory as a basis of our theoretical framework. Goal setting theory defines the elements that affect the relationship between goals, performance, and goal commitment. This theory was selected as goals activate various mechanisms related to learning such as direct attention to goal-relevant activities, mobilize the degree of effort, increase the persistence in pursuing the goals and promote the development of goal-relevant strategies (Locke & Latham, 2002).

Task engagement is defined as an effortful commitment to task goals (Matthews et al., 2002). Therefore, goal-setting theory was used to draw guidelines for the design of gamification in a MOOC assessment activity, as it sets out the basic principles that should drive goals (either they are performance-related goals or learning goals) in order to enhance learners' goal achievement and engagement.

4th phase: Game elements selection

Deterding et al. (2011) argue that gamification as a concept that derived from games, is inherently a goal-oriented activity. Goals are the key component for learning, as well as for game design process. Game designers use goals to create different levels in the gameplay and to keep players focused on an activity, while for players, goals serve as a measure of their progress. Moreover, goals are traditionally quantifiable, i.e., goals are entities that can be measured. By making goals measurable, it is possible to tell when the goals are reached. In a game, players typically know if they have reached a certain goal through feedback. This feedback can be communicated by using badges, points or unlocked new challenges.

In games, players get a feeling of satisfaction from level accomplishment and skill development. Player’s growth and skill development is known as “player’s progression”. The sense of satisfaction that players’ experience while they are progressing in the game, relates to the feeling of self-efficacy that leads to increased effort, persistence, and goal commitment. It should be noted that learners enjoy the same types of recognition. The sense of progression motivates learners’ continued effort. This effort is mobilized in proportion to goal difficulty. In educational settings, defining learning goals lead to higher engagement and performance than setting performance-oriented goals.

Also, Deterding et al. (2011) suggest that a gamified system should be designed around challenges that users face already in accomplishing the goals, rather than creating additional artificial challenges. This implies that the elements that are used to gamify a learning environment should promote learning and not impose learners to redundant challenges. Moreover, Tondello, Premsukh & Nacke (2018) suggest that learning can be used to set clear goals in gamification. Authors argue that in a well-designed system, goal difficulty should increase with the user's skills in order to continuously provide a challenging activity. This requires the ability to consistently monitor user's skills.

Table 6.2. Matching goal-setting theory principles to game design elements in order to design the dynamics of progression

Goal-setting theory			**Progression**
Principles		**Gameful design guidelines**	**Game design elements**
Basic principles	Specific goals	Goals must be specific in order to hold learner's attention and effort	Clear goals
	Difficult goals	Goals must be difficult enough to hold learner's attention, but they should be balanced with learner's skills	Levels
	Proximal goals	Completing several proximal goals will facilitate the attainment of distal goals	Levels
Mediators	Direction	Presenting the next best task once a goal is reached	Feedback
	Persistence	Allow learner to try again after failure. Provide aid to encourage persistence	Challenge, Feedback
	Task strategy	Balance task difficulty to learner skills and allow practicing before introducing harder tasks	Challenge
	Self-efficacy	Provide a larger meaning for their achievements	Feedback, Levels
Moderators	Ability	Task complexity should be balanced with learner's skills	Challenge
	Task complexity	A complex task should be divided into smaller tasks to reduce complexity	Levels
	Progress feedback	Provide information about how the player is doing at a task	Feedback
	Goal commitment	Learners should acknowledge task importance, accept the goals and feel self-efficient	Feedback
Goal types	Outcome goals	Accomplishment of a specific result	Feedback
	Performance goals	Goal to reach a certain performance level	Feedback
	Process goals	Learning goals based on Bloom's taxonomy	Challenge, Levels

Progression deals with those aspects of gameplay that stem from quality level design and mechanics that control player's progress through these levels. Game designers create levels in which players need to overcome a predefined set of challenges. Each challenge is built on a set of (proximal) goals. Completing a particular challenge often unlocks other challenges and in this way players progress towards a distal goal. In the present thesis, following the conceptual framework of Tondello, Premsukh & Nacke (2018), we match goal-setting theory principles to gameful design guidelines (Table 6.2). Furthermore, based on these guidelines we select specific game design elements, as shown in Figure 6.2, in order to design the element of progression for a MOOC activity.

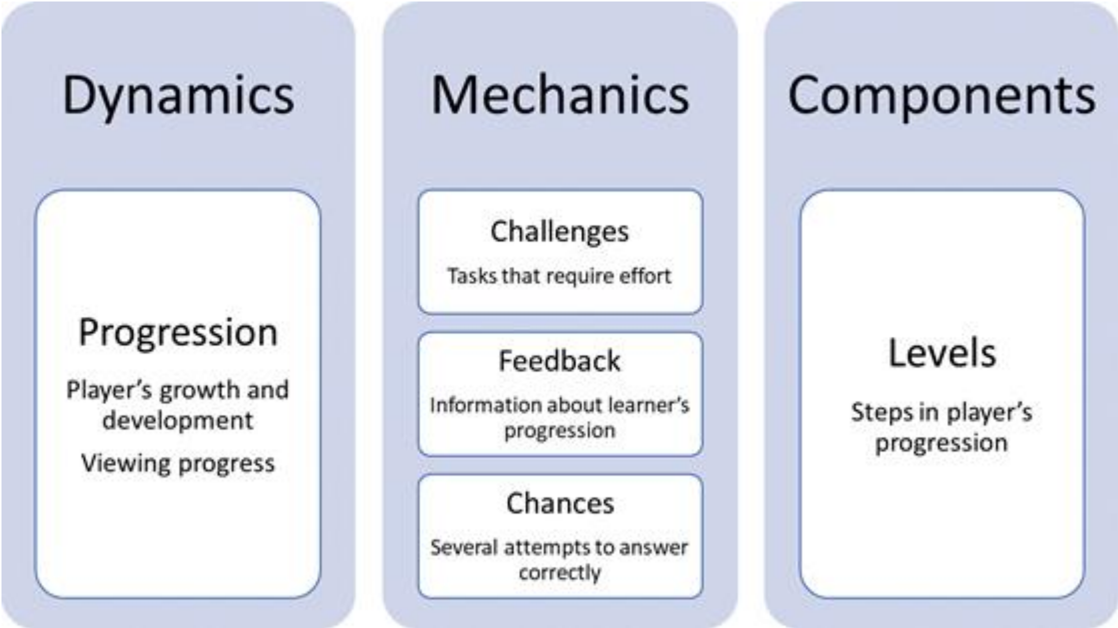


Figure 6.2. Game design elements that are used for the implementation of progression

As described in Chapter 4, based on Werbach & Hunter (2012) framework, the gamification elements are classified into dynamics, mechanics, and components. The element of progression belongs to the dynamics. Mechanics is the necessary element for implementing dynamics in a game or a gamified activity and the one that promotes users to engage in the game. Challenges (tasks that require effort to solve) and feedback (information about how the player is doing) are mechanics that we use to implement the dynamics of progression. Components are the substantiated form of dynamics and mechanics. Levels (i.e., denied steps in player's progression) are components that we also use to create to element of progression. Specifically, in the present thesis, we design the element of progression for a MOOC assessment activity using the following game design elements: clear goals, challenges, levels, and feedback (Figure 6.2).

5th phase: Design and implementation

Firstly, we describe the design of the selected game elements (clear goals, challenges, levels, feedback) on which the implementation of the progression element is based. Then, we present how gamification is applied to a MOOC platform.

Clear goals

Goals are most motivating when they are specific, measurable, attainable, realistic, and time-bound (Figure 6.3). Best practices for setting optimal goals are described in Chapter 4.

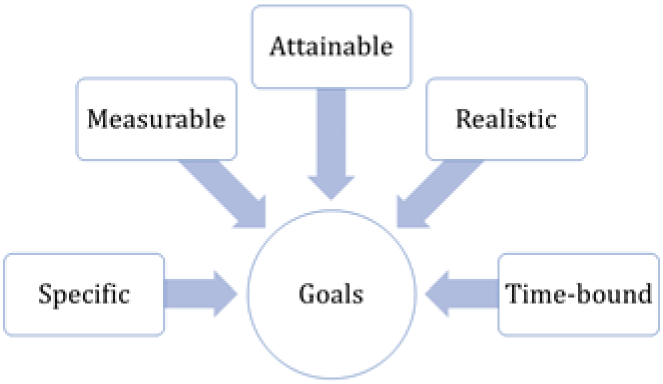


Figure 6.3. Setting optimal (SMART) goals (Moskowitz & Grant, 2009)

Using the revised Bloom's Taxonomy, we defined the following learning objectives which correspond to the first five levels of the taxonomy, namely “Remember”, “Understand”, “Apply”, “Analyze”, “Evaluate”.

Learners after the completion of the learning section titled “Autism Spectrum Disorder” will be able to:

- Recall the relevant terminology on Autism Spectrum Disorder and the basic characteristics of a person with ASD (1st level of Bloom’s taxonomy)
- Identify the characteristics of people with ASD and interpret their behavior based on these characteristics (2nd level of Bloom’s taxonomy)
- Apply the knowledge that they have acquired about ASD to new situations (3rd level of Bloom’s taxonomy)
- Analyze a problem that people with ASD confront in their daily life to its components and find the best solution to solve it (4th level of Bloom’s taxonomy)
- Combine information to solve complex problems and situations involving people with Autism Spectrum Disorder (5th level of Bloom’s taxonomy).

These goals concern the topic of Autism Spectrum Disorder and are related to the content of two video-lectures of the MOOC "Introduction of Special Education" that is hosted on Coursity MOOC platform. The total duration of the video-lectures was thirty (30) minutes. The highest level of the taxonomy, named "Create", is difficult to be assessed by using multiple-choice questions, as it requires the creation of knowledge. The goals that were articulated for the needs of the present thesis are described below.

Challenges

The above learning goals were used to create twenty-one (21) multiple-choice questions with four different choices. The questions were formulated based on Brame (2013) and was used to formulate five (5) challenges. Each challenge constitutes a formative assessment activity. The number of multiple-choice questions that were created for each learning goal was not equal (Figure 6.4).

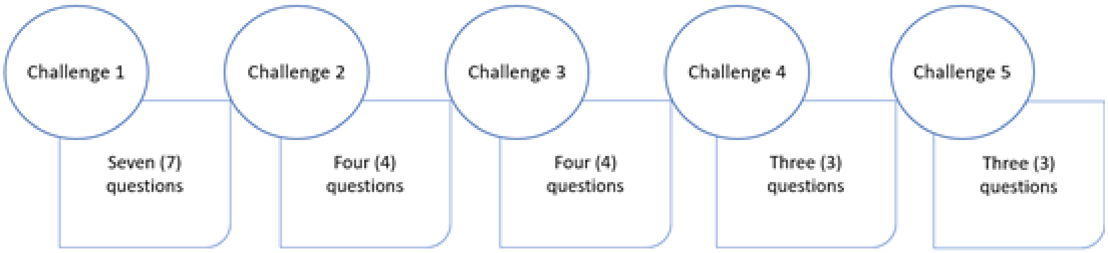


Figure 6.4. Number of multiple-choice questions that are assigned in each challenge

All questions were checked for the phrasing and the content by two Special Educators. The Special Educators reviewed all the questions and the available choices independently and gave their comments in written form. Based on their comments, the questions and the choices were revised appropriately. After the revision, the Special Educators checked the questions one more time and gave their approval.

Furthermore, to check the quality and the difficulty of the multiple-choice questions, item analysis was performed. A google form that comprised of all the multiple-choice questions were sent to more than three hundred (300) learners who enrolled in the MOOC "Introduction to Special Education" on Coursity MOOC platform in the period July-September 2020. All the learners that received the google form had attended the course either with free attendance or they had also applied to receive a Certificate of Training. Sixty-nine (69) learners answered the questionnaire. The learners' answers were used to analyze the questions regarding the ease/ difficulty of answering and the quality of the distractors in each item. The item analysis was performed to ensure that the multiple-choice questions were not too easy but rather challenging enough to activate learners' effort and engagement. All the items had a fifth choice “I don’t know”. The learners were able to submit their answers only once and they did not receive any feedback after their submission. The results of the item analysis are presented in the Table 6.3.

For each question, we have calculated the number of participants who answered the question correctly (frequency of correct answers), the item difficulty (p-value) which is the percentage of learners that answered the question correctly, the item discrimination which shows the point-biserial relationship between how well learners did on the question and their total score on the test (this is also referred as the Point-Biserial Correlation) and the number of learners that have chosen each distractor (Table 6.3).

Generally, p-values range from 0% to 100% and they are often written as a proportion ranging from 0.00 to 1.00. P-values above 0.90 are thought to be very easy, while p-values below 0.20 are thought to be very difficult. The optimum difficulty level is around 0.50 in order to achieve a maximum discrimination between high and low achievers. Based on Zimmaro (2016), the ideal value is slightly higher than midway between chance (1.00 divided by the number of choices) and a perfect score for the question i.e., 1.00. In our case, for a 4-option multiple choice questions the ideal value is about 0.63. In Table 6.3. we have underlined the items that had a p-value greater than 0.90 or less than 0.30. These items were revised in order to approximate a better difficulty level.

Item discrimination values range from -1.00 to 1.00. The higher the value is, the more discriminating the question. The value indicates that learners who had high test scores got the item correct whereas students who had low test scores got the item incorrect. In Table 6.3 we have underlined the items that had an item discrimination value less than 0.20. These items were revised to increase their discrimination level. Moreover, to examine distractors quality we have used a frequency table. In Table 6.3 we have noted the number of learners that have chosen each distractor. We have added an asterisk (*) to the correct choice. Also, we have marked in green the questions in which the correct item was chosen by the majority of the learners. Distractors that were not selected by learners was replaced.

Finally, we used the Kuder-Richardson formula 20 (KR-20) to calculate the reliability coefficient (alpha). The reliability coefficient shows how reliable is the overall test score, i.e., the internal consistency reliability. This value ranges from 0.0 to 1.0. High reliability indicates that the questions are all measuring the same construct. The acceptable range is from 0.60 or higher. In our case, the reliability coefficient was equal to 0.72. We did not perform item analysis after the revision of the questions.

Table 6.3. Item analysis of the quality of multiple-choice questions

# Item	Freq. of correct	Item difficulty (p-value)	Item discrimination	Response frequencies A	B	C	D	I don't know
1	65	0.94	0.39	*65	2	1	1	0
2	67	0.97	0.56	2	0	*67	0	0
3	57	0.83	0.49	5	*57	0	2	5
4	60	0.87	0.57	*60	1	3	3	2
5	64	0.93	0.58	1	4	*64	0	0
6	56	0.81	0.35	9	3	0	*56	1
7	65	0.94	0.29	3	1	0	*65	0
8	63	0.91	0.34	1	*63	1	4	0
9	59	0.86	0.56	*59	2	3	4	1
10	57	0.83	0.31	8	1	1	*57	2
11	67	0.97	0.59	0	1	1	*67	0
12	66	0.96	0.55	2	0	*66	1	0
13	67	0.97	0.05	*67	1	1	0	0
14	66	0.96	0.27	0	2	1	*66	0
15	62	0.90	0.15	*62	0	3	2	2
16	19	0.28	0.37	0	45	4	*19	1
17	36	0.52	0.33	25	*36	0	8	0
18	48	0.70	0.54	9	*48	5	2	5
19	61	0.88	0.53	*61	4	0	2	2
20	33	0.48	0.38	4	15	15	*33	2
21	54	0.78	0.63	3	*54	1	7	4

Levels

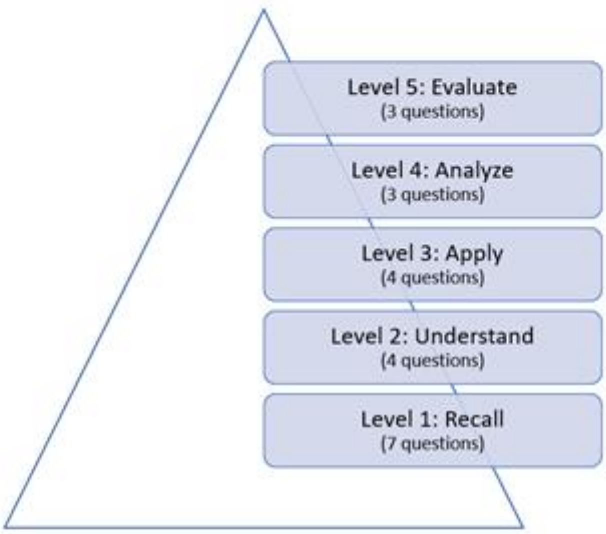


Figure 6.5. The MOOC activity comprises five distinct levels of increasing difficulty

The MOOC assessment activity that was created within this work is divided in smaller activities. Specifically, we defined five (5) distinct levels to reduce the complexity and create “skill levels”. This means that the multiple-choice questions that correspond to a different level, require a different level of cognitive skills as they were created based on Bloom’s taxonomy. The levels were presented with an increasing task difficulty regarding the level of skills required. Each challenge described above was used to form a distinct level in the MOOC activity. Figure 6.5 shows the levels that were defined. In each level, the learners were given two possible attempts to find the correct answer for all the questions in the level.

The multiple-choice questions are presented in Greek in Appendix I. Five levels have been created, which correspond to the five levels of the Bloom’s taxonomy. Each level included a set of multiple-choice questions. As the taxonomy is concerned, the questions were checked by the supervisor of the present thesis and the researcher.

Each level corresponds to a specific learning goal and includes a formative assessment activity (Figure 6.6). We created a scaffolding activity by presenting the levels with an increasing difficulty in terms of the level of skills required to complete them. The ideal would be to create a smooth learning curve for every learner. To create a smooth learning curve, the difficulty of each activity that the learner is requested to complete, should be in balance with his/her skills. Moreover, learners should be able to practice the skills that are required to complete the activities as they progress in a higher level. It should be noted that the level of difficulty should be appropriate to activate the learner's motivation to pursue goal achievement.

Figure 6.6. Five levels of the activity that corresponding to the first five levels of Bloom’s taxonomy

Feedback

Based on the literature, goals succeed better when combined with the element of feedback. As learning assessment activities are a part of the learning process, feedback can be used to enhance learner's skills. Also, through feedback learners receive information about their progress. In the present thesis, feedback is being implemented with the following ways:

Constructive feedback: This kind of feedback is given to the learners after submitting their answers (Figure 6.7). It concerns two types of information:

- Feedback is given as to whether an answer is correct or incorrect. The correct answers are signed with a green check mark while the incorrect answers are signed with red cross mark. This helps learners to identify the wrong answers in order to reconsider the available choices and select another answer (as they are given two possible attempts for submission). According to Johnson, Bailey & Buskirk (2017) this type of feedback is an outcome-based feedback and is usually called by the researchers as “error flagging”.
- Feedback is given for each correct and incorrect answer to explain why the chosen answer is correct or wrong, without revealing for the incorrect choices the correct one. The correct answers are also marked with the word “Correct” while the wrong answers are marked with the word “Incorrect”. Feedback on the correct answers is provided to enhance learner's knowledge in case the choice was made by chance. The information is presented in text form below each question. According to Johnson, Bailey & Buskirk (2017) this type of feedback is a process-based feedback and is usually called “response specific”.

Performance feedback: Provide information about how the player is doing at a task (or challenge). When submitting their answers, learners are informed about the number of correct answers to the total questions e.g., 5/7 points (correct answers). Based on their performance on each challenge, learners’ can decide whether they want to improve their performance by resubmitting their answers or not. This information is given in written form, in the upper side of the page. This is also an outcome-based feedback. This type of feedback helps learners to monitor their progress in the course. In the present thesis, progress feedback is given separately for each level.

Figure 6.7 presents the constructive feedback that is given for two of the questions of our activity.

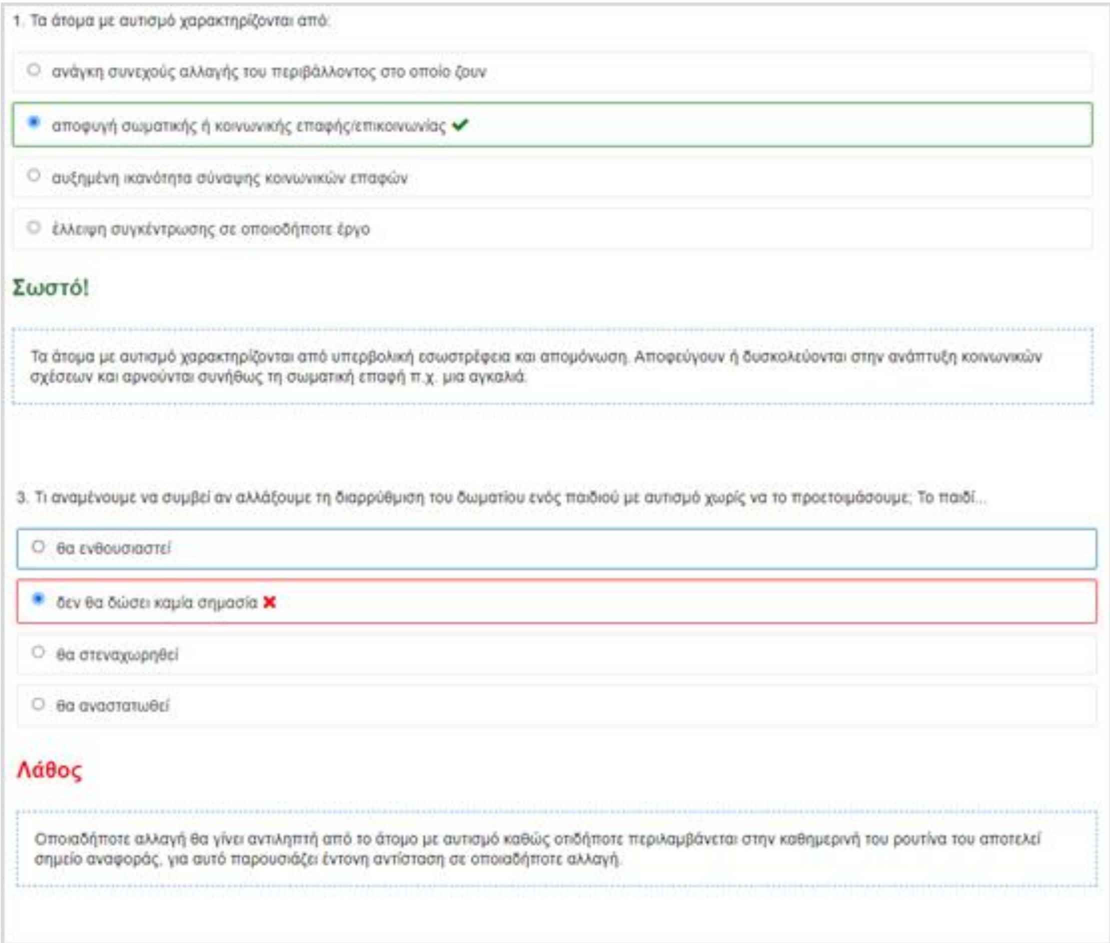


Figure 6.7. Example of the constructive feedback. Each question is marked either with a green check mark or a red cross to indicate whether the choice that was selected is correct or incorrect. Below of each question, in a dashed rectangle an explanation was given to justify the assessment result.

Purpose feedback: This type of feedback is presented before and after each level of the assessment activity. It includes information about what has been achieved so far and what is the next goal to be achieved. Based on the literature, learners should always be aware of what is being achieved so far, be able to determine whether a goal is reached in order to adjust the learning strategy and the amount of effort accordingly, and to be informed about the next goal to be achieved. In the present thesis, learning goals are used to define levels and measure learner's progress. This type of feedback is given in a written form and is presented in a separate page that precedes or follows each level (Figure 6.8). Moreover, this type of feedback provides information that explain the reasons the learning goals help to achieve an ultimate goal rather than providing skills which strengthens the goal commitment.

Figure 6.8. Example of a page that presents purpose feedback that precedes Level 3

Implementation of the gamified intervention

In a MOOC-based scenario the design and the implementation of game elements depend on the platform that is used, its technological features, the available budget and the technical skills of the gamification designer. The present thesis uses the Coursity MOOC platform to apply and evaluate the proposed intervention. The learning section "Autism Spectrum Disorder" which is a part of the course titled "Introduction to Special Education" is used to implement the element of progression. This section consists of:

- two (2) video-lectures (total duration 30')
- one (1) assessment activity. The activity includes five (5) distinct levels. Each level corresponds to a single challenge that comprises of a set of multiple-choices questions (as described above).

To evaluate the gamified activity, two different learning sections were created. Each of the sections included the two video-lectures and an assessment activity. The video-lectures were the same for both modules, while the assessment activity differed as to whether the element of progression was implemented or not. Below we describe both the gamified and the non-gamified activity.

I. Gamified activity

The gamified MOOC activity has been implemented based on the progression element. Thus, it includes the game elements as described above. Table 6.4 presents the components of the gamified activity and the way they differ from the non-gamified activity. Besides the components that are added in the activity, each challenge (quiz) has the typical structure of MOOC quizzes, i.e., a set of multiple-choice questions placed with a vertical alignment. At the end of each multiple-choice problem (i.e., challenge), there is a "Submission" button and usually, learners have two possible attempts to answer its questions correctly. Both gamified and non-gamified activity comprise of the same multiple-choice questions.

Table 6.4. Comparing elements in gamified vs non-gamified activity

Element	Gamified activity	Non-gamified activity
Goals	Goals are used to define levels. Goals are explicitly presented to learners through feedback.	Goals are not used to define levels. Goals are not explicitly presented to learners
Challenge	Each challenge is a set of multiple-choice questions. Learners are given two possible attempts.	Each challenge is a set of multiple-choice questions. Learners are given two possible attempts.
Levels	Levels have an increasing difficulty as they correspond to a different level of goals in Bloom's taxonomy	No levels. Questions were assigned randomly in each challenge.
Feedback	Constructive (response specific and error flagging), performance and purpose feedback are given to learners	Performance and error-flagging feedback are given to learners

After the implementation of the progression, pre-evaluation is used to investigate the factors related to the principles of the goal-setting theory and user's experience of the gamification design. The comments were used to reconsider the design of gamification. Eight (8) volunteers with diverse backgrounds evaluated the gamified activity. Specifically, two (2) software developers, three (3) Special Educators, one (1) Computer Science teacher, one (1) Special Teaching Staff, and one (1) Philologist. In the pre-evaluation phase, we requested the volunteers to watch the two video-lectures as many times as they wanted and then complete the activity. During the completion of the activity, volunteers could interact with the system in the way they wanted. For example, they could attempt each level of questions only once or two times, they could read the feedback that is given or not, they could go back and forth in the activity. The volunteers during the completion of the activity externalized their thoughts and reactions following a think-out-loud approach. Their comments were recorded in written form. After completing the activity, the volunteers were requested to give feedback about the gamification design and their experience focusing on the goal-setting theory principles. Specifically, they were asked to comment on the following:

- the goal corresponding to each level of the activity was clear and specific
- the purpose of the activity seemed important

- I knew what I had to do at every step of the activity
- I wanted to explore all the available choices of each question
- I felt I had the knowledge/ skills to complete each level
- I liked the activity/ the activity was boring
- the feedback that is provided helps to move on
- the feedback had a lot of information and that made me tired
- the feedback was given at the right time.

The volunteers' suggestions were classified based on the context, i.e., whether they were related to technical issues, gamification design issues or content issues. Also, they made comments regarding the aesthetics of the system (text fonts, images, etc.). The proposed changes were made based on whether a suggestion was proposed by more than four volunteers. Finally, after the changes had been implemented, the volunteers gave positive feedback before the experimental procedure.

