Adapting Gamification Elements to Learners' Personality dimensions

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Abstract

Gamification, adding game elements to non-game contexts, has been shown to improve users' motivation, engagement and satisfaction in different disciplines, including health and education. However, existing research has pointed out that users' attributes, such as personality and mood, can influence its effectiveness. This thesis therefore proposes a model that can be used to adapt gamification elements. One stable user attribute that can be employed as the basis for such adaptation is personality. The first step in building the model is to understand how personality dimensions interact with gamification elements in the online learning environment. We ran three experimental studies, each using the same approach and different gamification elements. In each study, we measured learners' motivation, knowledge gain and satisfaction. The results from these studies and those available in the literature were used to establish rules for building an adaptive model, which was shown to be beneficial to learners in a further study that was carried out to evaluate it.
The proposed adaptive model can be used as a starting point to build a dynamic adaptive model that will ensure that users have the best experience in any gamified system.

To the soul of my dad ..

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Chapter 1

Introduction

1.1 Introduction

Over the past two decades, online learning has become very popular because of its flexibility related to time and location (Anderson, 2008). However, one of the key problems associated with online courses is that most learners fail to complete the course owing to a variety of factors, such as lack of motivation (Kim and Frick, 2011; Onah et al., 2014). Motivation is a critical factor in the learning process, and several techniques have been employed to stimulate learners, one of which is the integration of gamification(adding game elements to non-game contexts (Huotari and Hamari, 2012)) into courses.

Although gamification has been successfully implemented in a variety of contexts, online learners respond differently to it. Some are motivated and respond positively (Cheong et al., 2013), while others may become distracted or annoyed (Jia et al., 2016).

It has been suggested that a model should be built to adapt gamification elements to a variety of learners' attributes. However, it is difficult to adequately embrace all of the key attributes, so, in this thesis, we only focus on personality.

The thesis explains how a model could be employed to adapt elements of gamification to learners' personalities. Several studies were conducted to better understand how different personality traits interact with different gamification elements to help build an adaptive model, which is then evaluated.

In this chapter, an overview of the background related to the relevant subject matter and research studies is given. The research questions and the main goal of the thesis are then be presented, followed by the methodology employed. Finally, the thesis contributions to the existing body of literature are presented.

1.2 Background and Motivation

Learning is a continuous and complex process that begins at an early age and never stops (Alexander et al., 2009). Because of its complexity, different theories have been developed to explain it (Ertmer and Newby, 2013), one of the oldest of which is behaviourism, which describes learning as a change in learners in response to a stimulus presented by a teacher (Ally, 2004). A second theory is based on cognitivism, which considers learners' minds to be a critical factor in the learning process (Winn, 1990). This theory is usually used to describe high-level processes, such as problem-solving strategies and critical thinking processes (West et al., 1992). These two theories suggest that learning occurs within the learner, without considering the outside world. To address this, constructivism was developed to explain learning as a process that occurs because of the interaction between learners and their experiences with others and their environment. This theory has been expanded into connectivism (Goldie, 2016), in which the learning process involves all information that exists on the internet. In connectivism, learners play a critical role in choosing what to learn and how to connect their previous knowledge with new information and, thus, a recent application of connectivism is online learning.

Online learning has become popular because of the development and evolution of the internet and the introduction of new technologies (Anderson, 2004). Online learning is different from traditional learning in the way that the educational materials are delivered. Learners can use the internet to access required information at any time and in any place (Anderson, 2008). However, one of the problematic issues with online learning is that many learners drop out of their courses after only a few weeks for a number of reasons (Allen and Seaman, 2008), including feelings of isolation and a lack of motivation (Willging and Johnson, 2009). Motivation is a critical factor in the learning process (Lee et al., 2013) and is defined as a condition or state that activates individuals' behaviour into a specific direction (Hartnett et al., 2011). Motivation is considered a significant influence in the learning process, and increased motivation can be a good predictor of improved learner outcomes (Lee et al., 2013). One common theory used to explain motivation is self-determination. This theory classifies learners' motivation as intrinsic, in which the task meets the learner's goals; extrinsic, which encompasses all the external factors that can enhance learners' motivation; and amotivation, the lack of motivation (Ryan and Deci, 2000).

Different techniques have been proposed to improve online learners' motivation and engagement, including gamification (Domínguez et al., 2013). There are a variety of gamification elements that can be integrated into online learning systems, including points, badges, leaderboards, progress bars, avatars and social elements (Dichev et al., 2014). Gamification can be classified into two types: content gamification, in which the content of the learning itself is changed to be more like a game, and structural gamification, in which the gamification elements are added to the online learning course as an extra layer without changing the content (Wongso et al., 2014).

This thesis focuses on structural gamification, in which gamification elements are integrated in an online learning system. However, for these elements to be effective, they must be related to the online learners' progress and success in the course, and must take into account their emotional and social characteristics (Domínguez et al., 2013). Gamification elements provide learners with quick and valuable feedback, and learners are less likely to experience fear of failure (Hamzah et al., 2014) as they imagine that they are playing a game (Dichev et al., 2014).

Despite all the benefits of gamification, some research studies have shown variations in its effects on learners. As Jia et al. (2016) reported, although most learners benefit from gamification, some find it annoying and boring, while others are distracted by its elements. Such learners may busy themselves with the collection of points and badges rather than focusing on the course contents (Sosnovsky and Dicheva, 2010). Further, Fernandes and Junior (2016) asserted that gamification is an effective technique in the short term only, and over time, learners begin to feel bored.

Due to the variation in learners' responses to gamification, it has been suggested that gamification elements should be adapted to match learners' different characteristics (Codish and Ravid, 2014b; Tondello et al., 2016). Different learner characteristics can be invoked to adapt gamification elements, including age, background, preferences, interests, experience, individual traits and physical environment (Brusilovsky and Millán, 2007). In this thesis, personality is a focus, as it tends to be a more stable attribute (Brusilovsky and Millán, 2007).

Personality is defined as a set of characteristics and psychological factors that can influence individual behaviour (Hofstee, 1994). Different theories and models have been developed to explain and classify personality, including the widely supported trait theory, which classifies individuals in terms of long-lasting behaviour, emotions and thought patterns (Carlyn, 1977). The most common model for this theory is the 'big five' model or five-factor model that classified personality into:(McCrae and Costa, 2008):

- Conscientiousness, which refers to individuals who tend to organise, plan and work hard;
- Extraversion, which refers to individuals who tend to be talkative and social and who prefer to be in leadership positions;
- Agreeableness, which refers to individuals who tend to be kind, gentle, caring and helpful;
- Neuroticism, which refers to individuals who tend to be emotionally unstable, anxious, neg-

ative and depressed;

- Openness to experience, which refers to individuals who tend to be imaginative and creative.

To adapt gamification elements to learners' personality dimensions, we first need to understand the relationship between the two. Some research studies have attempted to address this relationship (Codish and Ravid, 2014a,b); (Jia et al., 2016), but the results may not be reliable as some of the studies used short versions of personality tests, which suffer from reliability issues (Tondello et al., 2016). In addition, the results of these studies were based on self-report questionnaires collected from only those users who completed the entire experiment. Requiring users to complete the study may conflict with the primary objective of gamification, which is to enhance the motivation. At the same time, these studies ignore from the analysis the users who drop out in the middle of the studies. However, it is essential to identify their reason(s) for dropping out. More specifically, it is important to ascertain whether particular gamification elements were the cause. Having all of these issues in the methodology may introduce bias in the results of these related research studies. Therefore, in this research, a new approach is used to understand the relationship between gamification elements and personalities to conduct the process of adaptation. This understanding is used to build and evaluate an adaptive model that can be used to match online learners' personality profile with the most suitable gamification elements.

1.3 Research questions

This study addresses several research questions, all of which concern the gamification effects on online learners, which is evaluated in terms of learners' motivation, knowledge gained and satisfaction.

The overarching research question for this thesis is:

How can we adapt gamification elements based on learners' attributes?

The idea of adapting gamification elements is considered novel research, and only a limited number of research studies have attempted to address the process of adaptation. There are different internal and external attributes; such as learners' ages, moods, interests, backgrounds, experience and individual traits, affecting online learning success, but it is difficult to include them all. We will therefore focus on personality as it is a more stable attribute and is suggested by several studies that have tried to adapt gamification elements. Therefore, the key research question here is:

How can we adapt gamification elements based on learners' personality profile?

The relationship between gamification elements and learners' personality dimensions must be examined. Some research has attempted to address this relationship, but the results suffer from reliability issues related to the measurement tools used. As a first step, this thesis aims to address the relationship between gamification and personality by considering the following question:

Do learners with different personality dimensions respond differently to gamification elements?

Our understanding can be employed to construct the adaptive model, which is then evaluated to gauge its effectiveness. Thus, further questions must be answered:

How should an adaptive gamification model be built and evaluated?

Is matching learners with different personalities to their suitable gamification elements beneficial?

The working model will serve as the primary model, using only personality as the basis for adaptation. However, there are several other attributes that could be used. We should therefore also address the following question:

What other attributes should be used in conjunction with personality to adapt gamification elements?

1.4 Research Methodology

In the present study, several experiments were conducted to understand the relationship between gamification elements and the learners' personality. The results from those studies were used to build the adaptive model. Finally, an additional study was conducted to evaluate the proposed model.

Initially, to understand the relationship between gamification elements and personality dimension, three experimental studies were conducted, each following the same approach with different gamification elements and different learners. In these studies, an online learning website was built to teach Microsoft Excel in two versions. One version of the website included gamification elements and the other version did not. In each study roughly 200 learners, aged 16-18 years, were asked to register on the learning website and complete a demographic questionnaire, the Big Five Inventory (BFI), to assess their personality. The learners were also asked to take a pre-test related to the course to assess their prior knowledge. The learners were then divided into two groups, balanced by age, gender, prior knowledge level and personality profile. The learners were told that they could use the website at any time, and they were informed that they were free to drop out at any time. Dropout rates were used as a proxy for motivation. After confirming whether all the learners had either stopped using the learning website or completed the course, we asked them to complete a post-test related to the course and a satisfaction test. A few weeks after finishing the experiment, the learners were asked to complete another post-test to measure their long-term knowledge gain. The learners' dropout rate from the gamified version was compared to the dropout rate from the non-gamified version using the Kaplan-Meier estimator and the Cox hazard model (Allgulander and Fisher, 1986). The learners' knowledge gains were compared between the groups by subtracting the results of the pre-test from the results of the first post-test; long-term knowledge gain was calculated by subtracting the pre-test results from the second post-test results. Finally, the satisfaction of the groups was also compared.

In these experimental studies, it was hypothesised that learners with different personality dimensions would respond differently to various gamification elements.

After gathering the results from the three studies, a preliminary model was built by examining a common pattern in the responses to gamification of learners with specific combinations of personality dimensions. These patterns were then used along with the results from related studies to derive predictions that could be used to build an adaptive model.

In the final stage, the model was evaluated by using a matched and mismatched approach. We conducted an additional study by asking the learners (aged 16-18 years) to register on the website, complete a demographic questionnaire, including age and gender, the BFI and a pre-test. Then, the learners were divided equally into two groups; one group consisted of learners that used a version of the website that matched the learners' personality profile (this version can be integrated with gamification elements or lacked such elements), and the other group consisted of learners that used a version of website that did not match the learners' personality profile. This allowed the effectiveness of the model, to be examined as it was hypothesised that there would be a significant difference in the behaviours of the learners in these two groups. The learners who were assigned to the matched version were expected to exhibit higher levels of motivation and satisfaction and gain more knowledge than the learners assigned to the mismatched version.

1.5 Research contribution

The contributions of this thesis can be summarised as follows:

It contributes to the related literature by providing an understanding of how different personality dimensions interact with different gamification elements. This thesis evaluated the effect of gamification elements on learners' personality profile by measuring the learners' motivation, knowledge gain and satisfaction. Moreover, the thesis showed that there were differences in the responses based on the learners' personality profile under the same gamification elements in different measurements. This variation in the results can be used as evidence that personality can be considered as a good predictor for learners' behaviour in a gamified system.

This thesis also discusses how to use the findings with the results reported in several other research studies to build the adaptive model. The adaptive model matches each learner with a different personality profiles with the most suitable gamification elements. This adaptive model was evaluated in this thesis. It was shown that the model could be successfully used to improve the learners' motivation, knowledge gain and satisfaction.

1.6 List of publications

A number of research papers which were a part of this work have been accepted and published:

- **Ghaban, W.**, & Hendley, R. (2018). Investigating the interaction between personalities and the benefit of gamification. In Proceedings of the 32nd International BCS Human Computer Interaction Conference (p. 41). BCS Learning & Development Ltd.

- **Ghaban, W.**, & Hendley, R. (2019). How Different Personalities Benefit From Gamification, Interacting with Computers, Volume 31, Issue 2, March 2019, pp. 138-153, https://doi.org/10.1093/iwc/iwz009

- **Ghaban, W.** & Hendley, R. (2019). Understanding the Effect of Gamification on Learners with Different Personalities. In Proceedings of the 11th International Conference on Computer Supported Education, Volume 2, CSEDU, ISBN 978-989-758-367-4, pp. 392-400

- **Ghaban, W.**; Hendley, R. & Fleck, R. (2019). Investigating How Social Elements Affect Learners with Different Personalities. In Proceedings of the 11th International Conference on Computer Supported Education,Volume 2, CSEDU, ISBN 978-989-758-367-4, pp. 416-423.

- **Ghaban, W.**; Hendley R. (2020) Can We Predict the Best Gamification Elements for a User Based on Their Personal Attributes?. In: Fang X. (eds) HCI in Games. HCII 2020. Lecture Notes in Computer Science, vol 12211. Springer, Cham

1.7 Thesis structure

This thesis is comprised of seven chapters. In the second chapter, we explore the meaning of learning and the different theories that have been developed to explain it, with a discussion of the applications and limitations of each theory. We then discuss one of the common recent way to learn, which is an online learning and its advantages and disadvantages. One of the issues associated with online learning is a lack of motivation and engagement in the courses, and so we provide a brief description of motivation and one of the most common theories (self-determination theory) used to explain it. We then identify some of the possible techniques for improving learners' motivation and engagement, with a focus on gamification. The concepts and elements of gamification are outlined, and examples of its application are presented. Finally the benefits and drawbacks of gamification are identified and discussed.

Because of the various effects of gamification on users, we suggest personalising gamification for users. Chapter 3 therefore explains the concept of personalisation and provides an overview of the two most common types of personalising systems: recommender systems and adaptive systems. We focus on adapting gamification elements, presenting the different characteristics that can be used, providing examples of related research studies that have attempted to adapt gamification elements and identifying the issues with those studies.

In chapter 4, we present our suggested framework for adapting gamification elements to learners' attributes and how to implement this framework. In this thesis, we focused on a single attribute related to the learner, which is personality. Later in the same chapter, the three steps required to build the adaptive model were briefly discussed.

Chapter 5, 6, 7 and 8 explain the different studies that have been conducted to explain the interaction of different gamification elements with learners' personalities. We present an overview of the methods used in the studies and describe each study separately, including the methods and results in detail. We conclude with the combined findings from the three studies and present the implications of these findings.

In chapter 9, we use the understanding obtained from previous chapters together with suggestions from theory and related works to build the adaptive model. This model can be used to match gamification elements to learners' personalities. This chapter then explains how the proposed model is evaluated, including the approach and the experimental study. The results from this experiment are presented and discussed, including the limitations and drawbacks of the proposed model and how to resolve those limitations.

Chapter 10 reflects on the research questions and concludes with how the results provide answers. This chapter also presents the limitations of the study and suggests future research.

Chapter 2

Gamification in Online Learning

2.1 Introduction

Learning continues throughout an individual's life. This chapter presents an overview of learning and an outline of the most common learning theories. One of the most popular ways to learn is by participating in online courses, where the learners and the instructors are physically separated. Thus, online learning is described in more detail, and the advantages and disadvantages of online courses discussed. Two of the most important factors affecting the learning process are described, especially in online learning: *motivation and engagement*. Some techniques for enhancing motivation in online courses are identified, such as games.

Using games in an online learning environment may require some extra time and costs in the process of changing the learning content into a game (Dicheva et al., 2015). Further, applying games in learning may entertain learners more than educate them. Because of this, recent studies show that there is a movement towards using gamification, whereby game elements are incorporated in non-game contexts to increase motivation. At the end of the chapter, the concept of gamification is presented, followed by an overview of its benefits and issues from using this technique with online courses.

2.2 Learning

Learning is considered a core concept among educators and psychologists (Ormrod and Davis, 2004). Some studies consider learning to be a product, while others state that learning is a process (Alexander et al., 2009). However, Alexander et al. (2009) pointed out that learning can be both. They define learning as a process that explains the process of change and a product when we refer to learning outcomes.

No single definition can fully define learning. However, different studies have explained learning in different ways. For example, Schunk (2016) illustrated learning as a change in the human behaviour because of learners' experiences and their expertise in the world. Jonassen and Grabowski (2012) pointed out that learning is an enduring change in the performance of a human. This change occurs because of the individual's experiences and interactions with the outside world. Alexander et al. (2009) tried to encapsulate these concepts in one definition, expressing learning as multi-dimensional process that involves enduring changes in the learner's state. These changes in the individual's state can be physical, psychological, emotional and/or social. The change is caused by the learner's interaction with the world, their perception of it and their response to it.

The previous definitions share some common elements. Most researchers agree that learning is a change in itself. This change can be either explicit (e.g. learning how to skate) or implicit (e.g. understanding the logic of programming) (Alexander et al., 2009). In addition, most definitions claim that the change results from learners' experiences. Some researchers claim that learning is constant, while others state that learning changes over time (Anderson, 2008; Alexander et al., 2009). This is because an individual's ability to acquire knowledge and learn new skills may change over the years. The capability of an adult's mind regarding learning is different from that of a child (Alexander et al., 2009). Furthermore, some articles argue that learning never stops. Rather, it is a process that continues as long as the learner is alive, without any control by the learner (Bargh and Chartrand, 1999; Alexander et al., 2009).

Learning is a complex process that depends on many factors. Different theories have emerged to explain this process, how it occurs and what factors affect it. The most common theories include behaviourism, cognitivism and constructivism (Ertmer and Newby, 2013). Based on these theories and technological improvements, a new theory has appeared: connectivism. Connectivism tries to explain how learning can occur in the era of the internet and through social interactions with other learners via the internet (Goldie, 2016).

Although the above theories differ from each other, there is some overlap between them, and some of the theories complement others. In the following section, more details are provided about these theories (Anderson, 2008).

1- Behaviourism

Behaviourism assumes that learning occurs when there is a change in an individual's observable behaviour (Bechtel et al., 1998). This change can be either in the performance of the learner, or the frequency of the performance (Ertmer and Newby, 2013). This theory presents the learner as a 'black box' without any consideration for the learner's mind (Ally, 2004). Furthermore, behaviourism is concerned with the strength of the link between the learner's response towards a specific stimulus. For example, if the learner is provided with the stimulus '3 + 4', the learner must respond with '7' (Ally, 2004).

The learner's prior knowledge is considered a critical factor in behaviourism. It is important to decide where to start to teach the learner. It is the responsibility of the teacher to design the materials and the learning contents to be more efficient and effective for learners (Ertmer and Newby, 2013). Furthermore, the teacher is responsible for the strength of the link between the stimuli and the responses (Mayer, 2002). Teachers should use cues to stimulate the appropriate response initially, and reinforcements, such as rewards and reasonable feedback, to strengthen the required response (Winn, 1990; Ertmer and Newby, 2013).

Behaviourism ignores the mechanism of memory and the brain. The learner is considered to have a passive role in practice. Therefore, this theory cannot be used to explain high-level processes, such as problem-solving strategies. Instead, it can be used effectively for recollection, explanation and illustration purposes (Winn, 1990; Ertmer and Newby, 2013).

2- Cognitivism

In contrast to behaviourism, which ignores the role of the learner's mind, cognitivism assumes the learner has an active role in the learning processes (Winn, 1990). Educators and psychologists assume that learning is more complex than an observable change in behaviour; it must include more complex and cognitive processes (West et al., 1992). Thus, instead of concentrating on what learners do and how they respond, cognitivism is concerned with what learners know and how they know (Ertmer and Newby, 2013; Winn, 1990). Cognitive theory assumes that learning is a mental process in which the mind needs to receive, store, process and retrieve knowledge (Jonassen, 1991).

In cognitivism, the learner plays an active role by receiving, organising, processing and retrieving new information in order to produce the desired response (Ertmer and Newby, 2013; Winn, 1990). In addition, the learner's prior knowledge is an important factor that should be considered in the learning process (Ertmer and Newby, 2013). The teacher must assess learners' knowledge before starting to teach. The teacher is also responsible for organising the information in a sensible way (e.g. in hierarchical and analogical relationships) to allow learners to match their prior knowledge with the new information (Winn, 1990; Ertmer and Newby, 2013).

Cognitivism is very effective in describing high-level processes, for example, problem-solving strategies, reasoning, critical thinking, information processing and language development (West et al., 1992). It is clear that behaviourism and cognitivism differ from one another.

However, these two theories share some similarities (Ally, 2004). For example, both behaviourism and cognitivism rely on the influence of environmental factors and learners' previous knowledge on the learning process. Both theories emphasise the importance of feedback to ensure the effectiveness of the learning process. Behaviourism uses feedback to prompt the desired response from the learners, while cognitivism uses feedback to support the interaction with the brain. Behavioural and cognitive theories share the same goal: to transfer knowledge to learners effectively and efficiently (Ertmer and Newby, 2013; Winn, 1990).

3- Constructivism

Both behaviourism and cognitivism assume that learners are independent and that learning occurs inside the learners (Ertmer and Newby, 2013). However, constructivism does not ignore the existence of the outside world. This theory suggests that learning results from interactions between the learner and the world (Huang, 2002). Some educators consider constructivism to be an elaboration of cognitivism with more focus (Ertmer and Newby, 2013). Constructivism assumes that learning is the result of how learners interact with their environment and how they process these interactions to make their own interpretations and experiences (Bruner, 1966). Thus, this theory does not claim that knowledge is mind-independent, as cognitivism does. Instead, it considers learners' minds to be responsible for reasoning, retrieving and reflecting on the information. Furthermore, this theory suggests that information cannot be decomposed into hierarchical analyses and relationships, as in cognitivism (Winn, 1990; Ertmer and Newby, 2013). In constructivism, learners have a very active role. Learners must interact with their environment to construct, elaborate and integrate their knowledge. It is important to identify learners' prior knowledge and the context in which the knowledge and skills will be learned (Jonassen, 1991).

In addition, it is important that teachers facilitate the process of learning by designing a suitable experience that fits learners' prior experiences. In addition, teachers must present and design information in different formats by revisiting the exercises at different times or from different perspectives. Furthermore, it is important to assess learners' knowledge by presenting new problems to learners that differ from the condition in which they already learned the problem (Winn, 1990).

This theory works well to describe learners. Learners go to conferences and meetings; they talk to others (peers or professors), and they build their own interpretations and experiences.

They also read books and watch videos to build their knowledge. Constructivism effectively describes a specific kind of learners who is self-directed and relatively independent. However, many researchers argue that this theory may not always be productive. Learners cannot experience everything and sometimes need to be directed and taught (Winn, 1990; Harasim, 2012; Ertmer and Newby, 2013).

However, these three theories: behaviourism, cognitivism and constructivism suggest that the process of learning happens inside the learner's mind only, without considering the experience and knowledge that are stored in databases or the information that can be shared via technology and the internet. Such knowledge sources are growing. Goldie (2016) argued that the amount of information doubles every 18 months, according to the American Society of Training and Documentation. It would be impossible for learners to acquire all this knowledge; they cannot experience everything (Kop and Hill, 2008). Therefore, a new theory is required to describe how the growth of knowledge and improvements in technology can affect the learning process. One recent theory that attempts to do so is connectivism (Goldie, 2016).

4- Connectivism

Connectivism is considered an expansion of constructivism. It assumes that learning and knowledge can reside outside of the learner (e.g. in databases on the internet) (Goldie, 2016). It represents information sets as nodes in a network. It is essential for learners to understand how these nodes are connected. In this theory, knowledge can be conflicting, and it includes diverse opinions. Learners can decide what to learn based on their capacity for learning (Kop and Hill, 2008).

In connectivism, learning is a circular process that starts with learners. Learners need to connect to the network to find new information. Then, learners modify the new information based on their beliefs. Afterwards, learners may connect back to the network to share their new realisation (Downes, 2008). Connectivism concerns the building and sharing of learners' understanding. Learners play a very active role in the learning process. Learners are considered central to the learning process. They must define the content to be learned and how to make connections within this content (Tschofen and Mackness, 2012).

Connectivism changes the role of the teacher. In fact, it almost ignores the role of the teacher. Learners must find information and communicate with others based on their own preferences and interests (Goldie, 2016), while, the teacher may only guide the learner to their most suitable and beneficial course. For example, learners can choose their preferred course that is available online through the internet based on a suggestion from the teacher.

2.2.1 Summary

Learning is a continuous and multidimensional process that continues throughout an individual's life. Previous studies have defined learning from different aspects (Alexander et al., 2009). However, most of these definitions overlap and can be combined in a single definition. Learning is an enduring change in the state of the learner. The change occurs because of the acquirement of knowledge or the learner's experience (Bruner, 1966; Driscoll, 2002).

Different theories are used to explain learning. Behaviourism is one of the basic theories that focuses on learners' behaviour. This theory suggests that the learner's mind has no role in the learning process, and it is the responsibility of the teacher to transfer knowledge and strengthen the link between the stimuli (e.g. the equation), and the responses (e.g. the answer). This theory ignores cognitive processes and high-level skills. Cognitivism tries to address this problem. Cognitivists assume that learners have an active role in the learning process. They are responsible for receiving, storing, processing and retrieving information. Constructivists believe that the learning process cannot be isolated from the context in which the learning occurs. Learners need to interact with their environmental context to develop their own interpretations and experiences.

Learners cannot experience everything; they must, therefore, learn from others' experiences. This is why connectivism assumes that learning is a circular process. Learners need to connect to a community that consists of a large number of nodes, representing different sets of information. Learners need to gain an understanding of the new information and then share their understanding with the community (Winn, 1990; Ertmer and Newby, 2013; Goldie, 2016).

Connectivism theory can be used to describe one of the popular ways of learning today, which is online learning.

2.3 Online learning

Anderson (2004) pointed out that the improvement of the internet and related technologies has changed the concept of learning and the manner in which the content is delivered. Thus, the concept of distance education, in which learners and teachers are physically separated, has emerged. However, Brown (2007) showed that this concept of distance education is not new. Educators and teachers previously delivered learning contents to learners through different media, such as post, radio and television (Anderson, 2010). Later, when personal computers became popular, educators and teachers used these to build courses by using word-processing programs and other similar applications. Furthermore, they were able to install this content on CDs and DVDs for learners (Cantillon et al., 2017).

Currently, thanks to the internet and web-based networks, distance learning is being spread all over the world. In the literature, distance learning has been referred to as 'online learning', 'e-learning', 'distributed learning' and 'computer-assisted learning'. Kop and Hill (2008) tried to identify the difference between the most common concepts: distance learning, e-learning and online learning. They argued that distance learning or distance education is the most common concept used to describe learning when the instructor and the learners are geographically separated. In distance education or distance learning, learning contents and materials can be either electronic or printed; computers can be used to deliver the materials. This terminology (distance education or distance learning) can be used as an umbrella term, encompassing e-learning, online learning, technology-based learning and online collaborative learning (Kop and Hill, 2008).

The second common term is e-learning, which emerged in the 1980s. Kop and Hill (2008) defined e-learning strictly as any materials that can be accessed using technological tools, such as web-based and web-capable learning courses. Carliner (2004) added that e-learning courses can include any materials that can be delivered by CD-ROM, an intranet or the internet. Kop and Hill (2008) maintained that there is no certainty or agreement on the characteristics of a course described as an e-learning course. They showed that e-learning is considered a kind of online course.

The third most common concept is online learning, which is described as the most-recent version of distance education. Oblinger et al. (2005) showed that it is difficult to describe this concept, and it can involve all the previous kinds of learning. Furthermore, there is no single definition to describe online learning. Oblinger et al. (2005) simply described the concept as 'wholly' online learning, where the access to the material is non-traditional, and learners are provided with the connectivity, flexibility and ability to interact with the contents, learners and instructors (Anderson, 2004). Because of the popularity of the term 'online learning' in recent related research, this term is used throughout the rest of this thesis.

(Carliner, 2004, p. 4) defined online learning as 'any educational contents that are presented on the computers'. Hershkovitz and Nachmias (2009) added that all contents and materials for an online course must be delivered via the web and the internet. Online learning allows learners to access materials at any time and in any place, they are able to receive feedback about their progress (Ally, 2004); (Hershkovitz and Nachmias, 2009). Ally (2004) integrated all related definitions and defined online learning as the ability to use the internet and technologies to interact with learning materials, instructors and other learners to receive the required support during the learning process. The interaction allows learners to obtain knowledge, acquire skills and grow their experience. For online learning to be effective, Keller and Suzuki (2004) claimed that the courses must be relevant to the learners and must be built in an appropriate way to engage learners.

Reflecting on the different theories of learning, online learning is considered to be an application of connectivism. However, Ally (2004) showed that because of the overlap between the different theories, it is important to consider the other theories when designing online learning materials and instructional designs. For example, behaviourism considers the learning process as a 'black box' and is concerned with the behaviour and response of learners, who should be told explicitly what they should do and why. In addition, learners' knowledge levels must be assessed at the beginning of the course. Following that, learning materials must be designed sequentially from simple to complex, from known to unknown. Furthermore, learners should be provided with sensible feedback to let learners learn from their mistakes and improve their progress. At the end of the learning process, learners must be assessed to measure their outcome and their achievements (Bechtel et al., 1998); (Ally, 2004).

Cognitivism regards the learner's mind as a process that receives, processes, stores and retrieves information (Schunk, 2016). Thus, information in online courses must be designed appropriately so that the learner can catch and process it quickly (Tseng et al., 2008). For example, in designing the interface of an online course, the critical information must be highlighted, and must be presented in the centre of the page. Furthermore, when designing the course, the learning content must be connected to the learners' prior knowledge and must be organised relationally. Large chunks of information must be divided into smaller chunks to avoid overwhelming learners with content. In cognitive theory, it is important to motivate learners and ensure they engage with the course (Schunk, 2016). Enhancing learners' motivation improves their learning outcomes.