II. Non-gamified activity

The non-gamified activity has the typical form of a multiple-choice problem in MOOCs i.e., a set of multiple-choice questions placed at a vertical alignment. At the end of each problem, there is a "Submission" button. Learners usually have two possible attempts to answer the questions correctly. Typically, in MOOCs, multiple-choice problems include questions that correspond to the two lower levels of Bloom's taxonomy. In the present thesis, the non-gamified activity includes the multiple-choice questions that correspond to the first five levels of Bloom's taxonomy. In this activity the questions also divided in five quizzes. However, these quizzes do not form distinct levels of increasing difficulty as in the gamified activity, rather each question was randomly assigned in one of the quizzes.

Only performance feedback and error flagging feedback are provided, when learners submit their answers. This feedback informs learners about which questions were answered correctly and which did not. Learners are also informed about the number of the correct answers (e.g., 4/6 points). As in the gamified activity, the correct answers are marked with a green check sign, while the incorrect with a red cross sign. Figure 6.9. presents the components of the non-gamified activity.

We should note that, the control group participated in the non-gamified activity while the experimental group participated in the gamified activity.

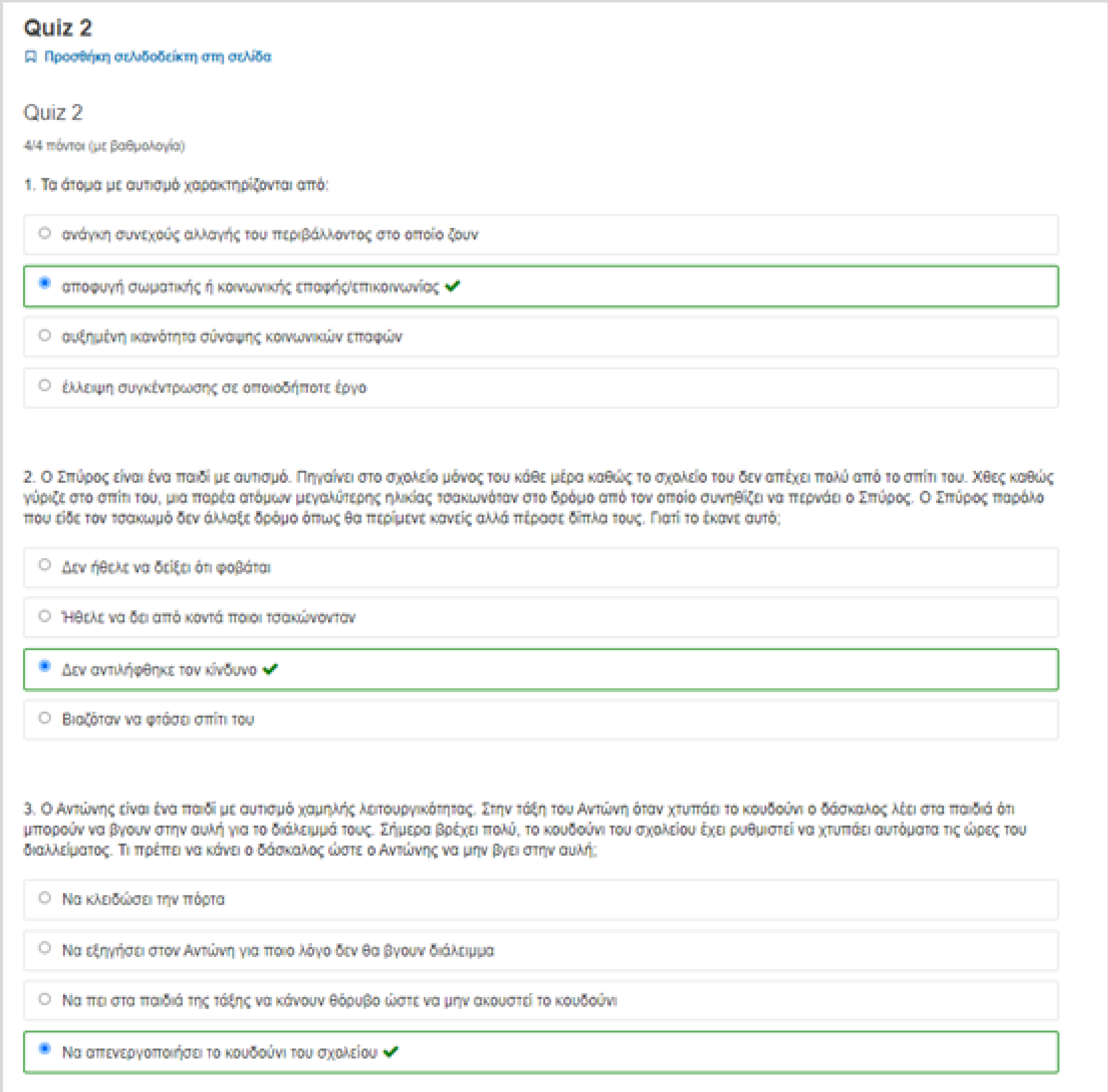


Figure 6.9. Example of the feedback that is given in non-gamified activity

6th phase: Evaluation

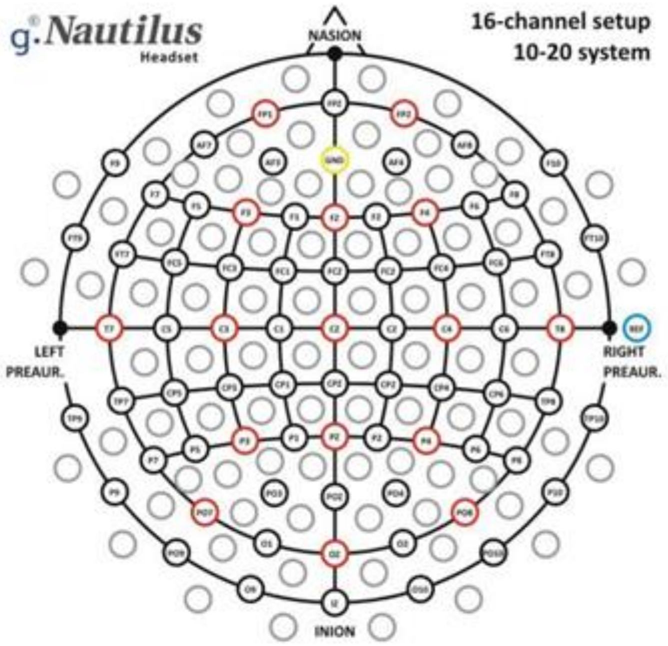
The evaluation phase aims to measure the effect of the implemented gamified intervention. In the present thesis, subjective and objective measures were used to assess the effect of the progression element in a MOOC assessment activity. Neurophysiological measures that were obtained by the spectral analysis of the participants' brain signals were correlated with data collected via a self-report questionnaire that was administered to the participants at the end of the experimental procedure. In the following section, the experimental procedure is thoroughly described, as well as the instruments and apparatus that were used to collect the data.

6.3. Apparatus and instruments

To record the participants' neurophysiological signals, a wireless EEG recording system was used, namely g. Nautilus, manufactured by g.tec Medical Engineering GmbH (Figure 6.10).

Figure 6.10. The g.Nautilus headset

The system consists of a cap with sixteen (16) dry electrodes that are uniformly distributed in accordance with the international 10–20 standard (Jasper, 1958). The ground and reference electrodes are located at the two mastoid bones (Figure 6.11). EEG signals were digitized with 24-bit resolution ADCs and sampled at 250 Hz. The system also contains a separate base station that receives the digitalized signals through a 2.4GHz wireless transmission and sends them to a PC through a USB port. EEG data obtained from g.Nautilus were visualized and processed by Simulink, a commonly used tool for dynamic simulation.



Electrode	Logical Channel
FP1	1
FP2	2
F3	3
FZ	4
F4	5
T7	6
C3	7
CZ	8
C4	9
T8	10
P3	11
PZ	12
P4	13
PO7	14
PO8	15
OZ	16

Figure 6.11. g.Nautilus 16-channel electrode setup

After the completion of the experimental procedure, the learners were requested to evaluate the activity (either it was gamified or not) in terms of perceived engagement. In order to acquire information about the participants' post-experiential engagement, the Whitton's (2007) engagement questionnaire was administered via a google form. The google form also included questions about the participants' demographics. Demographics included the following information: gender, age, education level, learning disability, occupation, ICT skills level, prior experience on Coursity, prior experience on online learning, prior knowledge on ASD (Table 6.1).

II. Perceived engagement questionnaire

A self-reported questionnaire was used to assess learners' task engagement. Whitton (2007) through her dissertation proposed several statements to evaluate the perceived engagement of participants in an activity (task engagement). Whitton's engagement questionnaire consists of 18-item in a 5-point Likert scale (strongly agree to strongly disagree). Each of the questions corresponds to a factor that Whitton argues to affect the engagement of the participants: Challenge, Interest, Control, Purpose, Immersion. This questionnaire has been used to examine and evaluated postexperiential engagement with educational games and other learning activities in Higher Education (Whitton, 2007, 2011). Two theories of engagement with games are the basis for this questionnaire, flow theory and Malone's theory in terms of challenge, curiosity, and control. Flow theory (Csikszentmihalyi, 1992) is a central component, but it should be acknowledged that flow is an extreme form of engagement and that it is possible to be engaged although not actually in a state of flow. However, the questionnaire also draws from theories of adult learning, such as the theory of andragogy (Knowles, 1988). This theory supports that adult motivations for learning differ from younger people. Adult learners need to know why they should learn something before they are willing to invest time and energy in learning it and they become ready to learn something when they need to apply it in real-life situations.

Table 6.5. presents the items that were used to assess the participant' perceived engagement. Engagement constitutes of five engagement factors. Each factor contributes to the overall sense of engagement. The model on which Whitton's questionnaire was developed, has been validated in research studies in various fields as well as in educational tasks, while the questionnaire was used in formative assessment studies (Ismail & Mohammad, 2017).

In Appendix II, we present the self-reported engagement questionnaire in Greek as it was administered to the participants.

Table 6.5. Learning engagement factors proposed by Whitton (2007). The negative phrasing marked with asterisks

Factor	Description	Question
Challenge	The motivation to undertake the activity.	I wanted to complete the activity (I had a motivation) I did not care how the activity ended (in terms of grades)
	Clarity as to what it involves.	I knew what I had to do to complete the activity I found it easy to get started
	A perception that the task is achievable.	I found the activity frustrating* I felt that I could achieve the goal of the activity
Control	The fairness of the activity, the level of choice over types of action available in the environment, and the speed and transparency of feedback.	It was not clear what I could and couldn't do* The activity would not let me do what I wanted* I could not tell what effect my actions had*
Immersion	The extent to which the individual is absorbed in the activity.	I felt absorbed in the activity I felt that time passed quickly I found the activity satisfying
Interest	The intrinsic interest of the individual in the activity or subject matter.	I found the activity boring* I was not interested in exploring the options available* I did not enjoy the activity*
Purpose	The perceived value of the activity for learning, whether it is seen as being worthwhile in the context of study.	It was clear what I could learn from the activity The activity was pointless* The feedback I was given was useful

6.4. Experimental procedure

The experimental procedure was divided in two phases. Figure 6.12 shows the experimental protocol that was followed. In the first phase participants were requested to watch two video-lectures about the Autism Spectrum Disorder. In order to have access to the video-lectures, the participants created an account on Coursity MOOC platform. They were able to access the content via the internet from their home or any other place they have chosen. The second phase included their arrival at Coursity's office in order to participate in the experimental procedure. This phase involved the recording of the participants' brainwaves and answering a self-reported engagement questionnaire.

Before the experiment

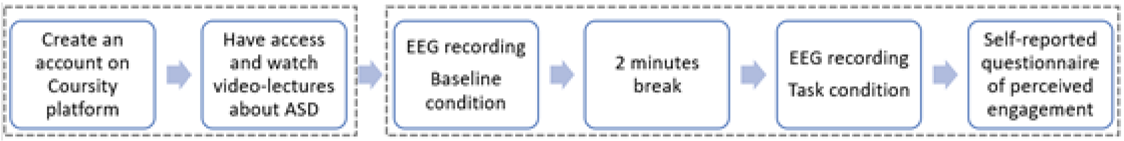


Figure 6.12. Experimental protocol

An informative email was sent to each participant a few days before the experiment. Through this email, the researcher explained the procedure in detail, the duration of the experiment and the research objectives. Also, the participants received instructions about their preparation for the experiment. Specifically, the participants were informed that they should not take any medication or substances that may affect their nervous system, or consume a large amount of caffeine or alcoholic beverages in the last 24 hours before the experiment. Also, they were instructed to wash their hair before the experiment and not to use any cosmetics for their hair (e.g., hairspray, gel, etc.) or hair cream as it may reduce the quality of the EEG signals. The participants were also instructed to sleep at least 8 hours the night before the experiment to feel relaxed. The participants that had a vision problem (e.g., myopia), was proposed to wear lenses during the experiment, if that was possible, to make it easier to apply the EEG cap. Finally, all participants were instructed to come for the experiment wearing a medical face mask due to Covid-19 regulations.

Before the experiment, each participant was requested to register on Coursity platform, in order to watch two video-lectures about Autism Spectrum Disorder via the MOOC platform (Coursity). Each video-lecture had a duration of about 15min. The participants were instructed to watch the video-lectures from their own place and to attend each lecture one or more times via the online platform. After that, the participants could choose through a doodle form, the day and the time that they wanted to come for the experiment.

During the experiment

The experimental procedure was completed in one session. The experiment took place at Coursity's office, at the Science & Technology Park of Epirus (Ioannina, Greece). After the arrival of the participant, the researcher briefly explained the experimental procedure and the participants were asked to read and sign a consent form. Each participant was first sited at the prep room and was provided with a wipe with 70% isopropyl alcohol to clean his/her forehead as well as the area behind their ears (mastoid bones). The researcher installed the electrode cap at the participants' head and carried out skull measurements to fit the cap properly. The Cz electrode location was found for each participant (according to the 10-20 reference system) and the cap was adjusted if needed. The reference and ground electrodes were placed at right and left mastoid respectively (Figure 6.13).

The g.NEEDaccess application was used to preview the signals before the recording in order for the researcher to correct any electrode that gave a signal with low quality. The researcher adjusted the placement of the electrodes to improve their contact with the skin. This was absolutely necessary because the electrodes that we used were dry and there was no conductive gel between the skin and the electrode. The researchers asked the participants to perform a set of actions, like blinking, chewing etc., in order to check the electrodes' contact quality, as well as to show the participants that any head or body movement creates large artifacts on the EEG signal, thus they should try to avoid facial expressions and body movements as much as they could.

Figure 6.13. A female participant while completing the activity

Afterwards, each participant was comfortably seated at eye level and about 100 cm away from a 22'' monitor in the test room. Before the beginning of the recording, the participants had a few minutes to adapt to the specific conditions, to relax and reduce the movements of their eyes. Each participant was familiarized with the environment of the MOOC platform for about 2 minutes.

During the experiment the participant's brain activity was recorded for two different conditions, the *baseline* and *task condition*. At baseline condition, the participants were instructed to stay calm and relaxed as much as possible, with their eyes open, without thinking something particular, for 2 minutes. This task served as a "reference task" against which the actual task was compared. After that, the participants took a 2-minute break. Before the task condition, the participants received instructions and information about the MOOC environment and the assessment activity that they were requested to complete. At task condition we recorded the participants' brain activity during the completion of the assessment activity. The researcher during the task condition kept notes about the participants' interaction with the learning environment and the assignment. Also, during the EEG data acquisition, the researcher was keeping notes about any particular or sudden event that would be useful to consider during data analysis. The participants were informed that there was not a time limit to complete the task.

When the participant finished the task, the researcher stopped the EEG acquisition at the recording computer and removed the cap from the participant's head. Then, participants were invited to complete a questionnaire to collect data about their demographics and their self-assessment of the task in terms of the perceived engagement and perceived effectiveness.

After the experiment

After each participant left the office, we cleaned the cap as well as all the surfaces using wipes with 70% isopropyl alcohol. Also, the researcher kept notes about participants' behavioral reactions during the task.

6.5. Data collection and analysis

6.5.1. EEG acquisition and subjective data collection

The EEG signals were recorded using a wireless EEG system (g.Nautilus). EEG raw data was recorded from Fp1, Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P3, Pz, P4, PO7, PO8, Oz electrode positions. The signals were referenced to the right mastoid. The EEG data acquisition system applied a digital bandpass 6^{th} order Butterworth filter (HP=0.1Hz and LP=60Hz) and a Notch filter at 50Hz to raw data. We note that the system allows to select either 250 Hz or 500 Hz as the sampling frequency. Because the frequency of the brain waves is approximately between 1Hz to 64Hz, we chose to apply a sampling frequency of 250Hz. EEG was recorded monopolarly from symmetrical frontal, central, parietal, occipital, and temporal lobes in the following conditions: "baseline with opened eyes" and "task". For each participant, the whole procedure lasted about 30-40 min, starting from the placement of the cap on participant's head until the completion of the session.

6.5.2. EEG pre-processing

Preprocessing is the first step in the process of offline signal analysis and is a necessary step before feature extraction. In preprocessing we aimed to produce artefact-free signals from the raw files that are recorded, by removing eye movements and other artefacts. In the present thesis, the EEG preprocessing was performed in Matlab (version 2017b, The MathWorks Inc), by using EEGLab toolbox (Delorme & Makeig, 2004). The preprocessing that we followed in the present thesis consisted of the following steps:

- Importing the raw data to EEGLab: EEG data were imported in the MATLAB R2017b (The MathWorks, Inc) environment and preprocessed by means of the open source EEGLAB toolbox (http://sccn.ucsd.edu/eeglab/). The recorded files were saved in .mat file format. In order to import the files into EEGLab we installed the necessary plugin that is provided by g.tec.

```
pop_eegfiltnew() - performing 827 point highpass filtering.
pop_eegfiltnew() - transition band width: 1 Hz
pop_eegfiltnew() - passband edge(s): 1 Hz
pop_eegfiltnew() - cutoff frequency(ies) (-6 dB): 0.5 Hz
pop_eegfiltnew() - filtering the data (zero-phase, non-causal)
firfilt(): |====================| 100%, ETE 00:00
Creating a new ALLEEG dataset 3
Done.
pop_eegfiltnew() - performing 111 point lowpass filtering.
pop_eegfiltnew() - transition band width: 7.5 Hz
pop_eegfiltnew() - passband edge(s): 30 Hz
pop_eegfiltnew() - cutoff frequency(ies) (-6 dB): 33.75 Hz
pop_eegfiltnew() - filtering the data (zero-phase, non-causal)
firfilt(): |====================| 100%, ETE 00:00
```

Figure 6.14. High-pass and low pass filters as shown in the MATLAB command window

- Filter: Raw EEG signals were digitally filtered in the band 1–30Hz by means of finite impulse response (FIR) filters. Specifically, we have applied a digital low-pass FIR filter (LP=30Hz) and a high-pass FIR filter (HP=1Hz) to the raw data to remove noise and muscular artifacts. We high-pass filtered the signals to remove slow drifts and have a better Independent Component Analysis (ICA) decomposition. The default filter implemented in EEGLAB is a zero phase Hamming-widowed sinc FIR filter. The length of the high-pass filter is 827, thus the filter order is 826 (i.e., filter length minus 1), while for the low-pass the order is 110. Figure 6.14 presents the parameters of the two filters such as, -6dB cutoff frequency, the pass-band edge, and the transition bandwidth. We did not apply a band-pass filter because high-pass filters often require narrower transition bands than low-pass filters.

- Artifact rejection: We performed visual inspection of the data to find channels that did not have a good signal quality in order to reject them. Power spectral density plots (spectopo function) of all channels were also examined in order to find the bad channels. Through visual inspection, we also rejected segments of the data that had large artifacts. Furthermore, we used EEGLAB function “Reject data using Clean Rawdata and ASR” with the default settings.
  In the present thesis, the data that were recorded from the electrode sites Fp1, Fp2, T7, T8, PO7, PO8 and Oz, were excluded from further analysis, as they were noisy enough for many participants. Due to use of dry electrodes, the size of the cap used for recording the EEG signals plays an important role in the quality of the recorded data. The above electrode sites were found to be more likely not to have a good contact with the skin.
- Independent Component Analysis (ICA): ICA employing the ‘runica’ algorithm was applied on the filtered signals in order to identify ocular artifacts (e.g., blinking and eyes lateral movements) sources. Bad ICA components were rejected by visual inspection of the component maps (IClabel) and power spectral density distributions (Figure 6.15).

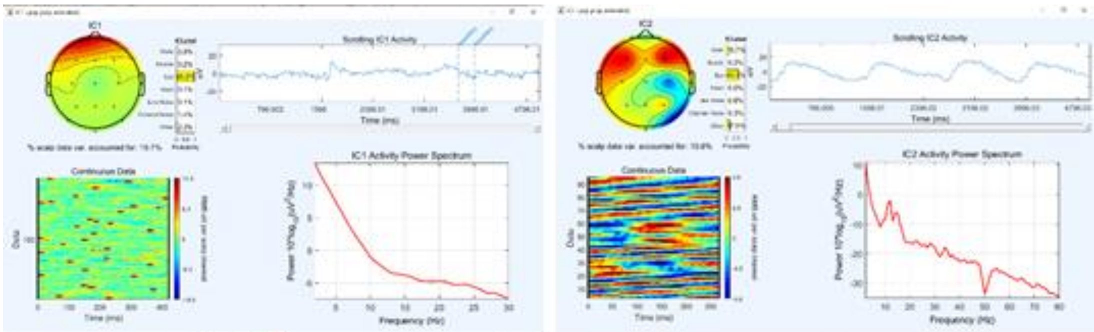


Figure 6.15. Artifactual ICA components. Blinking component (left) and lateral movements component (right) as suggested by ICLabel

We did not re-reference the data, after the recording, as the EEG signals were recorded from 16 electrodes placed on participant’s scalp which is not enough to provide a good coverage of the scalp in order to be able to convert the imported signals to the average reference.

For each participant, we have recorded two signals, one for the baseline condition and one for the task condition. We have followed the same procedure for all recorded signals, for each group (control/ experimental) and for each condition (baseline/ task).

6.5.3. Spectral analysis of EEG bands

In the present thesis the Welch periodogram method was used to compute an estimate of the power spectral density of the pre-processed EEG signals. The Welch method consists in averaging consecutive Fourier transform of small windows of the EEG signal with or without overlapping (Figure 6.16). In our case, the pwelch MATLAB function was performed on each channel to derive estimates of absolute spectral power in different frequency bands. Specifically, the bands of interest were theta (θ, 4–8Hz), alpha (α, 8–13Hz), beta (β, 13-30Hz) and low-beta (β1, 13-15Hz). We have considered a Hamming window of 2-sec with 50% overlap. This means that each channel of a signal was segmented into several overlapping and equal parts as described in detail in Chapter 4. The EEG data were segmented into 2-second windows overlapped by 50%. The resulting segments were multiplied by a Hamming window function to mitigate spectral leakage.

Figure 6.16. Welch's method feature extraction algorithm

For the FFT computation stage the algorithm takes the segments, in which the signal was divided, and computes a FFT in each of them. A FFT is used to extract 1-Hz bin power data segment for each channel.

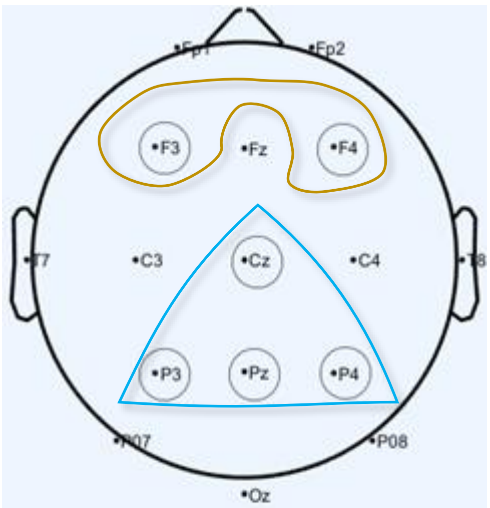


Figure 6.17. Two different groups of electrode sites are used for feature extraction. The electrodes are marked with a circle

As mentioned in the previous section, the data that were recorded from the electrode sites Fp1, Fp2, T7, T8, PO7, PO8 and Oz, were excluded from further analysis. For spectral analysis, frontal (F3, F4), parietal (P3, Pz, P4) and central (Cz) lobes were concerned.

Specifically, from each EEG file, two separate files were created by extracting a different group of electrodes. We created a file that consists of Cz, Pz, P3, P4 electrodes and a file that consists of F3, F4, P3, P4 (Figure 6.17).

Power Spectral Density (PSD) values for each electrode (i.e., Cz, Pz, P3, P4, F3, F4) in each band were averaged to obtain the power spectral features. Absolute and relative band powers were computed. Those values were further used to calculate ratios among the bands.

6.5.4. EEG feature extraction - Procedure and measurements

Feature extraction involves the process of describing the information about the brain activity by an ideally small number of relevant values. There are three main sources of information that can be extracted from EEG readings: spatial information (for multichannel EEG), spectral information (power in frequency bands) and temporal information (time windows-based analysis). In the present thesis the feature extraction was carried out using spectral analysis. In order to examine the participants' affective and cognitive states from their brain activity, we calculated the absolute and relative spectral power for each frequency band, in Cz, Pz, P3, P4, F3, F4 electrode sites:

- theta (θ, 4-8Hz)
- alpha (α, 8-13Hz)
- beta (β, 13-30Hz)
- low beta (β1, 13-15Hz).

Also, we calculated ratios between the above-mentioned frequency bands to obtain measures for assessing participants' level of engagement. We also have examined indices that are closely related to engagement such as attention, cognitive workload, arousal, and valence. We computed the above indices from absolute and relative band power values. The data analysis that was performed in the present thesis was a between-groups approach for the two groups: Group1(control group) vs Group2(experimental group), based on the baseline vs the task condition. Below we describe the ratios that were calculated. These ratios are described in detail in Chapter 5.

Engagement index

In the literature, several candidate indices were computed combining power values in the theta (θ, 4–8Hz), alpha (α, 8–13Hz), and beta (β, 13–22Hz) frequency bands, as they are considered to reflect cognitive engagement and to provide information on cognitive efforts. In the present thesis, we used the task engagement index proposed by Pope

(Freeman et al., 1999; Pope et al., 1995; Prinzel et al., 2000), i.e., $\beta/(\alpha+\theta)$, to evaluate participants' engagement. As it is obvious, the EEG measurement for task engagement is a ratio value without a unit. To calculate the values θ, α, and β of the index, we summed the absolute band power that was computed from the electrode sites Cz, Pz, P3, and P4. Also, we calculated the same index using the sum of the relative band power from the four electrodes.

This index, as described in Chapter 5, was built assuming that an increase in β power is related to an increase in brain activity during a cognitive task, whereas increases in α and θ activity is thought to be related with lower vigilance and alertness. Based on the relevant literature, this index has showed a great reliability in studies relevant to adaptive and automated task allocation (Chaouachi et al. 2010). In assessing learners' engagement in educational context, this index showed to provide an efficient assessment of learners' vigilance and cognitive attention (Chaouachi et al. 2010).

Attention index

We calculated an attention ratio as θ/β. This ratio is based on the assumption that an increase in alertness is related to an increase in beta power and a decrease in theta power (Gale & Edwards, 1983). The θ/β ratio is calculated as the sum of the absolute power in F3, F4 electrode sites, in the theta band (4-8Hz), divided by the sum of the absolute power in F3, F4 electrode sites, in the beta band (13-30Hz). This index is thought to be a potential biomarker for executive function, and in particular attentional processing (Angelidis et al. 2016). The theta/beta ratio has been negatively correlated with attention (Derbali & Frasson, 2012; Putman, 2010). This means that a larger value of this index is related to inattentive states.

Workload

The θ/α ratio (or Task Load Index, TLI) was calculated as an index for workload. This index is based on the assumption that an increase of cognitive load is associated with a decrease in alpha power and an increase in theta power (Gevins & Smith, 2003; Kamzanova, Kustubayeva & Matthews, 2014). The θ/a ratio was calculated as the sum of the absolute power in F3, F4 electrode sites, in the theta band (4-8Hz), divided by the sum of the absolute power in P3, P4 electrode sites, in the alpha band (8-13Hz).

Arousal and Valence

Arousal and valence were calculated based on the EEG signal from F3 and F4 electrodes site. Usually, researchers use four sites from prefrontal cortex i.e., AF3, AF4, F3, F4 (Diaz, Ramirez, Hernandez-Leo, 2015; Eldenfria & Al-Samarraie, 2019; Ramirez & Vamvakousis, 2012). Our apparatus could not provide measurement for AF3, AF4, thus, we measured the signals from the available site F3, F4. The arousal level was calculated as β/α. The ratio was calculated as the sum of the absolute power in F3, F4 electrode sites, in the beta band (13-30Hz), divided by the sum of the absolute power in F3, F4 electrode sites, in the alpha band (8-13Hz).

The ratio for estimating valence is based on the fact that left frontal inactivation is an indicator of a withdrawal response often linked to negative emotion and right frontal inactivation may be associated to an approach response or positive emotion (Aftanas et al., 2002, 2004; Pfurtscheller, 1999). Valence level was calculated with the following formula: Valence=$\alpha F4/\beta F4 - \alpha F3/\beta F3$ (Diaz, Ramirez, Hernandez-Leo, 2015). The ratio was calculated absolute powers of F3 and F4 electrode sites in the alpha band (8-13Hz) and in the beta band (13-30Hz).

We calculated the above values for the two recording conditions i.e., baseline and task. All data analyses were performed offline with MATLAB R2017b (The MathWorks, Inc) environment and custom code. Table 6.6. summarizes the measures that were calculated in this work.

Table 6.6. Neural measures that were calculated to assess learners' cognitive and affective states in the present thesis. Frontal area involves the recordings from F3 and F4 electrode sites, while parietal involves the recordings P3, Pz, and P4 electrodes

Frequency band power	**Frequency band power ratios**
Theta (frontal/ parietal)	Engagement: $\beta/(\alpha+\theta)$
Alpha (frontal/ parietal)	Attention: θ/β
Beta (frontal/ parietal)	Workload: θ/α
Beta low (frontal/ parietal)	Arousal: β/α
	Valence: $\alpha F4/\beta F4 - \alpha F3/\beta F3$

Finally, in the present work, we compare the participants' mental engagement with their subjective estimation of perceived engagement.

Chapter 7. Results

7.1. Introduction

In this chapter we present the results of the thesis. The results are separated into two sections based on the data used for analysis. In the section 7.2 we present the results that were generated by the participants' neural data. We examine and compare the values of absolute and relative power of four frequency bands, namely theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and low-beta (13-15Hz). These values were extracted from the spectral analysis of the recorded EEG signals for both groups: control group and experimental group, and in each condition: baseline and task. In the section 7.3. we present the results that were obtained from participants' answers on the self-reported engagement questionnaire. We analyze the results regarding each one of the five engagement factors, namely Challenge, Control, Interest, Immersion, Purpose. We also compare the overall values of perceived engagement between the two groups. Additionally, we investigate possible differences between the two groups in terms of perceived usefulness, perceived learning effectiveness, perceived cognitive benefits, and intention to continue the course.

The goal of this work is to investigate whether the measures defined in Chapter 6 could be used to characterize participants' learning experience in a MOOC activity. Moreover, we aim to evaluate the effect of the proposed gamification design on participants' cognitive states and assess whether the neural data agree with the subjective data in terms of engagement.

Data collected are described by the use of means and standard deviations as far as scale measurements are concerned, such as the engagement values, their normalized transformations, power values of frequency bands in the parietal and frontal areas, and the dimensions of the questionnaire, while frequencies and percentages were used for categorical data such as group membership or former course attendance. The independent samples t-test was used for comparisons between groups in all outcome measurements, while the paired samples t-test was used to assess the differences between the measurements in baseline and task condition of the experiment. The Shapiro Wilk test was used to assess the normality assumption in all cases. Correlations between scale measurements such as engagement values, θ frontal and α parietal power values were analyzed with the Pearson correlation coefficient. The statistical significance was set at 0.05 in all cases and all analyses were carried out with the use of SPSS v.23.0.

7.2. Comparing learners' cognitive state in a MOOC activity (neural data)

7.2.1. Comparison of the engagement values

In this section, we present the results that were generated from the participants' EEG signals. We present the results for the control and the experimental group, and for each condition, namely baseline and task. The engagement values were calculated as the ratio $\beta/(\alpha+\theta)$ using the absolute band power values as well as the relative band power values of θ (4-8Hz), α (8-13Hz) and β (13-22Hz) bands from Cz, P3, Pz, P4 electrodes. The absolute power of a band is the integral of all of the power values within its frequency range while the relative power of a band was derived by dividing the absolute power in these frequency band with the absolute power of the total frequency range. The following tables show the results of the comparison between the values in baseline and task condition, for each group separately. The normalized values of engagement are also compared (i.e., (task_value-baseline_value)/baseline_value). The engagement values are studied in order to assess the effect of the proposed gamification design on the participants' task engagement in the experimental group (Group2-GR2) in comparison to participants' task engagement in the control group (Group1-GR1).

Engagement values comparison between groups in the baseline condition

Table 7.1 presents the comparison of the engagement values in the baseline condition, for each group of the present thesis. Specifically, the Table 7.1 shows the mean value of engagement that was calculated from the relative and the absolute power values. The estimated mean for each of the two groups appears under the label "Mean" followed by the respective estimation of the standard deviation.

Table 7.1. Comparison of the engagement values in baseline condition for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
EngIdx_rel Baseline	GR1	28	,246	,075	,014	,173
	GR2	30	,216	,091	,017	
EngIdx_abs Baseline	GR1	28	,242	,077	,015	,193
	GR2	30	,211	,097	,018	

We compare the engagement values in the baseline condition to investigate whether the two groups differ in their participants' level of engagement before participating in the activity. The comparison of the engagement values of the two groups showed no statistically significant differences neither for the values of the engagement score that were calculated from relative power values (p=0.173), nor for the values of the engagement score calculated from the absolute power values (p=0.193).

Engagement values comparison between groups in the task condition

Respectively, in Table 7.2 we present the results that were obtained from the values of engagement in the task condition. The results show whether the proposed gamification design and subsequently the implementation of the progression element in the MOOC activity affected the level of participants' engagement. Specifically, Table 7.2 describes the mean value of the engagement scores in the task condition for each group. It is quite evident, even by the intuitive inspection of the means and standard deviations, that no differences between the two groups are observed. The conclusion is verified by the relative analysis that leads to a p-value of 0.471 for the engagement scores that were calculated from the relative power values and a p-value equal to 0.528 for the engagement scores that were calculated from the absolute power values.

Table 7.2. Comparison of the engagement values in task condition for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
EngIdx_rel Task	GR1	28	,228	,066	,013	,471
	GR2	30	,216	,058	,011	
EngIdx_abs Task	GR1	28	,228	,068	,013	,528
	GR2	30	,218	,059	,011	

Engagement values comparison between task and baseline condition by group

Apart from the baseline and task comparison of the two groups, a comparison is made to examine the change that was observed in each group separately. The obtained engagement scores, calculated from the relative and the absolute power values, for Group1 appear in Table 7.3, while the respective estimations for Group2 appear in Table 7.4. The p-values appearing on the last column of each table show that neither for the two measurements (i.e., baseline and task), nor for the groups the observed change is statistically significant. Therefore, the changes observed in both conditions and for both groups are similar and not statistically significant.

Table 7.3. Paired comparisons of engagement values in baseline and task conditions for Group1

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	EngIdx_rel Task	,228	28	,066	,013	,128
	EngIdx_rel Baseline	,246	28	,075	,014	
Pair 2	EngIdx_abs Task	,228	28	,068	,013	,297
	EngIdx_abs Baseline	,242	28	,077	,015	
a. Group = GR1						

Table 7.4. Paired comparisons of engagement values in baseline and task conditions for Group2

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	EngIdx_rel Task	,216	30	,058	,011	,977
	EngIdx_rel Baseline	,216	30	,091	,017	
Pair 2	EngIdx_abs Task	,218	30	,059	,011	,644
	EngIdx_abs Baseline	,211	30	,097	,018	
a. Group = GR2						

Normalized engagement values comparison between groups

As engagement indices are dimensionless and their values are subject dependent, it is important to consider values corresponding to the task condition with respect to an individual baseline (rest) condition (Coelli et al., 2018). Therefore, another comparison made, regarded the normalized changes in the engagement values, i.e., (task_value-baseline_value)/baseline_value. These comparisons also did not result in statistically significant differences. The p-value was 0.099 for the normalized engagement values calculated from the relative power values and 0.073 for the normalized engagement values that were calculated from the absolute power values. These estimations appear in Table 7.5.

Table 7.5. Comparison of the normalized engagement values for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
Normalized EngIdx_Rel	GR1	28	-,024	,294	,056	,099
	GR2	30	,167	,531	,097	
Normalized EngIdx_Abs	GR1	28	,014	,368	,070	,073
	GR2	30	,328	,838	,153	

The non-statistically significant differences between the two groups are depicted in the comparative boxplots of Figures 7.1–7.2. Although, the differences between the normalized engagement values are not significant, neither for the relative values nor for the absolute values, they are depicted because engagement is the main index in this thesis.

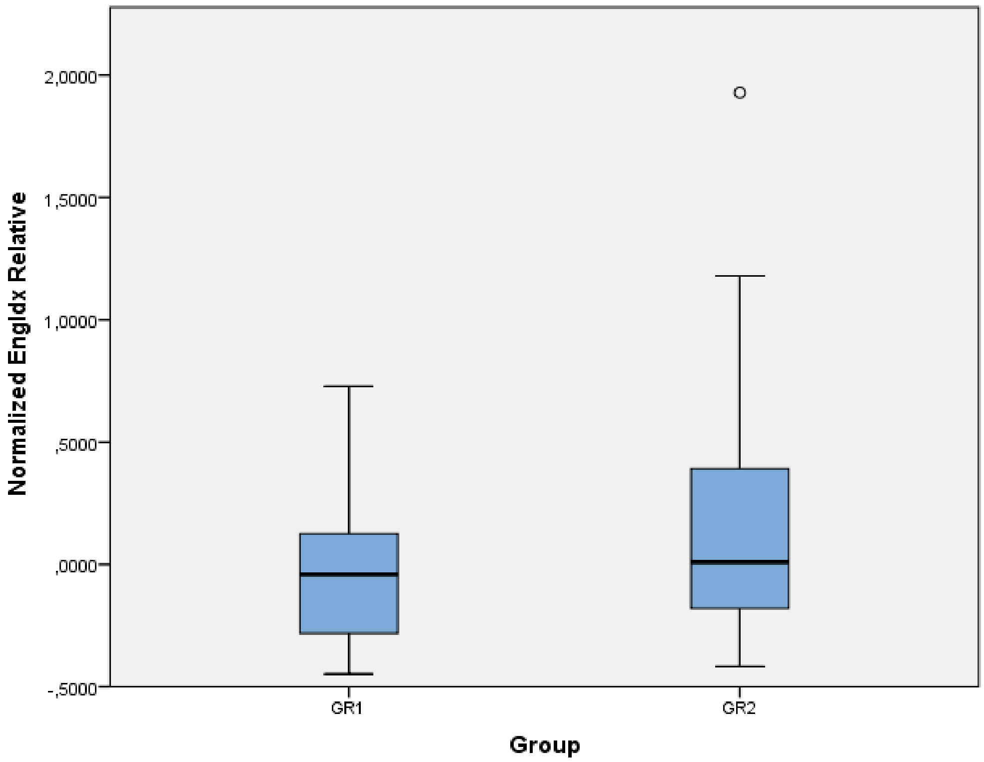


Figure 7.1. Comparative boxplot of normalized engagement values (from the relative power values)

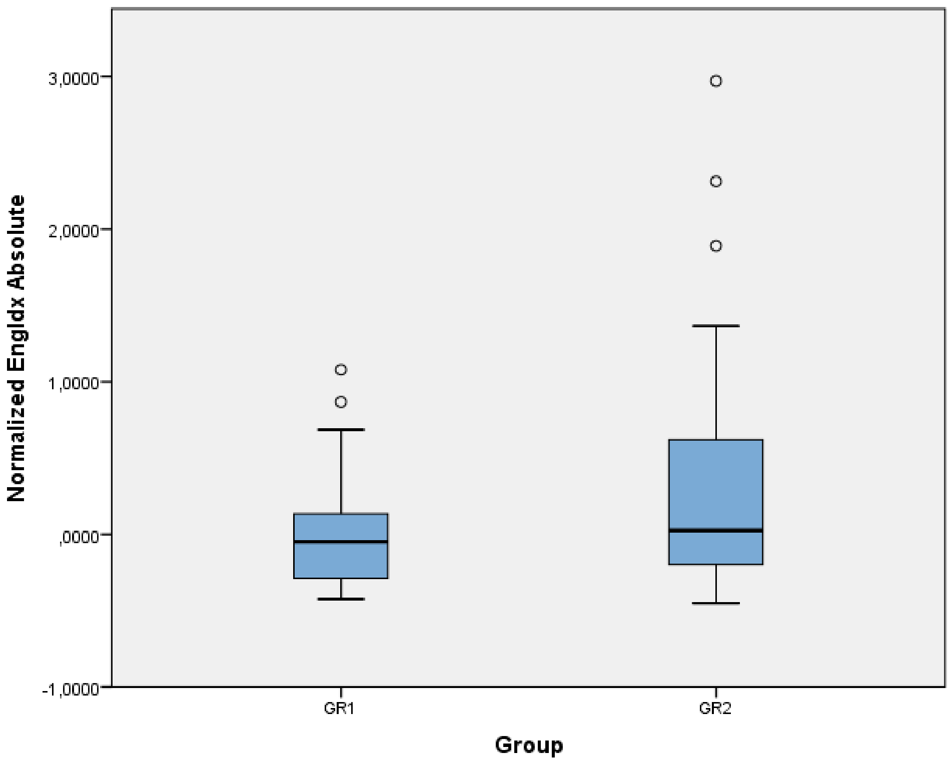


Figure 7.2. Comparative boxplot of normalized engagement values (from the absolute power values)

7.2.2. Comparison of the attention values

In this section we present the results that were obtained from the participants' EEG signals for both groups. The attention values that are presented in the following tables were calculated as the ratio θ/β of the absolute power values in θ (4-8Hz) and β (13-30Hz) bands, recorded at F3 and F4 electrodes. Also, using the same ratio, we calculated attention values, from the absolute power values of low β (13-15Hz) frequency bands. We named the values of the latter index as attention_low to distinguish them from the values of the former index. It should be noted that high attention ratio values are correlated with excessive θ power and consequently with inattentive state, while low attention ratio values are correlated with excessive β power and consequently with attentive state.

In the following tables, we present the results of the comparison between the baseline and task values of the attention index, for each group.

Attention values comparison between groups in the baseline condition

In Table 7.6 the comparison of attention index values in the baseline condition are presented for each group. We compare participants' attention values in the baseline condition to examine whether the two groups differ in their level of attention before the activity. Specifically, Table 7.6 shows the mean value of the attention scores for both indices, in the baseline. The estimated mean for each of the two groups appears under the label "Mean" followed by the respective estimation of the standard deviation. The comparison of the values of the two groups showed no statistically significant differences neither for the values of the attention score (p=0.274) nor for the values of the attention_low score (p=0.317).

Table 7.6. Comparison of attention scores in baseline condition for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-values
Baseline Attention	GR1	28	4,050	2,589	,489	,274
	GR2	30	5,530	6,631	1,211	
Baseline Attention_low	GR1	28	2,788	1,630	,308	,317
	GR2	30	3,428	2,959	,540	

Attention values comparison between groups in the task condition

Table 7.7 describes the mean values of the above indices in the task condition for each group. As in the case of the baseline comparisons, no differences between the two groups are observed. The conclusion is verified by the statistical analysis that leads to a p-value of 0.217 for the attention score and a p-value equal to 0.574 for the attention_low score.

Table 7.7. Comparison of attention scores in task condition for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-values
Task Attention	GR1	28	4,156	1,789	,338	,217
	GR2	30	4,844	2,352	,429	
Task Attention_low	GR1	28	3,048	1,122	,212	,574
	GR2	30	3,235	1,376	,251	

Attention values comparison between task and baseline condition by group

Apart from the baseline and task comparison of the two groups, a comparison is made to examine the change that was observed in the attention level between the two conditions in each group separately. The obtained scores of attention and attention_low for Group1 appear in Table 7.8, while the respective estimations for Group2 appear in Table 7.9. The p-values appearing on the last column of each table show that for neither of the two measurements and for neither of the groups the observed change is statistically significant and therefore the changes observed for both conditions and in both groups are similar and not statistically significant.

Table 7.8. Paired comparisons of attention scores in baseline and task conditions for Group1

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	Task Attention	4,156	28	1,789	,338	,840
	Baseline Attention	4,050	28	2,589	,489	
Pair 2	Task Attention_low	3,048	28	1,122	,212	,428
	Baseline Attention_low	2,788	28	1,630	,308	
a. Group = GR1						

Table 7.9. Paired comparisons of attention values in baseline and task conditions for Group2

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	Task Attention	4,844	30	2,352	,429	,505
	Baseline Attention	5,530	30	6,631	1,211	
Pair 2	Task Attention_low	3,235	30	1,376	,251	,657
	Baseline Attention_low	3,428	30	2,959	,540	
a. Group = GR2						

Normalized attention values comparison between groups

Another comparison made, regarded the normalized changes in the attention values, i.e., (task_value-baseline_value)/baseline_value. These comparisons also showed not statistically significant differences with a p-value of 0.792 for the normalized attention values and of 0.862 for the normalized attention_low values. These estimations appear on Table 7.10.

Table 7.10. Descriptive statistics for normalized attention values for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
Normalized Attention	GR1	28	,148	,434	,082	,792
	GR2	30	,187	,638	,117	
Normalized Attention_low	GR1	28	,203	,398	,075	,862
	GR2	30	,181	,545	,099	

Correlation between attention values and engagement values

Regarding the attention scores, a correlation coefficient was estimated to examine a potential relationship between the changes that were observed in the attention values with the changes in the engagement values. The changes were defined as the differences of task scores minus baseline scores. For this correlation we used the engagement values that were calculated from the absolute band power values. The correlation was found to be statistically significant for both indices of attention in the experimental group (Group2). The p-value for the correlation of the attention difference to the engagement difference equals 0.013 with correlation coefficient equal to -0.446 and the p-value for the correlation of the attention_low difference to the engagement difference equals 0.003 with correlation coefficient equal to -0.523 (Table 7.11).

In both cases the correlation is negative showing that an increase in the attention scores is followed by a decrease in the engagement scores. The inference stands for both attention and attention_low scores. The relevant relationships are depicted on the scatterplots of Figures 7.3 and 7.4. Even though the relationships are similar in both groups, it is stressed out that they are statistically significant only for the experimental group (Group2).

Table 7.11. Correlation between attention difference and engagement difference

Group			Engagement Difference		
			Correlation Coefficient	Sig. (2-tailed)	N
Spearman's Rho	GR1	Attention Difference	-,311	,107	28
		Attention_low Difference	-,304	,116	28
	GR2	Attention Difference	-,446	**,013***	30
		Attention_low Difference	-,523	**,003***	30

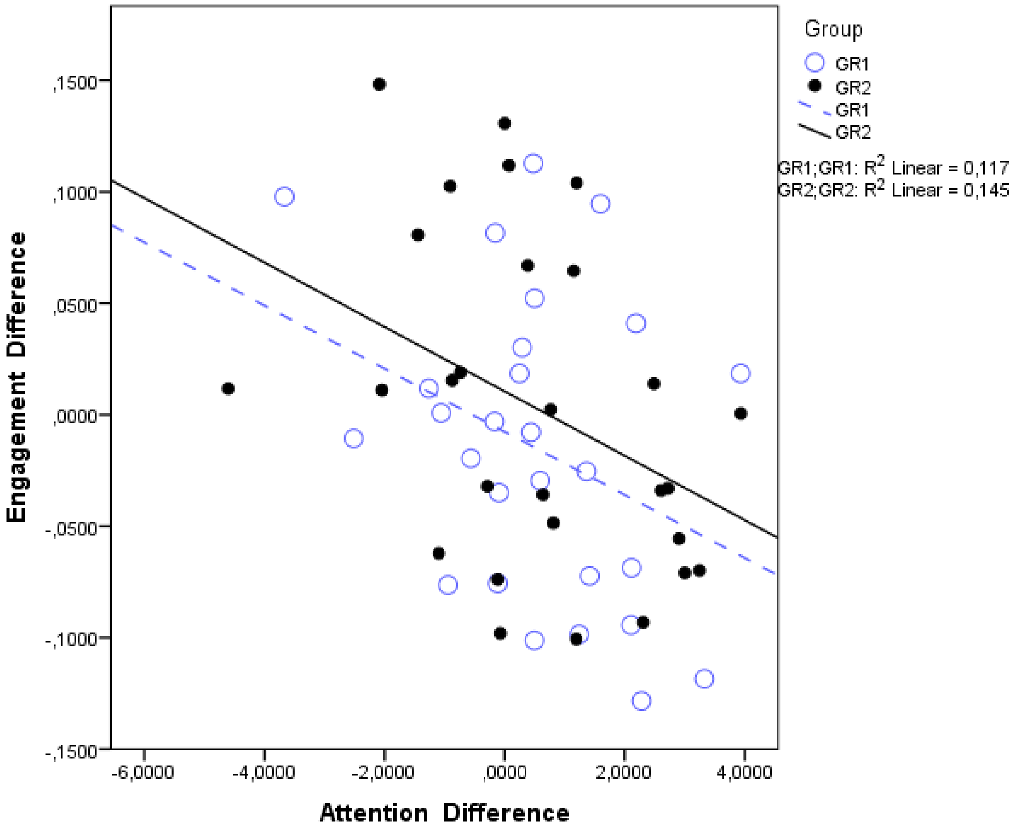


Figure 7.3. Scatterplot of attention score differences vs engagement score differences

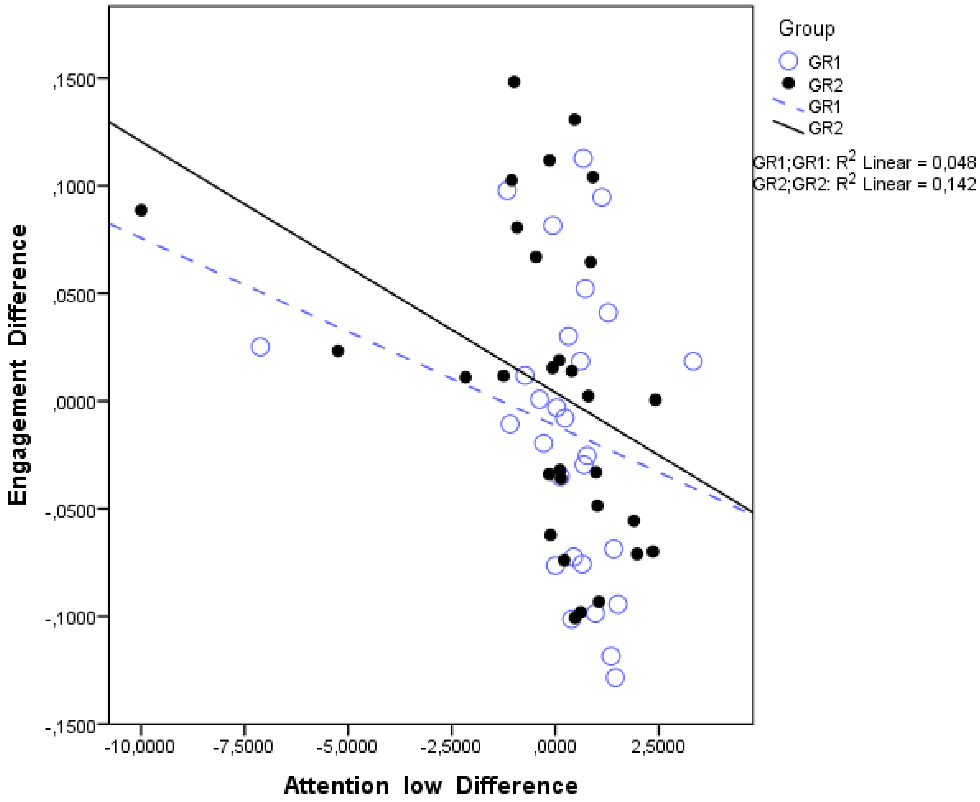


Figure 7.4. Scatterplot of attention_low score differences vs engagement score differences

7.2.3. Comparison of the workload values

The workload values we present in this section have been calculated as the ratio θ/α of the absolute power values of θ (4-8Hz) band from electrode sites F3 and F4, and of α (8-13Hz) band from electrode sites P3 and P4.

Workload values comparison in baseline and task condition between groups

Table 7.12 shows the mean value of the workload index in the baseline condition but also in the task condition. The estimated mean for each of the two groups appears under the label "Mean" followed by the respective estimation of the standard deviation. The comparison of the values of the two groups showed no statistically significant differences neither for the values at the baseline (p=0.496), nor at the task (p=0.583).

Table 7.12. Comparison of workload values in baseline and task condition for each group

	Group	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**p-value**
Baseline Workload	GR1	28	1,378	1,778	,336	,496
	GR2	30	1,097	1,332	,243	
Task Workload	GR1	28	1,675	1,250	,236	,583
	GR2	30	1,494	1,245	,227	

Workload values comparison between task and baseline condition by group

Apart from the baseline and task values comparison of the two groups, a comparison is made to examine the change that was observed between the two conditions in each group separately. The changes in the obtained scores of the workload appear in Table 7.13 for both groups. The p-values appearing on the last column of the Table 7.13 show that there is a statistically significant increase observed in the experimental group (p=0.005) but not in the control group (p=0.335).

Table 7.13. Paired comparisons of workload values in baseline and task conditions by group

		Mean	**N**	**Std. Deviation**	**Std. Error Mean**	**p-value**
Group 1	Task Workload	1,675	28	1,250	,236	,335
	Baseline Workload	1,378	28	1,778	,336	
Group 2	Task Workload	1,494	30	1,245	,227	**,005***
	Baseline Workload	1,097	30	1,332	,243	

The statistically significant change observed between the two conditions are depicted in the comparative boxplot of Figure 7.5.