In constructivism and connectivism, learners build their knowledge based on their experiences and the experiences of others. In these theories, an online course must be designed to ensure that learners are actively performing mental activities and high-level processes. In addition, learners must search for, and find, information that fits their expectations rather than accepting it from the instructors. Regarding these theories, collaborative and cooperative online learning is extremely important for learners (Cassidy, 2004).

2.3.1 Examples of online learning systems

There are many examples of recent web-based learning systems. One classic example of an online learning system is Blackboard. Blackboard was developed in 1997, and it aimed to provide virtual classrooms, real life learner-teacher interactions and online assessments (Hauger and Köck, 2007). Another common class of online learning system is Massive Open Online Courses (MOOCs), which first emerged in 2008. They became really popular in the summer of 2011, when a free course, Artificial Intelligence, was offered by the University of California. That course attracted almost 160,000 students from all over the world (Waldrop, 2013). Recently, MOOCs have had more than 270,000 registered learners and have been developed by many commercial providers, including Coursera, Udemy, FutureLearn and Edx (Sinclair et al., 2015).

Another example is Moodle, a free online learning system that emerged in 2002. According to the Moodle, this online learning system was developed based on the constructivism approach. There are nearly 70 million learners currently registered on Moodle (Cole and Foster, 2007). In addition to the previous examples, online learning systems exist at the university and academia level. One example is the Open University in the United Kingdom. This university provides entire online learning courses that can lead to academic qualifications. The secret behind the success of this university is that it clearly identifies learners' needs to provide them with the best support, such as providing books, television, online conferences and discussion groups (McKimm et al., 2006). In addition to the Open University, many other universities around the world provide online courses during coronavirus epidemic in 2020.

2.3.2 Advantages and disadvantages of online courses

The increasing amount of information that can be provided by online courses attracts many learners of different ages. Learners are able to access courses from anywhere in the world. Furthermore, learners are able to attend different international courses and learn from different locations. All of this can be done without any travel or accommodation costs. Learners can take any course anytime and anywhere, which is an important feature for learners who have jobs or other responsibilities (Anderson, 2008). One study by Linn (1996) found that the outcomes of online learners were the same or even better than the outcomes of learners in physical, traditional classrooms.

Online learning can be either synchronous or asynchronous. In synchronous online learning, both the teacher and the learners are available online at the same time, and the material is recorded and stored in the online learning system. In asynchronous online learning, the teacher, for instance, records a lecture and saves it in the learning system for learners to review (Anderson, 2008). In both types, learning materials are available to learners at all times, and learners are able to access and revise the content freely (Knowles and Kerkman, 2007).

Online learners can also use the social features of online courses to interact with other learners in the form of collaborative online learning. Knowles and Kerkman (2007) concluded that most of the learners who were assigned online courses were happy with the quick and reasonable feedback they received. Furthermore, learners in online courses usually receive up-to-date information, since the teacher can update the content at any time (Anderson, 2004).

Even with all the advantages of using online courses, they still suffer from several drawbacks. One of the main limitations of online courses is the feeling of isolation (Keller and Suzuki, 2004). Many online learners feel separated from others. To address this, many courses are moving towards using advanced technologies, such as teleconferencing and video conferencing. However, many learners describe these techniques as 'cold' and incapable of representing real interactions. Learners feel they miss physical interaction and eye contact in online courses (Hershkovitz and Nachmias, 2009). Furthermore, in online courses, learners need to judge and define the quality and authority of the teaching they received. However, in social and collaborative learning, some learners will produce unreliable and ineffective responses. For example, they spend their time in discussing irrelevant topics that are unrelated to the course (Kim and Frick, 2011).

Some learners claim that online learning courses do not save them time. Instead, learners spend more time finding relevant resources (Knowles and Kerkman, 2007). In addition, slow connections or any breakdown of the internet or technology may affect the learners by wasting their time and reducing their motivation to complete the course (Kim and Frick, 2011). Many researchers claim that learners' lack of motivation may be one of the core issues associated with the online courses, which is addressed clearly by Kim and Frick (2011). In their study, they found that the dropout rate in online courses is much higher than the dropout in the traditional classes. Researchers explain these results as due to the role of the online learners as they are passive receivers. However, some research has pointed out that it is the responsibility of the teacher in the online course to change the role of the learner from passive receiver to actively engaged learner (Anderson, 2008). Furthermore, the online learning course must be carefully designed to have a learner-centric approach. Learners differ in their characteristics, prior knowledge and experiences (Nash, 2005). Thus, the content of the course must be carefully designed to fit this variation.

2.4 Motivation in online courses

Online learning is growing because of its potential benefits. According to DeBoer et al. (2014), nearly 230 million individuals were enrolled in at least one MOOC course in 2014. Moreover, the popularity of online learning rapidly increased during the COVID-19 pandemic in 2020 (Kaufhold et al., 2020; Nijim and Grist, 2020). However, the main issue was that many learners dropped out of the online courses within the first few weeks of enrolment. Courses can be dropped for various reasons, such as feelings of isolation or a lack of motivation and engagement (Willging and Johnson, 2009). In MOOCs, for example, of 36,266 learners who registered for a course, approximately only 12% remained engaged during a week 5 assessment. Most of the learners became bored and lost their motivation, especially in long courses (Onah et al., 2014). For instance, in a short four-week course presented in Open2Study, Onah et al. (2014) found that the average completion rate was 30%. However, this percentage dropped to 8% for a longer 19-week course presented in Edx.

Therefore, as stated by Lee et al. (2013), enhancing learners' motivation and engagement is becoming a core issue in making the online learning process successful and enabling online courses to be effective. According to Chen and Jang (2010), improving motivation can have a direct or indirect effect in improving learners' outcome. For instance, if learners had a higher level of motivation in an online course, then their level of self-efficacy of technology and their satisfaction will increased; which may improve learning outcomes (Wang et al., 2013).

Motivation was defined by Hartnett et al. (2011) as a process that encourages and sustains goal-related activities, whereas Hershkovitz and Nachmias (2009) explained motivation as a condition or state that activates individuals' behaviour into a specific direction. Motivation influences what learners learn, how they learn and when they should learn (Hartnett et al., 2011). Hershkovitz and Nachmias (2009) argued that learners' motivation controls their behaviour in online courses. Motivation affects the ability of learners to seek challenges or not and to complete their courses or withdraw (Ryan and Deci, 2000).

Hershkovitz and Nachmias (2009) showed that the source of motivation can be either internal or external. Internal motivation can be present with online courses that are aligned with the learner's aims or goals. Furthermore, the nature of such courses can be simultaneously challenging and enjoyable for learners. Knowles and Kerkman (2007) showed that external motivation can be generated by an appreciation and commendation of good work. For instance, university students are usually motivated by agreements regarding loans or scholarships. Jacobson (2001) stated that the influence of extrinsic motivation differs according to age. For example, learners in their teenage years and early twenties are likely to be more motivated by external elements than individuals in other age groups.

Self-determination theory (SDT), which was proposed by Ryan and Deci (2000), is a common theory that is used to describe motivation in learning contexts. Pintrich and Schunk (2002) described this theory as the most comprehensive and empirically supported theory of motivation available these days. SDT has been applied successfully in different disciplines, such as traditional and physical learning (Standage et al., 2005), healthcare (Williams et al., 2006) and online learning (Chen and Jang, 2010).

SDT classifies learners' motivation into three main categories (Chen and Jang, 2010): intrinsic motivation, extrinsic motivation and amotivation.

Intrinsic motivation occurs when the task meets the learner's goal. The learner performs the task because it is enjoyable and satisfying (Chen and Jang, 2010; Ryan and Deci, 2000) illustrated the concept of intrinsic motivation in cognitive evaluation theory. This theory suggests that individuals have three essential needs (Pintrich and Schunk, 2002; Stannett et al., 2016):

- Autonomy (sense of control): This need can be addressed by designing tasks that match users' expectations and abilities. Learners should be able to say, 'I am in control, I am doing things that follow my values'. This effect is positively correlated with internal motivation. However, providing excessive choices to learners may demotivate them (Martens et al., 2004).

- Competence (feeling of competence and being able to accomplish the task): This need can be addressed when users feel that they are working towards their own goals and objectives. Learners should be able to say, 'Yes, I am doing it. I am getting better'. This effect positively influences learners' internal motivation. However, imposing pressure on learners and forcing them to perform may conflict with autonomy and thus demotivate learners (Martens et al., 2004).

- Relatedness (feeling of inclusion in the course): This need can be achieved when users feel that they belong and are part of groups and communities that share their goals and interests. The feeling of belonging enhances the internal motivation of learners (Martens et al., 2004).

Extrinsic motivation is the second category of SDT. Extrinsic motivation can be defined as 'the performance of the activity in order to obtain a specific outcome' (Ryan and Deci, 2000, p. 71). This category refers to any external factor that can enhance learners' motivation. Extrinsic motivation can be classified into four categories (Chen and Jang, 2010):

- External regulation: The learner performs the task to receive a reward or to avoid punishment.
- Introjected regulation: The learner completes the activity to meet others' expectations (such as his/her parents).
- Identified regulation: The learner accomplishes the activity because the results of the task or the activity have a personal value for him/her.
- Integrated regulation: The learner performs the task because it satisfies him/her and meets his/her psychological needs.

The last motivation category is amotivation, which denotes a lack of motivation. Amotivation is usually related to competence and involves learners saying, 'What is the point of doing this? I cannot see any value from this task or activity' (Chen and Jang, 2010). Figure 2.1 summarises these categories (Chen and Jang, 2010).

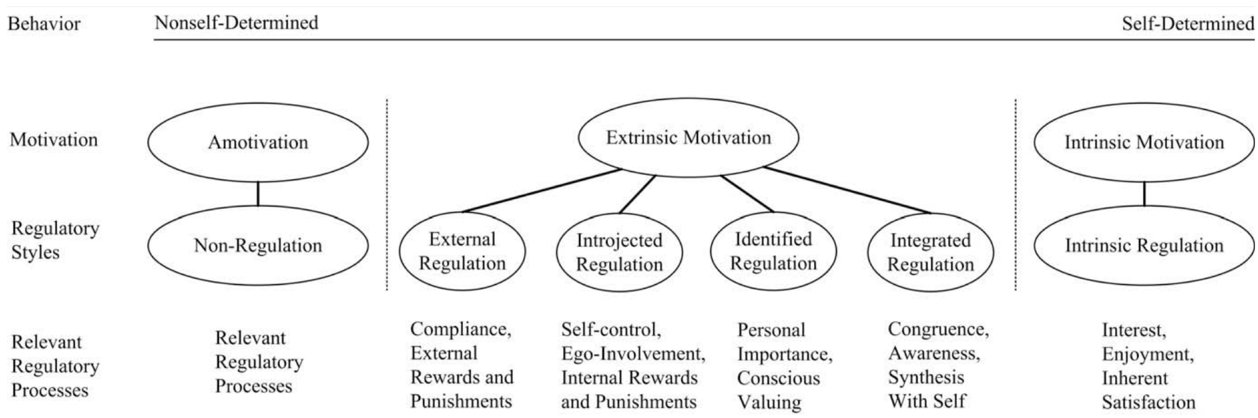


Figure 2.1: The self-determination theory (Chen and Jang, 2010).

Intrinsic and extrinsic motivations are both important for ensuring learning success. In particular, some studies predict that enhancing intrinsic motivation will enhance learning outcomes. For example, Martens et al. (2004) showed that improving intrinsic motivation enables learners to think deeply about an activity. Thus, learners will learn a considerable amount in a fixed time. Furthermore, increasing intrinsic motivation will increase learners' engagement with online courses and their persistence to achieve their goals. Nonetheless, the importance of extrinsic motivation must not be ignored. Ryan and Deci (2000) showed that extrinsic and intrinsic motivations are both valuable and complement each other. Martens et al. (2004) pointed out that it is important to relate the extrinsic motivation to the intrinsic motivation.

Four principles must be considered in designing online courses to increase learners' motivation. These principles can be defined as the components of the attention, relevance, confidence and satisfaction (ARCS) model. All four factors must be present in any online course to motivate learners. The first element is attention, which involves giving attention, constructing curiosity and attracting learners to the course. The online course must have different kinds of techniques, such as the use of graphs, figures and animation to attract learners. Furthermore, teachers must have interesting and varied challenges for learners. However, attention alone is not sufficient to motivate learners. The content and the context of an online course must meet learners' goals and expectations. For example, online materials must be presented in a manner that satisfies learners' learning styles and personal preferences (Keller, 2008). This component of the ARCS model, relevance, can be considered a source of internal and external motivations. Matching learners' aims and goals is an internal motivation, while improving the link with the context can be treated as an external motivation. The third component of the ARCS model with regard to designing online courses is confidence, which can be achieved by ensuring the suitability of online courses for learners' skills and abilities. It is important to help learners have good expectations from courses at the beginning and then allow them to have good experiences. Ryan and Deci (2000) explained that the above-mentioned elements are necessary to establish learners' motivation at the start of courses. However, learners must be satisfied to ensure that they will continue to be engaged and motivated, as suggested by the fourth component of the ARCS model, satisfaction. Some learners prefer being rewarded, while others are satisfied by sensible feedback (Keller and Suzuki, 2004).

Many studies show that most ARCS-based learning systems reduce learners' dropout rates and enhance their outcomes by effectively improving their motivation (Chen and Jang, 2010; Keller and Suzuki, 2004). Keller (2008) showed that after applying the ARCS model in an online course, the dropout rate halved from 44% to 22%.

Researchers have identified many different terms that are correlated with motivation. For example, learners who are more motivated are less likely to drop out from the online courses than less motivated learners (Kim and Frick, 2011). Consequently, learners' outcomes may be improved (Keller, 2008). According to Chen and Jang (2010), increased motivation and high levels of learner achievements and outcomes have a strong positive correlation. Another consequence associated with motivation is learners' satisfaction, whereas engagement is an important factor influenced by motivation. Some studies interchange motivation and engagement. However, they are not the same. According to Nayir (2017), engagement is a phenomenon that is essential for facilitating the learning process, and increasing learners' success. However, learners must be highly motivated in order to become engaged with the learning process.

Engagement can be represented as agreement to perform an activity (O'Brien and Toms, 2008). It consists of multiple components, such as behavioural components (e.g. participating in online courses) and affective components (e.g. feeling a sense of belonging) (Wang and Eccles, 2013). Appleton et al. (2006) classified engagement into three categories: behavioural, cognitive and emotional or affective.

- Behavioural engagement refers to actions and activities done by learners toward their learning environments, such as participating or being absent from school or their courses.

- Cognitive engagement pertains to cognitive efforts exerted by learners to achieve their goals. It is also related to self-regulated strategies used to learn.

- Emotional or affective engagement refers to, positive response and an interest in learning contents and contexts.

Nayir (2017) discussed different levels of engagement in the learning process: authentic, ritual, passive, retreatism and rebellion, all of which can be linked to self-determination theory. For example, authentic engagement, which is related to intrinsic motivation, occurs when learners find courses that match their interests and goals. Ritual engagement is when learners do what they are asked to do, despite the activity or task not satisfying their goals. This condition can overlap with extrinsic motivation, in which learners accomplish activities because of external factors, such as rewards and others' expectations. The third level is passive engagement, wherein learners perform activities to avoid negative consequences. This engagement can be influenced by extrinsic motivation, wherein learners accomplish tasks to avoid punishment. The fourth level is retreatism engagement, where learners refuse to do the given activity or task. This level is similar to rebellion engagement. However, in the latter, learners refuse to do the given activities and, instead, substitute their own activities, which match their goals. In retreatism engagement, learners can be influenced by extrinsic motivation. In rebellion, learners lack motivation (Nayir, 2017). Figure 2.2 shows the relationship between levels of engagements and self-determination theory (Gibbs and Poskitt, 2010).

Motivation and engagement are related but have certain differences. To ensure successful learning, learners must be both motivated and engaged. However, not all motivated learners are engaged. Therefore, in the remainder of this thesis, motivation is the focus.

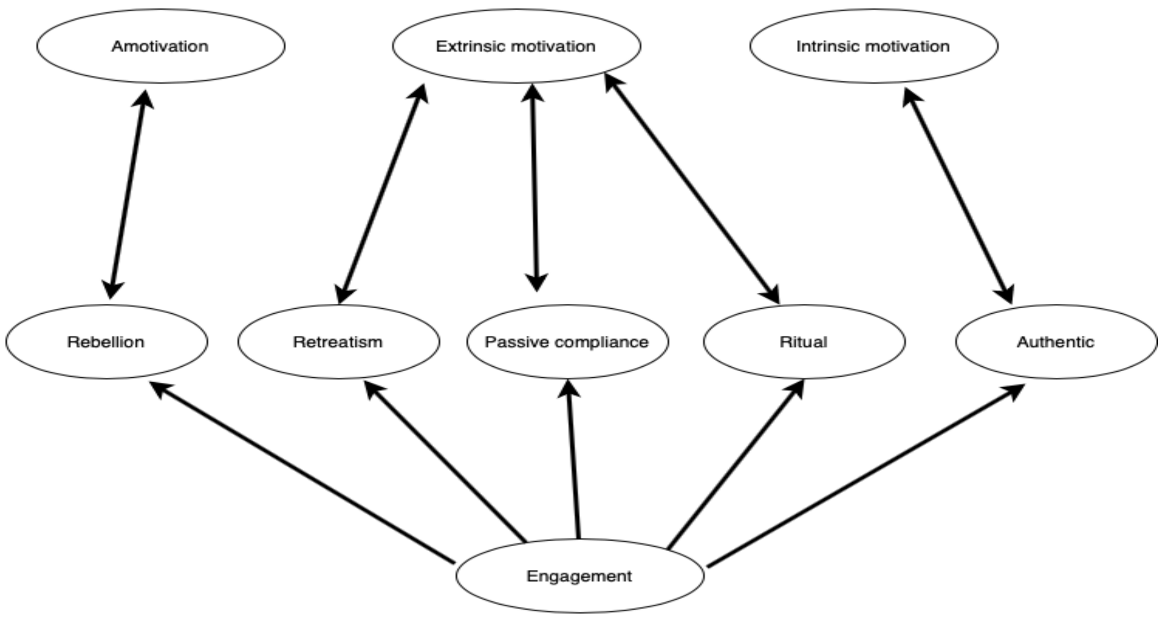


Figure 2.2: The relationship between motivation and engagement (Gibbs and Poskitt, 2010).

2.4.1 Different factors influencing motivation

Kim and Frick (2011) illustrated different elements that affect learners' motivation. They categorised these elements as internal factors (factors related to courses themselves), external factors (factors referring to context and environment) and personal factors (factors caused by learners). Internal factors refer to course content, particularly whether the content satisfies the elements of the ARCS model. In addition, the presentation of the course contents must be suitable for learners and related to learning theories, such as the division of a large amount of information into small parts. The presentation of the course contents, from easy to difficult influences online learners' motivation. Meanwhile, Kim and Frick (2011) stated that external factors are also important. According to Chyung et al. (1998), nearly 50% of online learners drop their courses because of environmental aspects. Such as a lack of time and technological difficulties (Onah et al., 2014). In addition, some learners may have had bad experiences with different online courses or from the behaviour of peers, which may affect their motivation towards online courses (Onah et al., 2014). Learners' motivation is also affected by personal factors. Learners have different needs and preferences, given their varied personalities, learning styles and affective states. Thus, online courses must be designed to suit such variations. For example, some learners do not need systems that are specifically for their preferred learning style, while others need systems that are tailored to them (Kim and Frick, 2011). In addition, the time when learners start to engage with the course affects their motivation. For example, learners who begin a course late are less likely to complete and engage with the course compared with learners who start on time (Onah et al., 2014).

2.4.2 How to measure motivation

Most current studies have used indirect measurements to measure the motivation of learners. For example, some studies used learners' achievements and outcomes as predictors of motivation. Other studies were based on learners self-ratings assessed by questionnaires, which may provide unreliable results (Martens et al., 2004). Furthermore, achievement during a course and the time spent on the task (Hershkovitz and Nachmias, 2009) can be used to predict and measure learners' motivation. Learners' satisfaction with an online course is deemed a strong predictor of motivation. Learners who are satisfied with a course, their peers and their teachers are likely to become motivated and engaged with the course (Willging and Johnson, 2009).

In Beck (2004), the researcher addressed motivation using the time consumed by learners in providing correct answers. Whereas, Cocea and Weibelzahl (2007) measured learners' motivation and engagement by monitoring the number of pages read and the time spent on a reading task. Qu and Johnson (2005) measured learners' motivation and confidence by observing the task duration and the number of completed tasks. De Vicente and Pain (2002) related learners' motivation to their confidence and satisfaction. The authors used task completion speed and dropout rates to measure motivation. Kim and Frick (2011) defined a new term, ALT, which is the amount of time spent by learners on a specific task. Kim and Frick (2011) found strong correlations between ALT and learners' motivation, and between ALT and learners' confidence and satisfaction.

2.4.3 Techniques for enhancing motivation

Enhancing learners' motivation in the learning process is a critical issue even in traditional classrooms. Thus, teachers typically use different techniques to motivate learners. For example, verbal rewards or positive feedback are used to enhance the intrinsic motivation of learners. As Deci et al. (2001) stated, verbal feedback improves learners' competence, thereby potentially enhancing their intrinsic motivation. Tangible or physical rewards also have an effect (Filsecker and Hickey, 2014). Researchers suggest that the use of physical rewards may enhance learners' extrinsic motivation. Meanwhile, Filsecker and Hickey (2014) suggested that the incorporation of contexts with verbal or physical rewards influences learners' motivation. Rewards that are related to a specific task and under the control of the teacher will enhance the intrinsic motivation of learners (Deci et al., 2001). Another technique used by teachers is introducing competition between learners. This technique can be very effective for some learners. Competition motivates some learners to enhance their knowledge and performance, while some compete merely to win (Udvari and Schneider, 2000). On this basis, Vallerand et al. (1986) argued that competitions must be designed carefully. Some learners can engage with the competition in a way that can increase the extrinsic motivation and decrease their intrinsic motivation. To address this issue, the researcher suggests adapting the presentation of the competition to students' personality (Jia et al., 2017).

As in physical classrooms, online learners need to be motivated through their courses, and different techniques have been introduced to achieve this goal. A popular and effective technique is the use of games and game elements to improve the enjoyment and playfulness of learners in online courses. Different kinds of games can be added to the context of online learning. The common techniques to enhance motivation in online learning are explained below.

Educational games or games for learning

Educational games provide learners with a great opportunity to improve with large amounts of feedback. Such games are developed with predefined learning goals and allow learners to engage actively and reflectively during play. Educational games include different types of games, such as: boards and video games (Filsecker and Hickey, 2014), and they are designed to teach users a predefined subject or a specific skill. However, educational games must be designed carefully, where the whole course is changed into a game. The whole course content is usually attached to such games, which may distract some learners from playing or competing with other players. Thus, educators and teachers typically need extra techniques to motivate learners with educational games (Filsecker and Hickey, 2014).

Many educational games are currently used in online courses to improve learners' outcomes. Two of the most popular games are Quest Atlantis and Taiga (Filsecker and Hickey, 2014).

A) Quest Atlantis multi-user virtual environment

This is based on a three-dimensional space where a player interacts with other players via chat (text-based interaction) or with a non-player through structured dialogues. The game proceeds in accordance with the response of the player to the script provided by the non-player. Most of the learner's activities are based on collecting information to provide sensible responses. The teacher's role is represented by the non-player character, who either accepts or rejects the learner's response and provides valuable feedback.

B) Taiga Ecological Sciences Curriculum

This game depicts a park alongside a river (Filsecker and Hickey, 2014)). In this game, learners are represented as real investigators who write multiple reports about different missions, which can be done by interacting with different virtual characters. This game is designed to enable students to learn about such topics as erosion and eutrophication through specific tasks (Barab et al., 2007).

Quest Atlantis and Taiga are both representative of good games to enhance learners' social skills by allowing them to interact with other players and with virtual characters. These techniques also improve the ability of learners to solve problems related to the real-world environment (Zemliansky, 2010). However, in both games, all learning content is changed to a game, thereby making the learning process more like a game than a learning experience. Furthermore, given the nature of these games, some learners will be overly engaged and, possibly distracted. These games are also based on several tasks that must be done by learners. To do these tasks, learners need initial motivation, especially if they receive a negative feedback on previous tasks. Opinions differ about the use of educational games. Some studies have shown that their use enhances learners' motivation and outcomes (Egenfeldt-Nielsen, 2010), but others have stated that such games can effectively improve learners' outcomes but not motivation (Kebritchi et al., 2010).

Serious games

This kind of game is designed for predefined learning aims and is combined with pure entertainment. Serious games were defined by Professor Michael Zyda as 'a mental contest, played on a computer with specific rules and guidelines that use entertainment to enhance and facilitate learning and education' (Alvarez and Djaouti, 2011, p. 11). Serious games can be applied in different domains, such as education, healthcare, engineering and politics (Alvarez and Djaouti, 2011). In general, the main aim of serious games is to change learners' behaviour, attitude, understanding and knowledge. Furthermore, many studies suggest that serious games involve all kinds of other games, such as educational games. That is, every educational game is a serious game (Figure 2.3; (Breuer and Bente, 2010)).

Common examples of serious games are advergames, military games, edugames and datagames (Bellotti et al., 2013).

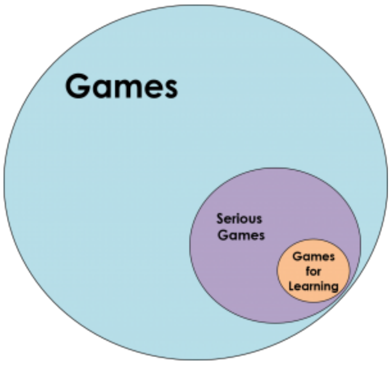


Figure 2.3: The relationship between serious games and educational games (adapted from Breuer and Bente (2010))

Game-based learning

Many studies have not considered game-based learning as an educational tool, although the main aims and goals of such games are teaching and learning through the use of games. One common example of this kind of game is simulation. Papastergiou (2009) showed that the use of game-based learning will enhance learners' academic achievements. These games are designed to be focused, easy to play and enjoyable. The learners prior knowledge must be identified to define the required information in advance.

Game-based learning is becoming popular even in physical classrooms. Common examples of game-based learning are Civilization, World of Warcraft, Minecraft and Portal 2. Figure 2.4 shows a snapshot of a Minecraft (Duncan, 2011).

Figure 2.4: A snapshot of a Minecraft game (Duncan, 2011).

Gamification

Gamification is similar to game-based learning in that neither is generally considered a game. However, gamification only features certain game elements rather than changing all of the learning system into a game.

The idea of gamification emerged in physical schools, where learners are offered badges or stickers related to their achievements. Meanwhile, in online learning, courses are integrated with some digital tokens and badges to improve learners' motivation and achievements (Filsecker and Hickey, 2014). Gamification was defined by Xu (2012) as the use of game elements in non-game contexts, such as business (Xu, 2012), marketing (Huotari and Hamari, 2012) and learning (Fitz-Walter et al., 2011).

The incorporation of gamification elements must be well designed. Most current studies have added points, badges and rewards that are not related to learners' performance and achievements and, therefore, do not carry any meaning. Moreover, in some cases, these elements are provided to the learners before they start their tasks (Filsecker and Hickey, 2014).

2.4.4 Summary

Online learning has become popular because of the potential benefits, such as the flexibility in time and location (Anderson, 2008). However, one of the main challenges in the online course is the feeling of isolation and the lack of motivation, which may increase the dropout rate (Hershkovitz and Nachmias, 2009); (Willging and Johnson, 2009).

Increasing the online learners' motivation and engagement is really important and can be considered as a predictor for learners' success (Lee et al., 2013). Motivation, as it is explained by SDT, can be classified into three main categories: intrinsic, when the contents of the course match learners' goals; extrinsic, when the learners do the task to receive a reward or to avoid a punishment; and amotivation, when the learners lack motivation (Ryan and Deci, 2000).

Different techniques have been introduced to improve learners' motivation. Using games may be considered as an effective technique to improve learners' motivation. However, by using games, the whole online course must be changed to be a game, which may distract some learners from concentrating on the course (Alvarez and Djaouti, 2011), because the main aim is to entertain users not educate them. For this, another technique has been introduced to increase learners' motivation, which is gamification. Gamification has been defined as the using of game elements in non-game contexts aiming to improve users' levels of motivation (Dichev et al., 2014). In gamification, the course is not changed to be game, while game elements, such as points and badges are integrated to it. Thus, if the learner is preoccupied or becomes bored with the game elements, they can be removed without any effect on the online course. For this purpose, in the rest of this thesis, the focus is on gamification, as a technique used to improve learners' motivation. More details about gamification and some examples of the effect of gamification are given below.

2.5 Gamification

Gamification has been applied in many different areas, such as industry, marketing, health and education. It has different definitions based on the area in which it is used. Huotari and Hamari (2012) defined gamification in marketing as a process used to enhance service, which allows for a gameful experience to support users' value creations. In industry, it is defined as integrating game dynamics in the site, service or community to engage participants (Bunchball, 2010). However, in education and learning, gamification has different definitions. For example, Caponetto et al. (2014) defined it as the process of using game thinking and game mechanics to solve problems. In a similar definition, Caponetto et al. (2014) stated that gamification elements are added to the learning environment for the purpose of enhancing learners' motivation and promoting a desired behaviour (Hamzah et al., 2014; Martí-Parreño et al., 2016). All of the above definitions can be combined to define gamification overall as the use of game elements (e.g. points, badges) in non-game contexts (e.g. learning, business). Domínguez et al. (2013) showed that it can be added and integrated into any software (desktop PC, mobile application, etc.) to increase users' motivation and engagement.

Gamification was not popularly used in education until 2008 (Škuta and Kostolányová, 2016). However, as Dicheva et al. (2015) pointed out, the use of game elements in the learning context is not a new concept. Teachers in the physical classroom commonly use gamification as a method and technique to motivate and engage learners. For example, teachers give students points when they complete tasks, or rewards when they accomplish specific behaviours (Hamzah et al., 2014). Further, in the physical classroom, teachers engage learners to build their own learning worlds from their imaginations, which is a similar concept to storytelling (one of the potential gamification elements). Such techniques have been very effective in classrooms to support learning and enhance learners' motivation and performance (Martí-Parreño et al., 2016).

Two kinds of gamification can be applied in the learning environment: structure gamification and content gamification (Wongso et al., 2014). In structure gamification, the learning system includes surface game elements to enhance the motivation and engagement of learners, without changing or converting the content into a game. In contrast, in content gamification, the content itself changes to become more like a game. An example of this type of gamification is positioning learners as characters in a story and giving them the ability to talk and compete with each other throughout the story.

Most of the research in this area is mixed between serious games and content gamification. Moreover, changing the content to be more like a game might entertain learners more than it will teach them. For this reason, the term 'gamification' refers to structure gamification in the rest of this research (Dicheva et al., 2015).

Another important model used to explain motivation is the ARCS model, which was discussed before. Some research has found that gamification can be aligned with two components of the ARCS model: confidence and satisfaction. Providing rewards, status and some sort of competition between them will instil confidence when using the learning system. In addition, when learners are recognised for their achievements, such as earning a new badge, or when they express themselves with avatars, they will feel more satisfied. Table 2.1 shows how to relate the two components of the ARCS model with gamification (Hamzah et al., 2014).

To make gamification more effective in online learning courses, some guidelines and principles should be followed. Simões et al. (2013) identified the following principles:

- Allow for repeated lessons and activities. Learners must imagine that they are in a game and must be able to repeat the same lesson several times. Stott and Neustaedter (2013) stated that the freedom to fail is especially important. Learners should be allowed to repeat the exercises many times without any fear of failure. However, this feature needs to be designed carefully. For example, it would not be useful to provide learners with four chances to solve a question that has four options.

- Include rapid and instant feedback. This gives learners valuable information to enhance their performance and achievements.

- Make the tasks and activities suitable and adaptable to learners' skills. As Stott and Neustaedter (2013) pointed out, this principle is a core element in any educational system even if a game is not incorporated. This is essential to motivate learners to complete the task successfully.

Table 2.1: The relationship between ARCS components and gamification (adapted from (Hamzah et al., 2014))

Category	Sub-category	Process questions	Strategies
Confidence	Rewards	How learners earn rewards?	Learners can get rewards by giving them points or scores
	Status	How can learners know their status?	By using levels in learning to show their progress and status
	Competition	How can learners compete?	Learners can compete with each other by using leaderboard and other social elements
Satisfaction	Achievement	How can learners be shown their achievements?	By using badges to reward learners on their achievements
	Self-expression	How can learners show their self-expression?	Learners can use avatars to express themselves. They are able to use virtual identities, such as virtual clothes and accessories.
	Altruism	How can learners be altruistic?	Providing gifts to other learners will fulfil the learners. This may also motivate the learner to send gifts to others.

- Break the complex task into small sub tasks, which matches the cognitive theory mentioned earlier in the same chapter. This is required to help learners deal with the difficulty and the complexity of some tasks.
- Allow learners different routes to finish tasks. This can be accomplished by giving learners access to any task they want, which may, in turn, enhance their autonomy, as explained in SDT.
- Allow learners to share their success and their badges with the teacher and the other learners, for example, by presenting the status of learners in their public profiles or sharing it via social media.

Regarding these design principles, Škuta and Kostolányová (2016) pointed out that the most common and desirable gamification design principles are visible status, social engagement, freedom to choose, rapid feedback, freedom to fail, goals and challenges. Figure 2.5 shows the distribution of research work by gamification design principles.

After defining these principles, it is important to choose the best gamification elements that

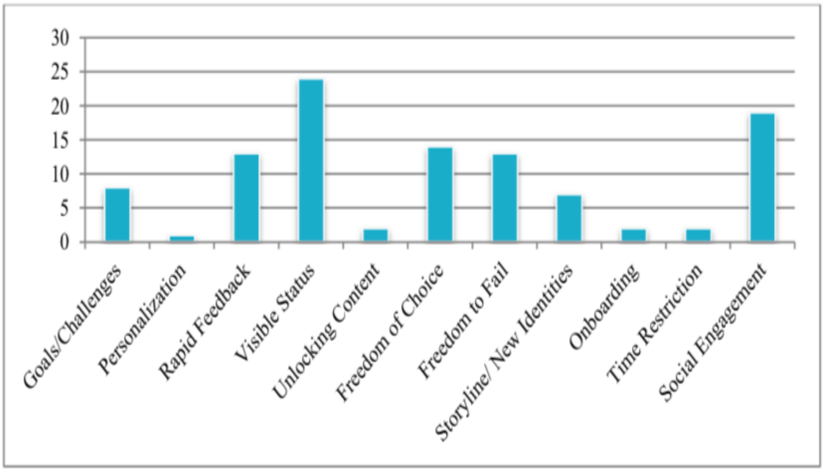


Figure 2.5: Work distribution by gamification design principles (Dicheva et al., 2015)

fit the users' needs and interests. Domínguez et al. (2013) showed that to make gamification elements more effective, the cognitive, emotional and social aspects of learners must be considered. For example, the emotional aspect can be seen clearly in the concepts of success and failure. If the learners answer a quiz or achieve a task, they will get positive and instant feedback by collecting points or receiving badges and trophies. Typically, when learners fail, they can become depressed. However, with gamification, learners feel they are just playing a game and are, thus, less likely to fear failure. Simões et al. (2013) showed that adding gamification elements will introduce the experience of fun to learners. Further, learners can play different roles in the gamified application. In addition, the gamification design must consider cognitive theory, such that the levels move from known to unknown tasks and from easy to difficult. Further, because of the lack of face-to-face interactions in the online learning environment, the social gamification elements can be incorporated to improve learners' social skills by encouraging them to interact, collaborate and compete with each other. In the following section, we will discuss some of the gamification elements.

2.5.1 Gamification elements

There is no agreement on a single definition or explanation of gamification elements. A popular framework used to define gamification elements is Mechanics-Dynamics-Aesthetics (MDA). This framework defines gamification elements as the game mechanics that can be added into any online learning system, such as points, badges, etc. The aim of these mechanics is to change the learners' run-time behaviour, for example, their position, state and level. These changes will lead to enhancing their feelings of satisfaction and pleasure, which are the aesthetic elements (Domínguez et al., 2013).

Different studies have pointed to the different gamification elements that can be applied in any context. Here, we will only describe the popular gamification elements used in online learning contexts.

Dicheva et al. (2015) identified that, due to their easy implementation, the most common gamification elements are points, badges and leaderboards. Further, these elements provide the required feedback to learners, which addresses their cognitive considerations. Moreover, providing learners with badges will enhance their feelings of happiness, and their social needs can be met by allowing them to compete with each other on the leaderboard.

Points can be integrated into any learning system for different purposes. For example, learners can be awarded a point for a specific achievement or a desired behaviour. Points are an example of rapid and instant feedback (Škuta and Kostolányová, 2016). Badges or trophies can be presented to learners as acknowledgement of a completed task. For example, learners may earn a badge when they complete a challenge task, or they may collect points for participating in a group discussion.

Another common element related to badges is rewards. According to Domínguez et al. (2013), rewards can be either tangible or non-tangible. However, Dichev et al. (2014) showed that implementing rewards in a gamified system is not a trivial task. It is important to consider what the reward is and when it will be given. Rewards can be classified into three different types: (1) the fixed-action reward is given to the learner because of a specific action, (2) the sudden reward is given when the reward is not expected and (3) the rolling reward is provided when the required action is completed. This third type of reward goes from one learner to another, until one learner is the eventual winner.

Another common element used with gamification is the level or progression. Learners can see their progress and level, which motivates them to achieve more, and when they do, they move to a higher level (Škuta and Kostolányová, 2016). Moreover, Domínguez et al. (2013) introduced other gamification elements that can provide quick feedback to learners, for example, scoring, experience points and personalised feedback.

In addition to the classic gamification elements, many research studies have pointed to the importance of integrating social gamification elements to engage and motivate learners. For example, ranking learners based on their success on a leaderboard introduces competition between learners and teams, which, in turn, may enhance learners' motivation and performance (Glover, 2013). Moreover, gamification elements can be used to improve the cooperation and interaction between learners. Learners can work in groups or teams in order to achieve a task, and they are able to engage with their peers in the process (Dicheva et al., 2015); (Su and Cheng, 2015).

Different systematic review studies have been conducted to identify the most common gamification elements and the disciplines in which they are typically integrated. For example, the systematic review conducted in 2017 by Mora et al. (2017) showed that 45% of the papers published on gamification were related to business, while only 15% of the papers were related to learning and education (Mora et al., 2017)).

Regarding the published papers related to education, different studies have tried to identify the most common gamification elements used in this area. For example, one study, Dicheva et al. (2015) showed that the most common gamification elements studied in different work were points, badges and leaderboards (Figure 2.6). Another study by Fitz-Walter (2015), in a review of more than 31 peer-reviewed articles, found that points and leaderboards were the most common gamification elements. Further, more than one gamification element can exist in a system (Table 2.2).

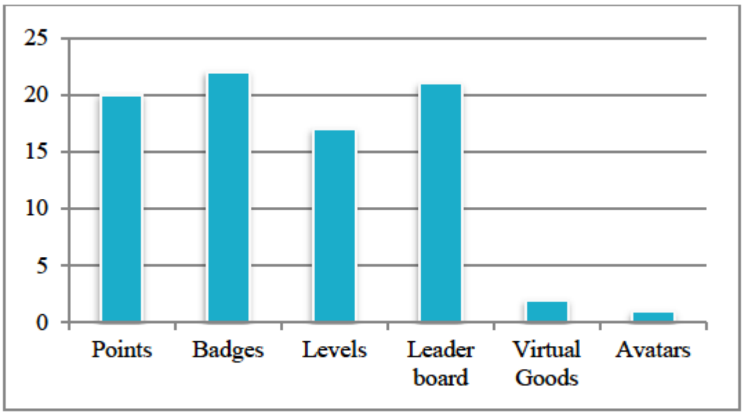


Figure 2.6: The popularity of different gamification elements (Dicheva et al., 2015).

2.5.2 Examples of gamified systems

A common example of gamification is the Foursquare application, a location-based system that rewards users when they check-in to new places or share places with friends (Frith, 2013). Another example is Nike+, which has been developed to encourage users to do more exercise. It provides badges and points to users for each new exercise or step count score, and allows learners to share their scores and compete with their friends on the leaderboard (Kuo, 2015).

One study used gamification elements (points and avatars) to examine the effect of gamified attention-bias modification training. The study was conducted with participants who suffer from anxiety, and its purpose was to engage users to participate in stress-relief activities. It found a positive effect from gamification (Dennis and O'Toole, 2014). In this regard, another

Table 2.2: The most commonly used gamification elements (Fitz-Walter, 2015)

Primary game element	Number of systems
Points	13
Leaderboards	12
Level-Rank	10
Competition	10
Avatars	9
Feedback/ Rewards	4
Achievements	4
Virtual goods	3
Teamwork	3
Fantasy	3
Tangible rewards	2

study related to health was used to evaluate gamification in the measurement of well-being. They used points, badges and social interactions, e.g. chats on Facebook, as gamification elements. The results showed the positive effect of gamification in changing users' behaviour. Users engaged more in answering survey questions and evaluating different tools (Hall et al., 2013).

Regarding gamified learning platforms, different systems have been developed to enhance learners' motivation and engagement. One of the most-popular learning platforms is that used by Khan Academy, which provides several materials and resources in different disciplines. This platform is embedded with gamification elements, such as points and badges. Further, it allows learners to see their progress and provides statistics about the learners' progress (Simões et al., 2013).

One platform that points to the positive effects of gamification in enhancing the motivation of learners is schoools.com, a Portuguese learning platform developed and evaluated in 54 different schools, with 18,000 K-6 learners. It is based on the social gamification elements which are considered a subsection of the wider concept of gamification, following wiki-philosophy and allowing learners to interact with their peers. Further, this platform provides the ability for parents to interact with teachers and allows them to see their children's progress (Simões et al., 2013). They found that the usability and the user experience improved after integrating the social gamification elements.

Table 2.3 shows some examples of studies related to gamification.

2.5.3 Benefits and issues with gamification

Different studies have pointed to the positive effects of gamification on online learners. Gamification has been shown to be an effective technique to enhance the motivation and the engagement of online learners (Domínguez et al., 2013). Hamzah et al. (2014) pointed out that gamified learning systems include elements that provide rapid and instant feedback for every mini-activity, such as visual cues and progress bars (Da Rocha Seixas et al., 2016). This allows learners to better understand the reasons for their progress, such as whether they expended enough effort or not. Further, it provides different acknowledgement elements for learners' achievements, all of which make the online learning system more attractive to learners (Dichev et al., 2014).

In addition, gamification can provide the social elements that allow learners to interact with their peers and teachers, which decreases the feeling of isolation they can experience in traditional online courses. Social gamification elements make learners feel like they are in a real physical classroom. Learners are also able to compete with their peers by interacting with the leaderboard or other ranking elements, and they are able to help and collaborate with others, which can enhance teamwork skills (Dichev et al., 2014).

Using gamification elements in online courses makes the learning process a combination of challenge, mastery, autonomy and socialisation. Since learners feel like they are in a game, they are less likely to fear failure. Even in cases of failure, learners' feelings of anxiety are reduced as they can redefine their failure and make the feedback more frequent, which makes it more useful. Providing real-time feedback allows the learners to feel more comfortable about challenging themselves and trying new exercises (Dichev et al., 2014).

Despite the potential advantages of gamification, some studies have pointed to the varied effects of gamification. For example, Dichev et al. (2014) found that gamification has a slightly positive effect (Dichev et al., 2014); (Viriyapong et al., 2014; De Oliveira et al., 2010). However, other studies found no particular effect of gamification on online learners in that the motivation and achievement of the learners in the gamified and non-gamified learning systems were the same (Jia et al., 2016; Dichev et al., 2014). Further, a few other studies have pointed to the negative effects of incorporating gamification elements in online learning systems (Darejeh and Salim, 2016; Ghaban and Hendley, 2019). Two studies investigated the distribution of the effects of gamification in research studies. The results showed

Table 2.3: Example of gamified systems (adapted from (Stannett et al., 2016))

Name	Area	Aim	Gamification elements	Results
MoviPill (De Oliveira et al., 2010)	Health	Engage users to take medication.	Social competition between patients	43\% to 54\% of users engaged more
Quick Quiz (Cheong et al., 2013)	Learning	Motivate learners	A progress bar decrease as time passes when the learners answered a quiz. For each answer, learners earn number of points	77.63\% of learners were engaged and motivated. *46.05\% of learners were happier.*
MSc Multimedia Content Production (MCP) (Barata et al., 2013)	Learning	Improve learners' motivation and engagement	- The course presented to learners in levels: beginners and advanced. -The number of posts by learners earn a new achievements. - Learners compete in the leaderboard by number of achievements	Learners had a better outcome. However, some of learners dislike and demotivated because of the ranking in the leaderboard.
Astro Graphy (Viriyapong et al., 2014)	Learning	Enhance learners' experience when they are learning Math	- The course is designed as an adventure and in levels from simple too difficult. - Each solved problem deserve a point. - Collecting number of points deserve a star.	65\% of learners were highly satisfied with the course.
RecycleBank (Xu, 2012)	Education and Behaviour change	Motivate and educate users about recycling	Users earn 4 points for each recycling actions. For example, buying recycling products.	97\% of learners increased their knowledge about recycling.
Teaching engineering (Berkling and Thomas, 2013)	Learning	Improve learners' motivation.	- Course composed of levels. - For each completed level, the learner earn a point. - Learners can see their and their friends progress. - Learners can compete with their friends in the leaderboard.	13.8% of learners finish the course. However, some learners find the gamification not useful.
Zombies Run! (Morford et al., 2014)	Sport	Motivate users to run and do more steps	storytelling, as the user is a part of a stimulated race. - The user can earn a reward for each completed race (5k).	Not reported.

that most of the studies pointed to the positive effects of gamification. Figures 2.7 and 2.8 show the variations in the effects of gamification.

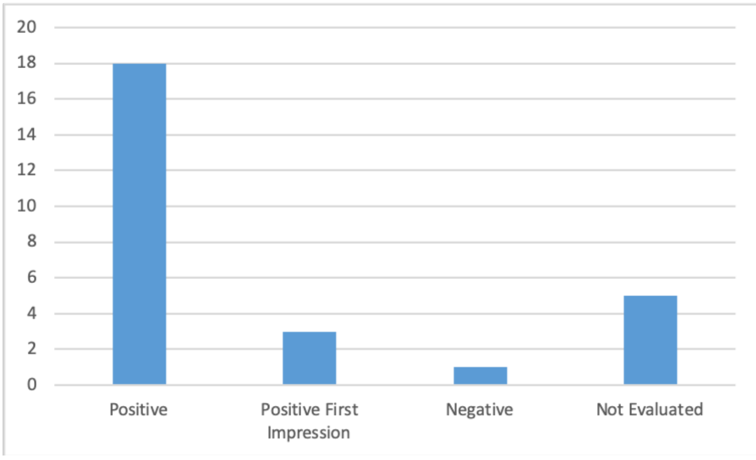


Figure 2.7: Variation in the effects of gamification reported in published papers (Dicheva et al., 2015).

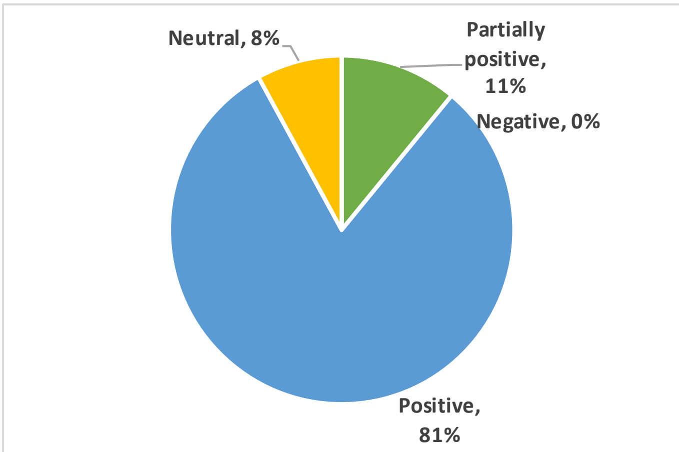


Figure 2.8: The various effects of gamification (Darejeh and Salim, 2016).

Regarding the negative effects of gamification, most studies reflect that the reason for these results is the poor design and incorporation of the gamification elements (Hamzah et al., 2014). As Stott and Neustaedter (2013) pointed out, some applications only apply surface gamification elements that do not have any relation to the course, such as, earning points and badges randomly. The design and implementation of the gamification elements can lead to certain problems. For instance, an overload of gamification elements and changing the content of the course to make it look like a game may distract and overwhelm learners (Sosnovsky and Dicheva, 2010).

Further, when designing the gamification elements in an online course, learners' abilities and skills must be considered. For example, awarding points and badges on the basis of easy tasks can cause learners to become bored. However, making gamification elements more challenging and difficult can demotivate learners and create anxiety and depression. Fernandes and Junior (2016) claimed that gamification does not enhance learners' motivation and engagement in the long term. The positive effects of gamification may be produced only in the short term, and afterward learners will become demotivated because of gamification elements they dislike or may prefer to use non-gamified online learning courses. Figure 2.9 shows variations in the effects of gamification from the short to long term, compared to a non-gamified online course. However, Tondello et al. (2017b) showed that learners differ in their attitude towards gamification. Some learners will become demotivated and dislike gamification, while others are attracted to these elements in both the short and long term. Some learners will be motivated by gamification and achieve well because of it, while other learners may get distracted by collecting points and competing with friends and neglect concentrating on the learning content (Isaksen et al., 2003). Further, some learners will dislike the game elements that they perceive as 'boring' techniques (Ghaban and Hendley, 2019). Due to these variations in the responses of online learners to gamification, it is generally agreed that it is essential to adapt gamification elements to match learners' needs and interests (Tondello et al., 2016).

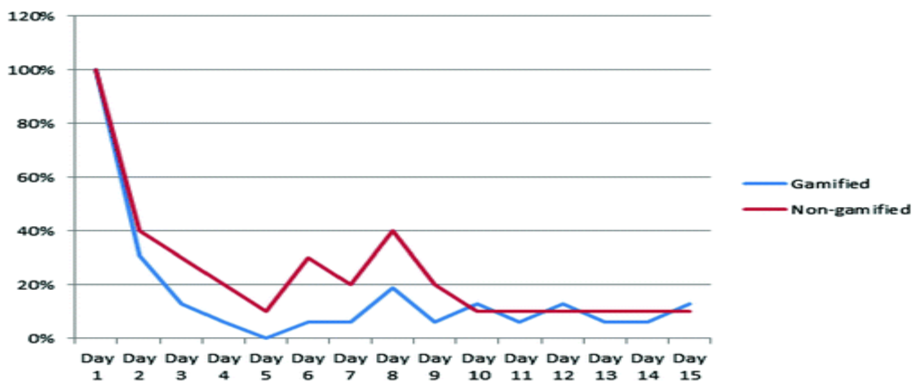


Figure 2.9: The frequency of access in gamified and non-gamified systems over a period of time (Fernandes and Junior, 2016).

2.5.4 Summary

Gamification is a technique that can be used to enhance the motivation and engagement of the learners in online courses. Different gamification elements can be integrated in online courses. Various studies have shown that points, badges and leaderboards are the most commonly used gamification elements. However, other elements can be used, such as levels, avatars and social gamification elements. Different research studies have pointed to some guidelines and principles that must be followed in order to make gamification more effective (Simões et al., 2013).

In using gamification, learners will receive feedback that is presented, for example, as points or badges. Learners will feel that they are part of a game allowing them to interact and compete with their peers. However, gamification elements may be distracting to some learners who become preoccupied with the gamification elements rather than concentrating on the learning content. In addition, there are other learners who will become bored with the gamification elements, which may demotivate them. Further, some learners may be motivated by gamification elements in the short term, for a few days or weeks, but then they come to dislike these gamification elements and become demotivated. To ensure the effectiveness of integrating gamification elements, it may better to adapt and personalise gamification elements to match learners' attributes.

2.6 Conclusion

Learning is an active process. There are a number of theories about how learning occurs and about the roles of learners and teachers in the learning process, including behaviourism, cognitivism, constructivism and connectivism. Connectivism suggests that learners cannot experience everything, so learning also occurs through others' experiences, which they share via the Internet and other technology. Distance education and online learning models emerged from this theory (Ally, 2004).

Online learning can be defined as any learning material that can be delivered via technology. In online learning, learners and teachers are physically separated, and learners can access the online courses at any time and from anywhere. This flexibility has made it popular. However, many studies have pointed out the issues with online learning courses; such as the lacking of motivation. Therefore, several studies have addressed the motivation of online learners and identified different techniques that can enhance the motivation and engagement of online learners; such as gamification.

Gamification is not a complete game but the addition of game elements in a non-game context to enhance participants' motivation (Xu, 2012). It has been widely used in different disciplines, including marketing, business and learning.

Different selections of game elements or mechanics have been used in studies on this topic. According to Dicheva et al. (2015), the most common gamification elements are points, badges and leaderboards because these features are easy to implement. Other gamification elements include rewards, progress bars, levels, avatars, and social elements. The latter, in particular, has received much attention in gamified online learning. The lack of connections between online learners and their feelings of isolation increase the importance of social gamification elements. Learners in gamified courses can compete and collaborate with each other and contact other learners using social media or network techniques.

Various studies have shown the benefits of integrating gamification into online learning systems. Learners can get rapid feedback about their progress through a points or levels scheme. Furthermore, in gamified systems, students imagine that they are in a game, so they are less likely to fear failure. However, despite gamification's many benefits, Hamzah et al. (2014) pointed out that incorrectly designed gamification in online learning systems can harm learners and demotivate them.

Different researchers have highlighted learners' varied responses to gamification. According to Dichev et al. (2014), some learners report extremely beneficial impacts, while other individuals experience only small benefits. Concurrently, a number of learners may experience negative effects from gamification elements. Jia et al. (2016) showed that some learners perceive the integration of gamification into online learning systems as 'silly' or 'childish'.

Because of these variations in responses, researchers suggest that instructors need to adapt and personalise the gamification elements (Tondello et al., 2017b). Thus, in this research, a model that can be used to personalise and match gamification to learners' attributes, such as learners' personality, learning styles or preferences is the aim.

Chapter 3

Personalising Gamification Elements

3.1 Introduction

In the previous chapter, the importance of online learning was discussed. Improving learners' motivation in online courses is essential for successful outcomes. Several techniques have been proposed to enhance motivation. One is the incorporation of gamification elements. However, presenting the online courses with the same gamification elements to all learners in the same way may demotivate some learners. Learners are different in their age, gender, interest and their personality. Therefore, it is essential to personalise the motivational techniques; such as gamification. In this chapter, the concept of personalisation is presented. Two common approaches for personalisation are a recommender system and adaptation; the approach provides the focus in this thesis.

After that, we discuss adapting in gamification.

3.2 Personalisation

Most current online systems present the same content for all users in the same way. This static presentation does not recognise the variation between learners. Learners have different knowledge, preferences, skills and personalities, which must be considered in building any system. To accomplish that, it has been suggested to personalise systems according to users' attributes (Tang and McCalla, 2003; Klašnja-Milićević et al., 2015).

Personalisation is a universal phenomenon in that all human activities are tailored, customised and reconfigured for human-made objects, such as: software systems, cars, houses and workplaces (Oulasvirta and Blom, 2008). Blom and Monk (2007) defined personalisation as a process that changes the system's functions or interfaces or contents to match the user's profile to maximise the benefit of the systems.

In online learning, personalisation has been shown to have a significant impact. It is difficult to build a static online learning website for all learners without considering their knowledge and background. For example, if the course is designed to be more advanced than the learner's knowledge, the learner may feel anxious about it, while if the course is designed to be too easy, this will cause the learners to become bored (Baylari and Montazer, 2009).
Two approaches of personalisation are commonly used: recommender systems and adaptation (Chatti et al., 2013).

3.2.1 Recommender systems (RSs)

This is one of the most common approaches for personalising systems. RSs have been commonly used to recommend contents to users, including products, books, music and more. Numerous applications have used RSs, such as information retrieval systems (e.g. search engines, such as Google) and various commercial websites (e.g. Amazon and eBay) (Baylari and Montazer, 2009). The recommendation can be made for an item or a product based on what has been chosen by the user in the past, or by grouping similar users together and providing the user an item that is similar to those that have been chosen by similar users (Park et al., 2012).
RSs have been defined by Dascalu et al. (2016) as a software tool or platform that is used to provide a suggestion or recommendation to the users. Chatti et al. (2013), however, describes the role of the RS as an aggregation of the user's data. These data are analysed and processed to build conclusions and recommendations about a system or an item that the user will be interested in.
In general, any RS consists of three components: user profile modelling, item profiling and RS approaches.

User profile modelling

In user profile modelling, the system needs to build a profile that contains the most relevant characteristics of the user (Song et al., 2012). Song et al. (2012) classified these as: demographic (age, gender and marital status), geographic (location, city and country) and psychographic (lifestyle, personality and mood). Building the user profile can be done by extracting the information from the user explicitly or implicitly. In the explicit extraction, users can rate the product or give answers to specific questions (e.g. user A rates X a 7 out of 10), whereas in the implicit extraction, the system observe users' behaviour (for example, user A purchased X) (Popescul et al., 2001).

Item profiling

Item profiling consists of a set of items that will be suggested and recommended to the user. Some RSs focus on one domain, such as music or films. In RSs that focus on a single system, the item profile can be divided into several components. For example: In a music RS, the item profile contains editorial metadata (information extracted by the editor, such as the cover and title), cultural metadata (information extracted by analysis of the textual information) and acoustic metadata (information extracted from the audio signal) (Song et al., 2012). While, in educational systems, for example, the item profile can be decomposed into the contents and the method that will be used to deliver the contents (Dascalu et al., 2016).

In some other cases, the RS can involve multiple domains, such as RSs in retail stores. In these RSs, the item profile can be decomposed into several categories, including the product types, cost and usage (Walter et al., 2012).

RS approaches

Different approaches can be used to match users with their recommended items. The most common approaches are content-based, collaborative-filtering and the hybrid approach.

- **Content-based approach**

  In the content-based approach, the user recommends an item or a product based on the items that have been previously rated favourably by the user. The item profile is represented as a vector with a set of records, and each record represents a key of the characteristics that describe an item. When an item is chosen by the user, the item profile is represented in the utility matrix associated with the user's profile as a numerical or Boolean value. This matrix is then used to predict the degree of the user's preferences for the item (Dascalu et al., 2016).

  The main benefit of this approach is that any new item can be recommended to the user, even if the user has not rated this item before. However, the main issue with this approach can be illustrated by the case of a new user who did not rate any item before. Popescul et al. (2001) show that this issue can be resolved by asking users explicitly about their preferences or asking the user to rate specific items. Nevertheless, the issue still emerges in cases when this approach will always recommend to the user the same items that have been rated, even if the user doesn't like these. For example, in movie RSs, if the user prefers comedy and romantic films but he/she always chooses to watch comedy movies, the RS will always recommend comedy movies without considering the preference to watch romantic movies, which may generate a kind of boredom in the user. Further, the recommended items in this approach are usually based on the quality of the user's ratings and the feature generation (Park and Chu, 2009).

- **Collaborative-filtering approach**

  The second approach in RSs is the collaborative-filtering approach. In this approach, users who have the same taste and preferences will be grouped together, and then the item will be recommended to the user if it is rated or used by any user in the group. For example, it has been suggested that if user A and B rate an item in a similar way, then these two users will behave the same way and rate other items similarly. This aggregation between users can be identified by using one of the machine learning techniques, such as clustering, classification, prediction and so on (Song et al., 2012).

  As in the content-based approach, the collaborative filtering approach will be presented as a utility matrix, where the item profile is present in the column and the user profile in the row. The similarity between the users is identified by using the distance between the rows in the matrix, which can be extracted through data mining (Dascalu et al., 2016).

  One major benefit of this approach is that it is content independent. Thus, it does not need any rating from the user or any feature to be selected. Park and Chu (2009) argue another benefit of this approach is it can provide 'serendipitous finding'. Thus, this system can, for example, recommend a romantic film to the user if the other similar comedy movie fans watch it. This feature is used in different applications, such as Amazon, Netflix and Google. Candillier et al. (2007) argue that the collaborative-filtering approach is considered a better approach than content-based if there are enough ratings by users. However, if the item is new and has no rating, or if the user is new and there are insufficient ratings to group the user with any similar users, then this approach will fail. This problem is called the 'cold-start problem'. Park and Chu (2009) suggest three cases in which this issue can occur: 1- recommending a new item for an existing user, 2- recommending an existing item to a new user and 3- recommending a new item to a new user.

  To resolve the cold-start problem in the collaborative-filtering approach, a new approach has been suggested: a hybrid approach.

- **Hybrid approach**

  Each of the two discussed approaches suffers from some limitations. Therefore, to maximise the benefit of the RS, it has been suggested to combine the content-based and the collaborative approaches. Thus, initially, if the user or the item is new, the content-based approach can be applied to use the historical rating or by asking users explicitly. Then, the collaborative-filtering approach can be used by grouping similar users together and providing recommendations based on the similarity between users (Burke, 2007; Song et al., 2012).