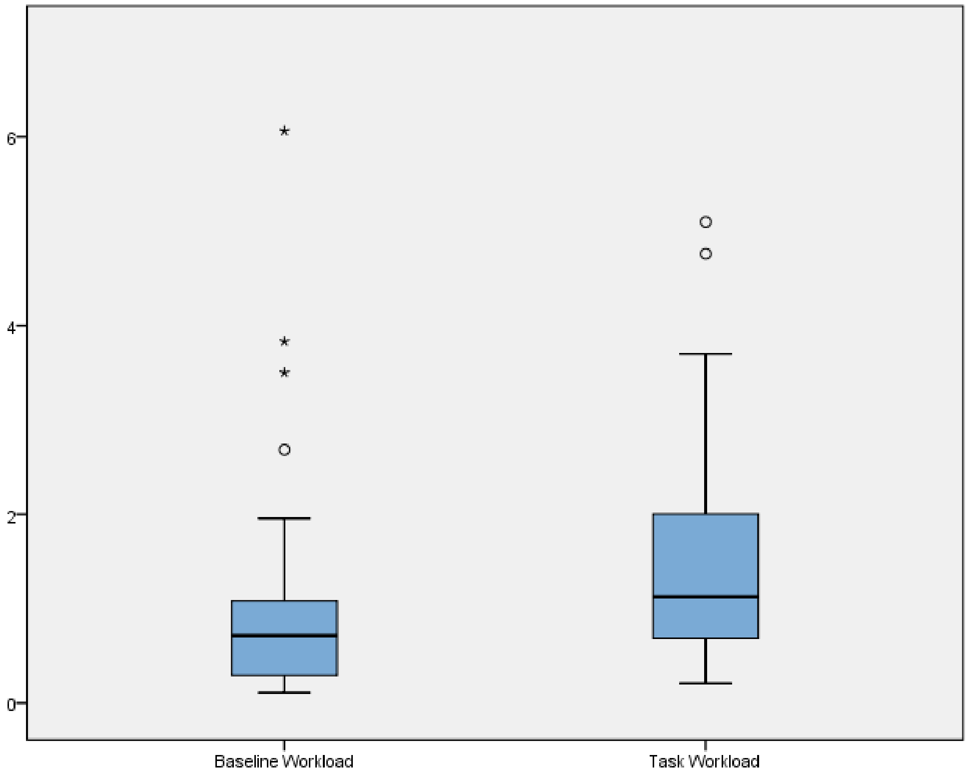


Figure 7.5. Comparative boxplot of the workload scores in baseline and task condition for Group2

Normalized workload values comparison between groups

Another comparison made, regarded the normalized values in the workload, i.e., the (task_value-baseline_value)/baseline_value. These comparisons also showed not statistically significant differences with a p-value of 0.925 for the normalized workload index. These estimations appear on Table 7.14.

Table 7.14. Descriptive statistics for normalized workload values for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
Normalized Workload	GR1	28	1,392	2,430	,459	,925
	GR2	30	1,335	2,184	,399	

Correlation between workload values and engagement values

Regarding the workload score a correlation coefficient was estimated to examine a potential relationship between the differences observed in its values with the changes in the engagement value. For the engagement we have consider the values calculated from the absolute band power. The correlation was found to be non-statistically significant for both groups. The p-value for the correlations equals 0.648 for the control group and 0.590 for the experimental group (Table 7.15).

Table 7.15. Correlation between workload values and engagement values

Group			Engagement Difference		
			Correlation Coefficient	Sig. (2-tailed)	N
Spearman's Rho	GR1	Workload Difference	,090	,648	28
	GR2	Workload Difference	,103	,590	30

These non-statistically significant correlations are depicted in Figure 7.6.

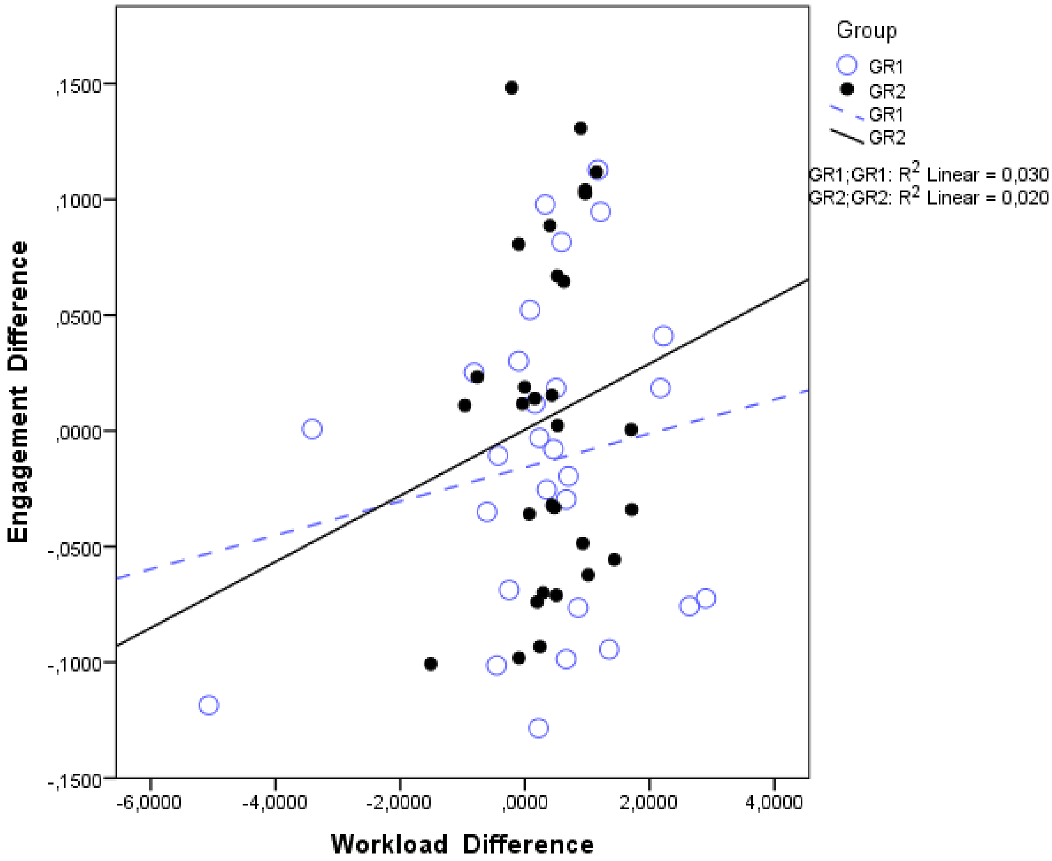


Figure 7.6. Scatterplot of workload score differences vs engagement score differences

7.2.4. Comparison of the arousal and valence values

The arousal values presented in this section were calculated as the ratio β/α of the absolute band power values in β (13-30Hz) and in α (8-13Hz) from electrode sites F3 and F4. The valence values were calculated as the difference between two ratios: αF4/βF4-αF3/βF3. The absolute band power values in β (13-30Hz) and in α (8-13Hz) from electrode sites F3 and F4 were used for the calculation of valence.

Arousal and valence values comparison between groups in the baseline condition

Table 7.16 shows the mean value of the arousal and valence values in the baseline condition. The estimated mean for each group appears under the label "Mean" followed by the respective estimation of the standard deviation. The comparison of the values of the two groups showed no statistically significant differences neither for the values of the arousal score (p=0.475) nor for the values of the valence score (p=0.113).

Table 7.16. Comparison of arousal and valence values in baseline condition for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
Baseline Arousal	GR1	28	,464	,186	,035	,475
	GR2	30	,423	,242	,044	
Baseline Valence	GR1	28	-,097	,384	,073	,113
	GR2	30	,648	2,428	,443	

Arousal and valence values comparison between groups in the task condition

Table 7.17 describes the mean of the above indices in task condition. As in the case of the baseline comparisons, no differences between the two groups are observed. The conclusion is verified by the statistical analysis that leads to a p-value of 0.612 for the arousal score and a p-value equal to 0.213 for the valence score.

Table 7.17. Comparison of arousal and valence values in task condition for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
Task Arousal	GR1	28	,519	,162	,031	,612
	GR2	30	,490	,256	,047	
Task Valence	GR1	28	-,092	,381	,072	,213
	GR2	30	,016	,264	,048	

Arousal and valence values comparison between task and baseline condition by group

Apart from the baseline and task comparison of the two groups, a comparison is made to examine the change that was observed in each of the two groups separately. The obtained scores of the arousal and the valence change for Group1 appear in Table 7.18, while the respective estimations for Group2 appear in Table 7.19. The p-values appearing on the last column of each table show that for both groups the observed changes in the arousal measurements are statistically significant and therefore the observed increase occurs in both groups (p=0.043 for the control and 0.049 for the experimental). The valence scores remain similar in both groups.

Table 7.18. Paired comparisons of arousal and valence values for baseline and task conditions in Group1

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	Task Arousal	,519	28	,162	,031	**,043***
	Baseline Arousal	,464	28	,186	,035	
Pair 2	Task Valence	-,092	28	,381	,072	,947
	Baseline Valence	-,097	28	,384	,073	
a. Group = GR1						

Table 7.19. Paired comparisons of arousal and valence values for baseline and task conditions in Group2

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	Task Arousal	,490	30	,256	,047	**,049***
	Baseline Arousal	,423	30	,242	,044	
Pair 2	Task Valence	,016	30	,264	,048	,176
	Baseline Valence	,648	30	2,424	,443	
a. Group = GR2						

Normalized arousal and valence values comparison between groups

Another comparison regarded the normalized changes in the arousal and valence scores, i.e., (task_value-baseline_value)/baseline_value. These comparisons also did not show statistically significant differences with a p-value of 0.223 for the normalized arousal values and of 0.218 for the normalized valence values. These estimations appear in Table 7.20.

Table 7.20. Comparison of normalized arousal and valence values for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
Normalized Arousal	GR1	28	,245	,429	,081	,223
	GR2	30	,462	,834	,152	
Normalized Valence	GR1	28	-,254	7,867	1,487	,218
	GR2	30	-4,398	15,866	2,897	

Correlation between arousal values and engagement values

Regarding the arousal score, a correlation coefficient was estimated to examine a potential relationship between the differences observed in its values with the changes in the engagement difference. For the engagement we have consider the values calculated from the absolute band power values. The correlation was found to be statistically significant for both groups. The p-value for the correlations equals 0.000 for the control group and 0.003 for the experimental group (Table 7.21).

Table 7.21. Correlations between arousal and engagement differences

Group			**Engagement Difference**		
			Correlation Coefficient	Sig. (2-tailed)	N
Spearman's Rho	GR1	Arousal Difference	,627	**,000***	28
	GR2	Arousal Difference	,519	**,003***	30

These, statistically significant correlations are depicted in Figure 7.7.

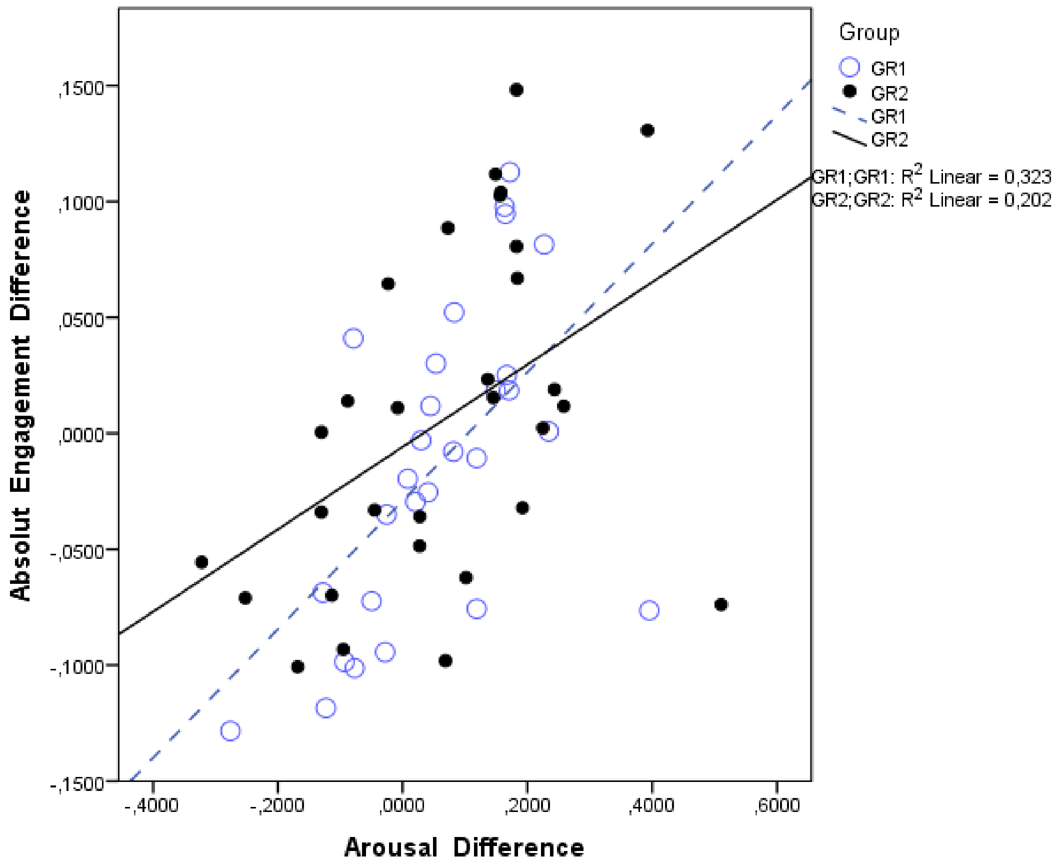


Figure 7.7. Scatterplot of arousal differences vs engagement differences

Correlation between valence values and engagement values

Regarding the valence score, a correlation coefficient was estimated to examine a potential relationship between the differences observed in its values with the changes in the engagement values. For the engagement we have considered the values calculated from the absolute band power values. The correlation was found to be non-statistically significant for both groups. The p-value for the correlations equals 0.148 for the control group and 0.121 for the experimental group (Table 7.22).

Table 7.22. Correlations between valence and engagement differences

Group			**Engagement Difference**		
			Correlation Coefficient	Sig. (2-tailed)	N
Spearman's Rho	GR1	Valence Difference	,281	,148	28
	GR2	Valence Difference	-,295	,121	30

These non-statistically significant correlations are depicted in Figure 7.8. One single outlier measurement was excluded to enhance to optical representation.

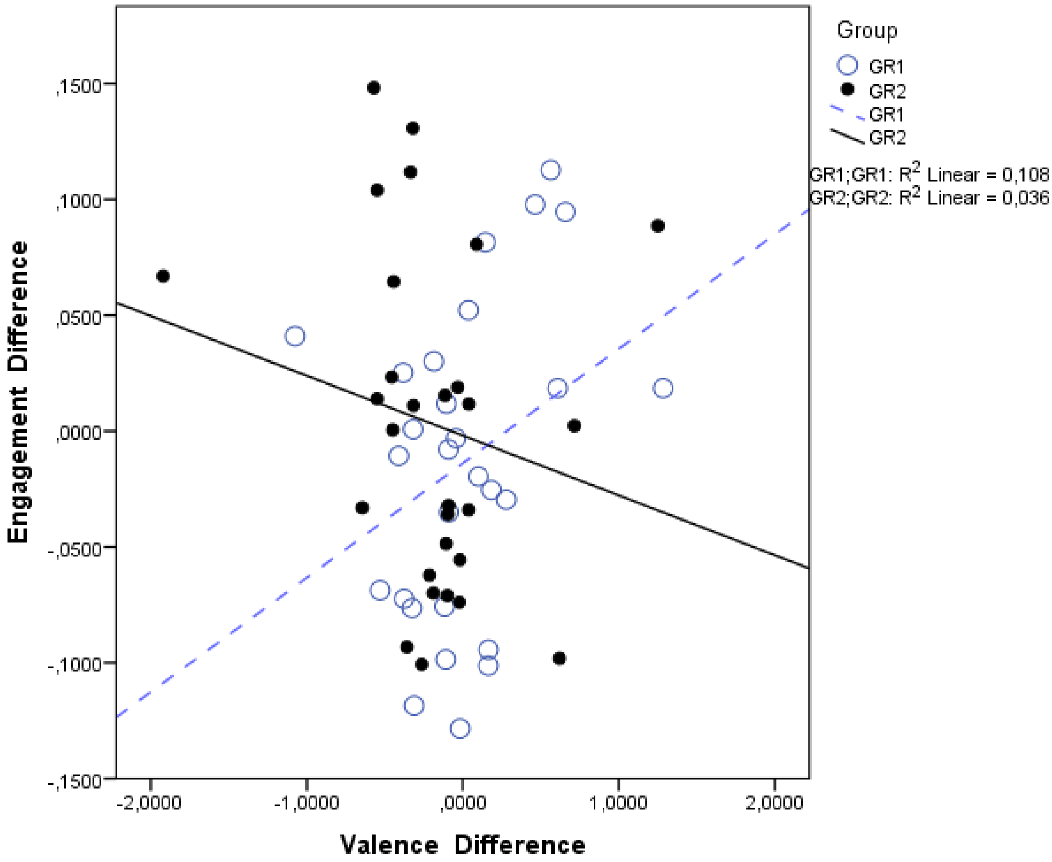


Figure 7.8. Scatterplot of valence differences vs engagement differences

7.2.5 Comparison of the θ, α, β power values in frontal and parietal areas

Tables 7.23 and 7.24 show the mean value of the absolute and relative band power values of θ, α, β and β_low in the parietal brain area, in the baseline and the task condition, for each group. We calculated each value in θ, α, β and β_low as the sum of the power values from P3, Pz, and P4 electrodes. The estimated mean for each group appears under the label "Mean" followed by the respective estimation of the standard deviation. The comparison of the power values in θ, α, β and β low band between the two conditions showed a significant decrease for the θ parietal (control, p=0.029; experimental p=0.006), α parietal (control, p=0.003; experimental p=0.002), the β parietal (control, p=0.026; experimental p=0.002), β_low parietal (control, p=0.074, *NS*; experimental p=0.001) and the relative α parietal (control, p=0.004; experimental p=0.001). Moreover, a statistically significant increase was observed for the relative θ parietal (control, p=0.001; experimental p=0.001). Except for the β_low parietal measurement that has a significant change only in the experimental group, in the two groups, the changes observed was almost identical.

Table 7.23. Paired comparison of power values in θ, α, β, β_low bands for baseline and task conditions in Group1. The values concern the parietal area.

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	θ Parietal Task	15,025	28	15,759	2,978	**,029***
	θ Parietal Baseline	21,207	28	20,423	3,859	
Pair 2	α Parietal Task	9,436	28	8,344	1,577	**003***
	α Parietal Baseline	17,498	28	14,865	2,809	
Pair 3	β Parietal Task	4,525	28	3,759	,710	**,026***
	β Parietal Baseline	7,024	28	7,016	1,326	
Pair 4	β low Parietal Task	6,782	28	6,097	1,152	,074
	β low Parietal Baseline	13,148	28	19,939	3,768	
Pair 5	θ_ParietalRel Task	1,506	28	,264	,049	**001***
	θ_ParietalRel Baseline	1,321	28	,285	,054	
Pair 6	α_ParietalRel Task	1,000	28	,238	,045	**,004***
	α_ParietalRel Baseline	1,180	28	,362	,068	
Pair 7	β_ParietalRel Task	,494	28	,150	,028	,834
	β_ParietalRel Baseline	,500	28	,170	,032	
Pair 8	β_low_ParietalRel Task	,709	28	,202	,038	,183
	β_low_ParietalRel Baseline	,781	28	,290	,055	
a. Group = GR1						

Table 7.24. Paired comparison of power values in θ, α, β, β_low bands for baseline and task conditions in Group2. The values concern the parietal area

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	θ Parietal Task	13,132	30	8,398	1,533	**,006***
	θ Parietal Baseline	22,468	30	19,906	3,634	
Pair 2	α Parietal Task	9,409	30	5,938	1,084	**,002***
	α Parietal Baseline	29,758	30	36,605	6,683	
Pair 3	β Parietal Task	3,942	30	2,485	,454	**,002***
	β Parietal Baseline	6,247	30	3,859	,705	
Pair 4	β low Parietal Task	6,211	30	4,006	,731	**,001***
	β low Parietal Baseline	10,434	30	6,393	1,167	
Pair 5	θ_ParietalRel Task	1,464	30	,224	,041	**,001***
	θ_ParietalRel Baseline	1,253	30	,416	,076	
Pair 6	α_ParietalRel Task	1,069	30	,226	,041	**,001***
	α_ParietalRel Baseline	1,321	30	,518	,095	
Pair 7	β_ParietalRel Task	,468	30	,133	,024	,099
	β_ParietalRel Baseline	,426	30	,198	,036	
Pair 8	β_low_ParietalRel Task	,712	30	,1738	,032	,989
	β_low_ParietalRel Baseline	,713	30	,369	,067	
a. Group = GR2						

All the differences described in detail in Table 8.25 and Table 8.26 are depicted on the comparative boxplots in Figures 7.9-7.14.

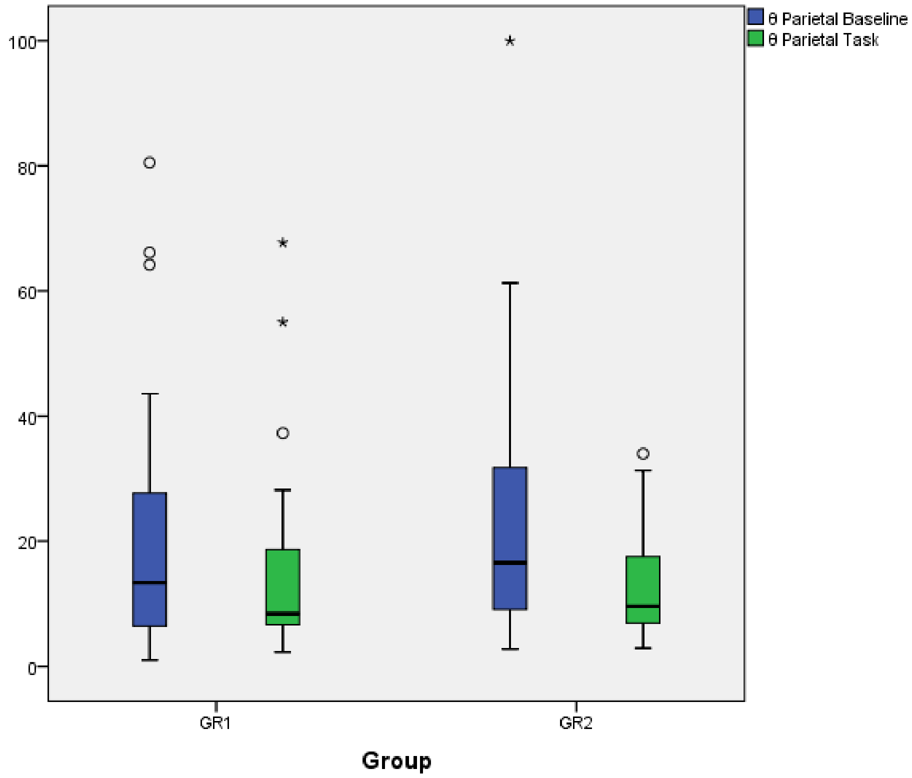


Figure 7.9. Boxplot of absolute power of θ band from parietal area for baseline and task condition for each group

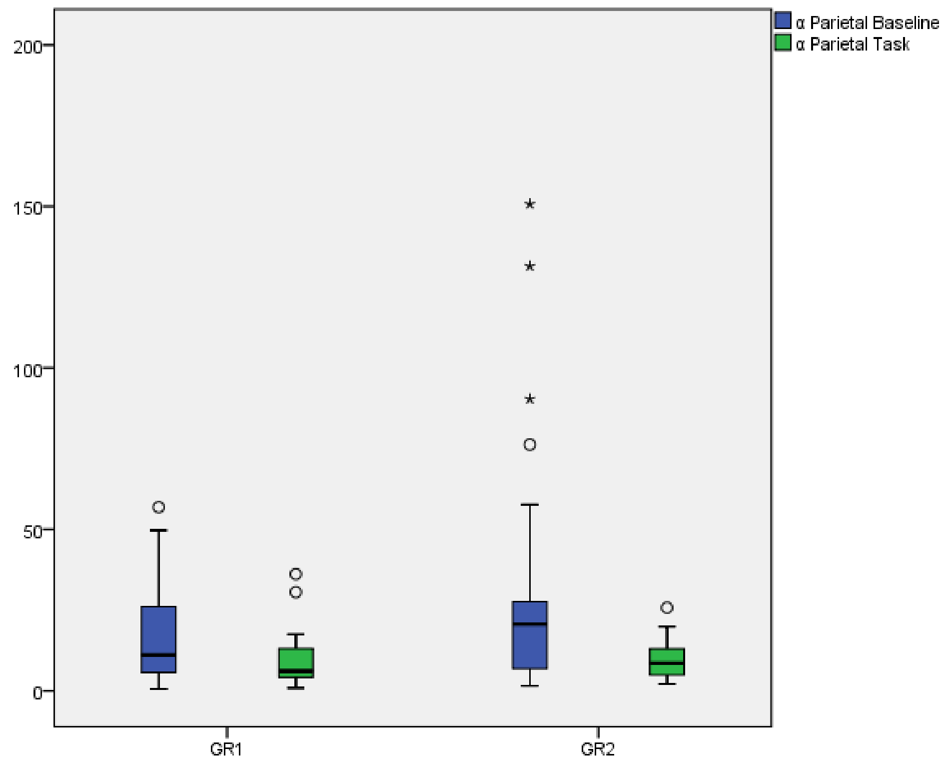


Figure 7.10. Boxplot of absolute power in α band from parietal area for baseline and task condition for each group

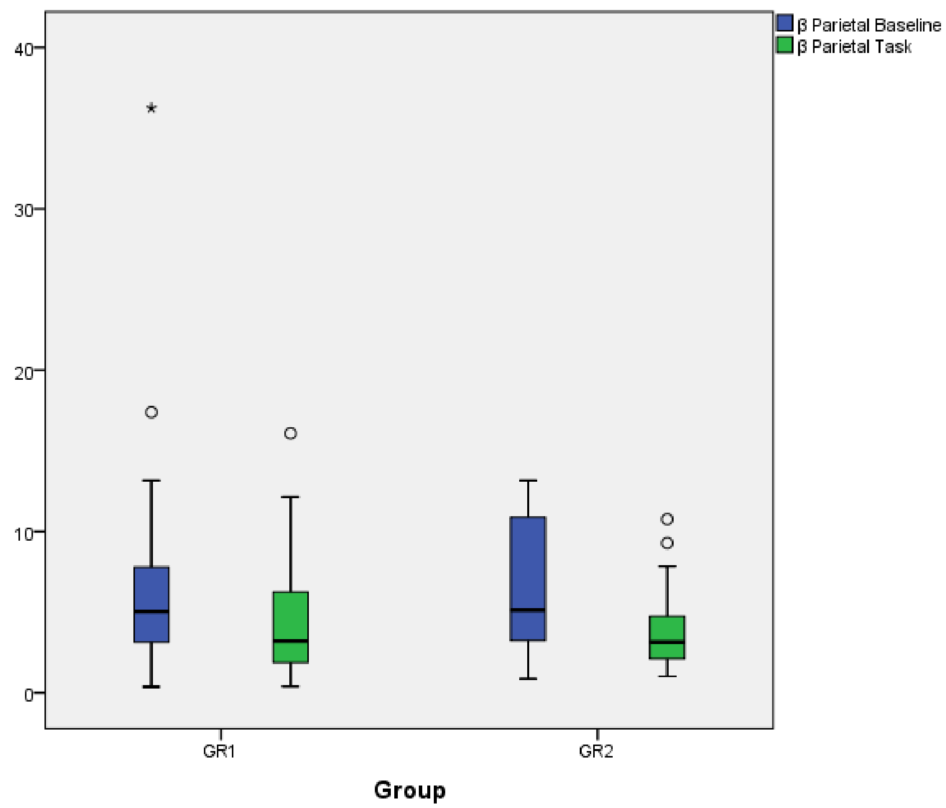


Figure 7.11. Boxplot of absolute power in β band from parietal area for baseline and task condition for each group