Summary

Most of the systems provide a huge amount of information to the users, and most of this information is considered irrelevant to them. To maximise the satisfaction and the user experience, it has been suggested to personalise systems.

One kind of personalisation approach is RSs, where a list of items will be recommended to the users based on their profile. RSs have been increasingly used in different applications, such as information retrieval applications and commercial applications.

In RSs, three components must be identified: user profile modelling (which contains information about the users), an item profile (which contains different classifications about items) and the approach that will be used to assign each item to the users. Three approaches have been discussed: the content-based approach, where the user is recommended an item based on the items that have been previously rated, collaborative-filtering, where the users are recommended an item based on the items that are rated by similar users and, finally, a hybrid approach that mixes the two approaches.

In this thesis, we aim to discuss personalising gamification elements to the online learner's profile. It is difficult to use RSs approaches in this research for several reasons: First, there is a limited number of studies that have tried to build RSs that can recommend gamification elements to users. Only one study, by Tondello et al. (2017a), was found. However, this study is presented as a preliminary framework for the RS without evaluating its effectiveness. Further, this suggested RS has been discussed in areas different from online learning. Thus, there is no study that can be used as a base, which causes the RS to easily suffer from the 'cold-start problem'. The second reason for the difficulty in applying RS is that most RSs require a large number of users to draw a conclusion and build a reliable and effective system (Klašnja-Milićević et al., 2011). However, in the present context it is difficult to have this large number of users. For all of these reasons, another approach of personalisation, which is called adaptation, was used in this study.

3.2.2 Adaptation

Adaptation is an alternative to a 'one-size-fits-all' personalisation approach (Maravanyika et al., 2017). Adaptation means the action and process of tailoring the system to users' needs and interests (Morales et al., 2009). Brusilovsky (1998) defined it as the components of technology that can change their behaviour to meet users' needs without any explicit instructions from the user. They also described adaptivity as support from technology in intelligent systems via mapping the structure and presentation of the media onto learners' characteristics (Paramythis and Loidl-Reisinger, 2003).

Regarding adaptation, two phenomena are often used interchangeably: *adaptive* and *adaptable*. However, these terms have different meanings, and it is important to distinguish them. *Adaptation* is a process that is undertaken by the users with some support from the system to change the system's function. In contrast, an *adaptive* system refers to static and dynamic adaptation carried out by the system for specific users. An important feature of adaptive systems is the explicit representation of the user's characteristics in the user model (Brusilovsky et al., 2004; Vasilyeva et al., 2007).

Adaptive systems aim to satisfy users' needs and to improve the user experience over time (Maravanyika et al., 2017). Alternatively, De Bra (2008) shows that the main objective of adaptation is to make the system responsible for enhancing its usability or the users' satisfaction. In other words, the main aim of adaptation is to improve users' experience when users interact with the system.

To adapt any system, three essential stages must be accomplished (Figure 3.1). The first stage is collecting data about the users to be employed as a basis for adaptation. This data can represent any of the users' traits or preferences. The next step in the adaptation process is to employ the user model to build the adaptive system. Finally, the system should update the adaptation model based on any changes in the user model. In most recent adaptive systems, the system builds the adaptation model (Drira et al., 2006). However, there is a new orientation to automate the whole adaptation process, including collecting data, building the user model and creating the adaptation model. Nevertheless, much research claims that these types of systems are unreliable. Researchers argue that some data, such as the learners' knowledge and background, must be collected from the users. Further, they show that any mistakes in collecting users' data will lead to ambiguity in building the adaptation model. However, the automated adaptive system can be successful in some limited areas, such as adaptive dialogue systems. These systems observe and track learners' behaviour, then build an expectation about the users' goals and generate a plan for adapting the system based on expectations (Brusilovsky, 1996).

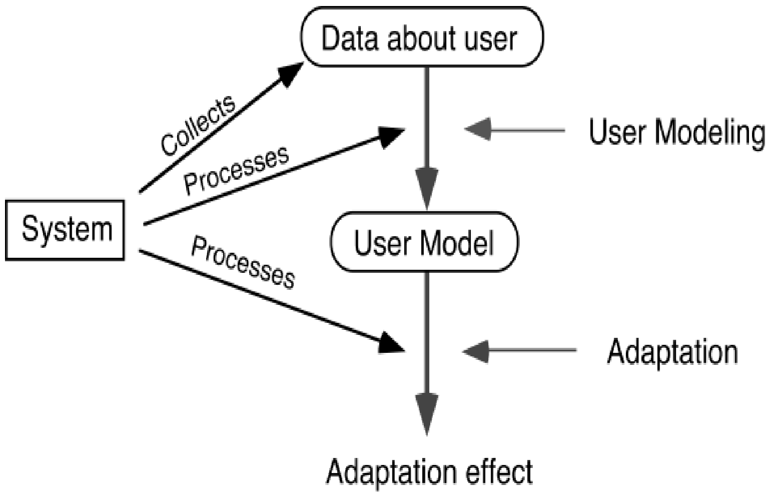


Figure 3.1: The process of adapting a system (Brusilovsky, 1996).

Any system to be adapted must be planned properly. It is important to understand the benefit of adapting a system and whether applying adaptation is worth the effort. Therefore, the following questions must be answered before adaptation is performed (Brusilovsky, 1996; Wu et al., 2000); ((Lin et al., 2004); (Figure 3.2)).

- Where can we apply adaptations?
- Why do we need to adapt?
- What can be adapted?
- How can we adapt?
- What attributes can be adapted to?

Motti and Vanderdonckt (2013) added another essential question:

- When can we apply adaptation?

The first question is related to the context and discipline used in the present research to apply adaptation. According to De Bra and Ruiter (2001), adaptation can be applied in any system that has a vast amount of information and different features and interfaces for different users, while most recent research studies have been related to information systems, educational systems, online-help systems, information retrieval systems and personalised views. These types of systems have different roles and interfaces for different users. For example, in adaptive information systems, a vast amount of information may not be relevant

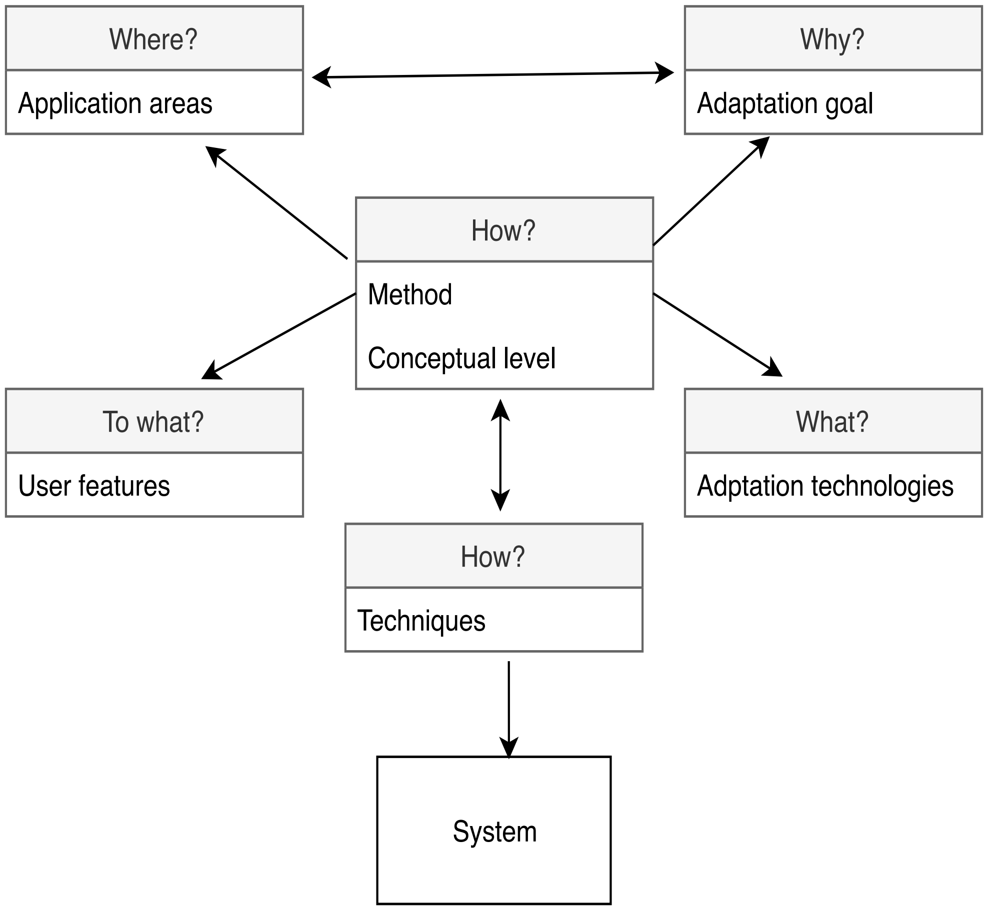


Figure 3.2: A possible classification of an adaptive system technique (Brusilovsky, 1996).

for some users. Thus, it is essential to adapt the presentation of this information based on the role or knowledge of the users.

The second question refers to the importance of adaptation. The objective of adapting can differ from system to system. For example, in some educational systems, the main aim is to increase the learners' outcomes and improve their progress, while other adaptive systems have multiple objectives, such as to increase usability and satisfaction (Maravanyika et al., 2017).

The third question identifies the area that will be used to apply the adaptation. It explains how the adaptation will be integrated into the system. For example, in some systems, the adaptation will relate to presentation, such as adapting the contents of the page (Brusilovsky, 1996).

The fourth question that must be answered before adaptation is how we will adapt. This includes the methods and techniques that should be used in the process of adaptation. For example, in adapting the contents, the most common approach is to hide some information that is not relevant to the users. Further, another approach is the prerequisite explanation, which provides users with some pre-information before presenting the main information. The comparative explanation is another method, and it is based on identifying the similarities between related systems. This identification can be done by providing the system based on the users' experiences in other systems. Several techniques are used to apply these methods, for example, dividing the content into small chunks and then presenting and hiding some of them based on the learners' attributes (Garzotto and Cristea, 2004).

The fifth question that should be answered is what attributes of users should be considered. These are the attributes that should be used as a basis for adaptation. Some of these characteristics, such as the user's background, learning style and personality, are more stable and related to the user. There are also some dynamic characteristics, such as the user's emotion, interest and experience, that can be used. Further, there are characteristics related to the environment, including the context, devices used and physical environment, that can be considered (Nguyen and Do, 2008).

The last question, suggested by Motti and Vanderdonckt (2013), is when the adaptation should occur. For example, the adaptation can be performed at the design time, compilation time or run-time (Motti and Vanderdonckt, 2013). In the same manner, it is important to identify if the process of adapting will be static and completed before using the system or dynamic and changeable while using the system.

Adaptive online learning courses

In recent years, adaptive educational and learning systems have been considered, attracting attention from many different researchers. According to De Bra et al. (1999), the main form of adaptation in such systems is either eliminating an existing problem or improving the system to make it more effective. While, the main aim from adapting learning courses is usually to improve learners' outcomes and increase their levels of motivation and satisfaction.

The most common models that must be included in any adaptive online learning system are discussed below.

Models in adaptive learning systems

In general, a *model* is described as a concept that abstracts the explanation of the components, properties and relationships of any system (O'Brien and Toms, 2008). Different models have been developed to explain adaptation in the online learning environment. One of these models is ADAPT, which explains how the users and domain are used together to support adaptation based on the context (Motti and Vanderdonckt, 2013). Another common model is the Munich reference model. This model is considered an objected-oriented approach that is based and written in Unified Modeling Language (UML). This model consists of three layers: the run-time layer, the compiler layer and the storage layer. In this model, the learner model and the domain model are placed in the storage layer (Koch and Wirsing, 2002).

Recently and according to different studies (Aroyo et al., 2006; Alshammari, 2016), the most common adaptation model applied in the learning environment is the adaptive hypermedia application (AHA) model, which is based on the Dexter hypertext reference model (De Bra and Ruiter, 2001). AHA divides the storage layer in the model into the user, domain and adaptation models. Moreover, Motti and Vanderdonckt (2013) updated the AHA model by including the context model, arguing that this influences adaptation (Figure 3.3; (Motti and Vanderdonckt, 2013)). In this research, the focus is on the component of the storage layer, as it includes the most important factors affecting the adaptation process.

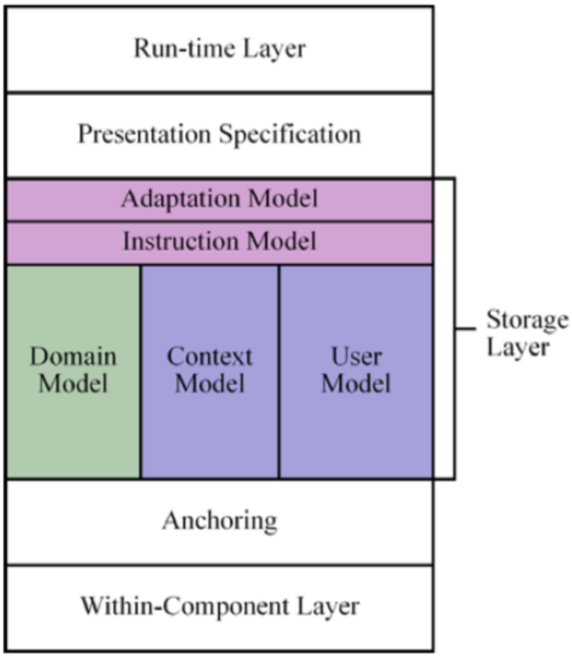


Figure 3.3: Adaptive hypermedia application model (Aroyo et al., 2006).

Domain model

This model contains the knowledge of the domain and the structure of the curriculum (Aroyo et al., 2006). It is used to answer the question, ‘What is used in the adaptation?’ According to Wu et al. (2001), this model consists of a set of concepts and their relationships. A concept represents information from the application domain. The concept can be divided into small sub-concepts, and each can represent an abstract piece of information (Motti and Vanderdonckt, 2013).

In this model, the concepts and relationships between concepts are identified. For example, Brusilovsky and Millán (2007) showed that different techniques could be used to represent concepts in the domain model. One of these is the vector model or set model. In this technique, knowledge is presented as a set of independent concepts. The main issue with this kind of representation is that, when the user model links to a specific concept, it is difficult to determine how to move to the next one. Other techniques have been proposed to address this. The first can be developed using a 'tree' of large educational objectives, which are gradually decomposed into smaller concepts. However, this approach is not as popular as the network model. In the network model, the concepts are represented by nodes, and the relationships between the nodes are represented by arcs (Mustafa and Sharif, 2011).

Context model

The context model refers to the circumstances that surround learners when they are interacting with the system (Motti and Vanderdonckt, 2013). This model is considered a new area of research; however, different studies have suggested that it cannot be ignored because the context model and the user model are usually related. In most cases, the context model contains features that are related to the users, such as their physical location.

A few research studies have considered the user context and adaptation based on this context. However, because of the improvement in mobile applications and ubiquitous systems, the research has focused more on the location of the user when interacting with the system. Thus far, no agreement has been reached on the dimensions that can be considered as belonging to the context model versus those that belong to the user model (Aroyo et al., 2006). Here, the most common model dimensions are described (Brusilovsky and Millán, 2007).

In mobile applications and ubiquitous systems, for example, it is important to identify the platform that is used in the system. This dimension includes different features of the system, such as hardware, software and network bandwidth (Brusilovsky and Millán, 2007).

The most commonly considered feature regarding the user platform is the screen size. The screen that is present on the desktop differs from the screen in mobile applications. Another common element is adaptation based on the internet and network speed. For example, if the system needs to upload a video stream but the network is down, the system can replace the video with static text or a link to the video (Brusilovsky and Millán, 2007).

Another important dimension in the context model is the user location. The location of the user is very important to consider, especially in some types of systems, such as those that offer guidance if the user wants a museum tour (Aroyo et al., 2006).

Göker and Myrhaug (2002) tried to summarise the most relevant dimensions that belong to the context model. They suggested that the context model can be divided into:

1- environmental context, which includes all elements related to the environment, such as light;

2- personal context, which includes the physiological context and the mental context. The physiological context contains information about the temperature and blood of the user, while the mental context contains such information as mood and energy;

3- task context, which contains information about the activities carried out by the users, if the user is reading or watching TV;

4- social context, which contains information about the social life of the user, such as friends and neighbours;

5- spatio-temporal context, which contains information related to the time and spatial context.

In the representation of the context, Brusilovsky and Millán (2007) suggest that this model can be represented as a vector, with each row of the vector containing a pair of the features, e.g. the screen size and the corresponding value.

User model

The first stage in the adaptation process is collecting information about users to build the user model (Figure 3.1). Sosnovsky and Dicheva (2010) pointed out that user modelling is an important element to consider when adapting systems. Furthermore, Kobsa et al. (2001) considered user modelling and adaptation as two processes that complement each other and that cannot be isolated from one another.

A user model is defined as a digital representation of the information that is extracted and obtained from users. This information is considered an essential element in the adaptation of the presentation to different users (Morales et al., 2009).

According to Hothi and Hall (1998), for adaptive systems, it is important to identify the user variables that will be used in the modelling and the level of details that will be obtained. Furthermore, Sosnovsky and Dicheva (2010) showed that it is important to identify how much the system will be tailored to the users' attributes. As Zigoris and Zhang (2006) pointed out, the type and amount of information extracted from users depends on the type of adaptation that will be provided to the user.

The components of the user model can be classified into three layers as follows: (1) what is being modelled (user model dimensions), (2) how to represent the users' characteristics (user model representation) and (3) how to obtain the characteristics (user model elicitation). An abstract explanation of these three layers is provided.

1) User model dimensions

This layer represents the information related to the users, which can affect the adaptation process (Manouselis et al., 2011). This information is considered to comprise the most essential elements, and it is the clearest layer in user modelling.

- **Knowledge and skills**

  Adaptation based on the learner's knowledge is considered the most common approach. The learner's knowledge can be represented quantitatively, e.g. using scores from 0 to 5, or qualitatively, e.g. novice, average and expert. The main issue with this representation is that the learner's level of knowledge is different within different parts of the domain. For example, when teaching word processing, the learner may be an expert in text annotation, but a novice in formula editing. Due to this shortcoming, many researchers moved to the structural model. In the structural model, the domain is divided into segments. Then, the learner's knowledge is mapped independently into each segment. One common example of a structural model is the overlay model in which learners' knowledge is represented as a subset of the domain model. Then, the model stores an estimation of the knowledge of the learner (Sosnovsky and Dicheva, 2010).

  The main issue with adapting any educational system based on knowledge is the changing nature of the learner's knowledge. The knowledge of the learner can either increase (learning) or decrease (forgetting). Thus, any adaptive educational system based on knowledge must recognise the changes in the knowledge of the learner and then update the adaptive system accordingly (Brusilovsky and Millán, 2007).

- **Background**

  Background refers to all knowledge and skills that are gained by the learner in the past, and it may not relate to the domain that will be taught (Nguyen and Do, 2008). (Sosnovsky and Dicheva, 2010, p. 34) described background as 'any relevant experience that is gained by the learner before using the system'.

- **Interest**

  Another element that might be considered in building the user model is user's interest.

According to Sosnovsky and Dicheva (2010), users' interest is considered the third most used element in adaptive systems after user's background and knowledge. Further, it is commonly used in adaptive information systems that deal with extensive amounts of information. However, this element was not employed in early adaptive research studies, especially those on adaptive educational systems, because it changes frequently. This situation has evolved in the past 10 years, and various adaptive systems focus on interest (Hoekstra et al., 2007).

It is essential to distinguish between users' short- and long-term interests. Short-term interest is dynamic; it expresses the user's interest during a session but is usually ignored by the end of the session. In contrast, long-term interest is more stable; it is expressed by the user before beginning to use the system (Sosnovsky and Dicheva, 2010).

- **Goals and tasks**

  Goals and tasks represent one of the features used as a source for adapting many systems. This feature can be described based on the nature of the system in use. For example, it can be explained as the goal in an application or the required information in an adaptive information system. Furthermore, it can be defined as what the user's needs and wants to learn in the adaptive educational system (Brusilovsky and Millán, 2007). The authors showed that this feature is the most mutable one. It can change from one session to another, and it can even be altered frequently in the same session; however, Sosnovsky and Dicheva (2010) pointed out that before building any adaptive system based on goals, it is necessary to identify a high-level goal, which is more stable, and low-level, detailed goals, which may change frequently.

- **Emotional state**

  Emotions are complex, multifaceted phenomena that can involve physiological, cognitive and social aspects of the user's behaviour (Canamero, 2001; Beale and Creed, 2009). According to Polzin and Waibel (2000), the emotional status of the users has an effect on users' progress when completing any activity. It has been suggested to use the emotional state as a source for adaptive systems. Polzin and Waibel (2000) showed that users' emotions can be extracted in two ways. The users can report their emotions explicitly by saying, 'I am angry' or 'I am sad', for example. In other cases, emotions can be identified by using non-verbal methods, such as using facial expressions and body gestures.

Adaption based on users' emotions is increasingly performed with systems in dynamic environments and in intelligent systems for human and robotic interactions (Suzuki et al., 1998).

- **Demographic information**

  In some types of systems, it is important to identify users' demographic information. This information can vary but is usually based on a user's gender, age, culture and native language (Sosnovsky and Dicheva, 2010).

- **Individual traits**

  Individual traits can be described as a group of user attributes that can be combined to characterise the user as an individual. The important feature in individual traits is that they may be either more stable or susceptible to change over a long period. Individual traits involve different categories, such as cognitive style, learning style and personality (Cercone, 2008).

  Users' individual traits are similar to users' backgrounds in that they are both more stable than any other user features. However, they differ in terms of how the information is extracted from users. A user's background can be simply determined via an interview. In contrast, individual traits must be identified via a specially designed psychological test (Shifroni and Shanon, 1992; Brusilovsky and Millán, 2007). In the following section, individual traits are discussed.

Cognitive style

Cognitive style is defined as an individual's preferred way of recognising and processing information and experiences (Magoulas et al., 2003). It is described as the best way for learners to perceive and undertake problem solving, decision making and creativity (Isaksen et al., 2003).

Different models have been proposed to describe the different dimensions of cognitive style. One model was developed by Riding and Wigley (1997). In the model, cognitive style is classified into two fundamental style dimensions, as follows (Riding and Wigley, 1997; Isaksen et al., 2003):

1- The whole-analytic approach, which refers to whether the learners prefer to process the information as a whole or in parts;

2- The verbal-imagery approach, which refers to the learner's preferred way of perceiving information either as informational text or using visual pictures (Sadler-Smith, 2001).

The whole-analytic approach is driven by another family of styles that classifies learners as independent or dependent. In adaptive learning systems based on cognitive style, independent learners will be provided with a learning system with which they can freely navigate the website, while dependent learners will be provided with sequential contents and will be supported in navigating the learning system. Riding and Wigley (1997) show that there is a relationship between learners' preferred cognitive styles and social abilities. For example, talkative and social learners prefer to perceive information as a whole and to receive text presentations. In contrast, shy people prefer analytical representations.

Learning style

Another common individual trait that is frequently used in adapting educational systems is learning style (Alshammari, 2016). Learning style can be defined as a learner's preferred way to learn or represent a domain. This is similar to cognitive style, but it has a narrower focus on learners. Different models have been proposed for classifying preferred learning styles (Sadler-Smith, 2001). One common perspective of learning styles is the Kolb model, which classifies learners as follows:

1- Convergers (abstract/active): Learners in this group prefer problem-solving strategies and decision making. These individuals do best with practical problems and technical tasks.

2- Accommodators (concrete/active): Learners in this group use others' experiences and analyses. These learners are good at problem solving; however, they usually prefer to adopt practical and experimental approaches.

3- Divergers (concrete/reflective): Learners in this group are usually more intuitive. They prefer to watch and to generate their ideas from their imaginations.

4- Assimilators (abstract/reflective): Learners in this group usually prefer a logical approach and a mathematical explanation rather than practical techniques.

To classify learners, they are usually asked to complete a survey using a tool called the Learning Style Inventory; however, this tool suffers from reliability issues (Furnham, 1992). Thus, most adaptive educational systems use the Felder-Silverman model, which is based on other learning style models, as well as the Kolb model. This model classifies learners into four dimensions, and each dimension has two categories. These dimensions are: information processing (active-reflective), input modality (visual-verbal), information understanding (sequential-global) and information perception (sensory-intuitive) (Huang et al., 2012).

The first dimension, information processing or active-reflective, involves the way the learners prefer to process information. For example, active learners prefer to learn by interacting with peers, while reflective learners prefer to think deeply about the information before acting.

The second dimension, input modality, classifies learners based on their preference for presenting information. Visual learners prefer to learn by using figures, charts and diagrams, while verbal learners may process and understand spoken and written information easily.

In the third dimension, the information understanding dimension, learners are classified based on their preferred way of structuring information, i.e. sequential learners prefer sequential and logical representation, while global learners learn based on a large and random set of information. These learners usually prefer to examine overviews and the big picture about a set of information.

The final dimension is information perception; this dimension classifies learners as either sensory, preferring facts and examples, or intuitive, preferring mathematical and theoretical explanations (Alshammari, 2016).

Learning style in general has been commonly used to adapt learning systems; however, different models have been developed to identify the preferred way to learn. Thus, it is important to choose the most suitable and the best approach, which is a difficult task (Alshammari, 2016).

Personality

According to Hofstee (1994), personality is defined as a set of characteristics that can affect how individuals feel, think, interact and communicate with others. This can be clarified via the results of research studies conducted to determine how personality is related to learners' achievements in online courses and employees' job performance (Ghaban and Hendley, 2018).

Various theories have been developed to explain personality, including biological theories, e.g. Gray's bio-psychological theory (Wilson et al., 1989). Other theories have been developed based on how individuals behave when they are interacting with the world, such as the Myers-Briggs Type Indicator (MBTI) (Carlyn, 1977).

According to Colbert et al. (2012), one of the common approach to study individuals' personality is the trait theory. This theory involves individuals' traits (which can be individuals' behaviour, emotion or thought). These traits vary between individuals (Colbert et al., 2012). One of the most-common models for this theory is the Big Five model or the Five-Factor Model (FFM). Many different articles have classified the FFM as a personality theory; however, the FFM implicitly adopts the basic tenets of the trait theory (McCrae and Costa, 2008).

In the following section, most common models and theories used to explain personality are described.

Eysenck's Giant Three was developed by Eysenck and Eysenck in 1964. This model classifies personality into the following three dimensions (Barrett et al., 1998):

1- Extrovert versus introvert: Individuals who have a high score on the extrovert scale are usually more energetic, optimistic and engaged with social interactions;

2- Neuroticism versus emotional stability: Individuals who are more neurotic are usually characterised as being unstable, anxious and depressed;

3- Psychoticism versus normality: Individuals who are more psychotic are usually described as independent thinkers, cold, antisocial and hostile.

The second model that is used to describe personality is the MBTI. This model was developed by Myers and Briggs during World War II to help individuals learn more about themselves. This model classifies personality into the following (Carlyn, 1977):

1- Extrovert - Introvert: This dimension is similar to the first dimension in the Eysenck model. Learners who are more extroverted are described as action-oriented and more social, while introverted learners usually prefer to work alone.

2- Sensing - Intuition: This dimension has some interaction with the information perception learning style developed in the Felder-Silverman model. Sensing learners prefer to learn from their experiments and recalling facts. In contrast, intuitive individuals prefer abstract concepts and enjoy thinking about possibilities.

3- Thinking - Feeling: This dimension refers to how individuals make decisions. Thinking individuals prefer to make their decisions based on logic and facts, while feeling individuals make decisions based on their feelings and emotions.

4- Judging - Perceiving: This dimension refers to how individuals interact with the outside world. Judging individuals are more organised and follow a structured plan, while perceiving individuals are more flexible.

In the FFM, personality traits are used to describe individuals (McCrae and Costa, 2008). According to Digman (1990), the FFM has become the most widely used model in recent studies, and most other personality theories and models are covered by it. Furthermore, it is assumed that the FFM is more stable. It also contains terms related to culture, intelligence and creativity.

The FFM classifies personality into five dimensions (McCrae and Costa, 1987; Mattheiss et al., 2017):

1. Conscientiousness: The tendency to be well-organised and goal-oriented. Individuals with this personality are usually described as organised and hard-working planners.
2. Extroversion: The tendency to be outgoing and to embark on new opportunities. Individuals who score highly in extroversion are described as excited, confident, energetic, talkative, assertive, active and excitement-seeking.
3. Agreeableness: The tendency to be cooperative and tolerant. Individuals with this personality are usually described as kind, gentle, caring, helpful, trustworthy and warm. They may prefer to cooperate rather than compete.
4. Neuroticism: The tendency to be emotionally unstable. Individuals with this personality are usually described as anxious, fearful, negative, depressed and stressed; they also have difficulty managing stress.
5. Openness to experience: The tendency to be imaginative and creative. Individuals with this personality are described as adventurous, explorative and open to trying new things.

The personality dimensions overlap between the models. For example, some dimensions in the Eysenck model are the same as those in the MBTI, such as the extroversion and neuroticism dimensions. Furthermore, Busato et al. (1998) identified some overlaps between the FFM and the other models. For example, they reported that there is a strong correlation between the conscientiousness dimension in the FFM and the thinking - feeling and judging - perceiving dimensions in the MBTI. Furthermore, the extroversion in the FFM was correlated with the Extroversion-Introversion dimension in the MBTI.

Some studies have reported a relationship between learning style and personality on the one hand and a relationship between cognitive style and personality on the other. For example, Furnham (1992) reported a correlation between the extrovert in the Eysenck scale and the activist and pragmatist in the Kolb model. Moreover, introvert learners (low extrovert) are usually high in reflection in the Kolb model; however, the neuroticism dimension does not show any correlation with any learning style models (Jackson and Lawty-Jones, 1996).

Sadler-Smith (2001) attempted to identify the relationship between personality, learning style and cognitive style. They found that, for example, highly extroverted learners tend to use critical and concrete processing in making decisions and solving problems. In contrast, highly agreeable learners are usually correlated more with memorising. These learners need external factors to motivate them. Learners with a neurotic personality must be provided with a structured learning system. These learners need to be told what they should do (Busato et al., 1998; Kamarulzaman, 2012).

According to Kamarulzaman (2012), three approaches to studying and learning are related to the FFM. These approaches are as follows. First, there is a deep approach (when the learner says, 'I am not prepared to accept this; I need to think about it'). This approach is correlated more with extroverts and open learners. The second approach is the surface approach ('I have to remember'). This approach is related to the neuroticism and agreeableness personality traits. Finally, there is the strategic approach, which is positively correlated with conscientiousness ('I know what I want from the course, and I will achieve it').