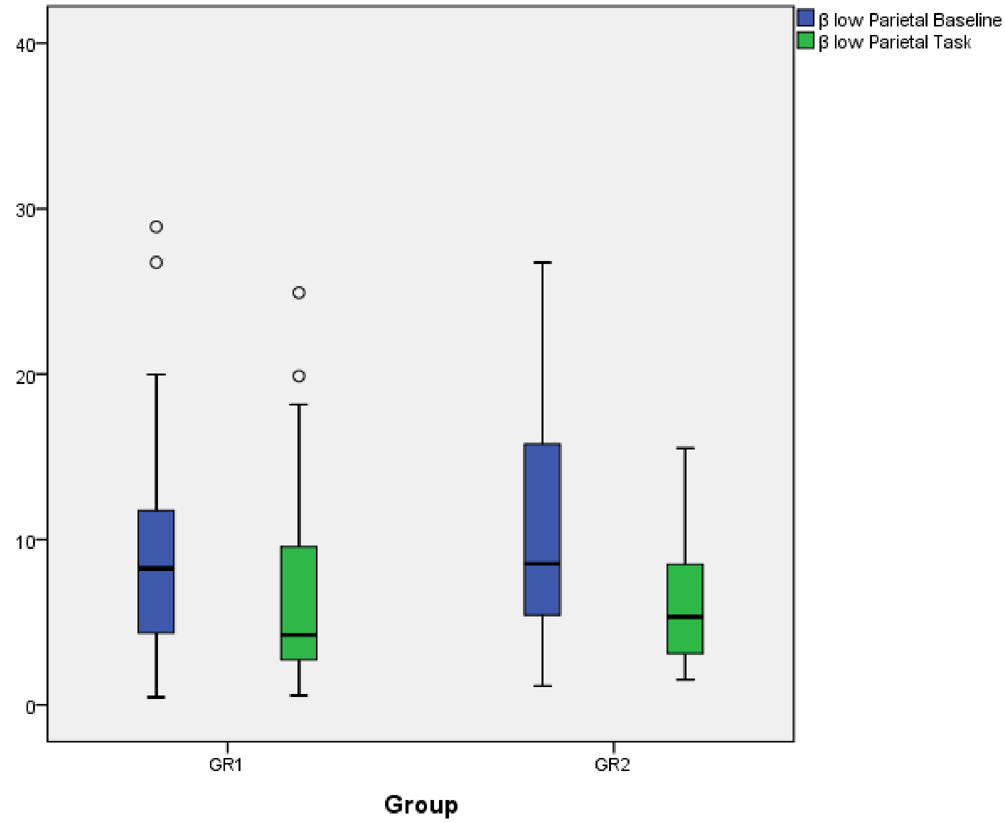


Figure 7.12. Boxplot of power values in β low band from parietal area for baseline and task condition for each group

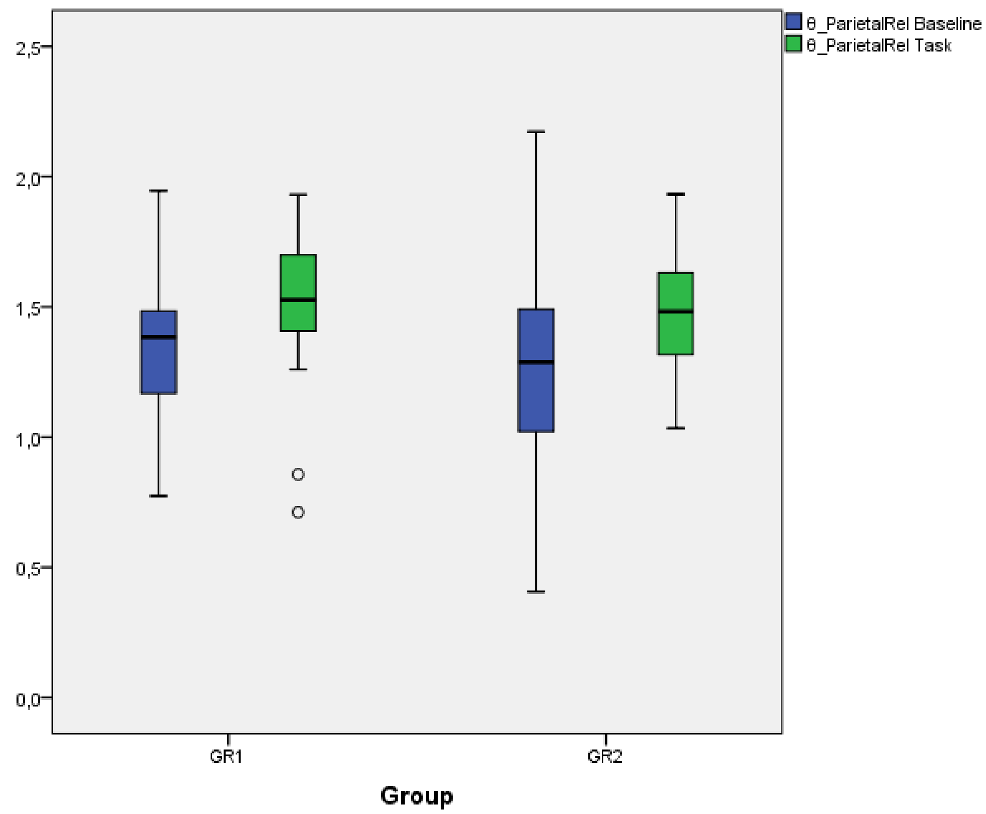


Figure 7.13. Boxplot of relative power in θ band from parietal area for baseline and task condition for each group

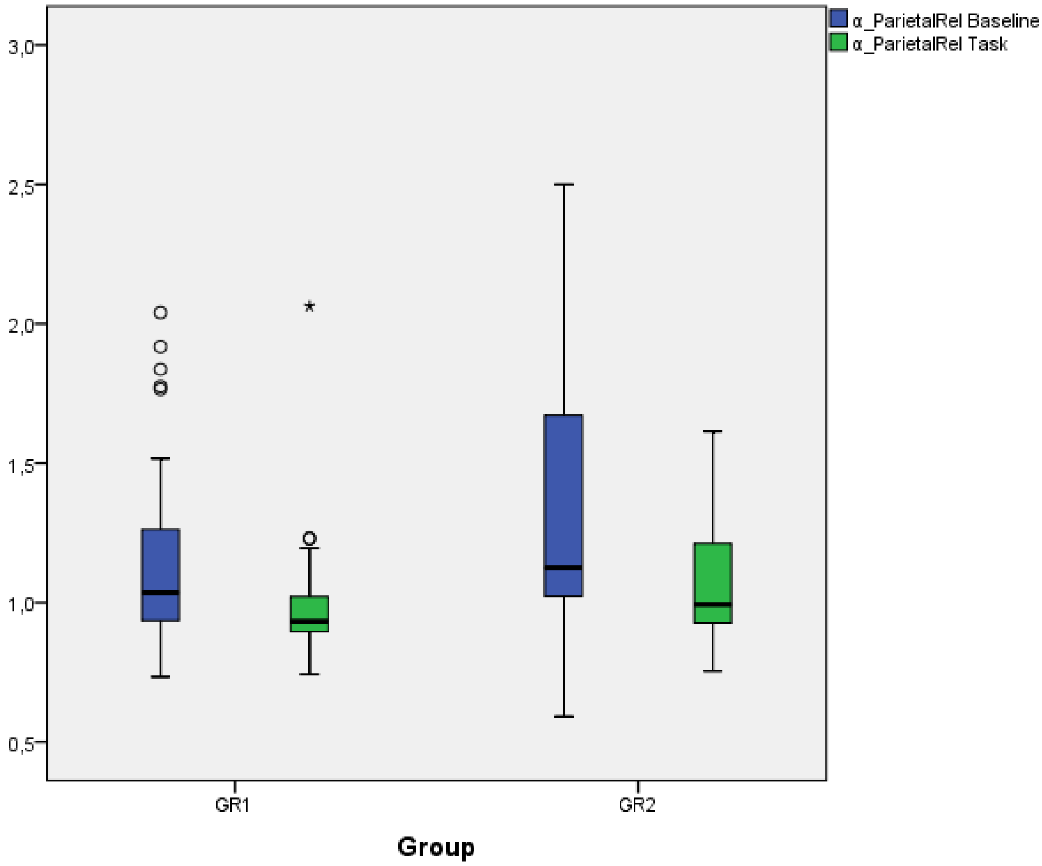


Figure 7.14. Boxplot of relative power in α band from parietal area for baseline and task condition for each group

We also examine the changes in the power values in θ, α, β, and β low, in frontal area. Tables 7.25 and 7.26 show the mean values of the absolute and relative power in θ, α, β and β_low bands, calculated from measurements at F3 and F4 electrodes, in baseline and task condition, for each group, respectively. We calculated each value in θ, α, β and β_low as the average of the power values of F3 and F4. The estimated mean for each of the two groups appears under the label "Mean" followed by the respective estimation of the standard deviation. The comparison of the values between the two conditions showed a significant decrease for the α frontal (control, $p=0.009$; experimental $p=0.012$), a significant increase for the relative θ frontal (control, $p=0.031$; experimental $p=0.010$) and a significant decrease for the relative α frontal (control, $p=0.006$; experimental $p=0.002$). Moreover, statistically significant decreases were observed for the control group for the θ frontal ($p=0.030$) and for the relative β_low frontal ($p=0.030$).

Table 7.25. Paired comparison of power values in θ, α, β, β_low bands for baseline and task conditions in Group1. The values concern the frontal area.

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	θ Frontal Task	3,974	28	3,915	,740	**,030***
	θ Frontal Baseline	5,650	28	5,940	1,123	
Pair 2	α Frontal Task	2,327	28	2,822	,533	**,009***
	α Frontal Baseline	3,681	28	3,882	,734	
Pair 3	β Frontal Task	1,167	28	1,338	,253	,090
	β Frontal Baseline	1,571	28	1,794	,339	
Pair 4	β low Frontal Task	1,576	28	1,885	,356	**,028***
	β low Frontal Baseline	2,340	28	2,714	,513	
Pair 5	θ_ Frontal Rel Task	,553	28	,081	,015	**,031***
	θ_ Frontal Rel Baseline	,511	28	,097	,018	
Pair 6	α_ Frontal Rel Task	,296	28	,055	,010	**,006***
	α_ Frontal Rel Baseline	,342	28	,096	,018	
Pair 7	β_ Frontal Rel Task	,152	28	,048	,009	,591
	β_ Frontal Rel Baseline	,147	28	,048	,009	
Pair 8	β_low_Frontal Rel Task	,198	28	,050	,009	,298
	β_low_ Frontal Rel Baseline	,207	28	,057	,011	
a. Group = GR1						

Table 7.26. Paired comparison of power values in θ, α, β, β_low bands for baseline and task conditions in Group2. The values concern the frontal area.

		Mean	N	Std. Deviation	Std. Error Mean	p-value
Pair 1	θ Frontal Task	3,330	29	2,357	,438	,129
	θ Frontal Baseline	3,881	29	2,427	,451	
Pair 2	α Frontal Task	2,179	30	2,144	,391	**,012***
	α Frontal Baseline	5,010	30	7,280	1,329	
Pair 3	β Frontal Task	,847	30	,615	,112	,125
	β Frontal Baseline	1,050	30	,636	,116	
Pair 4	β low Frontal Task	1,287	30	1,259	,230	,183
	β low Frontal Baseline	1,650	30	1,274	,233	
Pair 5	θ_ Frontal Rel Task	,552	30	,099	,018	**,010***
	θ_ Frontal Rel Baseline	,494	30	,146	,027	
Pair 6	α_ Frontal Rel Task	,305	30	,071	,013	**,002***
	α_ Frontal Rel Baseline	,370	30	,147	,027	
Pair 7	β_ Frontal Rel Task	,143	30	,072	,013	,526
	β_ Frontal Rel Baseline	,136	30	,071	,013	
Pair 8	β_low_Frontal Rel Task	,197	30	,070	,013	,900
	β_low_Frontal Rel Baseline	,199	30	,092	,017	
a. Group = GR2						

All the differences described in detail in Tables 7.25 and 7.26 are depicted on the comparative boxplots in Figures 7.15-7.19.

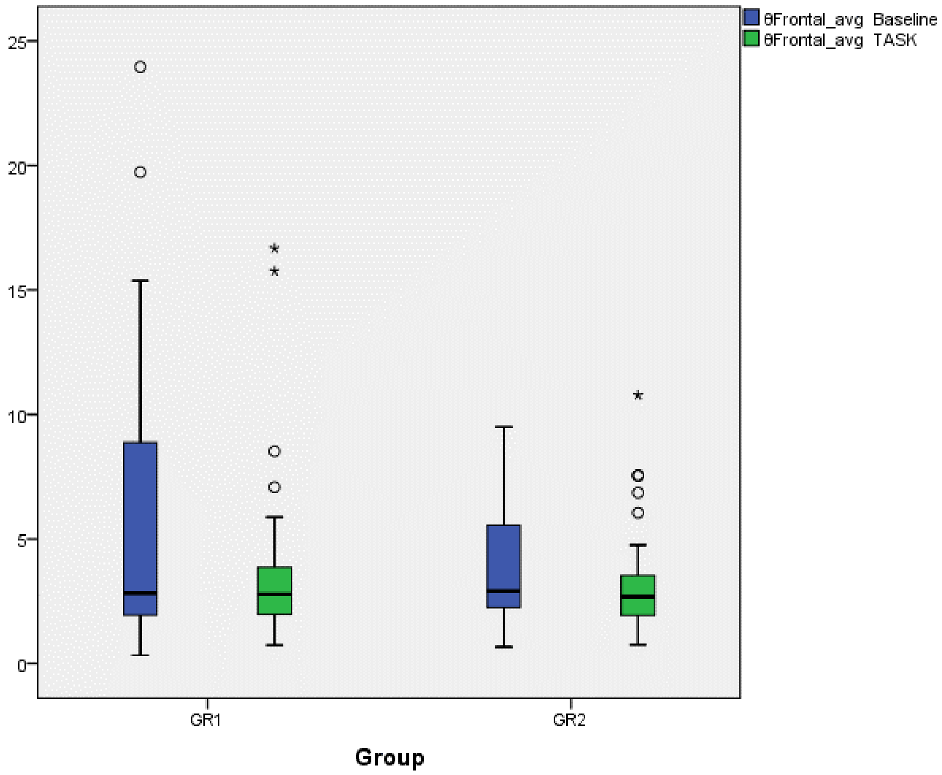


Figure 7.15. Comparative boxplot of θ frontal values in baseline and task condition

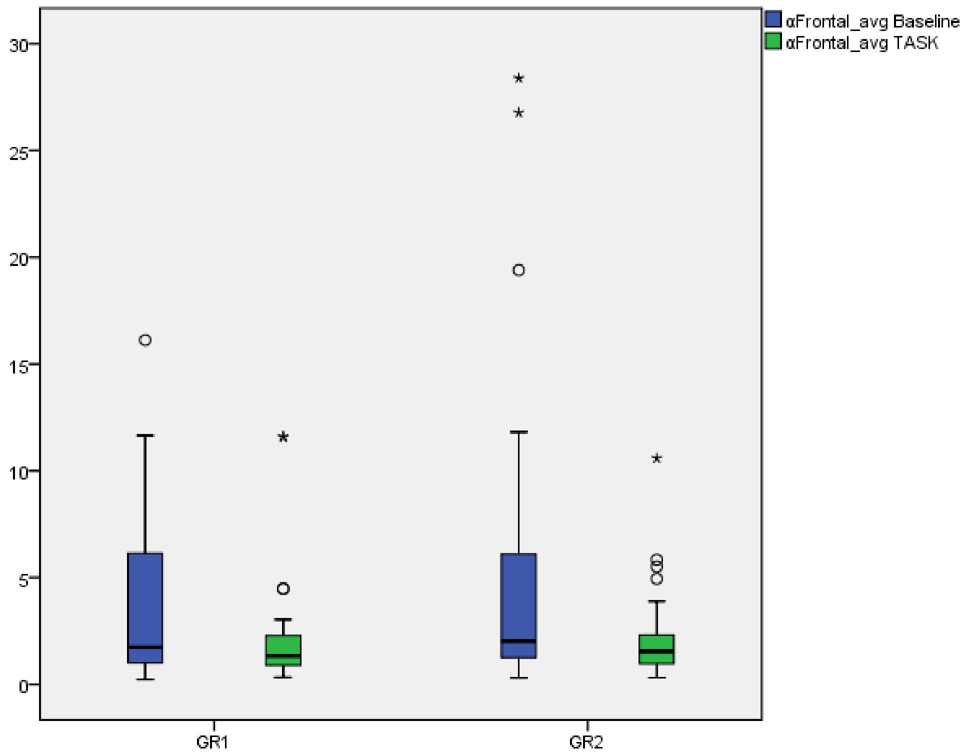


Figure 7.16. Comparative boxplot of θ frontal values in baseline and task condition

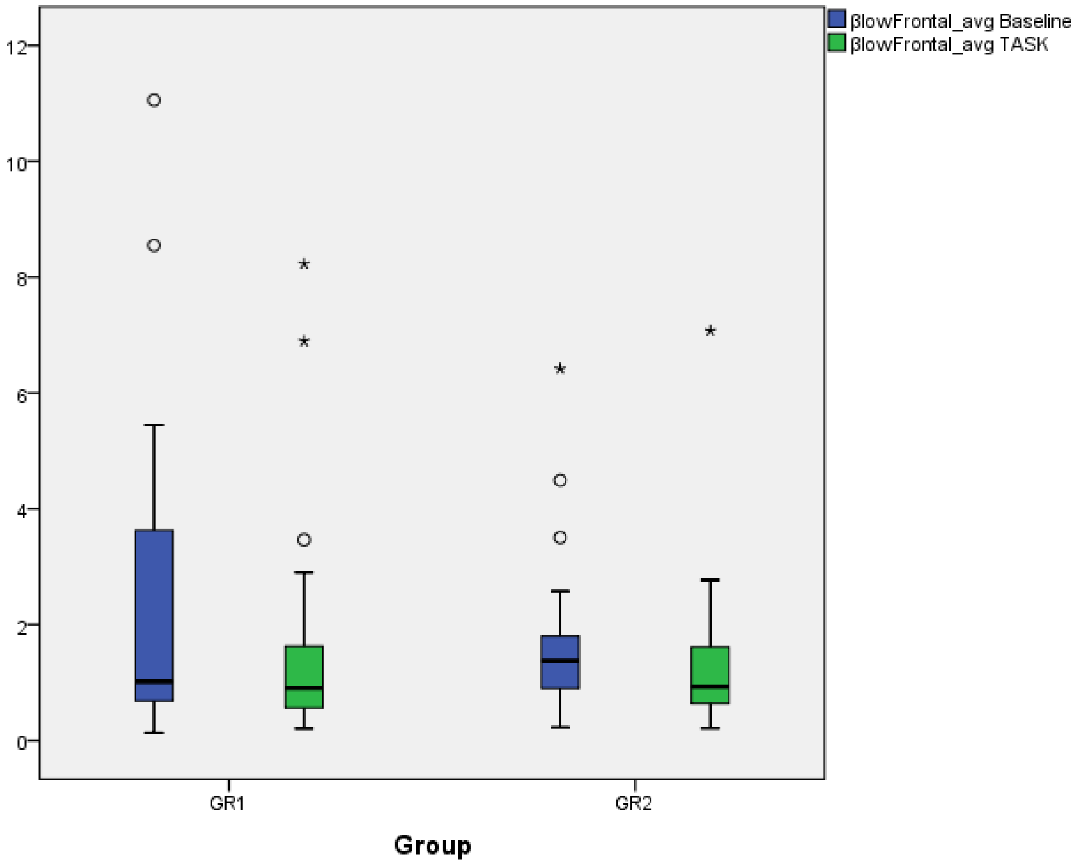


Figure 7.17. Comparative boxplot of βlow frontal values in baseline and task condition

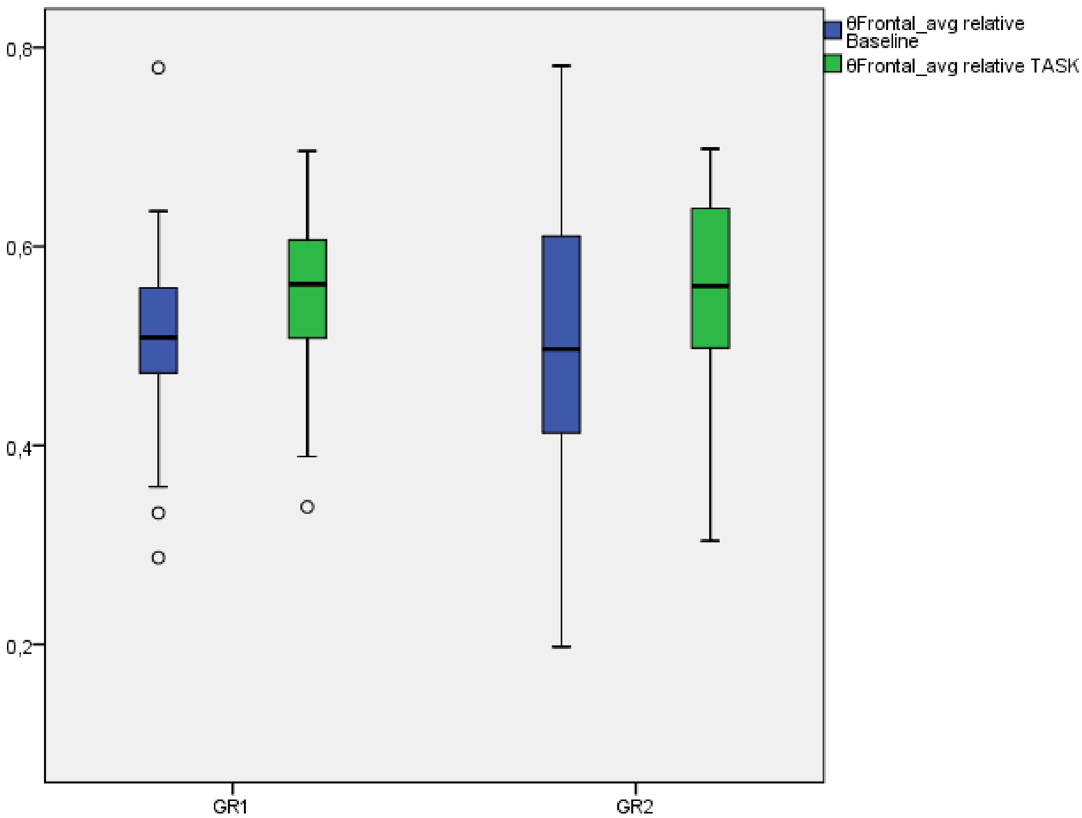


Figure 7.18. Comparative boxplot of θ frontal relative values in baseline and task condition

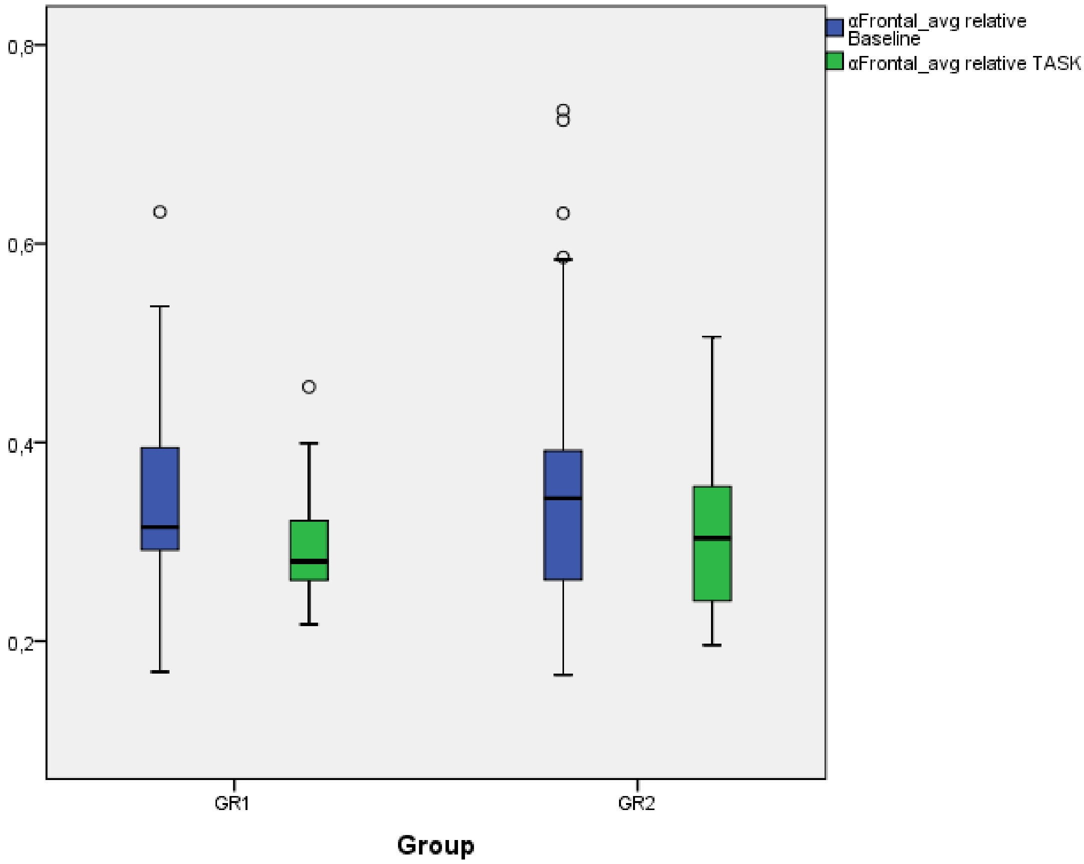


Figure 7.19. Comparative boxplot of α frontal relative values in baseline and task condition

Correlation between α parietal and θ frontal power values

The correlations of the absolute and relative power values of the θ frontal to α parietal scores, in baseline and task condition, have been proven to be statistically significant almost in all cases for the control and the experimental group, as shown in Table 7.29. Specifically, Table 7.29 shows that the absolute values of θ frontal and the α parietal scores have a statistically significant and positive correlations in both conditions in the experimental group, and a statistically significant correlation with the control group after the intervention. In all three cases higher α parietal values are expected for higher θ frontal values. Moreover, the θ frontal relative scores have a statistically significant and negative correlation to the α parietal relative scores at both conditions in both groups. In all correlations presented in Table 7.27 we have considered the averaged power values in θ from measurements at F3 and F4 electrodes and the averaged power values in α from measurements at P3, Pz, and P4 electrodes.

Table 7.27. Correlation between α parietal and θ frontal power values

		Control	Experimental
	θ Frontal (absolute) Baseline		
α_Parietal Baseline	Pearson Correlation	,203	,589
	Sig. (2-tailed)	,300	**,001***
	N	28	30
	θ Frontal (absolute) Task		
α_Parietal Task	Pearson Correlation	,485	,582
	Sig. (2-tailed)	**,009***	**,001***
	N	28	30
	θ Frontal (relative) Baseline		
α_ParietalRel Baseline	Pearson Correlation	-,629	-,734
	Sig. (2-tailed)	**,000***	**,000***
	N	28	30
	θ Frontal (relative) Task		
α_ParietalRel Task	Pearson Correlation	-,619	-,438
	Sig. (2-tailed)	**,000***	**,016***
	N	28	30

These relationships are attributed by the scatterplots in Figures 7.20-7.23.