To show the relationship between these three individual traits, Curry (1983) developed the 'onion' model. This model represents the three individual traits as onion layers, as shown in Figure 3.4. The surface layer is most influenced by external factors and is more changeable. This layer represents how learners learn, which refers to learning style. In the second layer is the information-processing approach, which represents the cognitive style. The central and final layer represents the most stable traits, which comprise the personality (Bennet and Fox, 1984).

Due to the stability of personality and its influence on the other factors, personality is the focus as a basis for adaptation in the remainder of the thesis.

2) User model representation

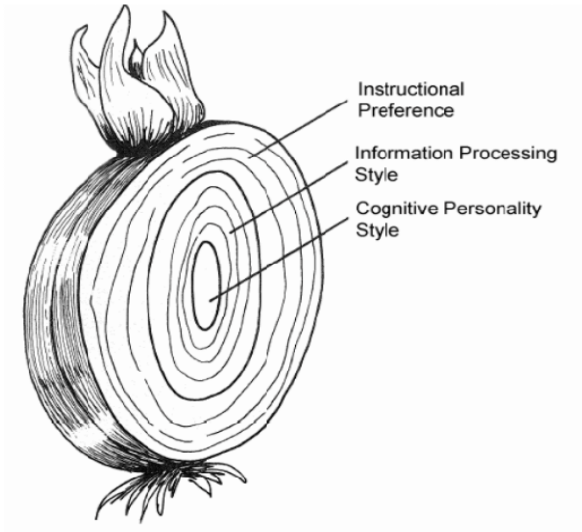


Figure 3.4: The layers of the onion model (Curry, 1983).

The user model representation describes how the chosen users' characteristics can be modelled and presented in the learner model. Different models have been developed for this purpose. The most common techniques are overlay user modelling, keyword representation and stereotype user modelling (Sosnovsky and Dicheva, 2010).

The oldest and most common approach in the adaptive educational system is overlay user modelling. This model represents the user's knowledge as a subset of the domain model that is designed by the expert or teacher. This model can be highly effective and flexible. Moreover, according to Sosnovsky and Dicheva (2010), overlay user modelling can be easily and dynamically adjusted to the user's knowledge. This model is commonly used to represent users' knowledge, skills and interests. According to Sosnovsky and Dicheva (2010), this model has many benefits, such as its flexibility and precision. This model is fine-grained and capable of adjusting to every detail of the learner; however, the model has some drawbacks. For example, it is necessary to have a precise representation that matches the users' knowledge, but this is difficult to achieve. The user may have different beliefs or different approaches to problem solving (Brusilovsky and Millán, 2007).

The second approach that is commonly used in information retrieval systems is keyword representation modelling. For this model, the adaptive system uses a vector to represent a set of terms or keywords that are related to the learners. The adaptive system predicts these keywords from the users' behaviours. For example, the system stores information about the learners (their interests and needs), and keywords are extracted from documents browsed by the user and lists of requested terms or rejected emails (Sosnovsky and Dicheva, 2010; Brusilovsky and Millán, 2007). Perceived as a shallow version of the overlay user model, this model is easy to implement. It is commonly used in text analysis and adaptive social systems; however, there are some problems associated with it, especially with some words that require advanced technology in natural language processing, such as the processing of homonymy (same word with multiple meanings) and synonymy (multiple words with the same meaning) (Sosnovsky and Dicheva, 2010).

The third model is stereotype user modelling. In this model, a group of learners use the system in a similar way and produce a similar outcome. These groups of learners can be grouped together and explained by similar features (Kobsa et al., 1998). In contrast to the overlay model, the stereotype model does not update frequently or after any changes with users. In the stereotype model, if the learner is assigned to a particular stereotype, the whole model will change. The learner can be mapped to one stereotype or to a combination of stereotypes. Hence, it is difficult to use the stereotype model to represent some of the learners' characteristics, such as changeable attributes, e.g. learners' knowledge and skills (Sosnovsky and Dicheva, 2010).

3) User model elicitation

This section presents how users' characteristics are identified. According to Sosnovsky and Dicheva (2010), most adaptive systems use two approaches to classify users' characteristics. The first is the explicit approach by asking learners directly to provide feedback about their interests and goals. This can be done through surveys and questionnaires or by conducting interviews with learners. Other user characteristics can be identified explicitly by using reliable psychological tests. This approach is usually used to ascertain learners' traits. For example, the learning style inventory is a tool used to identify learners' preferred learning styles (Alshammari, 2016), and the Big Five inventory is usually used to measure individuals' personalities (McCrae and Costa, 2008).

In contrast, the second approach obtains learners' information implicitly. For example, in the learning environment, the system will track the number of clicks on a specific lesson, the time required to finish the course and the speed to complete a specific task. In addition, collecting user data implicitly is commonly used in intelligent adaptive social systems. In this case, the system can be used in a dialogue to ask users fishing questions. Then, the data are cleaned and analysed to find patterns in the users' behaviours (Zigoris and Zhang, 2006).

After collecting the required information from the learners, the users' characteristics must be aggregated and analysed to find a common pattern and to generate a recommended and adaptive version of the system for each learner. The analysis of learners' patterns can be done manually by observing learners' behaviour or automatically by feeding learners' behaviour into one of the machine learning techniques; such as: classification and clustering. In classification, each class must be predefined before assigning learners; however, this may be challenging and difficult to accomplish. Therefore, most adaptive and recommender systems use clustering. In clustering, a group of learners with similar features and similar behaviours are grouped into one class without any need to predefine the classes (Kobsa et al., 2001).

Adaptation model

An adaptation model bridges the gap between the user and the domain models. It is used to create the best match based on learners' objectives and characteristics (Motti and Vanderdonckt, 2013). According to Paramythis and Loidl-Reisinger (2003), two dimensions must be identified clearly in the adaptation model: logic and action. Logic is responsible for identifying one or more characteristics of the other models (user and domain models) and for deciding whether the model is worth adapting based on these characteristics. Action refers to the steps the system must take to complete the adaptation process.

According to Mustafa and Sharif (2011), the adaptation model for most educational systems can be chosen based on the content of the page, the navigation and the links between pages or the multimedia integrated into the educational website (Figure 3.5).

The first type of adaptation, adaptive presentation, has garnered much attention in recent years. Two approaches to this type of adaptation can be used: adaptive text presentation and adaptive multimedia. Adaptive text presentation adapts course contents and materials based on users' characteristics. For example, in some educational systems, preliminary concepts which must be taught to novice learners. While there might be extra complicated details and concepts which must be presented to expert learners. Furthermore, some of the adaptive educational systems under this approach take learners' preferred learning style into consideration. Some learners prefer to study theoretical concepts, while others prefer to practise and complete exercises. For example, Kamarulzaman (2012) suggests that highly extroverted and open learners usually prefer to learn by discovering new things.

The second approach to adaptive presentation adapts the multimedia integrated into the course. With this approach, the adaptive system can consider users' learning styles, preferences and interests. For example, some learners may prefer to have figures and charts, while others may prefer to engage verbally with the content. Extra elements have recently been integrated into educational courses, such as social elements and digital rewards. These elements may be useful for some types of learners, but not all (De Bra et al., 1999).

Another type of adaptation is adaptive navigation. This can be done by deciding, for example, which page will be presented to the user next. Furthermore, it is possible to adapt the links of the system by sorting them differently for different learners (Brusilovsky, 1996; Garzotto and Cristea, 2004).

Paramythis and Loidl-Reisinger (2003) added another form of adaptation for educational systems: adaptive content discovery and assembly. This type of adaptation tailors and collects the course content to make it more suitable for learners. It can occur in two ways. One is to provide learners with the freedom to choose the optimal course. For example, if the learner is highly open, they may prefer to browse the course content freely (Kamarulzaman, 2012). The second type of adaptation, which is used by most adaptive systems, monitors learners' progress and behaviours and determines the most suitable course.

Magoulas et al. (2003) suggested another approach, adaptive collaboration support, which refers to management and communication between the learners in an online course. This adaptation is important because it prevents learners from feeling isolated. This adaptation can be made by directing collaboration and ensuring the best matches between collaborators (Magoulas et al., 2003).

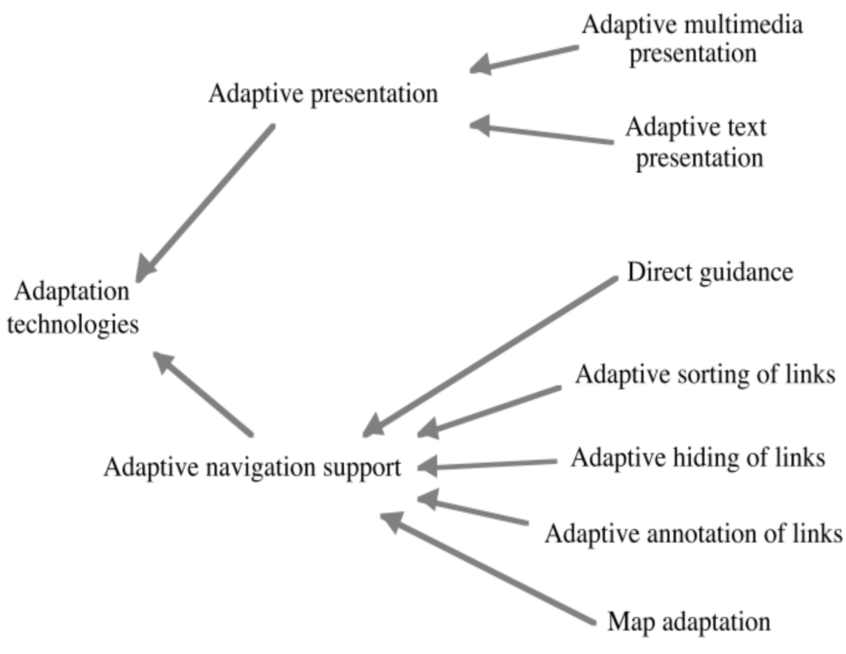


Figure 3.5: The updated taxonomy of adaptive system technologies (Brusilovsky, 1996)

Most recent studies have focused on adapting the content of online learning systems to be more suitable for learners' backgrounds and experiences; however, many studies have also focused on users' learning styles as a basis for adaptation (see (Graf et al., 2009; Popescu, 2010; Magoulas et al., 2003)). These studies have shown the positive effect of using learning style to enhance learning outcomes, but some studies have suggested that using the learning styles alone may not be sufficient and that both learning style and background must be used together. The results related to this claim have been scientifically positive (Alshammari, 2016).

Personality and cognitive style are both considered to be stable characteristics, and they may be used effectively to personalise learning contents (Triantafillou et al., 2002; Irani et al., 2003). Other research studies have suggested using learners' moods and affective states as sources for adaptation (Khan et al., 2010). Researchers have hypothesised that learners' emotions have an effect on their progress and engagement. For instance, happy learners are more satisfied and usually complete all learning tasks (Mukhopadhyay et al., 2020). In contrast, unhappy learners are hypothesised to be more angry and sad. Thus, they may need external elements to motivate them (Bakic et al., 2015). The problem with using a mood-based approach is the instability of this scale. Measuring emotion is not trivial and may require advanced tools (Ghaban and Hendley, 2019).

It can be observed from the literature that substantial research has been carried out on adapting the content of online learning materials based on different attributes of learners.

Summary

Most online learning systems adopt the same content and presentation for all learners; however, this may demotivate learners from using these types of systems. Moreover, these static online learning systems do not consider the differences between learners. Learners have diverse characteristics; for example, they vary in their backgrounds, skills, learning styles and personalities (Yarandi et al., 2011). Due to these variations, and to increase the effectiveness of online learning systems, adapting these online educational systems is suggested. Adaptation means tailoring the system to meet learners' needs and interests.

According to De Bra (2008), for the adaptation process, critical models should be identified. The domain model represents the knowledge that should be taught to learners. The context model represents the environmental attributes that may affect the process of using the system. Furthermore, the user model represents characteristics that are related to the learners. Finally, the adaptation model is tailored to fit all the domain models to build an adaptive system.

In the user model, different characteristics and attributes can be incorporated. Some of these are stable or may change frequently. However, it is difficult to adapt based on the changeable characteristics as the user model needs to alter with every change. Thus, using one of the more stable characteristics, such as learning style, cognitive style and personality has been suggested. These three traits are mutually related, and there is some overlap among them. However, according to Curry (1983), personality has a significant effect on the other two traits. It is also considered more stable. Thus, in the remainder of this thesis, personality is the focus, which is used as the basis for adaptation (Sosnovsky and Dicheva, 2010).

Many research studies have applied one or more user attributes and context models to adapt online learning systems. The most commonly used characteristics in adaptive learning systems are background and learning style. This adaptation is shown to be highly beneficial in enhancing learners' outcomes. In these systems, adaptation will usually occur at the content level and in terms of how to present the content to learners (Brusilovsky and Millán, 2007). However, for this research study, the content was unchanged, and the elements integrated into the learning website were adapted, such as gamification elements.

3.3 Personalised gamified systems

Gamification has been suggested as an effective technique for enhancing learners' motivation and engagement in educational online courses. However, different learners interact differently with gamification elements. For example, Jia et al. (2016) showed that some learners describe several gamification elements as 'silly' and 'childish'. This study also highlighted how every learner has different expectations for gamification. Thus, adding gamification elements for everyone to interact with may result in 'overloading' the user interface. Due to this, personalised gamification elements based on different learners' characteristics have been suggested.

The process of adaptation and personalisation is not trivial; it requires several decisions to be made before it is undertaken. One of these decisions concerns identifying the main objective of adapting the gamified elements. For example, some adaptive systems use social elements to enhance users' motivation and engagement. However, the social elements are not suitable for every user. Thus, the social elements may be personalised for some users and removed for others (Monterrat et al., 2014).

Another important decision that must be made is how the gamification elements will be presented in the system; that is, whether the gamification will be structure- or content-based.

In some adaptive gamified systems that target children, it may be best to implement content gamification, where most of the system's contents are modified to make it a game. For adult audiences, it may be preferable to design the gamification elements as structural aspects that are integrated into the system (Monterrat et al., 2014).

The third and most important decision is choosing which attributes or characteristics of the learners should considered and be used as the basis for system adaptation.

Klock et al. (2015) proposed a conceptual model for adapting gamification elements which discussed how to build an adaptive gamification model. Four dimensions must be clarified (Figure 3.6):

- **Why?** This question is answered by defining which required behaviours should be promoted in the learner. This can be done either through engaging and motivating learners (e.g. to answer questions, participate in the forum or use communication tools) or by providing access to more content (e.g. introducing new concepts or providing complementary materials and links).
- **How much?** This question identifies the extent to which gamification elements really work. This can be determined by applying quantitative and qualitative tests by way of an experiment with a control group and a group of gamified system users.
- **Who?** This question relates to understanding who the learners are. This can be accomplished by identifying the learners through such methods as surveys, interviews and marketing personas or by examining learner profiles (e.g. identifying learner gender, age, player type and personality).
- **What?** This question examines what sort of changes should be made to gamify a learning system. Any change in a system must be followed by measurement tools, such as usability or satisfaction tests.

Böckle et al. (2017) discussed a classification scheme for adapting gamification in online learning systems. This scheme includes the most relevant elements that are to be considered when adapting gamification elements: the target, reasons for adapting the system and the basis for adaptation (Figure 3.7). It is important to identify the target to determine which parts of the system need to be adapted. This might be the system's content or the addition of constraints, such as lock levels. The system also must identify which information will be used as the basis for adaptation, which may be characteristics related to the user or to the context. Finally, it is important to identify the reason for and the aim of adapting a gamified

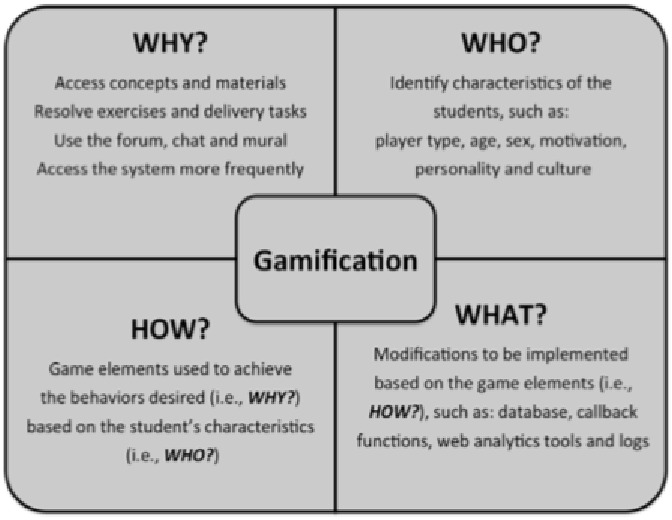


Figure 3.6: The conceptual model of Monterrat et al. (2014) for adapting gamification elements to a system.

system.

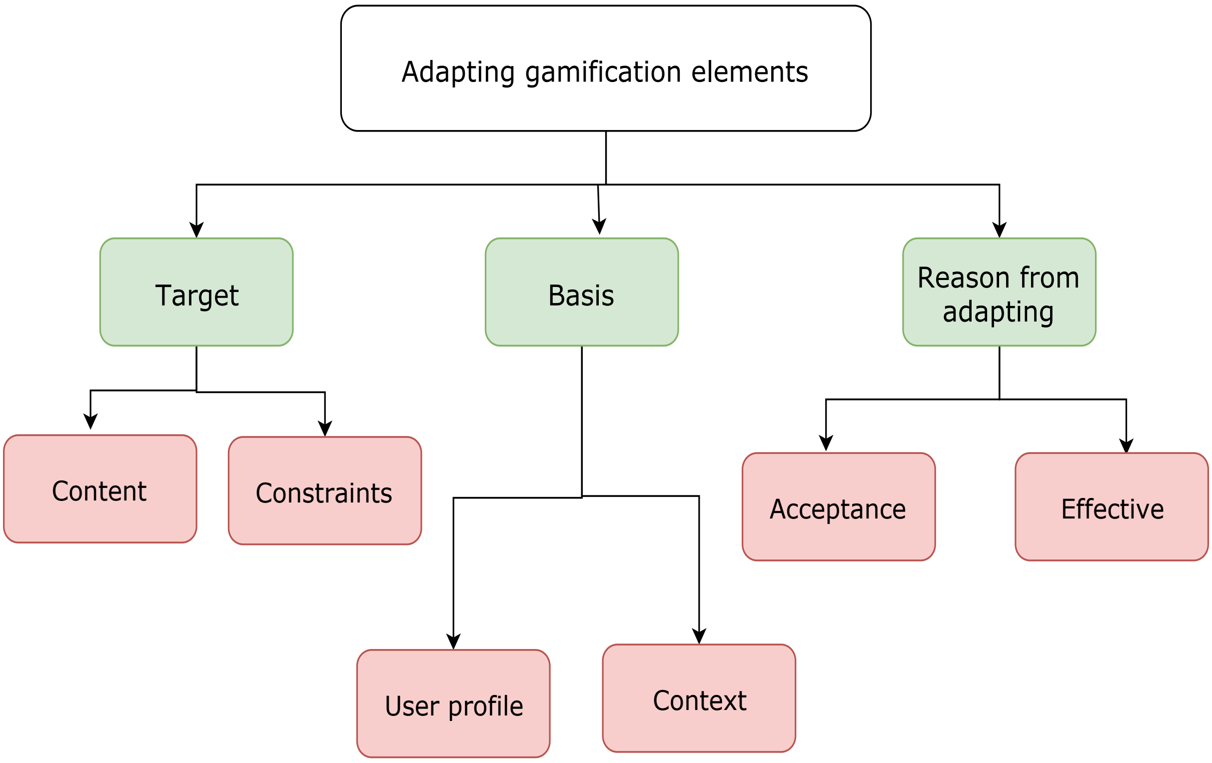


Figure 3.7: An example of a classification scheme for adapting gamification elements (adapted from (Böckle et al., 2017)).

To process and adapt a gamified system, Böckle et al. (2017) suggest four steps. The first is to capture learner characteristics either by observing their behaviours or by asking them directly about their preferences. The second is to analyse how gamification elements interact with various learner characteristics. In the third step, the system must tailor the most ideal gamification elements to one or more of each learner's characteristics. Last, the optimal gamification elements will be recommended for each group of learners with similar characteristics.

The first and the most important stage in the adaptation process is collecting the necessary user information. In the following section, we will explain some of the most common characteristics that are evaluated in the process and how they are used to adapt gamification elements in a system.

3.3.1 Examples of adapted gamified systems

A few studies have tried to adapt gamification elements. Böckle et al. (2017) found that in total 17 studies have attempted to personalise and adapt gamified systems. The main aim of these studies was to change user behaviour. Further, six other studies aimed to improve and support learners in the online learning environment by enhancing their learning-based effectiveness and satisfaction.

These studies used different and distinct characteristics for adaptation. As in any adaptive system, some characteristics were related to users and others concerned the online environment, such as the browser type, the screen size and resolution. The focus was on the learners themselves (Monterrat et al., 2014).

According to Klock et al. (2015), learner ages, genders and cultures can all be used to adapt gamification elements. In their study, they discussed how perceptions of gamification elements vary between adult and teenage learners. They revealed that teenagers are more likely to finish the requested tasks more quickly than adults because of the integrated gamification elements. Kim (2015) also reported variations in responses to gamification elements based on cultural orientation. Cultural individualism and collectivism, in particular, appear to affect users' entertainment levels and degrees of interaction with social networks.

In another study, Klock et al. (2015) showed that females are more likely to benefit from gamification elements than males and enjoyed competing with others more on the leaderboard.

By comparing the gamification element preferences of learners in Western countries (such as the United Kingdom, Spain and Netherlands) and Middle Eastern countries (such as Saudi Arabia, Iran and Egypt), Kim (2015) found that another characteristic that affects how gamification elements are perceived, is the learner's culture. Learners in Western countries appeared to benefit from feedback, which was essential for them, and benefit more with badges and customisation. Whereas, learners in the Middle East usually prefer to interact with others.

Böckle et al. (2017) reviewed the characteristics most frequently used by adaptive gamified systems and reported that many different and distinct characteristics have been used as the basis for system adaptation. One of these characteristics is the user's goal, which has been used in three studies conducted in the health field. Six other studies were found to have relied on adapting gamification elements from the learning environment, using learners' knowledge levels as the basis for adaptation. However, the majority of the remaining studies generally focused on two fundamental characteristics: player types and personality types (Böckle et al., 2017).

Player types

One of the most common characteristics used as the basis for designing video games and gamification is player type (Stannett et al., 2016).

Several different models have been proposed to describe the different player types. These models are either based on users' behaviour while playing and interacting with a game or aspects related to the personality dimensions (Stannett et al., 2016). In the following, we will provide an overview of the most common player models.

Bartle's Multi-User Dungeon (MUD)

The first common player model is Bartle's MUD, which is based on asking users what they want and what they prefer. Based on the results, players are classified into four groups (Stannett et al., 2016):

- Achievers: Individuals who prefer collecting points and achieving goals to obtain a sense of victory.
- Explorers: Individuals who prefer to explore and discover new, interesting knowledge.
- Socialisers: Individuals who enjoy interacting with others.
- Killers: Learners who like to dominate others.

Four Fun Keys Model

The second player model, Four Fun Keys, works by observing players' emotional patterns. It recommends four classifications based on these emotional responses (Stannett et al., 2016):

- Hard fun: Players in this group enjoy beating challenges and problem solving.
- Easy fun: Players in this group are similar to the 'explorer' group in MUD. Players enjoy exploring and discovering all the aspects of a game.
- Altered state: These players enjoy games that match their experiences.

- People factor: These players enjoy competing and collaborating with others.

Bartle's MUD and the Four Fun Keys models are quite different from each other. However, Stannett et al. (2016) demonstrated that there are some similarities between them. For example, members of the killer group in the Bartle model are correlated with members of the people factor and hard fun groups in the Four Fun Keys model, and easy fun players are like explorer players in the Bartle model.

Various studies have attempted to tailor gamification elements to each of the models' player types. One such study was conducted by Fernandes and Junior (2016), who showed that killers prefer points, achievements and rankings as gamification elements. Meanwhile, achievers preferred badges and rewards. Socialisers enjoyed interacting with others and are similar to the members of the people factor in the Four Fun Keys model. The preferred gamification elements of these players are social aspects, leaderboards and customisation. The last dimension is the explorer, who preferred to discover new places to find rewards and treasures (Fernandes and Junior, 2016).

The Hexad model

According to Tondello et al. (2016), the previously discussed models are designed to explain players' behaviour when they are interacting with a game. Players in a game experience extrinsic motivation. However, this is not the case with gamification. Gamification is not a real game, it only implements game elements. Further, users who are interacting with gamified systems are motivated extrinsically or intrinsically. Accordingly, Marczewski (2018) proposed another model to explain the behaviours of users of gamified systems. This model is driven by motivation theory (from intrinsic and extrinsic motivation). This model, called the Hexad model, classifies users based on their motivation when they are interacting with a game (Figure 3.8). The model classifies users as follows (Kim, 2015):

- **Philanthropists:** This type of user is motivated by his/her own purpose. These users do not need external rewards, and they are willing to perform tasks without any expectations. Thus, these users may not need gamification elements for motivation. Tondello et al. (2016) suggest that the best gamification elements for these users are collecting, gifting and sharing.
- **Socialisers:** These users are motivated by social connection. They prefer to interact and compete with others. These players are like the socialisers in the Bartle model and members of the people factor in the Four Fun Keys. The best gamification design for

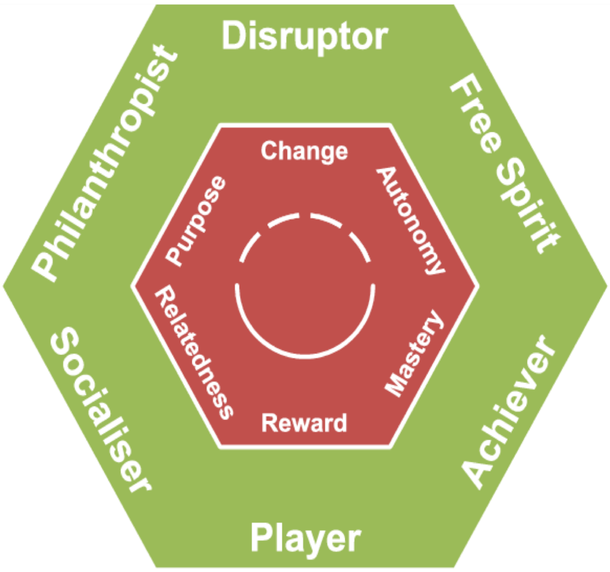


Figure 3.8: Hexad gamification user types (Marczewski, 2018)

these users is to provide them with opportunities for teamwork, social networking and competition (Tondello et al., 2016).

- **Free spirit:** Free spirit players are motivated by autonomy; they prefer to express themselves and explore contents without any constraints. This group is like the explorer and the easy fun dimensions in the Bartle and Four Fun Keys models, respectively. The optimal gamification designs for these users consist of exploratory tasks, non-linear structures and unlocked contents (Tondello et al., 2016).
- **Achievers**: This group is motivated by competence. These users progress by succeeding in complex tasks and overcoming challenges. The ideal gamification elements for these users are certificates of achievement, challenges, new levels and progression (Tondello et al., 2016).
- **Player:** This group is motivated by external rewards. They will complete tasks if they are given rewards for doing so. The best gamification designs for these users include bestowing them with points, badges, rewards and virtual goods (Tondello et al., 2016).
- **Disruptor** This group is motivated by triggering change and tends to like to change systems either directly or with others by promoting positive or negative changes. The most effective gamification elements for these users are voting systems (Tondello et al., 2016).

According to Stannett et al. (2016), different gamification elements can be mapped to the Hexad model. For example, a user classified as a player in the Hexad model must be provided with external gamification elements, such as badges and rewards. Socialisers will be more satisfied and engaged if they can interact with others. Table 3.1 presents the suggested gamification elements for each category of the Hexad model.

Table 3.1: The gamification elements recommended for each Hexad model user type (Tondello et al., 2016)

User type	**Suggested gamification elements**
Philanthropist	collecting elements, such as badges Knowledge sharing
Socialiser	Social networks (e.g. sharing scores on social media) Social competition (e.g. compete with friends in the leaderboard)
Free Spirit	Exploratory tasks (e.g. Browsing the contents) Unlockable content and levels Customisation (e.g. customise an avatar)
Achiever	Certificates of accomplishment (after finish each level) A progress bar shows learners' progress
Distruptor	Voting mechanisms Creative tools (e.g. storytelling)
Player	Points Rewards Leaderboard Badges or achievements

The Hexad model's user types correlate and overlap. For example, as Tondello et al. (2016) noted, achievers and players are both motivated by accomplishment. However, players are usually motivated by extrinsic rewards, while achievers focus on their own competence as an intrinsic motivation.

Hence, each user can be classified as one or more of the user types in the Hexad model. Tondello et al. (2016) also showed how some users can show characteristics of all these user types, which makes it difficult to adapt systems to such users.

Player types and the Hexad model of classifying users may not be the optimal sources of adapting gamified systems. Player types are changeable and are suggested based on the behaviours of users when they are interacting with a game, and the Hexad model classifies users based on their sources of motivation. Some users are motivated intrinsically, and others are motivated extrinsically. Gamification, in some cases, can be used to enhance the intrinsic and extrinsic motivation of the users. This makes it difficult to use this model to adapt. As a result, some studies recommend using individual user traits, such as their personality, to adapt a gamified system.

User personalities

An overview of personality was provided earlier in this chapter in section 3.2.2. Personalities comprise individual characteristics and serve as the basis for system adaptation (Hofstee, 1994).

3.3.2 Adapting gamification elements based on users' personality

Because adapting gamification elements based on individual personalities is a novel concept, examples of systems that have attempted to match different gamification elements to personality dimensions, are reviewed here, regardless of whether these systems are related to learning or not.

One related study by Codish and Ravid (2014a) aimed to assess how different personalities interact with gamification elements by focusing on introversion and extroversion to examine how extroverts and introverts perceive gamification elements. They integrated an academic course with different gamification elements, such as points, badges, rewards, progression and leaderboard, and asked 102 students in their third year (out of four) in an industrial management and engineering programme to study the gamified course materials throughout one semester. At the end of the term, the students were asked to complete a survey on their preferences regarding the existing gamification elements.

The study's results revealed distinctions between the responses of extroverted and introverted learners. Highly extroverted learners enjoyed receiving points, badges and rewards more than their introverted counterparts, and a negative correlation was found between extroverted personalities and the leaderboard: highly extroverted learners generally disliked tracking their progress on the leaderboard. However, both students who scored high and low as extroverts enjoyed and felt satisfied when their names were at the top of the leaderboard.

The study by Codish and Ravid (2014a) focused on one personality dimension, extroversion. In a follow-up study, the authors investigated the effects of gamification on other personality dimensions, developing a paper-and-pen prototype for a gamified academic course and asking 102 learners to complete it (Codish and Ravid, 2014b). Afterwards, they asked learners to take a personality test and a test to determine their gamification element preferences. The results showed a variation in the effects of gamification; introvert learners preferred badges more than extroverted learners did. However, highly conscientious learners liked to see their progress and achievements.

The results of these studies may not be reliable, however, because the gamified course was a required course for the participating students, which may have affected their behaviours; they were obliged to complete the course because it was necessary for obtaining their degree. So, the students may not have been motivated by the integrated gamification elements. Furthermore, the information was collected through self-report questionnaires, which may provide unreliable data (Tondello et al., 2016). Another limitation of this study is its small number of participants. Further, learner personalities were divided in the middle into those with high extroversion scores and those with low extroversion scores without considering learners in the middle. Additionally, the authors noted that their studies did not account for interactions between personalities (Codish and Ravid, 2014a,b).

In another study, Jia et al. (2016) attempted to understand the relationship between gamification elements and personality dimensions. They asked 248 participants to provide their demographic information. Then, participants were asked to complete a personality test (the five-item IPIP); which was used to calculate learners' personality. Users then watched a short video about gamification elements and completed a self-report questionnaire in which they explained whether they found each described gamification element helpful, enjoyable or reliable. The questionnaire was hosted via SurveyMonkey and Amazon Mechanical Turk (AMT).

The results of this study indicated that most participants disliked the leaderboard, which was explained by the researchers as resulting from a lack of a sense of competition. In addition, users did not want to share their tracking with others. Highly extroverted users reported that they enjoyed earning points, unlocking new levels and obtaining badges. Highly agreeable users reported that they preferred challenging elements, while conscientious participants liked levelling up and progressing. Finally, the highly neurotic learners enjoyed receiving rewards.

The study was, again, based on a self-report questionnaire obtained from the participants after watching a video about gamification elements. In addition, the study used AMT to collect information from users about their preferences. These issues related in the methodology may introduce a bias in the results and make it unreliable.

Tondello et al. (2017a) attempted to study the correlations between 59 gamification elements, user personalities and the users' Hexad classifications. They contacted 196 users from a number of countries and of various ages (15-71 years old) through email and social media. Participants were asked to fill in a 24-questions test related to Hexad model classifications, complete the Big Five Inventory, BFI-10 (a 10-question personality test), provide demographic information and complete another test intended to determine their preferred game elements.

At the beginning of their study, they applied different kinds of analyses, including principal component analysis and clustering, to reduce the number of gamification elements and to find correlations between them. This resulted in eight categories of gamification elements:

- Socialisation, elements that involve social interaction and collaboration, such as leaderboard and social elements.
- Assistance, elements that provide users with some sort of aid in their progression,
- Immersion, elements related to immersion and user curiosity.
- Risk/Reward, challenging elements and any rewards for winning.
- Customisation, elements that can be presented as personalised avatars.
- Progression, elements that can provide learners with a sense of progress or feedback, including progress.
- Altruism, elements that allow users to make useful contributions by, for example, sharing knowledge.
- Incentive, elements that involve incentives for users, such as badges, rewards and certificates.

Next, the authors calculated the correlation between users' Hexad model classifications and their preferred gamification elements. They found that socialisation elements were preferred by Hexad achievers and players. Further, preference for these elements was also significantly correlated with highly extroverted users. They also preferred the assistance elements. Elements of immersion were strongly correlated with Hexad free spirits and achievers. However, these elements were not correlated with any of the FFM dimensions. Risk and reward elements were preferred by achievers and players, and customisation was strongly preferred by highly open users.

These results did not indicate any one preferred gamification element for all personality dimensions. This may be due to the limited number of participants. Further, this study collected data from users in different countries and of various cultures and within a wide age range. This may affect the reliability and the validity of the results. Further, the authors argue that their results may not be reliable, as they were collected through self-report questionnaires. Further, the short version of the personality test that was used suffers from reliability issues (Tondello et al., 2017a).

Table 3.2 shows a summary of the related research studies that tried to adapt gamification on learners' personality. Based on the results of the related studies, it appears that personality can be considered a good predictor of user responses to gamification. Further, personality is considered a more-stable characteristic. Thus, the focus of this thesis is on how to adapt gamification elements to online learners' personalities.

Table 3.2: A summary of related research studies that present how different personalities benefit from gamification elements.

Personality	Points	Badges	Leaderboard	Social elements	Avatars	No gamification elements
High conscientious	1;2					3;4
Low conscientious	8;9	8;9	8;9	9		
High extrovert	1;2;8;9	3;7;8;9	1;2;3;5;6;8;9	2;3;9		
Low extroversion		4	6;7			
High agreeableness	1;2;8	4;8	1;2;5;8	2		
Low agreeableness						8;9
High neuroticism	3;6;8	8	8			9
Low neuroticism	9	9	5;9	9	1	
High openness	1;2;8;9	8;9	8;9	9	3	
Low openness	8;9	8;9	1;5;8;9	9	1;4	

The number in the table refers to the research paper that presented the suggested results.(1)(Orji et al., 2017); (2) (Tondello et al., 2016); (3) (Tondello et al., 2017b); (4) (Codish and Ravid, 2014b); (5) (Jia et al., 2017); (6) (Jia et al., 2016); (7) (Codish and Ravid, 2014a); (8) (Ghaban and Hendley, 2018); (9)(Ghaban. and Hendley., 2019)

3.3.3 Summary

Because of the varying effects of gamification on different users, personalising and adapting gamification elements to user attributes is recommended, especially in online learning environment.

It is, likewise, important to identify how gamification elements will be integrated into the system. In systems that target children, it may be to turn the system into a game, but it may be better to integrate gamification elements into other systems as surface elements without changing the content of the system itself. Other important aspects to consider in the process of system adaptation are the user characteristics such as age, gender and culture. Other adaptations may consider other variables related to the context, such as the kinds of devices used by learners and their physical locations (Monterrat et al., 2014).

Gamification element adaptation, as a field, is still under investigation. Most current studies use player or personality types as the basis for system adaptation. In this thesis, we focus on using of personality, which is argued to be more stable, as a basis for adapting. Different theories and models have been proposed to explain personality, such as the FFM, which classifies individuals according to five dimensions: conscientiousness, extroversion, agreeableness, neuroticism and openness (Hofstee, 1994).

To conduct gamification adaptations based on the personality, we first need to understand the relationship between gamification elements and learners' personalities. A number of studies have sought to address this relationship. For example, Jia et al. (2016) asked users which gamification elements they found to be the most enjoyable and helpful. They found that highly extroverted learners enjoyed gamification the most overall. These results are supported by other studies, including (Codish and Ravid, 2014a) and (Codish and Ravid, 2014b). The results of these studies show that learners with different personalities respond differently to gamification elements. However, the results of these related studies may not reliable. As these studies rely on self-report from users who completed the entire experiment. This may conflict with the main aim of gamification, which is to enhance motivation and engagement without forcing the users to complete the study. Further, these studies do not account for the users who dropped out from the experiments. It is necessary to identify who these users are and what their reasons are for dropping out and whether it happens because of specific gamification elements.

3.4 Conclusion

Gamification was developed as a technique to enhance users' motivation and engagement in systems. It has become widely used in many different disciplines. However, the responses of different users toward gamification vary; some are motivated by gamification elements, while others may only be motivated by these elements for a short period of time. Further, some users are distracted by collecting points and rewards and do not concentrate on the system's content (Martí-Parreño et al., 2016).

Because of this variation, it is recommended that gamification elements are personalised for users. One of the most stable attributes to be considered is learners' personality. A personality is defined as a set of characteristics that controls how individuals think, feel and interact with others. Several models and theories have been developed to describe personality. One of the best-known models, which various studies have used, is the FFM. In this model, personality traits are classified into five dimensions based on the features associated with each dimension. These dimensions are as follows:

1. Conscientiousness: Individuals who have high conscientiousness are hard-working, organ-

ised and like to plan.

2. Extroversion: Individuals who have high extroversion are social, talkative, energetic and positive.

3. Agreeableness: Individuals who have high agreeableness are kind, helpful and love to collaborate with others.

4. Neuroticism: Individuals who have high neuroticism are emotionally unstable, negative and depressed.

5. Openness to experience: Individuals who have high openness are imaginative and enjoy going on adventures.

Several researchers have moved towards adapting gamification elements based on learner personalities. Accordingly, an increasing number of studies have focused on understanding how different personality dimensions interact with various gamification elements, which can be used to develop guidelines or rules for building adaptive gamification elements. Codish and Ravid (2014a) sought to examine gamification's impact on learners by concentrating on one personality dimension and asking participants about their preferred gamification elements after they completed a gamified academic course. This research was followed by another study by the same authors that examined all personality dimensions (Codish and Ravid, 2014b). Jia et al. (2016) conducted a study that involved asking users about their preferences in gamification elements after they watched a video describing each element.

Previous studies confirmed that responses to gamification vary according to learners' personalities. For example, extroverted learners are the most likely users to enjoy elements such as points, badges and rewards, while conscientious individuals prefer to see their progress unfold.

Most previous studies have been based on self-report questionnaires that ask users about their preferred gamification elements, but this subjective approach may bias the results producing unreliable findings. Another problem with the most relevant research is the use of shortened versions of personality tests, which have reliability issues. In addition, in some studies, learners were asked for their opinions after finishing a compulsory gamified academic course, possibly introducing bias into the results, as learners needed to finish the course to get their degree. This aspect conflicts with the main aim of gamification, which is to enhance users' motivation. Additionally, the analyses of these studies did not consider learners who dropped out in the middle of the experiment, though understanding the reasons a learner may quit a course is essential for drawing accurate conclusions about whether learners drop out due to gamification or for other reasons.

Due to these limitations, a more objective, reliable approach to addressing this question must be applied to develop a better understanding of how gamification's benefits vary with user attributes -especially personality. With a fuller understanding, researchers will be better able to build systems that can adapt to meet learners' individual needs, thereby optimising their experiences and learning outcomes.

Chapter 4

Adaptive Gamification Elements Framework

4.1 Introduction

The previous chapter discussed the need to adapt gamification elements to learners' attributes. Several such attributes related to learners and their contexts can be considered. However, this thesis focuses on personality. Thus, the proposed framework for adapting gamification elements to learners' personalities is presented alongside the steps required to build an adaptive model.

4.2 Motivation

Gamification has been shown to be an effective technique to motivate and engage learners of online courses (Dichev et al., 2014). However, the effect of gamification on learners varies; some learners enjoy it and feel motivated by it (Cheong et al., 2013), while others find it boring and tedious (Jia et al., 2016). Some learners describe the integration of gamification elements as a waste of time. Thus, they are not universally liked by all learners. To improve learners' experiences when they interact with the gamified online courses, an adaptive model can be built to match gamification elements to learners' characteristics, while considering the context of the adaptation process. However, only a limited number of studies have tried to assess the relationship between gamification elements and learners' characteristics. Thus, the present work focuses on the learner's personality, as it is a relatively stable characteristic compared to other learner characteristics (Nguyen and Do, 2008).

Different models have been proposed to describe personality. This thesis uses the FFM because it has been used increasingly in recent works (McCrae and Costa, 2008). This model classifies personality into five aspects that can be experienced: conscientiousness, extroversion, agreeableness, neuroticism and openness (Hofstee, 1994; Codish and Ravid, 2014a,b; Jia et al., 2016; Tondello et al., 2016). Predictions about the most appropriate gamification elements can be made based on the facets associated with each personality dimension. For example, highly conscientious learners are usually described as organised and hard-working. These learners plan and carry out their tasks (Ciorbea and Pasarica, 2013). Various research studies report that individuals with this personality trait predictably score higher in their academic courses (Conard, 2006). Furthermore, highly conscientious individuals exhibit better job performance (Rothmann and Coetzer, 2003). It is expected that these learners do not receive a significant benefit from gamification, because they tend to complete their assigned tasks without needing any motivational technique, such as gamification. On the other hand, highly extroverted learners are talkative and sociable (Hofstee, 1994). These learners usually perform better in their jobs or courses if they are part of a team or take on the role of a team leader (Rothmann and Coetzer, 2003; Conard, 2006). These learners usually benefit from the gamification elements if they were able to compete and interact with others. Highly agreeable learners usually prefer to collaborate and help others. For such learners, it may better to provide social elements that allow them to discuss and help their peers. Highly neurotic learners are usually described as emotionally unstable. These learners may become discouraged quickly by gamification and may consider gamification elements as a waste of time. Therefore, the use of gamification elements is best avoided for such learners. Learners who exhibit a high level of openness are open to discovering new things and are more creative. Hence, some customisation and creative gamification, such as introducing unlockable levels, customised badges and avatars, are likely to be preferred by this group of learners. Given the variations in responses to gamification based on learners' different personalities, an adaptive model should be built to provide predictions for the most suitable gamification elements for each learner with different personality profile.

4.3 Adaptive gamification elements framework

Adaptive systems and frameworks have been studied extensively in many recent studies. An adaptive framework can be defined as a conceptual model that contains the main component models needed to generate the adaptive model (Alshammari, 2016). Few studies have attempted to discuss the design of a framework for adaptive gamification elements. The main components of the framework are highlighted in this section.

Most related studies share common models, such as user and domain models (González et al., 2014; Motti and Vanderdonckt, 2013; Andrade et al., 2016). Other studies suggest the addition of a context model as an essential component of the framework (e.g. (González et al., 2014) and (González et al., 2016)). These research studies recognise that learners engaged in online courses can be at different physical locations. It is important to consider where and when the interaction with gamification occurs.

Another essential element for adapting gamification was suggested by Andrade et al. (2016). This model involved integrating the online learning course with the best gamification elements for a specific user. This model must be implemented dynamically. Thus, each time the user model is changed, the adaptive model is updated by utilising new information from the user or based on his/her behaviour.

Figure 4.1 shows an abstract representation of the architecture of the proposed framework. The main aim of this framework is to maximise the benefits of gamification for each learner by providing him/her with the most appropriate gamification elements.

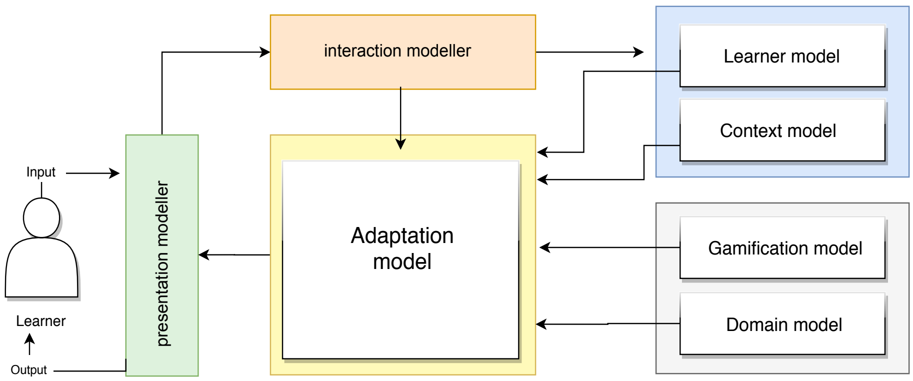


Figure 4.1: The suggested framework for adapting gamification elements

The proposed framework consists of a learner model, a domain model, a gamification model, a context model, an adaptation model and other auxiliary components.

1 - Learner model

The first component is the learner model, which is considered to be the most important element in the process of adaptation. This model consists of a set of characteristics related to the learner.

In the proposed framework, the first component of the learner model is a set of stable characteristics, such as age, culture and geographical location. This information can be obtained directly from the learners.

The second important element to consider in the learner model is the personality. As has been mentioned previously, personality can affect how learners feel and think, and how they interact with any system (Ghaban and Hendley, 2018). As per the literature, personality is a good predictor of learners' responses to gamification elements.

The third component in the learner model is the set of dynamic or changeable characteristics. These characteristics can change frequently over days (e.g. learners' interests) or from hour to hour (e.g. learners' moods). Measuring these elements is comparatively difficult. However, certain techniques have been developed, such as asking learners about their moods or using tracking measurements (e.g. eye tracking) (De Lemos et al., 2008).

The learners' level of knowledge is another important factor that affects their behaviours in online courses. This aspect represents how much a learner knows about the course before taking it. The knowledge level can be assessed by using a pre-test, which poses a number of questions related to the course to be taught.

The last element in the learner model is observational data. This component stores all the information related to the learners' behaviours in the online course, such as the frequency with which they access the course and the time they spend on each lesson. This information is obtained while the learners are interacting with the system, and it is then fed into the adaptation model.

2 - Context model

The second model is the context model. This model includes information about the device used to identify the screen size, operating system and web browser. These are important elements to consider when determining where gamification elements should be located in the user interface. Furthermore, the web browser and operating system play important roles in the identification of whether gamification elements need any support (such as sound or animation) to operate properly.

Another important factor concerns the physical environment of the learner. The main benefit of online courses is their flexibility with regard to time and location. Learners can access the course at home or at work, with friends or alone. These elements affect learners' reactions towards gamification elements. For example, the use of chat and social gamification elements is often less valuable if learners access the course in the company of friends.

In this framework, it is recommended that all the previous information obtained about learners be used and considered to build an adaptation model. However, because of the limitations mentioned in the literature and the novelty of the idea of adapting gamification, it is difficult to consider all these attributes in the adaptive process. Thus, personality was chosen as the basis for adaptation to control the process of evaluation, because personality is considered to be a stable characteristic, and it has been shown that personality has an effect on other behavioural attributes (Hofstee, 1994). Further, Various reliable psychological tools exist to evaluate learners' personalities.

3 - Domain model

This model consists of a set of concepts that are taught to the learners. Each concept can be divided into small topics and learning objectives. According to cognitive theory, two important principles must be considered while designing any domain model in any educational system (Ally, 2004). The first concerns the division of concepts into small topics and the division of big chunks of information into smaller sub-chunks. The second principle involves sorting the course lessons from the known to the unknown and from the easy to the difficult. This ensures that the learners will not be bored when they receive the content of the course and that the course is suitable for the learner.

4 - Gamification model

This model consists of the set of available gamification elements, such as points, badges, rewards and leaderboards. This model also provides rules and guidelines regarding how the aforementioned elements are to be integrated into the online learning system. For example, this model is responsible for defining how a learner will receive points and badges. In some systems, the points will dictate a learner's position on the leaderboard. Other systems use badges instead of points.

It is important to clarify that the gamification model is separate from the domain model. This is to ensure that if the gamification elements are removed from the system, the content of the course will not be affected.

5 - Adaptation model

This model can be presented as the adapting engine. In this model, the adaptation process is employed to provide learners with the best experiences with the gamified online learning system.

At the beginning of the course, this model receives all the required information from the users and the context model. The adaptive gamification model then processes the information provided by the users and the context model. The model then matches each learner with the best gamification elements provided by the gamification model. Consideration of the screen sizes and device types used by the learners is also important to ensure the best presentation of the gamified course.

6 - Auxiliary Components

Certain other components, such as an interaction modeller component, need to be integrated into the framework. This component is responsible for observing learners' behaviour by registering, for instance, the frequency of access and time spent on a task. In addition, the presentation modeller presents the adaptive version of the system to the learner.

4.4 Implementation of the adaptive gamification system

In the previous section, we discussed the main components of the framework for ideal adaptive gamification systems. However, the suggested framework cannot yet be built at this stage for several reasons. One reason relates to the low number of research studies on the investigation of the effects of different gamification elements on learners' various attributes. As a result, only one attribute, personality, is focused on in the adaptation process so as to provide the most suitable gamification elements to each learner based on his/her personality profile. Despite the limited number of studies on the subject, different issues have been detected with regard to these studies. For example, these studies relied on self-report questionnaires, which may skew the results. To combat this problem, the adaptation process is initiated by understanding the relationship between different gamification elements and learners' personalities. Then, the obtained understanding is used to build and evaluate the model.

The following section describes the steps required to build the adaptive model.

4.4.1 Steps required to build the adaptive model

The following three stages are involved in the building of an adaptive model that can be used to match gamification elements to learners' personalities (Figure 4.2): (1) Understanding the relationship between gamification and online learners' personality dimensions, (2) finding a common pattern in the behaiour of learners with a specific personality profile toward gamification in order to build the adaptive model, and (3) evaluating the adaptive model.

Figure 4.2: Steps required to build an adaptive model

Understanding the relationship between gamification and personalities

As mentioned previously, only a few studies have examined the relationship between gamification and learners' personalities, and certain limitations related to the methodologies of these studies may introduce bias in the results (see section 3.3.2; page 76). Thus, this research applies a more objective approach to understand the relationship between gamification and personality. Three different experiments were run with approximately 600 learners aged 16 to 18 years. Each of these experiments was conducted with various combinations of gamification elements, such as points, badges, leaderboards and avatars. Learners' dropout rates were measured and used as a proxy for motivation. Short- and long-term knowledge gains and learners' satisfaction were also captured.

Additional details about the design, execution and results of these experiments appear in Chapter 5, 6,7 and 8.

Building the adaptive model

The understanding of the relationship between gamification and personality was used to make the predictions and draft the rules for the most useful and suitable gamification elements for each learner based on his/her personality profile. To achieve this end, the results from the above-mentioned experiments and suggestions from the related theory and previous related research studies were used.

Chapter 9 provides more details about the model building process.

Evaluating the adaptive model

After building the adaptive model, we need to examine its effectiveness. We need to assess whether the chosen gamification elements will increase learners' motivation and engagement. In turn, this may help to improve learners' levels of knowledge gain and satisfaction. For this purpose, we ran another experimental study using matched/mismatched approach. One group of learners used a version that matched their personality profiles, while another group used a version that did not match their personality profiles (both the matched and mismatched groups used gamification elements or lacked them). Then, learners' motivation, knowledge gain and satisfaction were measured for both groups.

Additional details about the model evaluation are presented in Chapter 9.

4.5 Conclusion

Given the various effects of gamification on learners, it is suggested to adapt gamification elements on learners' attributes. From this perspective, a framework to adapt gamification elements was proposed. This framework consists of different models that were integrated to provide learners with the best experience with a gamified learning system (i.e. to improve learners' motivation, engagement, satisfaction and knowledge gain).

The proposed framework is intended to receive learners' data from the learner and context models. Then, the framework processes this information to choose the best gamification elements for the learners. The chosen gamification elements are integrated into the learning materials obtained from the domain model. During the interaction between learners and the adaptive gamified system, the system tracks learners' behaviours to assess the possibility of any type of risk occurrence (e.g. learners losing attention or motivation). Should such a risk exist, the gamification adaptive model will update the learners with other gamification elements or block unhelpful elements.

However, because of the novelty of the idea of adapting gamification elements, not all of the suggested attributes related to the learner and the context can be used. Instead, only one factor in the adaptation, namely personality, was focused upon. Unfortunately, few studies have attempted to address the relationship between gamification elements and learners' personalities. Furthermore, the methodology of existing studies provided results that may not be reliable for various reasons. To address this issue, the first step in building the model involved running different experiments studies to understand the relationship between different gamification elements and learners' personalities. The results of these experiments can be combined with other findings from related works as well as suggestions from theory explain the various facets of learners' personalities to build an adaptive model. This model must then be evaluated to assess its effectiveness.

This chapter provides a broad picture of the process of building an adaptive model. The details of the processes are explained further in the following chapters.

Chapter 5

Understanding the Relationship Between Gamification and Personalities

5.1 Introduction

In the previous chapters, the need for gamification to be adapted and personalised for learners was discussed. One attribute chosen as a basis for adaptation is personality. To perform the adaptation, several stages are required, as discussed in Chapter 4. The first step is understanding the relationship between gamification elements and personalities. The present chapter presents an overview of the methodology employed and obtained results.

5.2 Motivation

Because of the various effects of gamification on learners, it is important to build an adaptive model that can be used to match gamification elements to learners' personality. A limited number of studies have tried to assess the various effects of gamification on learners with different personality profiles (Codish and Ravid, 2014a,b; Jia et al., 2016; Tondello et al., 2016). However, these studies have several issues related to their methodology. Some of these studies used short versions of personality tests, many of which suffer from reliability issues (Tondello et al., 2016). Further, these studies were based on self-report questionnaires from participants who completed the whole study. Forcing users complete the whole study may conflict with the main aim of gamification: improving motivation and engagement. In addition, these studies did not analyse the data for users who dropped out in the middle of the study. Moreover, these learners may be considered the most critical ones. It is essential

to identify the reason why they dropped out. Was it because of a particular gamification element? All of these issues may bias the results from these studies (Ghaban and Hendley, 2018); (Ghaban and Hendley, 2019). For this reason, we aim first to build an understanding about the relationship between different gamification elements and learners' personality by using a more-objective approach. Three different experiments with various gamification elements were run. The effect of gamification was measured by using three different quantitative measurements: motivation, knowledge gain and satisfaction.
A detailed explanation about the method used to build the understanding is presented below.

5.3 Method

Several hypotheses regarding the responses of learners to gamification were formulated. It was hypothesised that gamification elements have an overall benefit, especially in short-term motivation, satisfaction and knowledge gain. Therefore, the first hypothesis is:

> **H1:** Overall, learners use the gamified version for longer periods, and they are more motivated by the gamification elements.

> **H2:** Overall, learners in the gamified version have a better knowledge gain than in the non-gamified version.

> **H3:** Overall, learners in the gamified version have a better satisfaction than in the non-gamified version.

It was also hypothesise that learners respond differently based on their personality profile. For example, highly conscientious learners are usually described as hard workers. Several previous studies found that high performance and achievement were associated with learners with this personality (Laidra et al., 2007). Some studies also showed that such learners did not need external elements to motivate them (Jia et al., 2016); (Ghaban and Hendley, 2019). They were self-driven to finish a course. Hence, we can formulate our hypothesises for this personality dimension, as follow:

> **H4:** Highly conscientious learners display the same motivation in the gamified and non-gamified versions.

> **H5:** Highly conscientious learners display the same knowledge gain in the gamified and non-gamified versions.

H6: Highly conscientious learners display the same satisfaction in the gamified and non-gamified versions.

Highly extroverted learners are typically talkative, active and have high energy levels. Previous studies showed that this type of learner enjoyed collecting points and badges (Hofstee, 1994; Tondello et al., 2016). Yahaya et al. (2011) found that such learners were more engaged with social elements than others. Jia et al. (2017) show that highly extrovert learners enjoyed with competition elements, such as: leaderboard. Therefore, gamification may have a positive effect on improving the motivation and engagement of these learners. However, Judge et al. (1999) claimed that highly extroverted learners are easily distracted. Gamification elements may then distract them. Therefore, the following hypotheses were formulated:

H7: Highly extroverted learners motivated more in the existing of gamification elements.

H8: Highly extroverted learners have a better knowledge gain in the gamified version than non-gamified version.

H9: Highly extroverted learners are more satisfied in the gamified version.

Highly agreeable learners have been described as kind and as preferring to collaborate with others (Hofstee, 1994). Several previous studies showed the benefits of offering points, badges and leaderboards to highly agreeable learners. In addition, Hallifax et al. (2019) argued that highly agreeable learners preferred social elements, such as discussion board. Hence, it was expected that these learners enjoy and are motivated by gamification elements, leading to the hypothesis:

H10: Highly agreeable learners have a better motivation by gamification elements.

H11: Highly agreeable learners gain more knowledge in using the gamified version.

H12: Highly agreeable learners are more satisfied in the gamified version.

Highly neurotic learners are usually described as emotionally unstable (Hofstee, 1994). These learners may dislike gamification elements and described these elements as childish. Hence, they may find points and badges annoying and boring. Furthermore, the leaderboard that shows learner ranks based on their achievements and other competitive elements may demotivate highly neurotic learners who care about others' opinions (Costa and McCrae, 1980). If these learners see their names in unsatisfactory positions, they may become nervous or depressed. Hence, they may be demotivated by gamification elements. Therefore it is hypothesised:

H13: Highly neurotic individuals are demotivated by gamification elements.

H14: Highly neurotic learners have greater knowledge gain in using the non-gamified version.

H15: Highly neurotic learners are more satisfaction in using the non-gamified version.

Learners who are highly open to new experiences are usually described as imaginative (Hofstee, 1994). Hallifax et al. (2019) show that these learners are motivated by social elements and to be part in a team. Further, Denden et al. (2018) argued that highly openness learners prefer most of the gamification elements. Hence, they may enjoy creative gamification elements, such as designing and customising avatars. They may also enjoy role-playing if the learning system is based on storytelling and the content is structured as a story. It is therefore hypothesised that:

H16: Learners who are highly open to experience are more motivated by gamification elements, such as avatars.

H17: Learners who are highly open to experience gain more knowledge in using the gamified version.

H18: Learners who are highly open to experience are more satisfied in using the gamified version.

5.3.1 Setup

To conduct the experiments, an online learning system was built `https://ilearn.study`. Learners could freely register on the website by clicking the 'Register' icon. Figure 5.1 shows the home page of the website. This online learning website was designed to teach learners how to use Microsoft Excel. This software program was chosen because it had not been taught to the target learners, and it contained many topics that range from simple to complex. The course was divided into 15 lessons, beginning with simple introductory topics, such as creating tables, and then moving to more advanced and complex topics, such as using the text function and protecting Excel files. Table 5.1 shows the lessons included in the course, and Figure 5.2 shows an example of a lesson on the website.

Two versions of the course were designed. One version included various gamification elements, and the other version did not.

Different gamification elements were integrated in each study, explained in detail below.