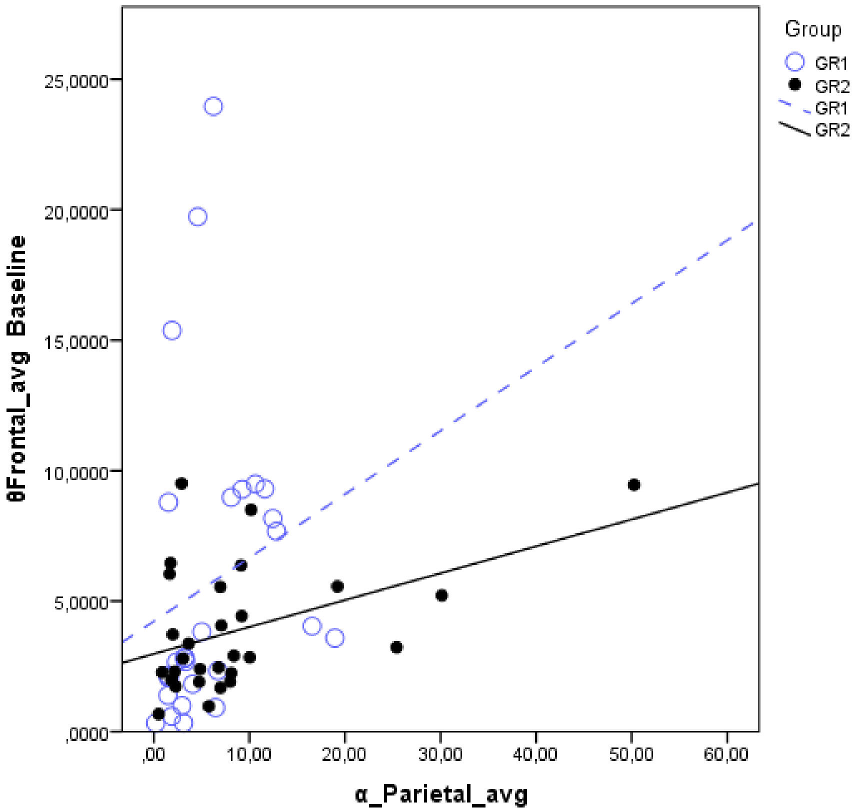


Figure 7.20. Scatterplot of absolute power values in θ frontal vs α parietal in baseline condition

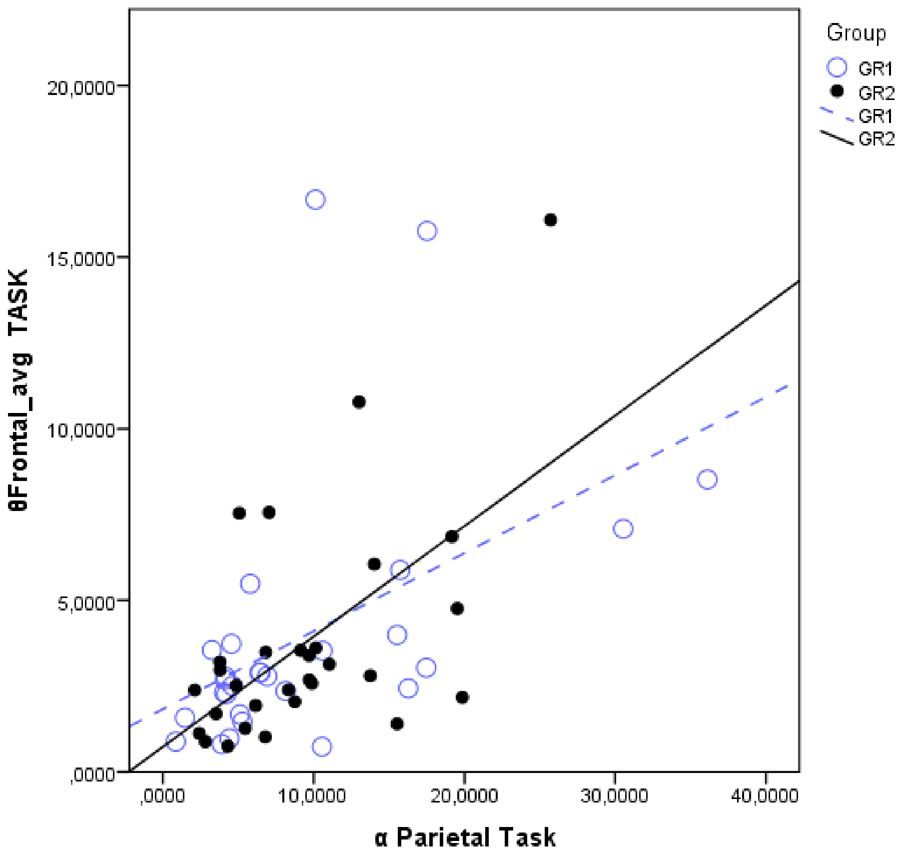


Figure 7.21. Scatterplot of absolute power values θ frontal vs α parietal in task condition

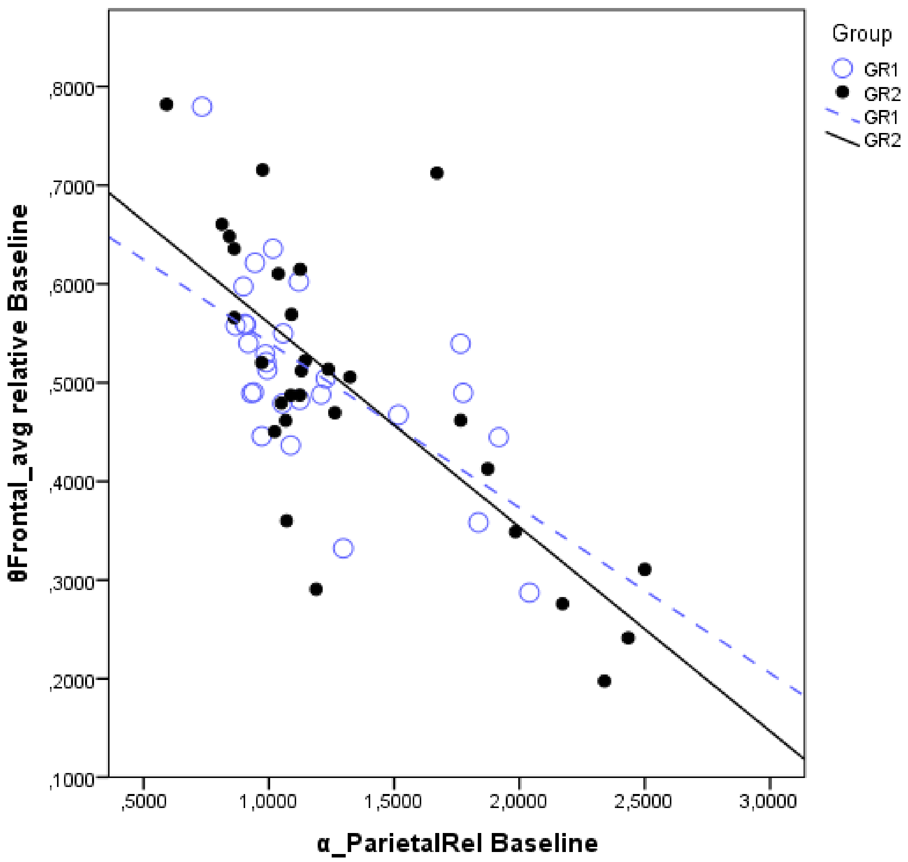


Figure 7.22. Scatterplot of relative power values in θ frontal vs α parietal in baseline condition

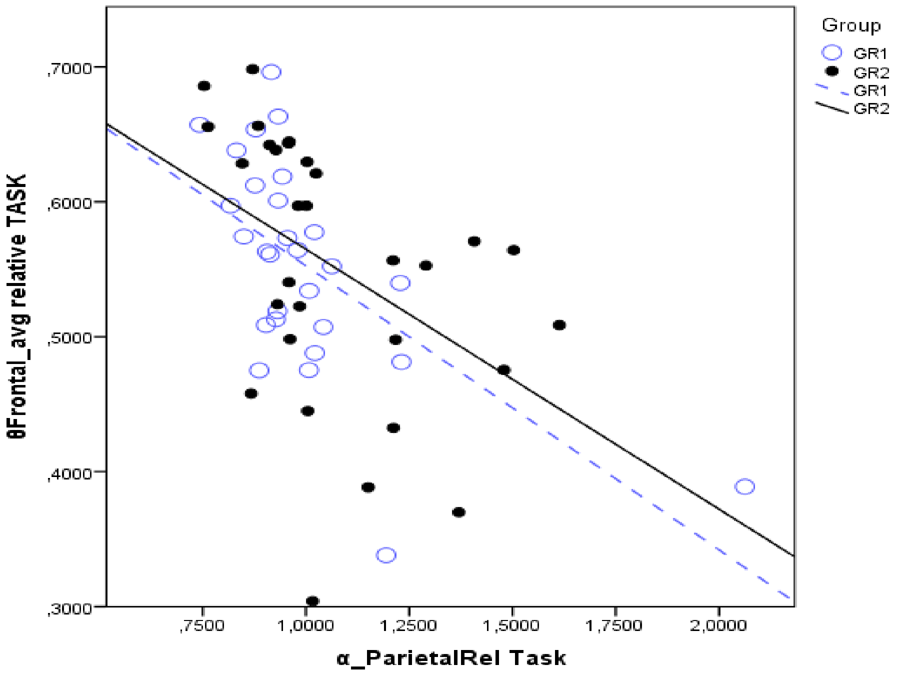


Figure 7.23. Scatterplot of relative power values in θ frontal vs α parietal in baseline condition

7.3. Comparison of learners' self-reported state in a MOOC activity (subjective data)

After the completion of the EEG recordings, a questionnaire was given to each participant. The questionnaire administered comprised of five (5) main dimensions namely, perceived engagement, perceived usefulness, perceived learning effectiveness, perceived cognitive benefits, and intention to continue.

Table 7.28. Reliability statistics for questionnaire's dimensions

	Reliability Statistics	
	Cronbach's Alpha	N of Items
Perceived engagement	0,844	18
Perceived usefulness	0,945	4
Perceived learning effectiveness	0,882	8
Perceived cognitive benefits	0,792	4
Intention to continue	0,788	3

Before getting to analyze the collected answers, the results of the reliability analysis are presented in Table 7.28. The Cronbach's α coefficient estimated for each of the questionnaire's dimensions was found to be over the based on the literature cut off of 0.7, showing that the concepts under study are reliably measured and can lead to sound interpretations of the inference that will be reached.

7.3.1. Comparison of engagement factors and overall perceived engagement

The dimension of the perceived engagement is also be subdivided to the dimensions of "Challenge", "Interest", "Control", "Immersion" and "Purpose". These dimensions, as well as their total, are examined in Table 7.29 for differences between the control and the experimental group. As proven by the p-values that appear on the last column of Table 7.29, no statistically differences were observed in any case between the two groups. The estimations of partial eta squared for each of the engagement factors supports the findings of the p-value of the statistical tests carried out, as in all cases where rather low.

Table 7.29. Comparison of engagement factors and overall engagement for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value	Partial Eta Squared
Perceived engagement	GR1	28	4,399	,481	,091	,371	,014
	GR2	30	4,494	,314	,057		
Challenge	GR1	28	4,589	,409	,077	,455	,010
	GR2	30	4,511	,381	,070		
Interest	GR1	28	1,595	,705	,133	,200	,029
	GR2	30	1,400	,414	,076		
Control	GR1	28	1,762	,731	,138	,125	,042
	GR2	30	1,511	,477	,087		
Immersion	GR1	28	4,321	,533	,101	,995	<,001
	GR2	30	4,322	,459	,084		
Purpose	GR1	28	4,250	,701	,132	,060	,062
	GR2	30	4,533	,388	,071		

Table 7.30. Comparison of perceived engagement and its dimensions in terms of prior experience on Coursity in Group1

	Prior experience on Coursity	N	Mean	Std. Deviation	Std. Error Mean	p-value
Perceived engagement	No	18	4,441	,375	,088	,541
	Yes	10	4,322	,648	,205	
Challenge	No	18	4,620	,361	,085	,599
	Yes	10	4,533	,502	,159	
Interest	No	18	1,482	,551	,130	,259
	Yes	10	1,800	,919	,291	
Control	No	18	1,722	,725	,171	,707
	Yes	10	1,833	,774	,245	
Immersion	No	18	4,315	,491	,116	,932
	Yes	10	4,333	,629	,199	
Purpose	No	18	4,296	,497	,117	,648
	Yes	10	4,167	,997	,315	

Tables 7.30 and 7.31 examine the differences in the perceived engagement and its subdimensions based on whether the participants have attended Coursity's courses in the past, for each group respectively. The analysis showed that no statistically significant differences were observed in any of the two groups.

Table 7.31. Comparison of perceived engagement and its dimensions in terms of prior experience on Coursity in Group2

	Prior experience on Coursity	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**p-value**
Perceived engagement	No	18	4,556	,289	,068	,196
	Yes	12	4,403	,339	,098	
Challenge	No	18	4,537	,373	,088	,656
	Yes	12	4,472	,407	,118	
Interest	No	18	1,296	,377	,089	,093
	Yes	12	1,556	,434	,125	
Control	No	18	1,389	,461	,109	,086
	Yes	12	1,694	,460	,133	
Immersion	No	18	4,370	,426	,100	,491
	Yes	12	4,250	,515	,149	
Purpose	No	18	4,574	,319	,075	,490
	Yes	12	4,472	,481	,139	

Table 7.32. Comparison of engagement and its dimensions in terms of prior experience on online courses in Group1

	Prior experience on online courses	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**p-value**
Perceived engagement	No	6	4,463	,528	,215	,720
	Yes	22	4,381	,480	,102	
Challenge	No	6	4,583	,456	,186	,969
	Yes	22	4,591	,407	,087	
Interest	No	6	1,500	,587	,240	,716
	Yes	22	1,621	,744	,159	
Control	No	6	1,667	,817	,333	,726
	Yes	22	1,788	,724	,154	
Immersion	No	6	4,389	,574	,234	,733
	Yes	22	4,303	,534	,114	
Purpose	No	6	4,389	,491	,200	,593
	Yes	22	4,212	,753	,160	

Tables 7.32 and 7.33 examine the differences in the perceived engagement and its subdimensions based on whether the participants have attended any online courses in the past, for each group respectively. The analysis showed that no statistically significant differences were observed in any of the two groups.

Table 7.33. Comparison of engagement and its dimensions in terms of prior experience on online courses in Group2

	Prior experience on online courses	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**	**p- value**
Perceived engagement	No	5	4,589	,422	,189	,471
	Yes	25	4,476	,295	,059	
Challenge	No	5	4,533	,545	,244	,889
	Yes	25	4,507	,355	,071	
Interest	No	5	1,333	,408	,183	,701
	Yes	25	1,413	,423	,085	
Control	No	5	1,267	,435	,194	,215
	Yes	25	1,560	,478	,096	
Immersion	No	5	4,467	,380	,170	,450
	Yes	25	4,293	,475	,095	
Purpose	No	5	4,600	,435	,194	,681
	Yes	25	4,520	,386	,077	

Tables 7.34 and 7.35 examine the correlations of the perceived engagement and its subdimensions with the participants' level of knowledge on Special Education and Autism Spectrum Disorder (ASD) specifically. The analysis showed two statistically significant and negative correlations in the control group and two statistically significant and positive correlations in the experimental group. Specifically, Table 7.34 shows that participants in Group1 (control group) who score higher on perceived engagement and perceived learning effectiveness are expected to know less about Special Education and ASD. Of course, the opposite relationship is also true. Thus, the participants who know less on the subject of Special education and ASD are expected to score higher on perceived engagement and perceived learning effectiveness. These relationships appear in Figures 7.24 and 7.25.

Table 7.34. Correlations of questionnaire's subdimensions with participants' level of knowledge on ASD, for Group1

		Participants' level of knowledge on ASD Πόσο καλά γνωρίζεις το πεδίο της Ειδικής Αγωγής και συγκεκριμένα της Διαταραχής Αυτιστικού Φάσματος;		
		Correlation Coefficient	Sig. (2-tailed)	N
Spearman's Rho	Perceived engagement	-,532	**,004***	28
	Perceived usefulness	,053	,790	28
	Perceived learning effectiveness	-,413	**,029***	28
	Perceived cognitive benefits	-,210	,283	28
	Intention to continue	-,059	,767	28
a. Group = GR1				

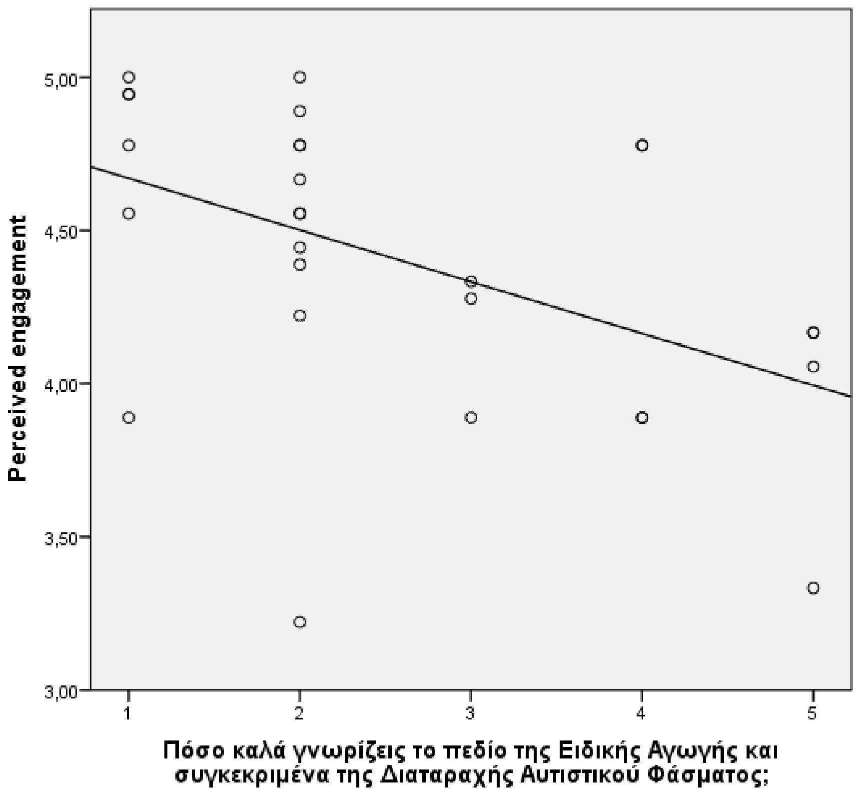


Figure 7.24. Scatterplot of perceived engagement vs ASD awareness

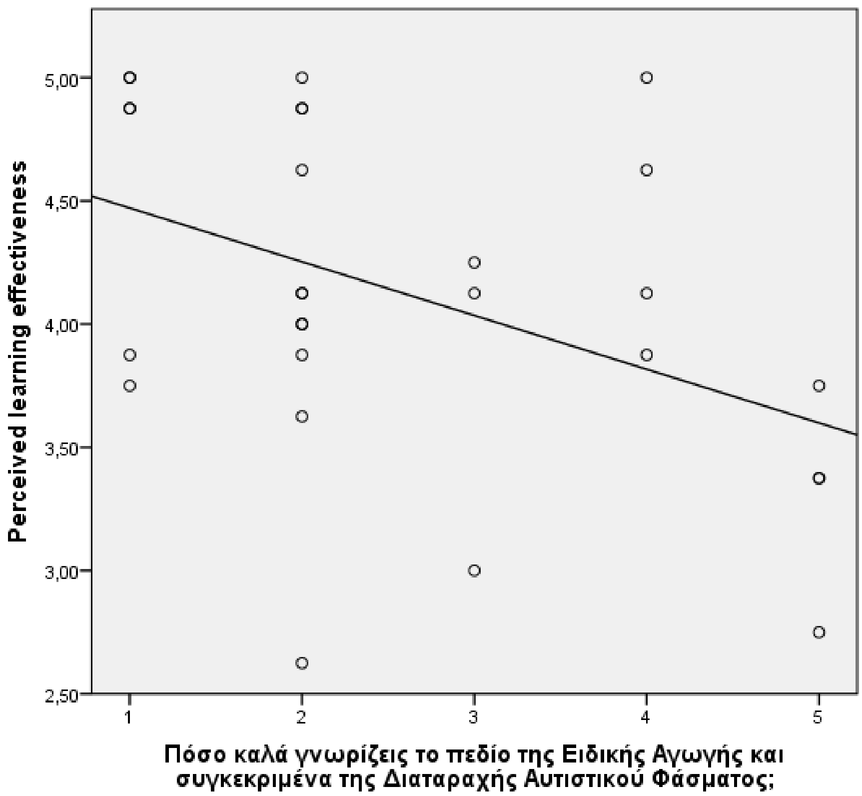


Figure 7.25. Scatterplot of perceived learning effectiveness vs ASD awareness

On the contrary, Table 7.35 shows that participants in Group2 (experimental group) who score higher on "Intention to continue" and "Perceived learning effectiveness' are expected to know more about Special Education and ASD. These relationships appear in Figures 7.26 and 7.27.

Table 7.35. Correlations of questionnaire's subdimensions with participants' level of knowledge on ASD, for Group2

		Participants' level of knowledge on ASD Πόσο καλά γνωρίζεις το πεδίο της Ειδικής Αγωγής και συγκεκριμένα της Διαταραχής Αυτιστικού Φάσματος;		
		Correlation Coefficient	Sig. (2-tailed)	N
Spearman's Rho	Perceived engagement	,101	,595	30
	Perceived usefulness	,255	,173	30
	Perceived learning effectiveness	,369	**,045***	30
	Perceived cognitive benefits	,123	,518	30
	Intention to continue	,628	**,000***	30
a. Group = GR2				

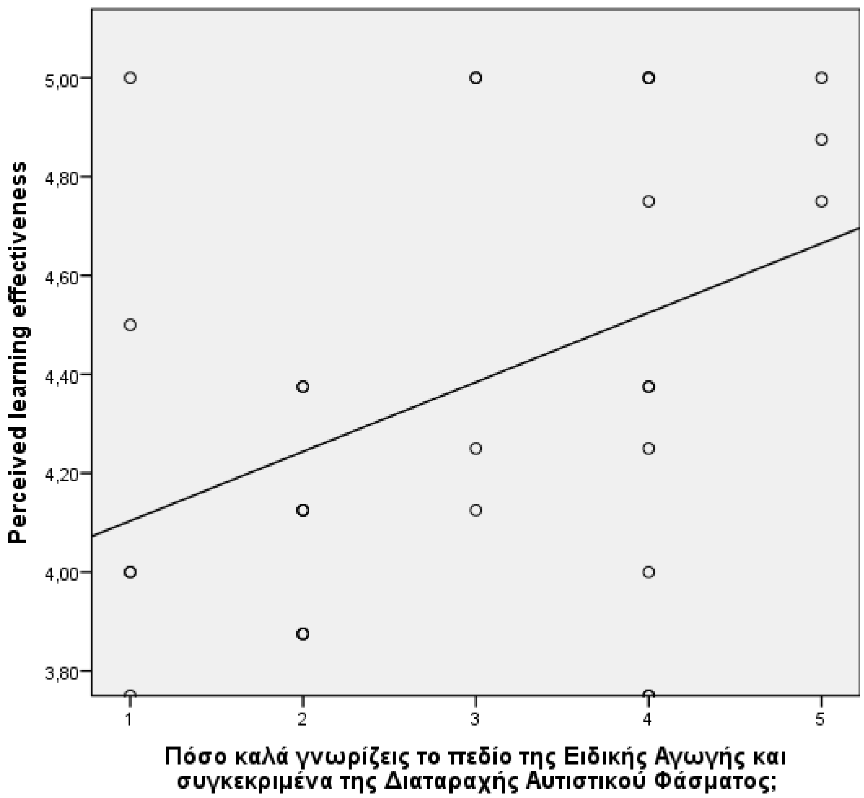


Figure 7.26. Scatterplot of perceived learning effectiveness vs ASD awareness

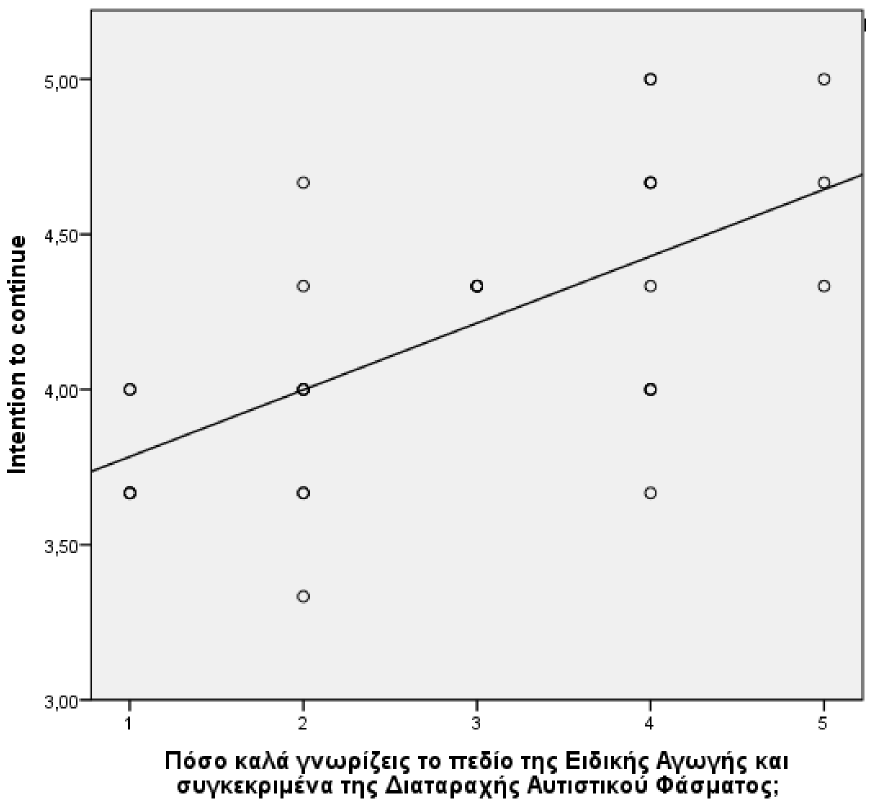


Figure 7.27. Scatterplot of Intention to continue vs ASD awareness

7.3.2. Comparison of perceived usefulness, perceived learning effectiveness, perceived cognitive benefits and intention to continue

Table 7.36 presents the differences in the perceived usefulness, learning effectiveness, cognitive benefits and intention to continue, between the two groups. The analysis showed that there is one statistically significant difference regarding the perceived cognitive benefits (p=0.024). Specifically, as shown in Table 7.36 and on the comparative boxplot in Figure 7.28, higher values of the perceived cognitive benefits were observed in the experimental group.