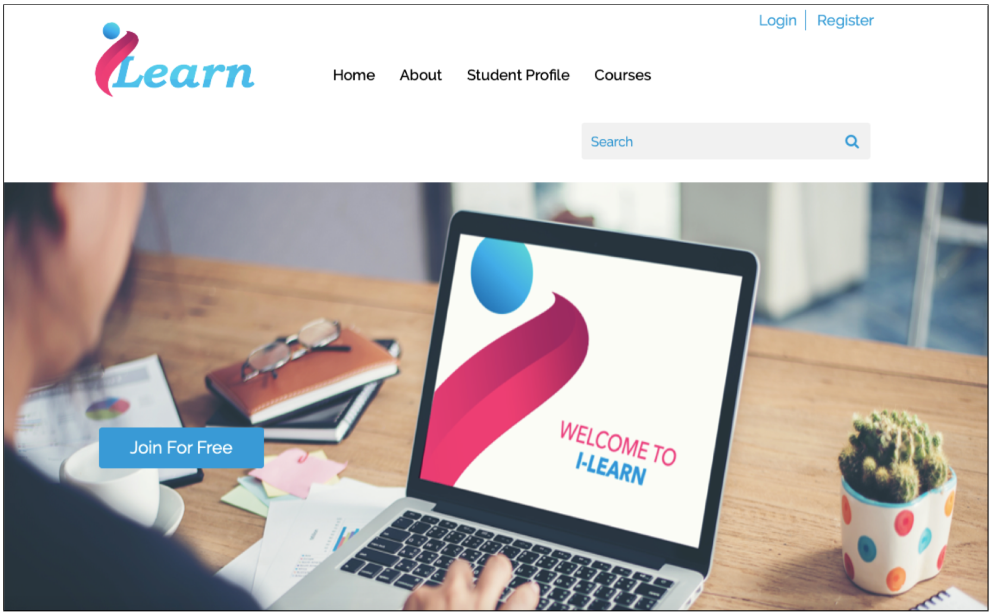
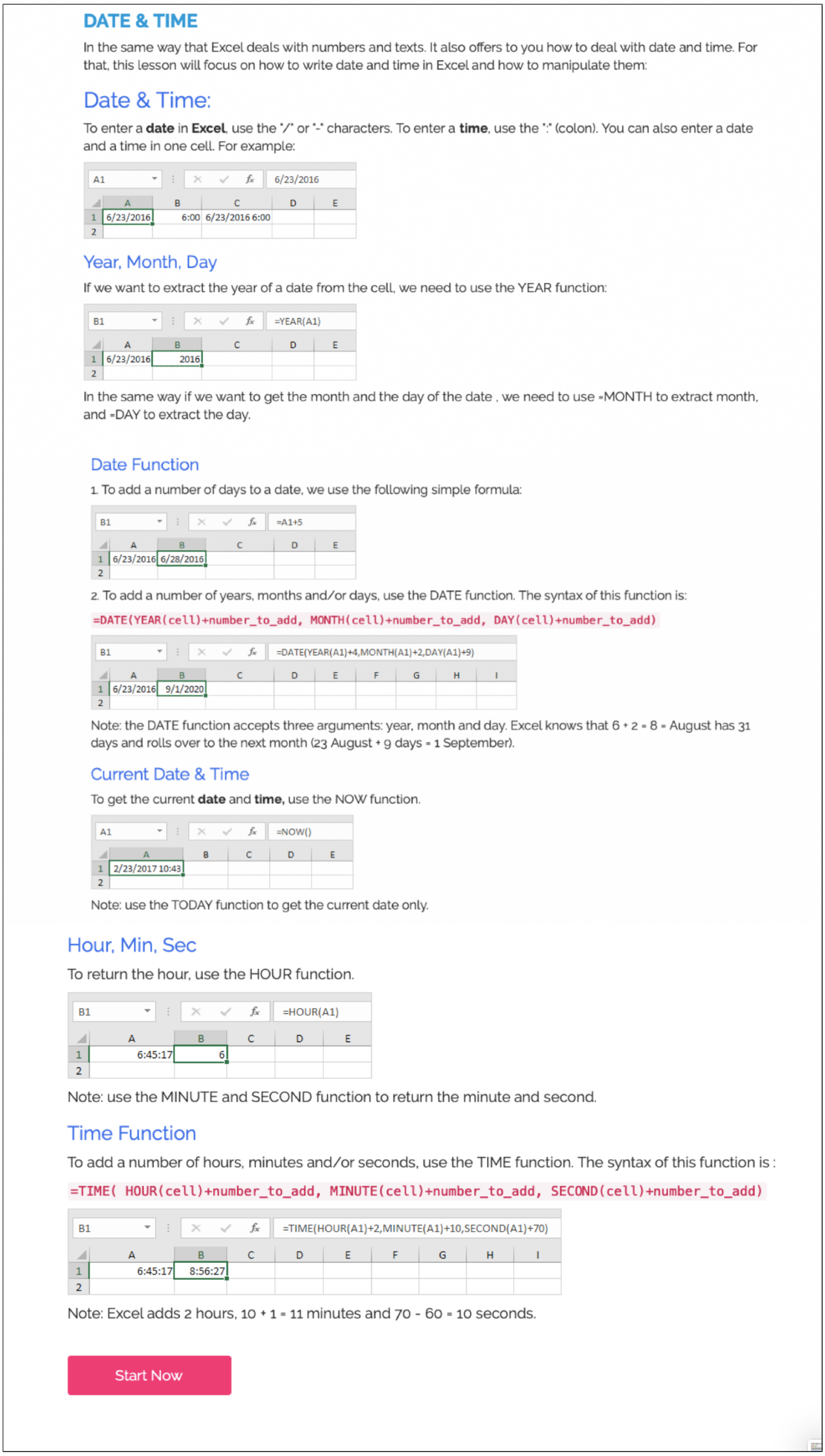


Figure 5.1: Screenshot of the home page on the website created for this study (i-learn.study).

5.3.2 Participants

The participants were learners aged 16 to 18 years at different high schools in Saudi Arabia. This age range was chosen for the following reasons. First, as Klock et al. (2015) pointed out, students, in their late teens are more interested in using- and who are motivated by gamification elements. Furthermore, personality characteristics are more stable in adolescents than in young children, whose personalities are still forming (Caspi and Roberts, 2001); (Cobb-Clark and Schurer, 2012). Second, there was a significant number of learners with a diverse range of personality characteristics. However, in drawing the sample from student populations at universities, there would be potential difficulties; for example, the number and kinds of personality could potentially be limited to learners who had the ability to succeed and who had relatively high levels of self-esteem as well as social connections (Neyer et al., 2014).

Consent forms were sent to the schools to obtain their approval for the study. These were then sent to the learners and their parents, which explained the purpose of the study, and stated that all the data obtained would be encrypted and stored securely. The learners and



DATE & TIME

In the same way that Excel deals with numbers and texts. It also offers to you how to deal with date and time. For that, this lesson will focus on how to write date and time in Excel and how to manipulate them:

Date & Time:

To enter a **date** in **Excel**, use the "/" or "-" characters. To enter a **time**, use the ":" (colon). You can also enter a date and a time in one cell. For example:

A1 | 6/23/2016

	A	B	C	D	E
1	6/23/2016	6:00	6/23/2016 6:00		
2					

Year, Month, Day

If we want to extract the year of a date from the cell, we need to use the YEAR function:

B1 | =YEAR(A1)

	A	B	C	D	E
1	6/23/2016	2016			
2					

In the same way if we want to get the month and the day of the date , we need to use =MONTH to extract month, and =DAY to extract the day.

Date Function

1. To add a number of days to a date, we use the following simple formula:

B1 | =A1+5

	A	B	C	D	E
1	6/23/2016	6/28/2016			
2					

2. To add a number of years, months and/or days, use the DATE function. The syntax of this function is:

```
=DATE(YEAR(cell)+number_to_add, MONTH(cell)+number_to_add, DAY(cell)+number_to_add)
```

B1 | =DATE(YEAR(A1)+4,MONTH(A1)+2,DAY(A1)+9)

	A	B	C	D	E	F	G	H	I
1	6/23/2016	9/1/2020							
2									

Note: the DATE function accepts three arguments: year, month and day. Excel knows that 6 + 2 = 8 = August has 31 days and rolls over to the next month (23 August + 9 days = 1 September).

Current Date & Time

To get the current **date** and **time,** use the NOW function.

A1 | =NOW()

	A	B	C	D	E
1	2/23/2017 10:43				
2					

Note: use the TODAY function to get the current date only.

Hour, Min, Sec

To return the hour, use the HOUR function.

B1 | =HOUR(A1)

	A	B	C	D	E
1	6:45:17	6			
2					

Note: use the MINUTE and SECOND function to return the minute and second.

Time Function

To add a number of hours, minutes and/or seconds, use the TIME function. The syntax of this function is :

```
=TIME( HOUR(cell)+number_to_add, MINUTE(cell)+number_to_add, SECOND(cell)+number_to_add)
```

B1 | =TIME(HOUR(A1)+2,MINUTE(A1)+10,SECOND(A1)+70)

	A	B	C	D	E	F	G	H	I
1	6:45:17	8:56:27							
2									

Note: Excel adds 2 hours, 10 + 1 = 11 minutes and 70 - 60 = 10 seconds.

Start Now

Figure 5.2: An example of a lesson on the i-learn website.

Table 5.1: The lessons included in the course.

Lesson number	**Lesson's title**	**The contents of the lesson**
Lesson 1	Getting start with Excel	Explaining what Microsoft Excel is and how to insert data to it.
Lesson 2	Create table and draw charts	Explaining how to create tables and how to visualise data.
Lesson 3	Basic Mathematical operation	Discussing how to implement simpler operation, such as: +, -, x, /.
Lesson 4	Advanced mathematical operations	Explaining how to use the built-in function in Excel, such as: AVERAGE, SUM, COUNT.
Lesson 5	Logical operation	Explaining how to implement logical operation, such as: AND, OR.
Lesson 6	What-If analysis	Explaining how learners can apply, if...then in Excel, and how this function is used to find a solution for complicated problems.
Lesson 7	Round	Explaining how to implement round function in the course.
Lesson 8	Date and time	Explaining how to present date and time by using specific functions.
Lesson 9	Text function	Explaining how to convert numbers to text in Excel.
Lesson 10	Creating HLOOKUP and VLOOKUP Functions	Explaining different Lookup functions and the purpose of these functions.
Lesson 11	Pivot Tables	Creating Pivot Tables in order to display and summarise large quantities.
Lesson 12	Charting Pivoted Data	Adding specialist pivot charts to the pivot Table feature.
Lesson 13	Introducing Macros	Explaining macros and their benefits.
Lesson 14	Protecting the worksheet and the workbook	Discussing how to secure and protect the Excel file.
Lesson 15	Sharing an Excel file	Explaining how to share the Excel file easily.

their parents were made aware that the participants were free to drop out of the study at any time.

5.3.3 Procedure

After obtaining ethical approval from schools, parents and learners, the study began. In an orientation session at each school, the learners registered on the website by filling in three forms about:

- Demographic information, such as username, chosen password, age and gender.
- A pre-test questionnaire that consistis of eight questions related to the course [see Appendix B].
- A form to assess learners' personality. The FFM was used because of its popularity and because most studies in this field use it (Codish and Ravid, 2014a; Tondello et al., 2016).

  Several tools have been proposed to measure the FFM. The most commonly used tools are the Neo-Five Factor Inventory (NEO-FFI), the Big Five Inventory (BFI) and the International Personality Item Pool (IPIP).

  The NEO-FFI test was developed by Costa and McCrae (1980). This test is based on the longer NEO-PI, which contains 180 questions. However, because of the length of this test, it is difficult to use in scientific studies. For this reason, the NEO-FFI was developed, reducing it to 50 questions. According to Thalmayer et al. (2011), the NEO-FFI is reliable, and it has been widely used in several research studies (Topping and O'Gorman, 1997). This test is available in many languages. However, it is a commercial measuring tool, so it is not free (Thalmayer et al., 2011).

  The second most commonly used test is the BFI. This test is considered more reliable than the NEO-FFI, and it is freely available. This test contains 46 questions (John and Srivastava, 1999). Furthermore, the BFI is available in multiple languages. Moreover, there are versions for use with adults, parents and children (Thalmayer et al., 2011; Aluja et al., 2005). Several short versions of this test have been developed, each of which consists of 10 questions. However, some researchers have argued that these suffer from multiple reliability issues (Tondello et al., 2016).

  The last measurement instrument is the IPIP, which contains 50 questions. This instrument is inherently different from the BFI, and it varies from the NEO-FFI and BFI in its definitions of openness and agreeableness in personality (Goldberg et al., 2006).

The 46-item BFI was used in the present studies because it is free, and is more reliable than the other tools. Moreover, it is available in different languages, and there is a version for use in studying children, which is the focus of the current research (Thalmayer et al., 2011). A copy of this test is attached in Appendix A.

After registration, three different studies were conducted at varying times. These experiments were based on a between-subjects experimental design. In this design, the participants experience only one condition. Most previous research has shown that this experimental design is more appropriate for this type of study than a within-subject design, in which the participants experience two different conditions (Alshammari et al., 2014). Moreover, in a within-subject design, the participant could carry a learning effect from one condition to another. In contrast, the between-subjects design requires many participants. The results may be affected by noise and variations that must be eliminated or explained before drawing conclusions (Alshammari, 2016).

First, learners were divided equally into two groups. One group used the learning website with the gamification elements, and the other group used the website without gamification. The two groups were balanced in number, age, gender, personality profile and levels of prior knowledge.

All the learners' data were stored in a secure database, including usernames, passwords, ages, gender, scores on each personality dimension, and scores on the pre-test.

The learners were free to use the website at any time and at any location. They were told that they were free to drop out and could stop using the website at any time. When the learners used the online learning website, the system tracked their progress and stored it in the database.

The dropout rate was used as a proxy for motivation and engagement. After ensuring that learners had either stopped using the website or had completed the course, they were asked to complete a post-test that was similar to the pre-test. The results were used to measure the short-term knowledge gain. In addition, learners completed a satisfaction test (Appendix C).

After a period of time, we asked learners to complete another post-test, similar to the other tests. This is to measure learners' long-term knowledge gain.

Figure 5.3 shows the design of the experiments.

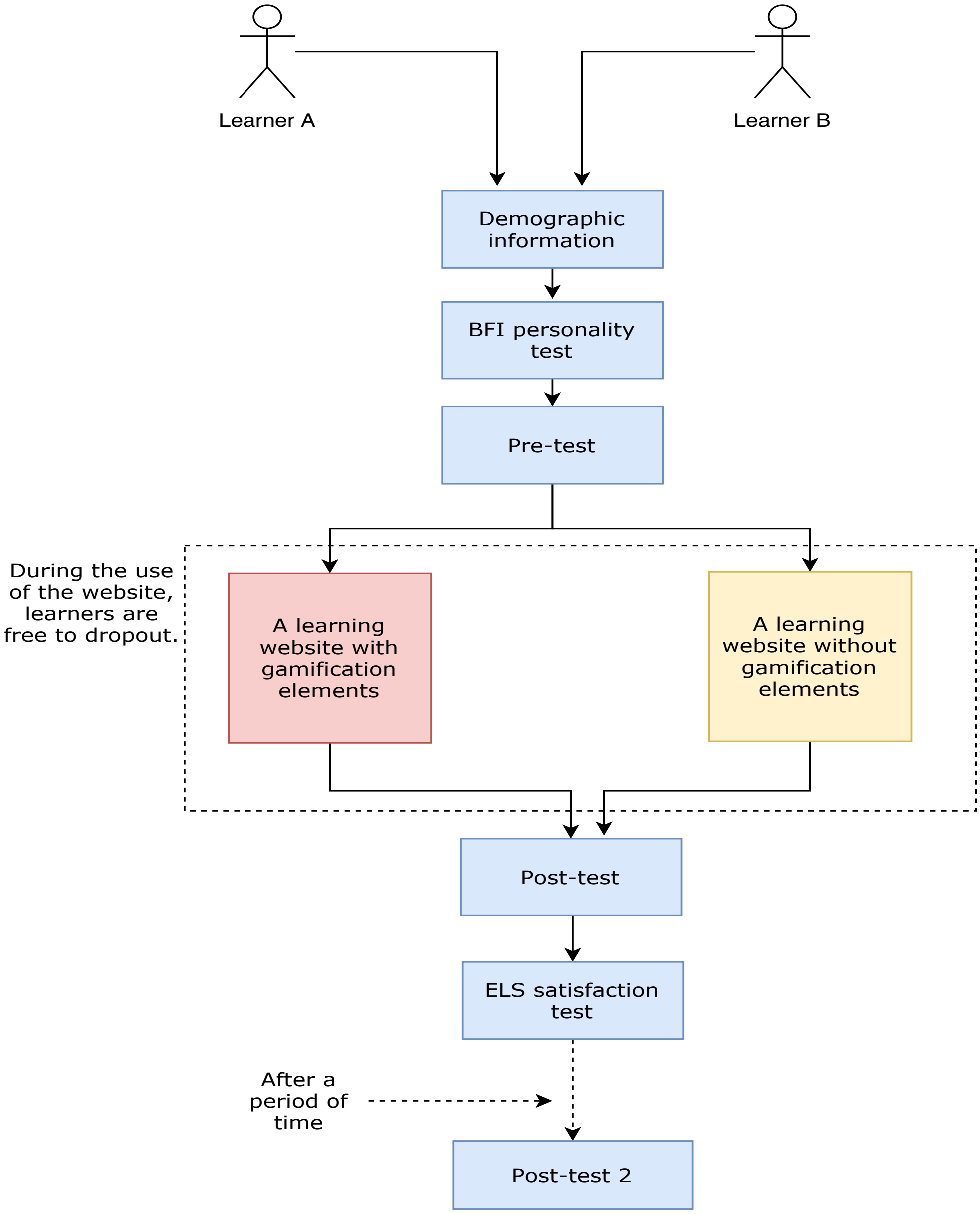


Figure 5.3: The flow of the experiments.

5.3.4 Classification of personality dimensions

To examine the relationship between gamification elements and different personality dimensions, the BFI was used. The BFI provides a score from 0 to 5 for each personality dimension. However, (Ghaban and Hendley, 2019) argued that the dimensions are correlated. For example, Gershuny and Sher (1998) showed a strong correlation between a low-extroversion personality and a high neuroticism personality. A high extroversion personality is positively correlated with high agreeableness and openness to experience, and high conscientiousness is correlated with high agreeableness (Sung and Choi, 2009). In this thesis, for the sake of simplicity, each personality dimension is dealt with individually without considering the interactions between them.

Another issue was the difficulty in measuring the effects of gamification on each scored area of the learner's personality, especially because of the large number of learners. Hence, it was necessary to classify each personality dimension to group learners who had similar scores. However, there were several problems in applying this classification, such as classifying a personality dimension and deciding the scores that should be considered high or low.

Most previous studies that used the personality dimensions did not mention how to perform this classification. However, the few studies that discussed this classification based it on calculating the mean score of each personality dimension and then dividing each dimension into high and low dimensions (Codish and Ravid, 2014a). Scores over the mean were classified as high, which meant that individuals who scored higher than the mean were classified as high in that personality dimension. Similarly, individuals with a score lower than the mean were considered low in that personality dimension (Noftle and Robins, 2007; Wolfe and Johnson, 1995). However, we believe that the classification of personality dimensions into only two classes divided at the midpoint is not sensible, which was argued by Codish and Ravid (2014a); Ghaban and Hendley (2018, 2019); Ghaban. and Hendley. (2019). Most individuals are neutral, and only a few are either high or low. Furthermore, the effects of gamification or any other motivational technique on individuals who are neutral may not be as visible as they are on the individuals who are extremely high or low in their personality dimensions. In addition, dividing the personality score in the middle could bias the results. The reason is that the results for individuals whose personality scores were at high or low extremes would be affected by the results for individuals with neutral personalities. For this reason, we decided to classify each personality dimension as high, average or low by using an arbitrary cut-off point, taking into account the mean (μ) and standard deviation (σ). Scores lower than $\mu - \sigma$ were classified as low, scores between $\mu - \sigma$ and $\mu + \sigma$ were classified as average, and scores greater than $\mu + \sigma$ were classified as high in that personality dimension. The scores of all personality dimensions from the three experiments were combined to facilitate the classification process. Table 5.2 shows the classification of each personality dimension.

It was expected that the effects of gamification would be clear in learners who were either at the high or low extremes in each personality dimension. Hence, in the analysis, the effects of gamification on both high and low extremes of each personality dimension were considered.

5.3.5 Measurements

In the three studies, the effects of gamification on learners with different personality dimensions using three measurements, motivation, knowledge gain and satisfaction, were examined.

Table 5.2: The classification of each dimension of personality.

Personality	μ	σ	$\mu + \sigma$	$\mu - \sigma$
Conscientiousness	2.68	1.25	3.93	1.43
Extraversion	2.56	1.16	3.72	1.4
Agreeableness	2.7	1.15	3.85	1.55
Neuroticism	2.71	1.19	3.9	1.52
Openess to experience	2.37	0.93	3.3	1.44

Motivation

Unlike previous studies based on self-report questionnaires, learners' dropout rates were used as a proxy for motivation and engagement. Because of the use of this different methodology, a different kind of analysis to compare the dropout rates in the gamified and non-gamified versions was used. Survival analysis is commonly applied when the time of an event must be considered. This analysis, which is commonly used in medical and engineering research, can also be used to analyse the duration in which the event of interest will occur. The events of interest can be diverse; for example, death (in medicine) and machine failure (in engineering). In each subject, only one event can occur. In survival analysis, the duration of the event is the time from the beginning of the observation, such as the beginning of the treatment or the start of the experiment, to the occurrence of the event. The length of time could be days, months or years (Allgulander and Fisher, 1986).

Another common term used in survival analysis is censoring data, in which there is no observed event for a specific subject. For example, in medical studies, if an observation starts at the beginning of treatment and if the patient dies, then the patient's corresponding data are censored because there is no future event (survival) recorded.

Moreover, different common statistics are associated with survival analysis, such as the Kaplan-Meier (KM), log-rank, and Cox proportional hazard model. The KM, which is also called the product limit estimator, is used to visualise and estimate the survival function. The KM is useful in understanding the basics of a survival analysis and providing descriptive results. Furthermore, the KM can be used to visualise and compare the survival functions in two or more groups (Efron, 1988); (Walters, 1999). The log-rank test is also used to compare survival rates. This test is based on calculating the p-value obtained from a chi-square test. Both the KM and log-rank are considered easy to apply. Because both are considered non-parametric, they do not require assumptions. However, these two tests may provide unreliable results if they are applied using continuous data. Furthermore, both tests are effective in using a small set of data and comparing only a limited number of groups. Neither of these two tests allows for multiple covariates or multiple controls in the survival data (Mills, 2010). Furthermore, the KM and log-rank measure significant differences between groups without indicating which group has more or fewer events of interest.

Because of these limitations, the Cox proportional hazard model has been proposed. This model can also be used with numerical and categorical data by encoding the categorical data with a 1 or a 2 or another dummy variable. The Cox model involves a semi-parametric statistical technique that is based on the concept of the hazard function, which is the probability that the subject or individual would experience an event of interest (e.g. death) within a short time interval. The Cox hazard function assumes that the hazard function in any two subjects is proportional. Walters (1999) illustrated this as follows: if subject A has twice the risk of death at some time point as subject B, then subject A is twice as likely to die at all times. For this reason, in some cases, the Cox model is called the Cox proportional hazard model (Lin and Wei, 1989). The main aim of this model is to explore the effects of one or more treatments or factors on the hazard function (Cox, 2018).

The learners' dropout rates at various points during the gamified and non-gamified versions of the course were used as a focus. Thus, the event of interest was dropout, and the time that was considered was the number of lessons completed. The gamified group was encoded as 1, and the non-gamified group as 2. At the beginning, the KM was used to visualise the dropout rates in the two groups. Results were validated using the Cox hazard model, which was chosen over the log-rank test for several reasons. First, as argued by Crowley (1974), the log-rank test is considered a special case of the Cox hazard model. It can be performed by using the Cox model. The results of the Cox model can be used to determine which groups had better or worse dropout rates by using the sign of the covariate. In addition, the hazard ratio (HR) can be used to find the level of differences between the two groups (Walters, 1999).

Several statistical computing tools and programming languages can be used to apply the KM and Cox models to the data. In this thesis, we used RStudio to analyse the data by installing two packages: *survival, survminer*. To draw the KM graph, it was first necessary to compute the survival curve by using the following formula (Walters, 1999; Mills, 2010; Kassambara, 2019b):

```
fit <- survfit(Surv(time, status) ~ version, data = Mydata)
```

Then, the KM graph can be drawn by using the *ggsurvplot* function, as in (Kassambara, 2019b):

```
ggsurvplot(
   fit,                       # survfit object with calculated statistics.
   pval = TRUE,               # show p-value of log-rank test.
   fun = "cumhaz"             # Draw the cumulative hazard.
)
```

For the Cox hazard, we used the same packages as required for KM. Then, one line of code was used to apply the Cox model, as described by (Kassambara, 2019a):

```
res.cox <- coxph(Surv(time, status) ~ version, data = Mydata)
summary(res.cox)
```

It is important that the results of the Cox model be interpreted correctly. An example of the results of a Cox model is presented in Table 6.1. The sign of the *coef* is important to consider in identifying whether the event of interest is higher or lower in the second group (non-gamified version) than in the first group. In the case of a positive sign, the rate of occurrence of the event (dropout) is higher in the second group, whereas a negative sign means that the rate of occurrence is lower. Furthermore, the results of *Exp(coef)* represent the *HR*, which represents the effect size of the covariates (i.e. the amount of difference between the two groups). Another measurement is statistical significance, which is marked as 'z', referring to the ratio of the coefficient to the standard error. The final result is the p-value, which refers to the statistically significant difference between the two groups. The Cox model provides the *p-value* derived from the three different tests (i.e. the likelihood ratio test, the log-rank test and the Wald test).

Knowledge gain

The second measurement that was considered was the amount of knowledge that the learners gained from the course. Because the main aim was to examine the effects of gamification in an online learning environment, the amount of knowledge gained from the website was measured. In addition, from the literature review, motivation could be considered a predictor of learners' success, especially in online learning courses. Thus, how much the learners learned in using the website should be measured. Short-term knowledge gain was measured directly after the experiment was completed. This can be considered as the immediate effects of gamification on improving learners' knowledge. However, the short-term benefit of gamification may be reduced over time. Different studies argued that the immediate learners' knowledge gain may be different that their knowledge gain after two or three months (Alshammari, 2016). For that, to have a deep understanding of how much learners benefit from the course, we measured learners' long-term knowledge gain. To measure the long-term knowledge gain learners completed another test four to six weeks after they completed the study.

To measure the short-term knowledge gain, the results of the first post-test completed directly after they finished the experiment were used. The following formula was applied (Alshammari, 2016):

```
Learners' knowledge gain =
Learners' post-test scores - learners' pre-test scores
```

While, the long-term knowledge gain can be measured by using the results from the second post-test, as follow:

```
Long-term knowledge gain =
Learners' post test2 scores - learners' pre-test scores
```

Some previous studies suggested using normalised knowledge gain instead of the real score of knowledge gain (Jones and Castellano, 2018; Kinoshita et al., 2017). However, this was difficult to apply in the study. Most learners had the same level of prior knowledge about the topics that were taught. In addition, according to Hake (1998), normalised knowledge gain cannot be applied if learners were allowed to drop out during the course, which was the case in the present studies.

Satisfaction

The least frequent measurement used to assess the effects of gamification is learners' satisfaction. However, it was necessary to determine whether the learners enjoyed the gamified course and whether they were satisfied when they interacted with it. Most related studies aimed to examine whether gamification was enjoyable for individuals or not (Jia et al., 2016). Some studies showed a positive correlation between satisfaction and motivation (Wilkes and Burnham, 1991; Chen and Chih, 2011). Gatian (1994) found that satisfaction is considered a good predictor of a system's effectiveness. Hence, the degree to which the learners were satisfied with their assigned version of the course were measured. The average satisfaction scores of the learners in both the gamified and non-gamified versions of the course were compared.

Several tools can be used to measure learner satisfaction in an online learning environment, such as (Bailey and Pearson, 1983; Wang, 2003; Mahdavi et al., 2008; Jung, 2014). However, the E-Learning Satisfaction tool (ELS) was chosen to measure the learners' satisfaction with their experience (Wang, 2003). This tool was used in most previous studies that measured learner satisfaction (Alshammari, 2016; Siritongthaworn and Krairit, 2006). The ELS tool (Appendix C) consists of 26 items that are measured on a 7-point Likert scale ranging from 'strongly disagree' to 'strongly agree'. The learners' satisfaction was measured from different perspectives, including how satisfied they were with the learning interface, learning content, learning community and learning personalisation. The ELS also measured the learners' overall satisfaction with the online learning system and its components.

5.3.6 Overview of the experiments

To achieve a strong understanding of the relationship between gamification elements and personality, a series of experimental studies with several combinations of gamification elements were used. In each study, a new gamification element was added to study its influence.

In the first experiment, three different gamification elements: points, badges and leaderboards were used. Because of time limitations, we were not able to conduct a study of each gamification element, independently. Hence, the first study was conducted to examine the combined effects of points, badges and leaderboards, as these elements are popular, and they have been defined as the most-common gamification elements (Jia et al., 2016). The gamification elements in the first study could improve learners' intrinsic motivation. Gooch et al. (2016), argued that points and badges can give learners feedback about their progress. Furthermore, gamification could be related to extrinsic motivation because it can serve to entertain learners. For example, receiving badges or improving the position on the leaderboard could increase a learner's satisfaction. More details about this experiment will be provided in Chapter 6.

After the effects of the points, badges and leaderboards, were understood, another experiment with a more 'costly' gamification element that could distract learners was conducted. In the first study, a leaderboard as a social element that allowed the learners to compete with others was used. However, it was felt that using the leaderboard to satisfy the social needs of the learners was insufficient. Learners in online courses usually feel isolated, and they miss the sense of belonging and communicating with other learners, teachers and the educational institution (Swan and Shih, 2005; Ghaban. et al., 2019). Hence, the social gamification elements were increased to help learners feel that they were communicating and interacting with their peers as if they were in a physical classroom. Domínguez et al. (2013) argued that it is important to consider learners' social needs in designing any online learning.

Previous studies have reported conflicting ideas about which social elements could be considered gamification, such as chat and discussion boards. Some researchers claimed that these are not gamification elements, but others argued them to be so (Bista et al., 2012; Seaborn and Fels, 2015; Khaleel et al., 2016). Hence, in the second study, social gamification elements were integrated. More details about this experiment will be provided in Chapter 7.

The third experiment aimed to increase understanding by using different gamification elements that some learners might enjoy, such as avatars and motivational phrases.

Avatars are images that represent a user in the virtual world or that represent the system or an application in the system. It is important to note that they are usually separate entities, and the course content was not affected by their integration (Sheth, 2003). Fabri et al. (2007) showed that avatars could be useful in the learning process because they could influence learners' emotions and improve their cognitive processes, thus enhancing their skills and strategies in problem-solving.