Table 7.36. Comparison of perceived usefulness, effectiveness, cognitive benefits and intention to continue for each group

	Group	N	Mean	Std. Deviation	Std. Error Mean	p-value
Perceived usefulness	GR1	28	4,188	,760	,144	,665
	GR2	30	4,267	,623	,114	
Perceived learning effectiveness	GR1	28	4,121	,697	,132	,102
	GR2	30	4,375	,451	,082	
Perceived cognitive benefits	GR1	28	4,161	,562	,106	**,024***
	GR2	30	4,475	,470	,086	
Intention to continue	GR1	28	4,238	,684	,129	,802
	GR2	30	4,200	,451	,082	

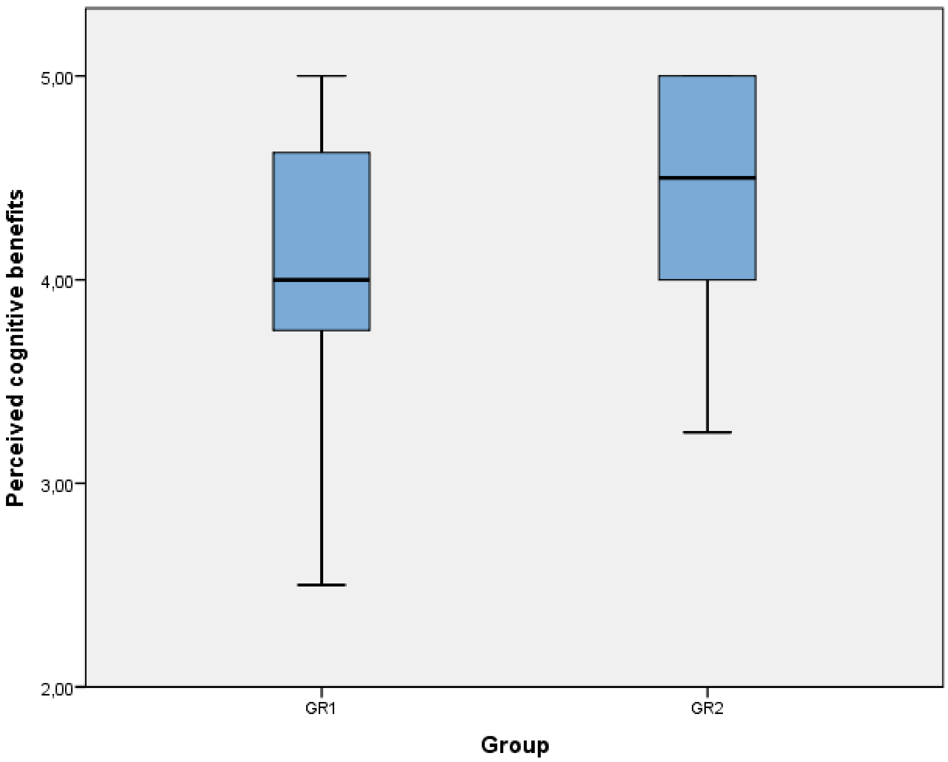


Figure 7.28. Comparative boxplot of perceived cognitive benefits for each group

7.4. Comparison of learners' mental engagement and perceived engagement

Finally, a correlation analysis between the perceived engagement, as measured by the questionnaire, and the mental engagement values showed that no statistically significant relationships were detected for either of the two groups. The results regarding Group1 (control group) appear in Table 7.37 while the results of Group2 (experimental group) appear in Table 7.38.

Table 7.37. Correlations of mental engagement and perceived engagement in Group1

		Perceived engagement		
		Correlation Coefficient	Sig. (2-tailed)	N
Spearman's Rho	EngIdx_rel Task	-,233	,233	28
	EngIdx_abs Task	-,250	,199	28
a. Group = GR1				

Table 7.38. Correlations of mental engagement and perceived engagement in Group2

		Perceived engagement		
		Correlation Coefficient	Sig. (2-tailed)	N
Spearman's Rho	EngIdx_rel Task	,108	,570	30
	EngIdx_abs Task	,076	,689	30
a. Group = GR2				

Chapter 8. Conclusions - Discussion

8.1. Introduction

The present thesis examines the effect of the proposed gamified design on participants' cognitive states in terms of engagement. It also investigates the potential value of neural data in the evaluation of participants' cognitive states in a MOOC assessment activity. The application of EEG in gamified educational settings is relatively recent. Research studies usually investigate whether the EEG data could provide reliable indications on learners' cognitive and affective states as they progress in learning e.g., continuously monitoring learners' attention levels. The research interest of such data lies on the fact that they could be incorporated into real-time learning systems to adapt them once a learner is predicted to be on an unproductive learning path or could be used to facilitate the design process in order to develop more effective learning environments.

Engagement, which is a basic concept in this work, is thought to reflect estimates of several cognitive processes, such as information gathering, visual scanning (Berka et al., 2007), and is considered to be a measure of effortful cognitive activity (Matthews et al., 2002). As a construct, engagement is closely related to other cognitive states such as attention, cognitive workload, as well as to emotional states.

The present thesis has considered two different groups of participants, i.e., a control group and an experimental group. Each group interacted with a MOOC activity. The activity differed between the two groups regarding the implementation of the element of progression. Specifically, the control group interacted with a non-gamified activity i.e., the activity did not incorporate the progression element, while the experimental group interacted with the gamified activity i.e., an activity in which the progression element was implemented. A comparative study was conducted based on the electrical brain activity of the participants of the two groups while interacting with the MOOC assessment activity.

EEG was used to investigate whether the proposed design and implementation of the progression element had an effect on participants' mental states, as well as, whether the extracted neural measures have the potential to characterize participants' learning experience. Participants' cognitive states were evaluated in terms of mental engagement, attention, and mental workload, while affective experience was evaluated based on two dimensions, arousal, and valence. Moreover, to evaluate learners' experience subjective measures were also used to compare participants' self-reported perceived engagement with the measures extracted from participants' neural data regarding their engagement level. Other measures that characterize participants' experience, such as perceived usefulness, perceived learning effectiveness, perceived cognitive benefits and intention to continue, were also compared between the two groups through subjective scales.

This work draws conclusions regarding the effect of the proposed gamification design methodology of a MOOC assessment activity on participants' mental states and participants' perceived learning experience. This chapter presents and discusses the conclusions that emerged from the results of this work.

8.2. Comparison of learners' mental state in a MOOC activity (neural data)

8.2.1. Comparison of the engagement values

The comparison of the mental engagement values of the two groups showed no statistically significant differences. Thus, we can argue that the proposed intervention did not have a significant effect on the participants' engagement. According to Berka et al. (2007), task engagement is related to cognitive processes, such as information gathering, visual scanning and sustained attention. Considering the definition that is given by Berka et al. (2007), we argue that the gamified intervention did not require a different activation of cognitive processes such as information processing and visual scanning. Also, we can claim that the duration of the task was not long enough to require the activation of the sustained attention. However, we expected an augmentation in information gathering for the experimental group, as participants were given more information through the various types of feedback. As engagement showed no differences between the two groups, we assume that the element of feedback probably was not utilized by the participants. This assumption can be confirmed up to a degree by their behavioral reaction (involvement) during the task. From the notes that were taken during the experiment, many participants in the experimental group did not utilize elements such as the "response specific" feedback given for each correct and incorrect answer. They only dealt with submitting their answers to the multiple-choice questions. It should be also noted that most of the participants used this type of feedback (i.e., "response specific") only in the cases of incorrect answers (and not for the correct ones). We should mention that, at the end of the activity, several participants stated that they did not notice that feedback was given for all their answers, which raises issues about the design of this element. Other participants mentioned that they did not take the time to read the feedback because the material was quite easy, while they pointed out that in a more difficult or more technical course such as computer programming, the feedback would be very particularly useful and would provide the necessary support to continue.

Taking into account that the two activities comprised of the same multiple-choice questions (challenges) which however differed in their presentation order (levels) and in whether additional information was provided or not (feedback), we can assume that engagement reflects the effect that is generated as a result of the challenges that participants should confront, and not by the effect generated from levels or feedback.

The comparison between the engagement values in the baseline and in the task condition for each group separately also shows that for none of the two groups the engagement had a statistically significant change. Since the engagement is defined as a measure of effortful cognitive activity (Matthews et al., 2002) or as a measure of energy mobilization in the service of cognitive goals (Gaillard, 2001) we can argue that both the gamified and non-gamified activity were not demanding for participants. Although performance is not a measure studied in this work, we should mention that all participants got a grade over 85%, which shows that the activity was not difficult for none of them. Therefore, we can conclude that the participants were skilled (efficient) enough to mobilize cognitive resources to complete the activity. This can also be supported by several other observations such as participants' performance and their behavioral reaction during the completion of the activity.

Finally, it should be noted that the EEG-based engagement index that we used in this work, has been used more frequently in research studies related to vigilance tasks to assess users' alertness in a certain task (Freeman et al., 1999), or to non-vigilance tasks to differentiate high intensity game events from general game play (McMahan, Parberry & Parsons, 2015). Also, in studies relevant to distance learning, researchers argue that the EEG-based engagement index was not able to predict learners' engagement as compared to human annotators (Booth, Seamans & Narayanan, 2018). This might indicate that an augmented mental engagement is not necessarily positive in educational settings as it can reveal high levels of stress which is related to an increase in β and a decrease in θ. In any case, we argue that other measures should always be studied along with mental engagement in order to evaluate participants' learning experience.

8.2.2. Comparison of the attention ratio values

The comparison of the attention ratio values of the two groups showed no statistically significant differences for neither of the two attention ratios that were calculated. To understand what the no statistically significant change means, we should consider that this ratio is a neural marker of executive control and is associated with various aspects of attentional control (Angelidis et al., 2016; Putman et al., 2010) and motivated decision making (Massar et al., 2014). Executive control describes individuals' mental processes (e.g., working memory) that are deployed to perform goal-directed task, while attentional control refers to individual's ability to deploy strategically top-down control attention to bottom-up information processing to support performance. In other words, attentional control is described as an individual's ability to concentrate, i.e., to choose where to pay attention and what to ignore. For example, a higher TBR in baseline is correlated to a large decline in attentional control when an individual is under stress. Moreover, attentional control is considered to be related to other executive functions such as working memory. Therefore, we can argue that attentional control and mental processes such as working memory, were not affected by the intervention.

The comparison between the attention ratio values in the baseline and in the task condition for each group separately also shows that for neither of the two groups the attention ratio had a statistically significant change. We should note that high theta/beta_low ratio is usually correlated with an augmented θ and consequently inattentive states, while a low value for this ratio is normally correlated with excessive low β activity which reflects normal states in adults. For example, low beta activity is considered to increase during retention in working memory (Spitzer & Haegens, 2017). Therefore, since the ratio is influenced by the θ and β power values, we should consider whether this non-statistically significant change in values is due to a decrease in the θ and low β activity in the frontal region, or an increase in both values, in order to argue about the level of attention and executive control of the participants. For example, a lower θ activity and a lower β activity during a task in comparison to the baseline shows that the task difficulty is low, decreased requirement for memory resources, lower alertness and may be also related to emotions such as boredom.

Regarding the correlation between the attention ratio values and the engagement values, we found a statistically significant negative correlation for both indices of attention in the experimental group. This means that, an increase in the attention scores is related to a decrease in the engagement scores. This negative correlation is reasonable as it shows that people with lower attention scores are expected to show higher engagement. We can also argue that the ratio θ/ β_low as compared to θ/β, expresses a more certain result for this correlation.

In the next section, other measures related to the study of attention will be evaluated, such as the changes in the θ and α activity.

8.2.3. Comparison of the workload values

The comparison of the workload values of the two groups showed no statistically significant differences. Thus, we can argue that the proposed intervention did not have a significant effect on the participants' mental workload. Mental workload is of primary interest as it has a direct impact on learners' performance in executing tasks. Workload can be explained in terms of cognitive resources or mental energy expended, including mental effort, alertness or decision making. According to Kahneman (1973), is also related to the amount of attention that is allocated to perform the task. Other researcher relates mental workload with the level of learners' involvement (Chaouachi, Jraidi & Frasson, 2011). In general, mental workload is a complex construct that reflects participants level of cognitive engagement and effort in a task (Babiloni, 2019). Therefore, the evaluation of workload is considered to be a quantification of mental activity. It describes in what extent cognitive resources that are required from the task have been actively engaged. We should note that, an increase or decrease in workload could not be considered as a positive or negative indication as there is always an optimal level of workload to reach an optimal performance. In our case, both groups deployed the same amount of mental resources to perform the task.

A statistically significant increase was found only in the experimental group between the two conditions (baseline-task). We assume that this increase reflects an increase in learners' mental effort and cognitive engagement in the task which is attributed to the intervention. The increase of mental workload is associated with either an increase in frontal θ and/or a decrease in parietal α. Both EEG oscillations are highly sensitive to variations in mental workload. The α parietal activity tends to decrease in power as tasks become more difficult (e.g., Gevins et al., 1979, Sterman et al., 1994). On the contrary, the frontal θ activity has been found to increase as tasks require more focused attention. As frontal θ activity is considered to be a reliable metric to evaluate workload, we evaluate the changes in its power values in the next sections.

Regarding the correlation between the workload and the engagement, no statistically significant correlation was found. We assume that there is not a linear relationship between mental workload and engagement. It has been found that very low or very high mental workload may result to a decreased engagement. This can be explained by the fact that the mental workload evaluates the total cognitive load and components that represent the inherent difficulty of the task. It should be noted that the most acceptable hypothesis for the relationship between mental workload and performance is described through an inverted U-shape function. Therefore, we can assume that the same relationship exists between mental workload and engagement.

Finally, it is interesting to mention that, according to Kamzanova, Kustubayeva & Matthews (2014), the ratio θ/α is suggested to be a valid indicator for task engagement.

8.2.4 Comparison of the arousal and valence values

The comparison of the arousal values of the two groups showed no statistically significant differences. Arousal refers to an emotional reaction and is studied in this work as it plays an important role in decision making, information processing, memory, and cognitive performance. Arousal can be considered as a task-related feedback relevant to the importance of current thoughts. Therefore, we argue that the intervention did not have a significant effect in the level in which the activity was perceived as important by the participants. We assume that the level of task importance was mainly influenced by the challenges of the activities and not by the other elements that were also implemented in the gamified intervention, namely levels and feedback. These elements could have an impact on arousal in cases that there was a discrepancy between participants' current skill level and the required by the activity skills.

A statistically significant increase was found for both groups between the two conditions (baseline-task). We argue that both gamified and non-gamified task were able to activate emotionally the participants. This is very important as attention and arousal are considered critical to human performance in various type of task such as assessment tasks (Whyte, 1992). Arousal has been thought to have an optimal level for any particular task depending on task difficulty. Therefore, we can argue that the task difficulty for both groups was the same.

Regarding the correlation between arousal and engagement, both groups showed a statistically significant positive correlation. This is reasonable as emotions are thought to have an important and pervasive role in learners' engagement in academic and other educational settings (Pekrun & Linnenbrink-Garcia, 2012). It should be noted that, maintaining a task-appropriate level of attention and arousal is a core feature for learning.

The comparison of the valence values of the two groups showed no statistically significant differences. We argue that the intervention did not affect participants' emotions regarding the valence (positive vs negative emotions). Valence describes the degree of positive (approach) or negative (withdrawal) emotions for a task or a stimulus. We can argue that the task was neither too satisfying nor too disappointing for the participants.

Regarding the correlation between valence and engagement, no statistically significant correlation was found. This finding is in agreement with the literature as it has been shown that both positive and negative emotions activate learners' attention and engagement mainly when it is compared with neutral emotions. Nevertheless, it should be noted that positive emotions promote engagement more efficiently than negative emotions (Heddy & Sinatra, 2013).

8.2.5. Comparison of the θ, α, β power values in frontal and parietal areas

We evaluated the changes in power values of θ, α, β, and β_low bands between the two conditions (i.e., baseline and task), in the frontal and the parietal lobes, as they are controlling processes related to cognitive and emotional processing. In general, the parietal lobe involves sensation, perception and integration of sensory input (primary visual input). Sensory information is processed to form a single perception i.e., cognition.

Our results showed that brain activity in the parietal lobe showed almost the same patterns of activation for the two groups. The changes in the power values of θ, α, β, bands are the same for the two groups regarding both their absolute (θ↓, α↓, β↓) and their relative power values (θ↑, α↓). These measurements justify our previous conclusions regarding the fact that the proposed intervention did not have a significant impact on participants' engagement.

In both groups, the absolute α power is significantly decreased in the task condition as compared to the baseline. This decrease in α activity during the performance of cognitive tasks is a common observation in EEG. Alpha suppression represents a general response related to the task complexity and the level of attention that is allocated (Ray & Cole, 1985). In our case, the level of alpha suppression in the two groups shows that both groups experienced the same level of task difficulty. In another task with an increased level of difficulty, the level of alpha suppression could be used to evaluate how the cognitive processes are required by the task. Therefore, alpha activity has a negative correlation with arousal and attention (Knyazev, 2007). In our case, alpha suppression justifies the increase of arousal that was found in both groups. It should be noted that, researchers have shown that decreases in alpha band have been associated with individuals' attentional engagement and cortical activation (Babiloni et al. 2004; Klimesch et al., 1998). Moreover, alpha power is suggested as a measure to evaluate alertness (Kamzanova, Kustubayeva & Matthews, 2014). In our results, the decrease in alpha activity is related to the increase of attentional demands required by the task, in relation to the baseline condition where there was no requirement for attention (i.e., participants were instructed to relax and not to think anything in particular).

In both groups there is a statistically significant reduction in θ, α, β regarding their absolute values (θ↓, α↓, β↓). A general decrease in power values of the θ, α, and β frequency bands is related with a state of internal concentration. Researchers also report that a suppression in alpha and beta activity over the occipito-parietal lobe reflects an increased cortical excitability. A decrease in absolute power of θ frontal has been associated with immersion (Nacke & Lindley, 2009). In our case, this general decrease shows that the task had a moderate difficulty for the participants and was able to engage the participants.

According to Berta et al. (2013), parietal and frontal regions have low activity when an individual is in flow. Klasen et al. (2012) also argue the general decrease in brain activity is considered to be related with flow state. In flow, alpha activity is decreased because it demands a high level of visual attention and concentration (Barry et al., 2007), while a decrease in the low beta band activity represents a decrease in active attention (Jenkins & Brown, 2014). Other researchers argue that alpha is positively correlated with flow, while beta is negatively correlated with flow (Nah et al., 2017). In our case, a general decrease was found in parietal area only for the experimental group. We should note that all participants from both groups achieved a high score in the task. This shows that the level of the task difficulty was in balance with their skill level. Bruya (2010) argues if an individual is flow state, a decrease in the alpha and the frontal theta activity occurs without any reduction in participants' performance. Although, task engagement is the basic cognitive state in this work, we should acknowledge that cognitive states such as flow define optimal states to promote an individual's development in an activity (Csikszentmihalyi, 1990). However, in order to assess whether participants were in flow we should also examine the other brain regions as well.

There is a statistically significant decrease in the low β (↓) band of the parietal lobe for the experimental group. This decrease in low beta together along with a decrease in alpha activity shows that the participant experiences an effortless focused attention (Ergenoglu et al., 2004; Guo et al., 2016). Other researchers argue that the statistically significant reduction in low beta in combination with the decrease in alpha activity (in occipitoparietal areas) is related to high arousal (Schubring & Schupp, 2021). This confirms the results from arousal values that were calculated using the ratio β/α. In the parietal brain region, there is a statistically significant decrease only for the experimental group however we can notice that there is a decrease in low β in control group as well but the decrease is not statistically significant.

Regarding the relative values, we have a statistically significant decrease in α and statistically significant increase in θ in both groups. This applies for both the parietal and the frontal area. Generally, the changes in θ and α power are associated with evaluation of the level of cognitive load (Dan & Reiner, 2016; Pellouchoud et al., 1999). The increase in θ activity is defined as a correlate of increased cognitive effort.

The frontal lobe is considered to be associated with emotional processing, problem solving, planning, memory, impulse, judgement and social behavior. It is considered to control an individual's personality. A general comment regarding the results from the frontal lobe is that, unlike parietal lobe, there is a different activation pattern between the two groups.

In the control group, there is a statistically significant decrease in θ, α, και β low bands, while there is no statistically significant change in β band (θ↓, α↓, β low↓, β -). Frontal theta power decreases as cognitive effort decreases (Antonenko & Niederhauser, 2010; Castro-Meneses, Kruger & Doherty, 2020; Gevins et al., 1997). The reduction in frontal theta activity is related to less cognitive control, decreased attention, and decreased sustained neuronal activity reflecting active maintenance of working memory representations (Gevins et al., 1997). Moreover, a decrease in θ in the frontal region is associated with a decrease in arousal (Aftanas et al., 2002).

We found that low β (↓) is only significantly decreased for the control group. Beta wave activity is related to an active state of mind and is most prominent in the frontal cortex during intense focused cognitive activity. According to Berka et al. (2013), low beta activity can be used to discriminate among gaming conditions. Also, the authors have shown that low beta is an important source of information for distinguishing the flow levels. We assume that participants in the control group were less concentrated in the task as compared to the experimental group.

In both groups there is a decrease in frontal alpha activity (↓) that suggests a lower load on the working memory.

A statistically significant decrease in frontal theta is associated with emotional processing (McFarland et al., 2016) and is related with positive emotional experience and specifically relaxation state from anxiety (Suetsugi et al., 2000). For example, the intensity of a happy experience is positively related to theta power in the frontal midline region (Aftanas & Golocheikine, 2001). Frontal theta activity is a manifestation of sustained attention during a skilled performance and optimal attentional engagement. While, is has been found that a decrease in frontal theta activity is considered to be beneficial for successful skilled performance. Therefore, we can assume that although participants' performance did not differ between the two groups, it is possible that the activity was considered easier by the control group. This shows the need for more personalized gamified interventions that would take into account learners' characteristics such as background knowledge, skill level, personality characteristics, etc.

Regarding the relative values, the results are consistent for both groups. There is an increase in θ (↑) and a decrease in α (↓) band, as it was recorded in parietal region. The increased theta oscillation in frontal lobe and decreased alpha lobe in parietal components reflect the cognitive demands and attentional requirements of the task (Pellouchoud et al., 1991).

8.3. Comparison of learners' self-reported state in a MOOC activity (subjective data)

8.3.1. Comparison of engagement factors and overall perceived engagement

There are no statistically significant differences either for the overall perceived engagement or for each of the engagement factors between the groups. This finding agrees with the results that were obtained from the neural data. Also, we should note that for the "Purpose" there is a p-value of 0.060. This might show that there is a tendency for its values to be different between the groups. We assume that with a larger sample we could examine whether there is indeed a differentiation between the two groups for this factor. This would be useful as the specific factor relates to the perceived value of the activity for learning as well as to the purpose feedback that was provided to the experimental group.

Moreover, participants from the control and the experimental group evaluated positively the task in terms of the overall perceived engagement, as well as each of the engagement factor. This means that participants found both tasks to be engaging. It should be noted that participants perceived engagement may also reflect their general evaluation about the technological and design features of MOOCs. The way that two groups interacted with the activity, is typical for a MOOC problem with multiple-choice questions. However, based on their answers, prior experience of participants' on Coursity as well as prior experience on online courses did not affect the perceived engagement for none of the groups.

For the control group, there is a statistically significant negative correlation between the level of knowledge on Special Education and ASD and two dimensions of the questionnaire, namely "Perceived engagement" and "Perceived learning effectiveness". This means that participants who know less on the subject of Special education and ASD are expected to score higher on perceived engagement and perceived learning effectiveness. Consequently, participants who had less knowledge on ASD found the activity effective and engaging. The negative relationship between engagement and level of knowledge is reasonable, as participants with less knowledge found the activity more challenging and they felt that they learned more than participants who had already a good level of knowledge.

For the experimental group, there is a statistically significant positive correlation between the level of knowledge on Special Education and ASD, and two dimensions of the questionnaire, namely "Intention to continue" and "Perceived learning effectiveness". This means that participants who have more knowledge on ASD are expected to score higher on "Perceived learning effectiveness" and "Intention to continue". Consequently, participants who had more knowledge on ASD found the activity effective but they also expressed a willingness to continue attending MOOCs. We would expect a negative relationship between the level of knowledge and the perceived learning effectiveness. However, we can assume that this positive relationship between level of knowledge and the two dimensions of "Intention to continue" and "Perceived learning effectiveness" may reflect participants' willingness to attend other courses with the same gameful design elements. The perceived engagement was not affected by the level of participants' knowledge on ASD.

8.3.2. Comparison of perceived usefulness, perceived learning effectiveness, perceived cognitive benefits and intention to continue

The participants from both groups gave a high score for each of the questionnaire's dimensions, namely perceived usefulness, perceived learning effectiveness, perceived cognitive benefits and intention to continue. Statistically significant differences were found between the two groups only for the "perceived cognitive benefits". Specifically, participants in the experimental group gave a higher score in the dimension. This means that participants in the experimental group considered that they have gained more cognitive benefits through the activity e.g., the activity facilitated their understanding of information that was given through the video-lectures etc.

8.4. Comparison of learners' mental engagement and perceived engagement

From the comparison of the values of mental engagement and perceived engagement we report that the two metrics show no statistically significant relationships. This means that the values of mental engagement do not correlate with the values of the perceived engagement. Therefore, we assume that the engagement questionnaire that was administered is not appropriate to evaluate participants' task engagement in a MOOC scenario. Whitton's questionnaire was validated in tasks such as digital games in which the level and the type of interaction may vary significantly.

Table 8.1. Comments on the ratios that were used in the present thesis

Measure	Description	Conclusions
Task engagement	Measure of effortful activity	Task engagement is affected by the element of challenge, which in our case corresponds to the multiple-choice questions that comprised the assessment activity. Task engagement can be affected by the elements of levels and feedback, but only when the challenges require higher skills than learners' current skill level.
Attention	Level of attentional control	Game elements should be incorporated into a MOOC assessment activity with caution as they can impede learner's concentration on the task.
Cognitive Workload	Cognitive effort, cognitive engagement	Elements such as feedback should be presented only when learners lack the necessary skills to complete the activity. When learners do not need support to achieve the task goals, the additional elements may increase the workload unnecessarily.
Emotional arousal	Task-related feedback relevant to the importance of current thoughts	The optimal level of arousal for any task depends on the on the task difficulty. For learning to be effective, a task-appropriate level of arousal should be maintained. The level of challenge (task difficulty) should always be a little higher than learners' current skill level.
Valence	Positively valenced emotions/ negatively valenced emotions	Approach-related emotions enhance learning. These emotions are relevant to learners' motivation to participate in a course, e.g., satisfaction, self-efficacy. Scaffolding activities that take into account learners' current skill level can generate such emotions.

8.5. General conclusions

This chapter presents the conclusions that derived from the results of the present thesis. We should note that, it is the first time that the evaluation of a gamified intervention in a MOOC platform is being studied in terms of neural measures. Although our results do not confirm the effectiveness of the intervention to increase learners' engagement, we can draw useful indications about learners' cognitive states while interacting with a MOOC assessment activity. These indications will help us to improve the design of future interventions. In this section we present the general conclusions of this work and some useful comments. In Table 8.1 we present a synopsis of the ratios that were used to evaluate learners' cognitive states. Although statistically significant differences were not found between the two groups for none of these ratios, we can draw some clues which will be reconsidered in a future work.

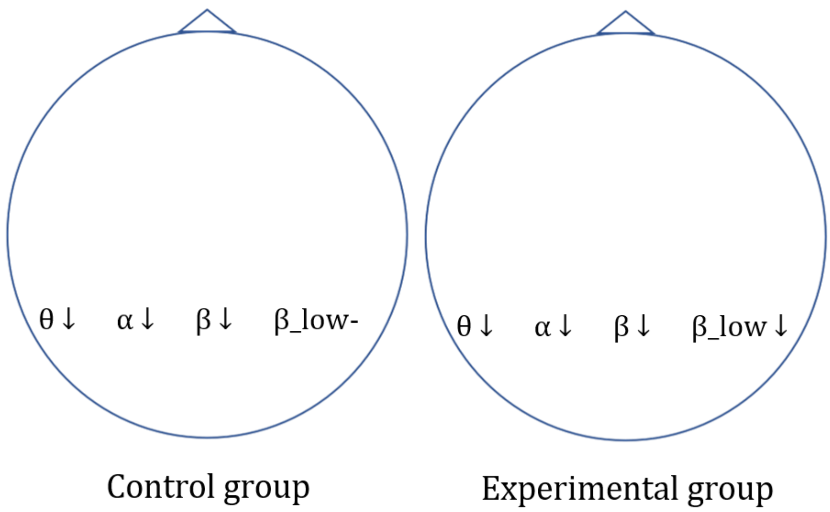


Figure 8.1. Statistically significant changes in power values in θ, α, β and β_low bands (parietal area)

Regarding the changes in the power values of θ, α, β, β_low bands in the parietal lobe, as we can see in Figure 8.1, participants' brain activity shows almost the same patterns of activation between the two groups. In Table 8.2. we present our findings and some useful indications.

Table 8.2. Research findings and useful indication from the power values of θ, α, β, and β_low at parietal lobe

Findings	**Indications**
α↓	Increased attentional demands
θ↓α↓β↓	Moderate task difficulty, internal concentration
α↓ β↓	Increased cortical excitability
α↓ β_low↓	High arousal, effortless focused attention
β_low↓	Decreased active attention

Regarding the changes in the power values of θ, α, β, β_low bands in the frontal lobe, as we can see in Figure 9.2, participants' brain activity shows some differences between the two groups.

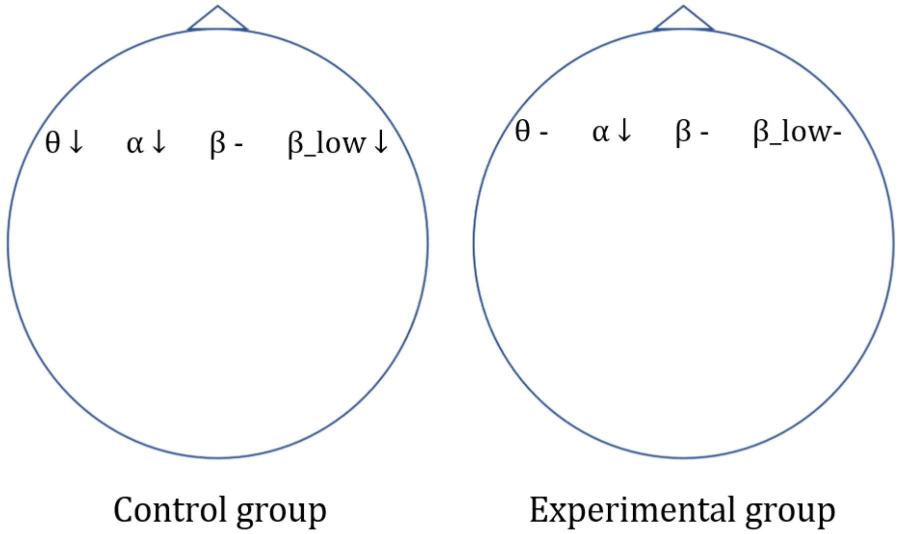


Figure 8.2. Statistically significant changes in power values in θ, α, β and β_low bands

In Table 8.3 we present our findings and some useful indications based on the power values changes of the frequency bands in the frontal lobe.

Table 8.3. Research findings and useful indication from the power values of θ, α, β, and β_low at frontal lobe

Findings	Indications
α↓	Decreased working memory load
θ↓ β↓	Decreased requirements for memory resources, lower alertness, low task difficulty
θ↓	Immersion, low cognitive effort, less cognitive control, decreased attention, positive emotional experience e.g., relaxation state from anxiety
α↓ θ↓	Indicator for flow state

Apart from the neural data and the data collected through the questionnaire, it is also useful to report and evaluate participants' behavioral reactions and thoughts that were expressed after the experiment.

The participants at the end of the experimental procedure stated that they liked the questions that were included in the activity, as they were requiring not only knowledge retrieval, but they were also testing higher skills of knowledge. This shows that the challenges involved in every learning activity have a significant role on learners' engagement. Researchers suggest that the challenges involved in a gamified learning activities should always be within learners' zone of proximal development.

All participants gave very positive feedback about the design of the platform. Therefore, we can assume that the subjective measures reflect the general feeling of the participants about the technological and pedagogical elements of MOOCs. Moreover, the participants of the experimental group stated that they liked the activity and gave a positive feedback about elements that were implemented in the gamified activity (Vygotsky, 1978)).

Moreover, we should note that many researchers mention in their studies the EEG-based index for the evaluation of mental (or task) engagement and they argue that they measure the cognitive engagement. According to Anderson et al. (2004) cognitive engagement is defined as the willingness to exert the necessary effort to comprehend complex ideas, acquire difficult skills, use flexible problem-solving strategies, choose challenging tasks and generally go beyond the requirements of the activity. Also, cognitive engagement has positively associated with self-regulation which is very important for MOOC learners in order to determine their involvement in a MOOC. Based on this definition, we argue that the flow state and other cognitive states could be more effective in describing an optimal state for MOOC learners than task engagement.

To conclude, gamification design for a MOOC assessment is a process that is influenced by many factors related to the subject of the course, learners' characteristics, learners' diverse background knowledge and skill level, learners' personality (e.g., more sociable learners has been found to enjoy more game elements such as leaderboards than less sociable learners), etc. It should be noted that neural measures such as engagement, attention, etc., had a large dispersion in our results. This probably reveals the need for more personalized gamified interventions. The neural measures obtained through EEG could help MOOC designers to acquire a better understand of learners' cognitive states in order to design more engaging and effective learning activities for MOOCs' diverse audience. The use of mixed methods that combine neural and subjective measures could help us better understand and establish our knowledge on factors that influence learners' cognitive states. Generally, gamified interventions in digital educational environments can be used to address problems such as low engagement, loss of learners' attention, enhance learning outcomes, etc. Motivational theories should be used in the gamification design phase taking into account the problem that has been set and the application scenario. In every case, gamified interventions applied in educational settings in order to be successful they should be aligned with learners' zone of proximal development.

8.6. Limitations of the research

The following limitations have to be taken into account regarding the present thesis:

- The participants' cognitive states were examined using measurements from electrode sites F3, F4, P3, Pz, P4, and Cz. Measurements from the temporal lobe were not included in the results as well as electrodes C3 and C4. Also, electrodes Fp1, Fp2, PO7, PO8, Oz were excluded in the pre-processing step due to extensive artifacts.
- Due to covid-19 regulations the experimental procedure was completed in one session. Therefore, we could not have multiple sessions per participant to familiarize them with the research area and the learning environment.
- The questionnaire that was used to evaluate participants' perceived engagement is not validated in MOOC scenarios. To our knowledge, there is no such validated instrument in Greek and the procedure of validating this instrument was out of the purpose of our study. Our intention to use this instrument was encouraged by the rather high and in all cases acceptable Cronbach's α values regarding the reliability of the instrument used. Therefore, despite the fact that the instrument is not validated, we are confident that it does reflects participants perceived engagement.

8.7. Suggestions for further research

The present thesis examined the effect of a gamified MOOC activity on learners' cognitive and affective states. In order to evaluate learners' engagement, we applied a multi-method approach. We examined the neural data recorded from men and women volunteers of ages 19-47 years and we combined the results obtained from EEG signals with subjective self-reported data regarding the participants' perceived engagement. Furthermore, we examined the changes in θ, α, β power values, in frontal and parietal areas, between the baseline and task condition, and we investigated possible significant statistical differences between these values. We also studied possible significant statistical differences between the ratios of these bands that represent indices relevant to engagement such as attention, workload, arousal and valence.

Suggestions for further research concern the following:

- Measurements from temporal and central electrodes could be used in the calculation of task engagement index. There are few studies that mention to have used all the available electrodes for the calculation of the engagement index and not only the four electrodes proposed by Pope et al. (1995).

- Combine EEG measures with other physiological measurements such as heart rate, skin conductivity, respiration rate, eye blinking, etc. Also, combine EEG measures with behavioral observations or objective measures such as response time, performance grades, etc.
- Calculate the instantaneous EEG-based task engagement to examine how engagement is varying during the activity and assess which parts of the activity should be redesigned.
- Application of the gamification methodology in other more demanding MOOC subjects such as computer programming.
- Time-frequency analysis could be used instead of spectral analysis to provide useful information about the temporal evolution of the spectral power in various frequency bands. These methods can show in detail the complexity of brain electrical activity in relation to cognitive and affective processes. Time-frequency analysis methods can overcome the problem of non-stationarity of EEG signals and highlight individual differences.
- Gender differences could be examined due to cognitive transgender differences that are referred on research studies.

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Appendix I

Multiple-choice questions that are presented in the MOOC assessment activity (in Greek)

Level 1

1. Ο όρος «Αυτισμός» είναι συνώνυμος με τον όρο ...

(x) «Διαταραχές αυτιστικού φάσματος»

( ) «Διάχυτες διαταραχές αυτισμού»

( ) «Διαταραχές νοητικού φάσματος»

( ) «Διάχυτες διαταραχές φάσματος»

2. Από ποια ελληνική λέξη προέρχεται η λέξη Αυτισμός;

( ) Αυτί

( ) Αυτός

(x) Εαυτός

( ) Αυτοτελής

3. Ποιο από τα παρακάτω χαρακτηριστικά ταιριάζει στα άτομα που χαρακτηρίζονται από «κλασικό αυτισμό τύπου Kanner» με βάση τις παρατηρήσεις του αυστριακού ψυχιάτρου Kanner το 1946;

( ) Εμφάνιζαν δεξιότητες υψηλής λειτουργικότητας

(x) Δεν ήθελαν επαφή με τους γύρω τους

( ) Είχαν έντονο ενδιαφέρον στο να καταπιάνονται με νέα πράγματα

( ) Εμφάνιζαν αυξημένες δεξιότητες στην επικοινωνία

4. Τα άτομα με σύνδρομο Asperger σε σχέση με τα άτομα που έχουν τυπικό αυτισμό τύπου Kanner...

(x) παρουσιάζουν δεξιότητες υψηλής λειτουργικότητας

( ) παρουσιάζουν δεξιότητες χαμηλής λειτουργικότητας

( ) παρουσιάζουν τα ίδια χαρακτηριστικά

( ) παρουσιάζουν ταυτόχρονα και άλλα σύνδρομα

5. Ένα άτομο με αυτισμό χαρακτηρίζεται από:

( ) τυπική φαντασία και προβλεπτικότητα

( ) αυξημένη φαντασία και προβλεπτικότητα

(x) μειωμένη φαντασία και προβλεπτικότητα

( ) καλές επικοινωνιακές δεξιότητες

6. Ως προς την επικοινωνία και την κοινωνική αλληλεπίδραση, ένα άτομο με αυτισμό χαρακτηρίζεται από:

( ) μείωση του λεξιλογίου κατά την εφηβική ηλικία

( ) επίμονη βλεμματική επαφή

( ) αυξημένη φαντασία

(x) περιορισμένη ή καθόλου ομιλία

7. Ο αυτισμός χαρακτηρίζεται από:

( ) διαταραχές στην κοινωνική αλληλεπίδραση

( ) ελλείμματα στην επικοινωνία

( ) στερεότυπα σχήματα συμπεριφοράς

(x) όλα τα παραπάνω

<u>Level 2</u>

1. Τα άτομα με αυτισμό χαρακτηρίζονται από:

( ) ανάγκη συνεχούς αλλαγής του περιβάλλοντος στο οποίο ζουν

(x) αποφυγή σωματικής ή κοινωνικής επαφής/επικοινωνίας

( ) αυξημένη ικανότητα σύναψης κοινωνικών επαφών

( ) έλλειψη συγκέντρωσης σε οποιοδήποτε έργο

2. Ως προς την καθημερινή ρουτίνα τα άτομα με αυτισμό...

(x) επιδιώκουν την ομοιομορφία

( ) επιζητούν να αλλάζουν τις συνήθειες τους

( ) μιμούνται τις συμπεριφορές των άλλων

( ) δυσκολεύονται στην τήρησή της καθημερινής τους ρουτίνας

3. Ποια από τις παρακάτω επιλογές δεν συγκαταλέγεται στις Διαταραχές Αυτιστικού Φάσματος:

( ) Η αποδιοργανωτική διαταραχή

( ) Ο μη διαφορετικά προσδιοριζόμενος αυτισμός

( ) Το σύνδρομο Asperger

(x) Διαταραχή Ελλειμματικής Προσοχής / Υπερκινητικότητα (ΔΕΠ-Υ)

4. Αν ένα παιδί με αυτισμό βρίσκεται δίπλα από τρία παιδιά που παίζουν, τι από τα παρακάτω είναι πιο πιθανό να κάνει το παιδί με αυτισμό;

( ) να αρχίσει να κλαίει

( ) να πλησιάσει τα άλλα παιδιά

( ) να τους φωνάξει για να έρθουν κοντά τους

(x) να τους αγνοήσει

Level 3

1. Ο Σπύρος είναι ένα παιδί με αυτισμό. Πηγαίνει στο σχολείο μόνος του κάθε μέρα καθώς το σχολείο του δεν απέχει πολύ από το σπίτι του. Χθες καθώς γύριζε στο σπίτι του, μια παρέα ατόμων μεγαλύτερης ηλικίας τσακωνόταν στο δρόμο από τον οποίο συνηθίζει να περνάει ο Σπύρος. Ο Σπύρος παρόλο που είδε τον τσακωμό δεν άλλαξε δρόμο όπως θα περίμενε κανείς αλλά πέρασε δίπλα τους. Γιατί το έκανε αυτό;

( ) Δεν ήθελε να δείξει ότι φοβάται

( ) Ήθελε να δει από κοντά ποιοι τσακώνονταν

(x) Δεν αντιλήφθηκε τον κίνδυνο

( ) Βιαζόταν να φτάσει σπίτι του

2. Ο Σπύρος είναι ένα παιδί με αυτισμό υψηλής λειτουργικότητας. Ο παππούς του αγόρασε στον Σπύρο ένα καινούριο παιχνίδι και συγκεκριμένα ένα αυτοκινητάκι καθώς αρέσουν πολύ στον Σπύρο. Ποιο από τα παρακάτω ταιριάζει περισσότερο στον τρόπο με τον οποίο αναμένουμε να αλληλεπιδράσει ο Σπύρος με το παιχνίδι;

(x) θα περιεργαστεί με λεπτομέρεια το νέο παιχνίδι επαναλαμβάνοντας περίπου τις ίδιες κινήσεις

( ) θα αναζητήσει άλλα παιδιά για να παίζει μαζί τους με το νέο του παιχνίδι

( ) θα αδιαφορήσει για το παιχνίδι γιατί έχει πολλά αυτοκινητάκια

( ) θα αρχίσει να κλαίει γιατί περίμενε ότι θα πάρει άλλο δώρο από τον παππού του

3. Τι αναμένουμε να συμβεί αν αλλάξουμε τη διαρρύθμιση του δωματίου ενός παιδιού με αυτισμό χωρίς να το προετοιμάσουμε; Το παιδί...

( ) θα ενθουσιαστεί

( ) δεν θα δώσει καμία σημασία

( ) θα στεναχωρηθεί

(x) θα αναστατωθεί

4. Ο Αντώνης είναι ένα παιδί με αυτισμό χαμηλής λειτουργικότητας. Στο σχολείο τον πλησιάζει ένας συμμαθητής του και τον ρωτάει «θέλεις να παίξουμε;». Ο Αντώνης δεν του απαντάει και ο συμμαθητής του τον ξαναρωτάει. Τι από τα παρακάτω συμβαίνει;

(x) Ο Αντώνης δεν αντιλήφθηκε ότι το παιδί απευθύνεται σε αυτόν

( ) Το παιδί ρώτησε τον Αντώνη χαμηλόφωνα και πιθανότατα ο Αντώνης δεν τον άκουσε

( ) Ο Αντώνης ντράπηκε να του μιλήσει

( ) Ο Αντώνης γνωρίζει ότι δεν πρέπει να μιλάει σε ξένους για αυτό δεν απάντησε

<u>Level 4</u>

1. Ο Αντώνης είναι ένα παιδί με αυτισμό χαμηλής λειτουργικότητας. Στην τάξη του Αντώνη όταν χτυπάει το κουδούνι ο δάσκαλος λέει στα παιδιά ότι μπορούν να βγουν στην αυλή για το διάλειμμά τους. Σήμερα βρέχει πολύ, το κουδούνι του σχολείου έχει ρυθμιστεί να χτυπάει αυτόματα τις ώρες του διαλλείματος. Τι πρέπει να κάνει ο δάσκαλος ώστε ο Αντώνης να μην βγει στην αυλή;

( ) Να κλειδώσει την πόρτα

( ) Να εξηγήσει στον Αντώνη για ποιο λόγο δεν θα βγουν διάλειμμα

( ) Να πει στα παιδιά της τάξης να κάνουν θόρυβο ώστε να μην ακουστεί το κουδούνι

(x) Να απενεργοποιήσει το κουδούνι του σχολείου

2. Ο Αντώνης είναι ένα παιδί με αυτισμό υψηλής λειτουργικότητας (σύνδρομο Asperger). Η δασκάλα του αφού εξηγήσει στους μαθητές πως γίνεται η πρόσθεση δύο αριθμών λέει, «Ας πάμε τώρα στο πίνακα να λύσουμε μια άσκηση». Η πρόταση αυτή θεωρείται μη δόκιμη. Γιατί;

( ) Έπρεπε να καλέσει ονομαστικά έναν μαθητή στον πίνακα για να τη λύσει

(x) Μπορεί να παρερμηνευτεί η προτροπή για την επίλυση της άσκησης

( ) Μπορεί τα παιδιά να μην θέλουν να ασχοληθούν με την άσκηση

( ) Έπρεπε να σηκωθεί πρώτα η ίδια στον πίνακα

3. Ο Γιώργος είναι ένα παιδί οκτώ ετών που του αρέσει να παίζει μόνος του και δεν ενδιαφέρεται για το παιχνίδι των άλλων παιδιών που παίζουν δίπλα του στην παιδική χαρά. Συχνά ο πατέρας του τον στέλνει στο ψιλικατζίδικο της γειτονιάς του για να του αγοράσει μια εφημερίδα. Ο Γιώργος αφού ζητήσει την εφημερίδα από τον ιδιοκτήτη, δίνει τα χρήματα που του έχει δώσει ο πατέρας του και στη συνέχεια αφού μετρήσει τα ρέστα που πήρε, γυρίζει στο σπίτι του. Ποιο από τα παρακάτω είναι περισσότερο πιθανό να ισχύει για τον Γιώργο;

( ) έχει αυτισμό τύπου Kanner

(x) έχει αυτισμό υψηλής λειτουργικότητας (σύνδρομο Asperger)

( ) είναι ντροπαλός

( ) έχει αποδιοργανωτική διαταραχή

Level 5

1. Ο Αντώνης είναι ένα παιδί με αυτισμό. Με τον Σπύρο (μαθητής τυπικής ανάπτυξης) κάθονται στο ίδιο θρανίο. Οι δύο μαθητές έχουν κάτω από το θρανίο τους από ένα κουτί. Ο Αντώνης πριν βγει στην αυλή για το διάλειμμα έβαλε μέσα στο κουτί του μια μπίλια. Ο Σπύρος πήρε την μπίλια και τη μετακίνησε στο δικό του κουτί χωρίς να τον δει ο Αντώνης. Ο Αντώνης μετά το διάλειμμα θα έρθει και θα ψάξει για την μπίλια του

(x) στο δικό του κουτί

( ) πρώτα στο δικό του κουτί και μετά στο κουτί του Σπύρου

( ) πρώτα στο κουτί του Σπύρου και μετά στο δικό του κουτί

( ) στο κουτί του Σπύρου

2. Ο Αντώνης είναι ένα παιδί με αυτισμό υψηλής λειτουργικότητας. Στην καλοκαιρινή σχολική γιορτή η δασκάλα της τάξης του Αντώνη θα δώσει στα παιδιά ποιήματα και ρόλους για ένα θεατρικό έργο. Στο θεατρικό έργο θα υπάρχει ένας αφηγητής και δέκα ακόμη ρόλοι οι οποίοι συνδιαλέγονται μεταξύ τους στις διάφορες σκηνές του έργου. Τι θεωρείτε ότι είναι πιο κατάλληλο να δώσει στον Αντώνη η δασκάλα του κατά τη διανομή;

( ) Για να μην τον δυσκολέψει δεν πρέπει να του δώσει τίποτα

( ) Οποιοδήποτε ρόλο από το θεατρικό έργο

() Ένα ποίημα ή οποιονδήποτε ρόλο στο θεατρικό έργο

(x) Ένα ποίημα ή τον ρόλο του αφηγητή

3. Ο Αντώνης είναι ένας μαθητής με αυτισμό χαμηλής λειτουργικότητας. Συνήθως γυρίζει σπίτι μόνος του. Στο δρόμο προς το σπίτι του αρκετές φορές δέχεται επιθετική συμπεριφορά από ομάδα συμμαθητών του. Τι από τα παρακάτω αναμένουμε να κάνει ο Αντώνης τις επόμενες μέρες;

( ) θα γυρίζει σπίτι από άλλο δρόμο

(x) θα συνεχίσει να γυρίζει σπίτι από τον ίδιο δρόμο

( ) θα ενημερώσει άμεσα τους γονείς του για να έρχονται οι ίδιοι να τον παίρνουν από το σχολείο

( ) θα γυρίσει πίσω στο σχολείο όπου νιώθει ασφαλής όταν συναντά τα συγκεκριμένα άτομα στο δρόμο

Appendix II

The questionnaire that was administered to the participants comprised of five dimensions: Perceived engagement, perceived usefulness, perceived learning effectiveness, perceived cognitive benefits, and intention to continue.

Perceived engagement

The engagement questionnaire that was administered to participants in order to evaluate their perceived engagement level in the MOOC assessment activity (in Greek) is presented in Table 1 (Whitton, 2007, 2010). Whitton's engagement questionnaire consists of 18-item in a 5-point Likert scale (strongly agree to strongly disagree). Each of the questions corresponds to a factor that Whitton argues to affect the engagement of the participants: *Challenge, Interest, Control, Purpose, Immersion.*

Table 1. The self-reported engagement questionnaire that was administered to participants (Whitton, 2007, 2010)

#	Question	Engagement factor
1	Ήθελα να ολοκληρώσω τη δραστηριότητα	Challenge (motivation)
2	Δεν με ενδιέφερε να εξερευνήσω όλες τις διαθέσιμες επιλογές	Interest
3	Δεν ήταν σαφές τι έπρεπε να κάνω σε κάθε βήμα της δραστηριότητας	Control
4	Ήξερα τι έπρεπε να κάνω για να ολοκληρώσω τη δραστηριότητα	Challenge (clarity)
5	Αισθάνθηκα ότι μπορώ να επιτύχω τον στόχο της δραστηριότητας	Challenge (achievability)
6	Βρήκα την δραστηριότητα αποθαρρυντική	Challenge (achievability)
7	Η δραστηριότητα δεν μου επέτρεπε να αλληλεπιδράσω με τον τρόπο που ήθελα	Control
8	Δεν μπορούσα να καταλάβω τι αποτέλεσμα είχαν οι ενέργειές μου	Control
9	Αισθάνθηκα ότι η ώρα πέρασε γρήγορα	Immersion
10	Αισθάνθηκα απορροφημένος στη δραστηριότητα	Immersion
11	Βρήκα τη δραστηριότητα βαρετή	Interest
12	Δεν μου άρεσε η δραστηριότητα	Interest
13	Η δραστηριότητα ήταν άσκοπη	Purpose
14	Η ανατροφοδότηση που μου δόθηκε ήταν χρήσιμη	Purpose
15	Η δραστηριότητα μου δημιούργησε το αίσθημα της ικανοποίησης	Immersion
16	Ήταν σαφές τι μπορούσα να μάθω από τη δραστηριότητα	Purpose
17	Δεν με ένοιαζε το πως τελείωσε η δραστηριότητα (σε σχέση με τη επίδοση μου)	Challenge (motivation)
18	Το βρήκα εύκολο να ξεκινήσω με τη δραστηριότητα	Challenge (clarity)

In Table 2 we present Whitton's original questionnaire (Whitton, 2007). Questions are presented in the same order as in Table 1.

Table 2. Whitton's questionnaire as it was presented in her PhD thesis (Whitton, 2007)

#	Question	Engagement factor
1	I wanted to complete the activity	Challenge (motivation)
2	I was not interested in exploring the options available	Interest
3	It wasn't clear what I could and couldn't do	Control
4	I knew what I had to do to complete the activity	Challenge (clarity)
5	I felt that I could achieve the goal of the activity	Challenge (achievability)
6	I found the activity frustrating	Challenge (achievability)
7	The activity would not let me do what I wanted	Control
8	I could not tell what effect my actions had	Control
9	I felt that time passed quickly	Immersion
10	I felt absorbed in the activity	Immersion
11	I found the activity boring	Interest
12	I did not enjoy the activity	Interest
13	The activity was pointless	Purpose
14	Feedback I was given was useful	Purpose
15	I found the activity satisfying	Immersion
16	It was clear what I could learn from the activity	Purpose
17	I did not care how the activity ended	Challenge (motivation)
18	I found it easy to get started	Challenge (clarity)

The other dimension was evaluated with a questionnaire that comprised of the following items in a 5-point Likert scale.

Perceived usefulness

Απάντησε στις παρακάτω προτάσεις σχετικά με τη χρησιμότητα της δραστηριότητας όσον αφορά τη μάθηση μέσα σε ένα διαδικτυακό μάθημα (MOOC). Η δραστηριότητα (ως προς τη δομή της και την ανατροφοδότηση που προσφέρει)...

1. θα μου επιτρέψει να βελτιώσω τον ρυθμό μάθησης σε ένα διαδικτυακό μάθημα (MOOC)
2. θα βελτιώσει την επίδοσή μου σε ένα διαδικτυακό μάθημα (MOOC)
3. θα κάνει πιο αποτελεσματική τη μαθησιακή μου εμπειρία σε ένα διαδικτυακό μάθημα (MOOC)
4. είναι χρήσιμη για τη μάθησή μου μέσα σε ένα διαδικτυακό μάθημα (MOOC) γενικά

Perceived learning effectiveness

Απάντησε στις παρακάτω προτάσεις σχετικά με τη μαθησιακή αποτελεσματικότητα της δραστηριότητας μέσα σε ένα διαδικτυακό μάθημα (MOOC)

1. Η δραστηριότητα με έκανε να ενδιαφέρομαι να μάθω περισσότερα για τη ΔΑΦ
2. Αποκόμισα πολλές τεκμηριωμένες πληροφορίες για τη ΔΑΦ
3. Απέκτησα μια καλή κατανόηση γύρω από τις βασικές έννοιες που αφορούν τη ΔΑΦ
4. Έμαθα να αναγνωρίζω τα κύρια και σημαντικά θέματα γύρω από τη ΔΑΦ
5. Ενθαρρύνθηκα μέσα από τη δραστηριότητα να μάθω περισσότερα για τη ΔΑΦ
6. Είμαι σε θέση να συνοψίσω ό,τι έμαθα και να καταλήξω σε συμπεράσματα
7. Η δραστηριότητα μου φάνηκε ουσιαστική
8. Αυτά που έμαθα μέσα από τη δραστηριότητα, μπορώ να τα εφαρμόσω και σε πραγματικό πλαίσιο

Perceived cognitive benefits

Απάντησε στις παρακάτω προτάσεις σχετικά με τα γνωστικά οφέλη που θεωρείτε ότι αποκομίσατε μέσα από τη δραστηριότητα

1. Η δραστηριότητα διευκολύνει την κατανόηση των πληροφοριών που παρακολούθησα στις βιντεοδιαλέξεις
2. Η δραστηριότητα διευκολύνει την απομνημόνευση των πληροφοριών που παρακολούθησα στις βιντεοδιαλέξεις
3. Η δραστηριότητα με βοηθάει να εφαρμόσω αποτελεσματικότερα ό,τι έμαθα μέσω των βιντεοδιαλέξεων
4. Η δραστηριότητα με βοηθά να αναλύσω πιο αποτελεσματικά προβλήματα που σχετίζονται με το περιεχόμενο των βιντεοδιαλέξεων

Intention to continue

Απαντήστε τις παρακάτω ερωτήσεις σχετικά με το αν σκοπεύετε να χρησιμοποιήσετε τα Μαζικά Ανοικτά Διαδικτυακά Μαθήματα (MOOCs) στο μέλλον

1. Σκοπεύω να παρακολουθώ διαδικτυακά μαθήματα (MOOCs) στο μέλλον
2. Θα παρακολουθώ διαδικτυακά μαθήματα (MOOCs) ολοένα και περισσότερο στο μέλλον
3. Θα συνιστούσα έντονα και σε άλλους να παρακολουθήσουν διαδικτυακά μαθήματα (MOOCs)