Avatars can be integrated into a system in several ways. One of the oldest ways of using it is to help and support users (Michael and Chrysanthou, 2003). A common example is an animation that was integrated into Microsoft Office, which asked users if they needed any help according to certain triggers initiated by the user (Sheth, 2003). In addition, an avatar can be used if the learning system is presented as a story (Adams and Makramalla, 2015). The most common form of avatar is one that represents the user's own characteristics. Here, the user is allowed to choose a character that resembles them, which can be used to ask questions or experience adventures in a virtual learning environment (Sailer et al., 2014).

However, Vasalou and Joinson (2009) showed that several factors control the process of choosing an avatar. For example, one that is used to represent the user in a dating application would be different from one used to represent the same user in a learning application. Furthermore, Vasalou and Joinson (2009) argued that some users choose to use an avatar that represents their lifestyle, their aspirations and their hobbies. In the present study, it would have been difficult to choose the latter approach. Allowing learners to choose their own avatar may have affected the results, particularly variations in the colours or the accessories attached to the avatar. Hence, a universal avatar that would guide and help the learners was chosen. This experiment will be presented in details in Chapter 8.

5.4 Conclusion

Because of the various effects of gamification on learners, it is suggested that gamification elements be adapted to an individual's attributes. One of the most stable attributes of an individual is personality.

To adapt gamification elements to learners' personality, three steps must be done in order. First, we need to understand the relationship between gamification and personality. This understanding will be used later to build and evaluate the adaptive model.

This chapter was presented the methodology that will be used to understand how different personality dimensions interact with different gamification elements. We conducted three different experiments that each applied the same methodology but that had different combinations of gamification elements and different users. In the first study, we integrated points, badges and leaderboard. In the second study, we added the social elements. While, in the third study, we added avatars. More details about these experiments will be presented in Chapters 6,7 and 8 respectively.

Chapter 6

Experiment One

6.1 Introduction

In Chapter 5, we introduced the approach that will be used to study the relationship between gamification and personality dimensions. This chapter will present, in more details, the first experiments and the corresponding results.

6.2 Experiment 1

This experiment was conducted to understand the effects of points, badges and leaderboard on learners' behaviour.

6.2.1 Method

Two versions of the same online learning website were designed. One included gamification elements related to the course, and the other did not. In the gamified version, we tried to follow the principles suggested by Simões et al. (2013) to integrate gamification elements in any learning system [see section 2.5] page 31.

In the lessons, there were a small quiz consists of five questions. Each correct answer was awarded a point; as an instant feedback. After collecting five points, the learner receive a badge. The number of badges collected controlled the learner's position on the leaderboard. In the experiment, the learner is free to take the quiz twice; and he/she cannot go to the next lesson until he/she answer correctly half of the questions in the first or second attempt. We did this to follow the principle (allow for repeated activities). If the learner fail in the two attempts, then the system will show the learner the correct answer and the learners will move to the next lesson. The leaderboard will be presented to the learner as a pop-up window after finishing each lesson and the corresponding quiz.

The number of points and badges will be presented to the learners, all the time, at the right corner of the website. However, if the learner want to know more details about the number of collected points and badges and the position on leaderboard, the learner can click on "student profile" button on the top of the page.

Figure 6.1 shows an example of how the gamification elements were displayed. Figure 6.2 shows a screenshot of the non-gamified version.

197 learners (16-18 years old) at four different high schools in Saudi Arabia participated in this experiment. The participants included 107 girls and 90 boys. After the participants were selected, the approach shown in Figure 5.3 was followed

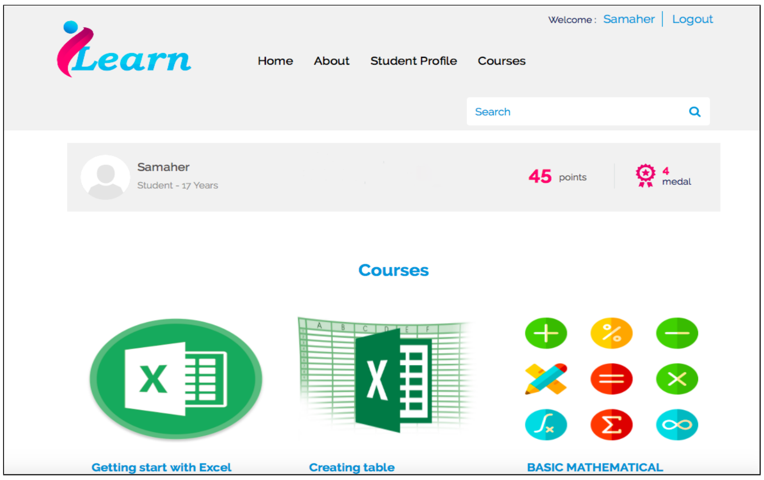


Figure 6.1: Screenshot of the gamified version of the website (experiment 1).

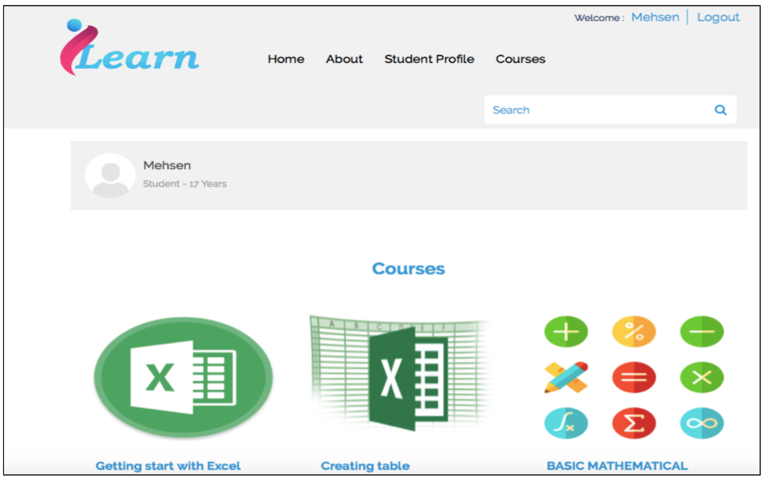


Figure 6.2: Screenshot of the non-gamified version.

6.2.2 Results

The effects of gamification on all the learners, regardless of their personality were measured first. Figure 6.3 shows the KM of the cumulative dropout rate in the gamified and non-gamified versions. The Cox hazard model was then used to find the differences between the two versions. Table 6.1 shows the results of the analysis.

In the next step, the KM and Cox hazard models to both high and low extremes of each

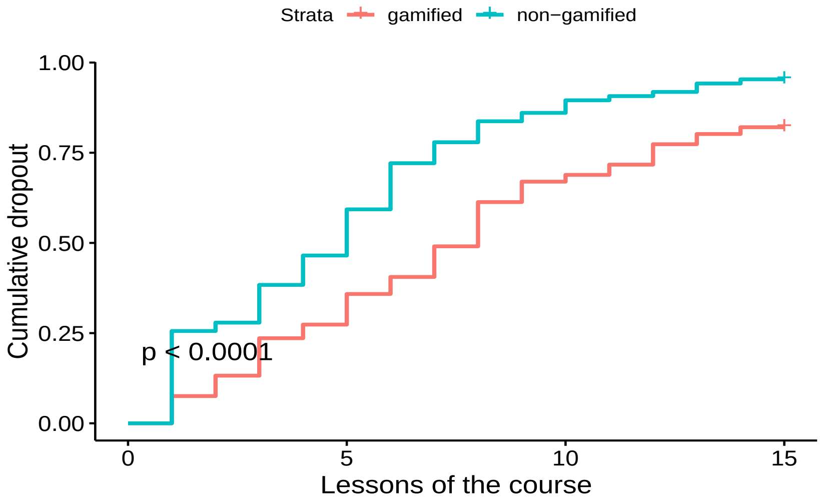


Figure 6.3: Kaplan-Meier (KM) graph of learners in both the gamified and non-gamified versions (experiment 1).

Table 6.1: The result of the Cox regression being applied to all learners (experiment 1).

	Coef	Exp(coef)=HR	Se(coef)	z	Pr(>|z|)
Version	0.66	1.9417	0.1563	4.2	2.18e-05
Likelihood ratio test= 17.63 on 1 df,				p= 3e-05	
Wald test = 18.02 on 1 df,				p= 2e-05	
Score (Logrank) test= 18.64 on 1 df				p= 2e-05	

personality dimension were applied.

Figures 6.4, 6.5, 6.6, 6.7 and 6.8 show the KM for the 'high' and 'low' scores of the conscientious, extroverted, agreeable, neurotic and open personality dimensions, respectively. Table 6.2 shows a summary of the results obtained from the Cox model.

In this experiment, the learners could not be contacted to complete the post-test and the satisfaction test. Therefore, it was impossible to determine the learners' satisfaction with the online course or their knowledge gain.

6.2.3 Discussion

The results of this study support the results of previous studies in the literature, showing the positive effects of gamification on enhancing motivation and engagement, as seen in the KM of all learners (Figure 6.3). The curve of the dropout rate in the gamified version was lower than the dropout curve in the non-gamified version; which supports H1. Furthermore, the results of the Cox hazard showed a significant difference in the dropout rates in the two versions. The sign of the coefficient was positive, indicating that the dropout rate was higher in the second group (i.e. the learners assigned to the non-gamified version). The difference in the dropout rates in the two groups can be explained by the HR: the dropout rate in the non-gamified version was 1.9 times higher than the gamified version.

It was observed that there was a variation in the effects of gamification on learners with

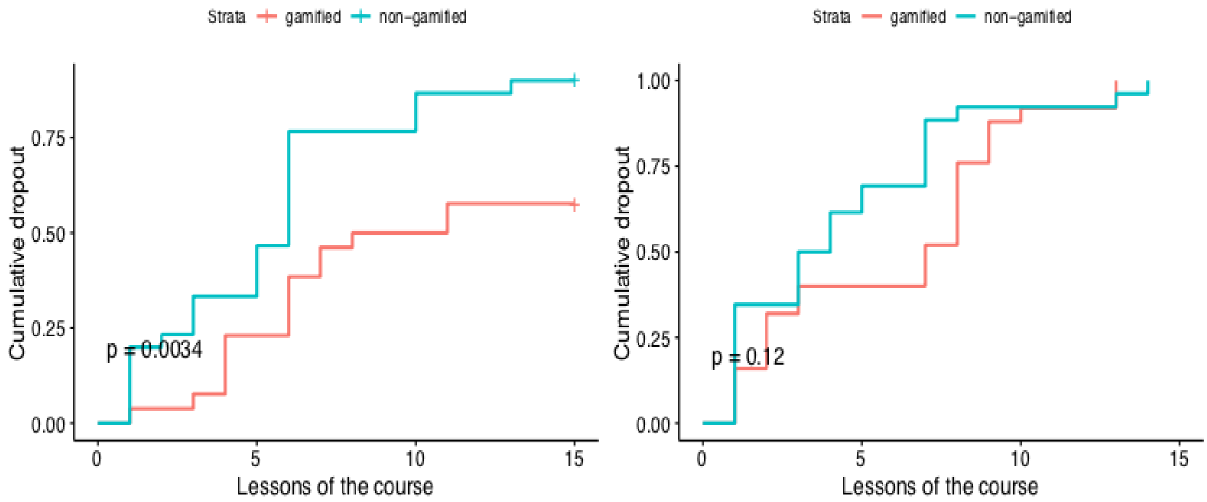


Figure 6.4: KM for the conscientiousness personality (experiment 1): On the left, the KM graph for low conscientious learners, and on the right for the high conscientious learners.

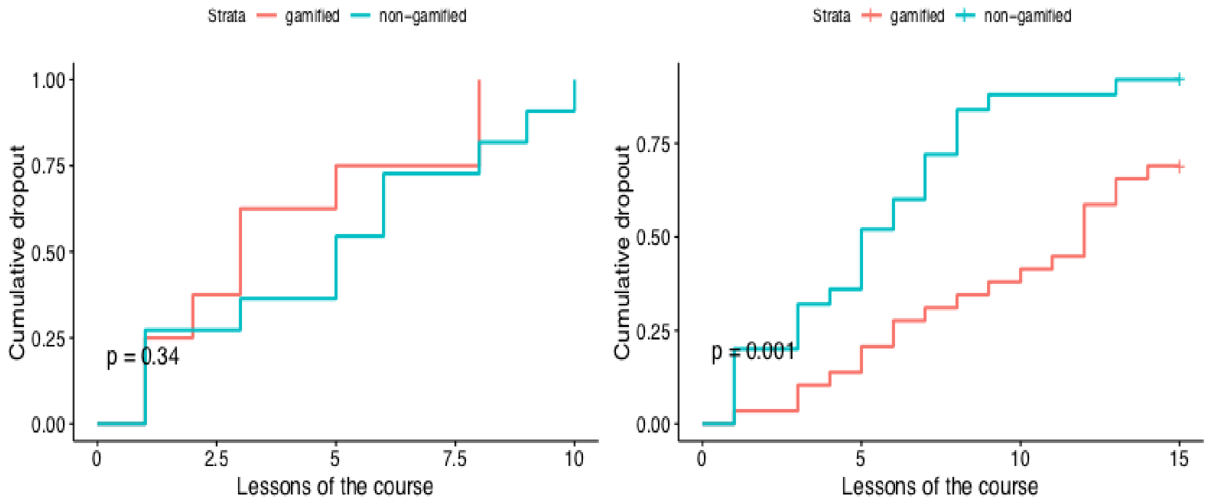


Figure 6.5: KM for the extroversion personality (experiment 1): On the left, the KM graph for low extrovert learners, and on the right for the high extrovert learners.

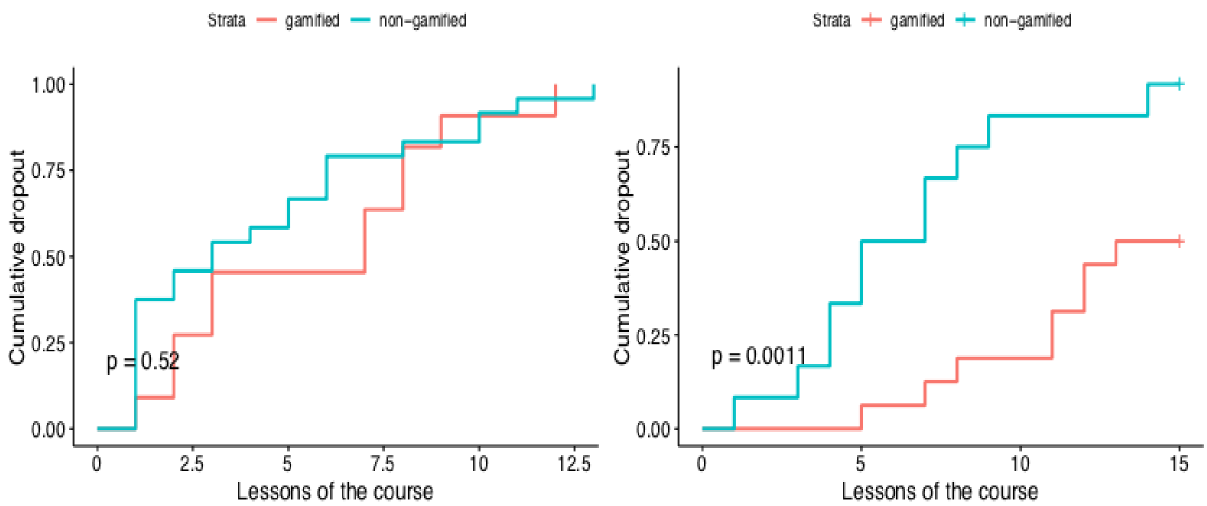


Figure 6.6: KM for the agreeableness personality (experiment 1): On the left, the KM graph for low agreeable learners, and on the right for the high agreeable learners.

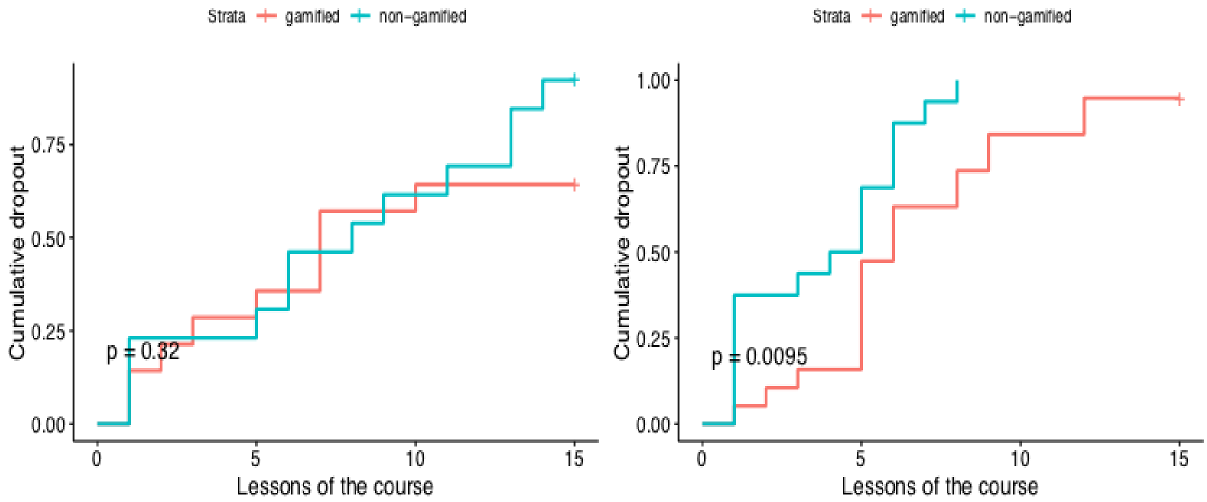


Figure 6.7: KM for the neuroticism personality (experiment 1): On the left, the KM graph for low neurotic learners, and on the right for the high neurotic learners.

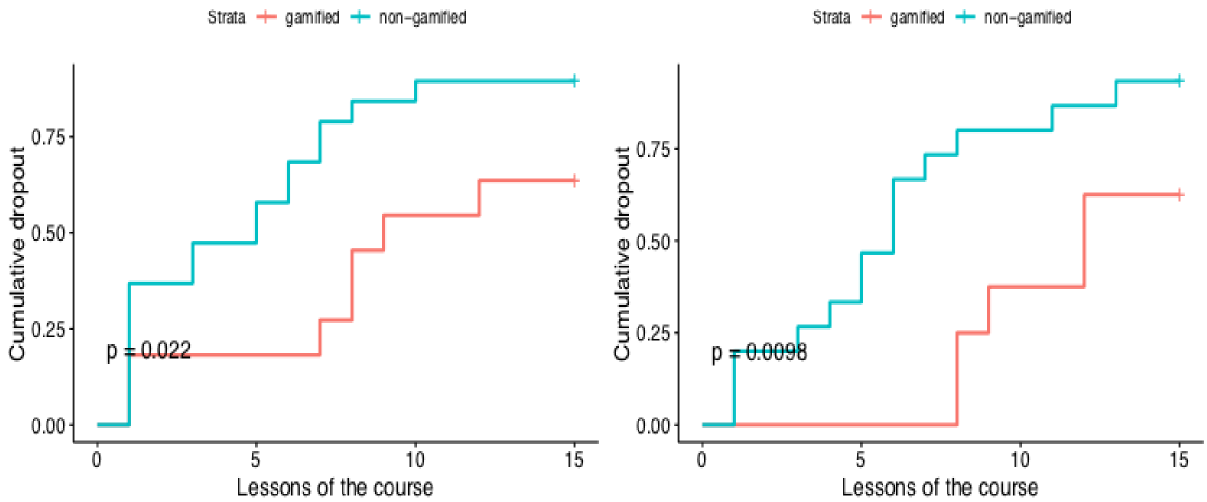


Figure 6.8: KM for the openness to experience personality (experiment 1): On the left, the KM graph for low openness learners, and on the right for the high openness learners.

Table 6.2: A summary of the results of the Cox hazard model (experiment 1).

Personality	Number of learners	Coef	Exp(coef)=HR	p-value
High conscientious	43	0.485	1.625	0.12
Low conscientious	51	0.847	2.331	0.003
High extraversion	41	1.009	2.745	0.001
Low extraversion	19	-0.474	0.6224	0.34
High agreeableness	28	1.44	4.227	0.001
Low agreeableness	35	0.258	1.294	0.52
High neuroticism	35	0.926	2.525	0.009
Low neuroticism	27	0.4334	1.54	0.32
High openness	23	1.269	3.557	0.009
Low openness	30	0.9954	2.70	0.02

different personality dimensions. For instance, the high conscientious learners did not seem to benefit as much as the low conscientiousness learners did (Figure 6.4). This result may be explained by the traits associated with this personality dimension. Learners who are highly conscientious are typically hard workers and always do their work. These learners tend to receive good marks and perform better than their peers (Poropat, 2009). Thus, it was expected that these learners would not benefit from gamification, and their motivation would be the same in the gamified and non-gamified versions; which is supported H4. In contrast, the low conscientiousness personality dimension is usually careless and rarely completes work (Ciorbea and Pasarica, 2013). The results indicated that gamification helped the learners with this personality dimension stay in the course, thus improving their motivation.

Highly extrovert learners are usually talkative and inclined to compete with their peers but are easily distracted. Some researchers suggest a correlation between this personality dimension and low achievement (Poropat, 2009). Jia et al. (2016) and Tondello et al. (2016) argued that points and badges could help these learners improve their motivation and engagement. The results of the study support this argument H7: the high extrovert learners gained a significant benefit from gamification. The low extroverted learners (i.e. introverts) showed almost the same dropout rates in the gamified and non-gamified versions (Figure 6.5). Furthermore, when the Cox model was applied to the low extroversion learners, the sign of the coefficient was negative, indicating that in the non-gamified version, the motivation and engagement of these learners was better during some parts of the course.

Highly agreeable learners usually prefer both challenges and social elements (Jia et al., 2016); (Tondello et al., 2016). The leaderboard and the collection of points and badges helped these learners improve their levels of motivation and engagement; which is suggested by H10. In contrast, the low agreeableness learners showed the same level of motivation and engagement in both versions (Figure 6.6).

It was expected that highly neurotic learners may find many gamification elements to be childish or silly. Nevertheless, they benefited from gamification. Their level of motivation and engagement was better than in the gamified version; which conflicts H13. However, the results showed that the low neuroticism learners did not receive any benefit from the gamification elements (Figure 6.7). This unexpected result could be explained by a few factors. One explanation is the interaction between personality dimensions. Each learner had a different score for each personality dimension. For example, some highly neurotic learners were also high extrovert. In addition, the experiment was conducted with 197 learners. However, when we considered only the high and low extremes of personalities, the number of learners in the sample dropped to a range between 30 and 40 regarding the extremes of each personality dimension in both versions.

Both high and low openness learners showed significant benefits from gamification in motivation and engagement as suggested in H16 (Figure 6.8).

However, we did not find any negative effects of the gamification elements. Most learners motivated by gamification elements. The presentation of the elements in the top-right corner of the page did not cost the learners' anything and would not have bothered or annoyed them. Further, one of the issues in designing the experiment is that it was not known which of the gamification elements motivated learners, individual elements or their combination. The design of the gamified system was very conservative. Thus, when the learner answered correctly, he/she earned a point. However, the system was simply recording the number of points without attracting the user's attention, such as sounds to notify the user of a new badge. The system could have used animation to show the increasing number of points and badges.

6.3 Conclusion

This chapter had explained the first study of a series of three studies that ran to understand the relationship between gamification and personality.

In this experiment, we integrated the most common gamification elements: points, badges and laderboard. We followed the same approach explained in Chapter 5.

The results from this chapter show that overall, gamification has a positive effect on learners. However, learners respond differently to gamification. Some have a statistical significant benefit from gamification and others are not. However, the design of the experiment was conservative and may not feasible to all learners. For that, and to get more insight about the effect of gamification on learners' behaviour, we aim to run another experiments to have more understanding.

Chapter 7

Experiment Two

7.1 Introduction

This chapter explains the second experiment from a series of experiments conducted to understand the relationship between gamification and personality.

7.2 Experiment 2

The second experiment aimed to understand the effects of additional gamification elements on learners' behaviour. Another gamification element, namely social elements, was integrated to deepen analysis.

The existence of the social element should improve the learners' outcomes and satisfaction, as suggested by social learning theory (Richardson and Swan, 2003; Swan and Shih, 2005). In a study by Cobb (2009), learners were asked for their opinions about the social elements, and the responses showed that interactions with other learners helped motivate them and increased their understanding of the course's concepts, and helped them become acquainted with their peers (Ghaban. et al., 2019). Thus, chats between learners were added as the new gamification element.

7.2.1 Method

The same approach used in the first experiment was followed with 194 learners (91 boys and 103 girls) aged 16 to 18. In the gamified version, points, badges, a leaderboard and chat were used. The chat was accessible only by learners who were assigned to the gamified version, provided via a button marked 'Talk to a friend'. When activated a new, small screen was presented. Figure 7.1 shows a screenshot of the website, and Figure 7.2 shows a screenshot of the chat screen.

In the chat screen, learners thought they were talking to a friend, but they were actually communicating with the researcher. This scheme was planned for several reasons, including the ethical issues related to parents and schools in Saudi Arabia. Furthermore, all learners who used the chat would see the same type of response. By replying to the learner, the topics discussed could be controlled and the number and the kind of topics discussed analysed.

In the chat screen, the researcher usually followed learners in the topic that the latter introduced. If the learner asked a question, then the researcher would reply by returning the question back to the learner. For example, if the learner asked 'What do you think about the topic X?' then, the researcher would reply 'I am not sure, What do you think?'. We tried to not have any bias or redirect the conversation. However, because the researcher was behind the chat screen, the learner may anticipate some delay in the response. For example, if multiple learners started conversation in the same time.

The learners followed the procedure presented in Figure 5.3. However, we were not able to measure learners' long-term knowledge gain.

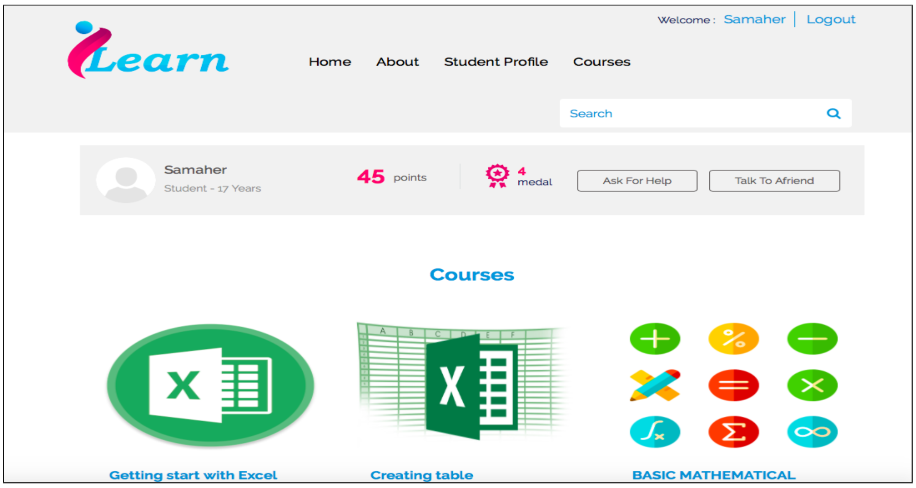


Figure 7.1: Screenshot of the gamified version of the website in the second experiment.

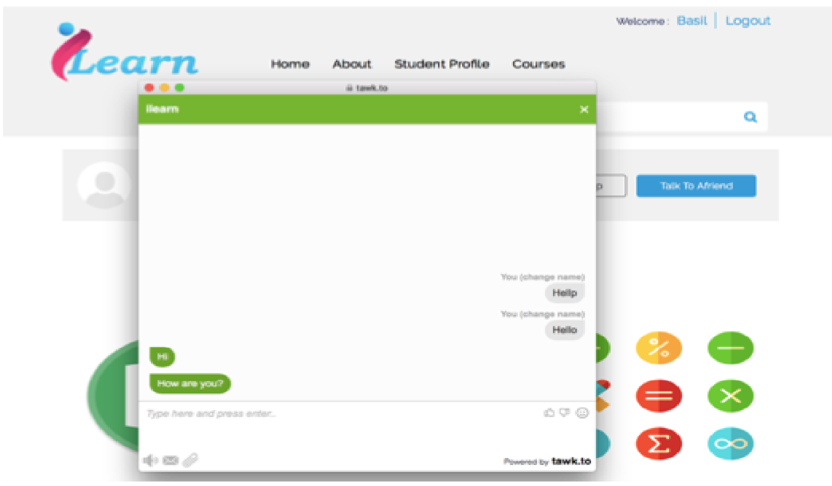


Figure 7.2: Screenshot of the social element included in the gamified version of the online learning website.

7.2.2 Results

As in the first experiment, we measured the difference in the dropout rates in the gamified and non-gamified versions. Figure 7.3 shows the KM applied to all learners, and Table 7.1 shows the results of the Cox hazard model.

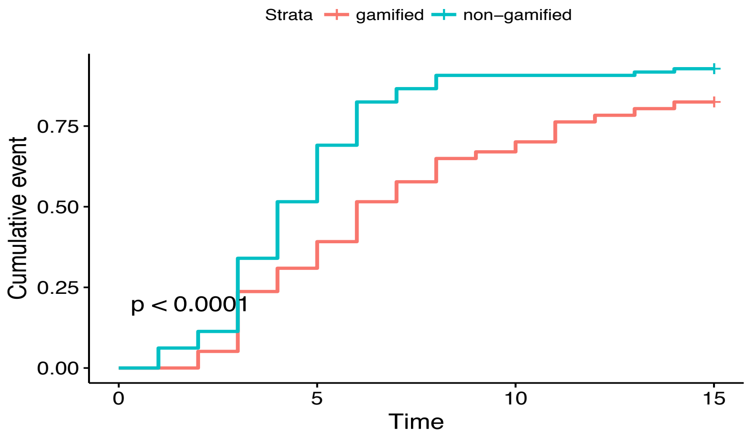


Figure 7.3: Kaplan-Meier (KM) graph of all learners in the gamified and non-gamified versions (experiment 2).

Table 7.1: The result of the Cox regression when applied to all learners (experiment 2).

	Coef	Exp(coef)=HR	Se(coef)	z	Pr(>|z|)
Version	0.6343	1.8856	0.1570	4.041	5.32e-05
Likelihood ratio test= 16.29 on 1 df,				p= 5e-05	
Wald test = 16.33 on 1 df,				p= 5e-05	
Score (Logrank) test= 18.82 on 1 df				p= 4e-05	

The same kind of analysis to the extremes of the personality dimensions was followed as in experiment 1. Figures 7.4, 7.5, 7.6, 7.7 and 7.8 show the KM for personality dimensions, and Table 7.2 show summaries of the Cox hazard results.

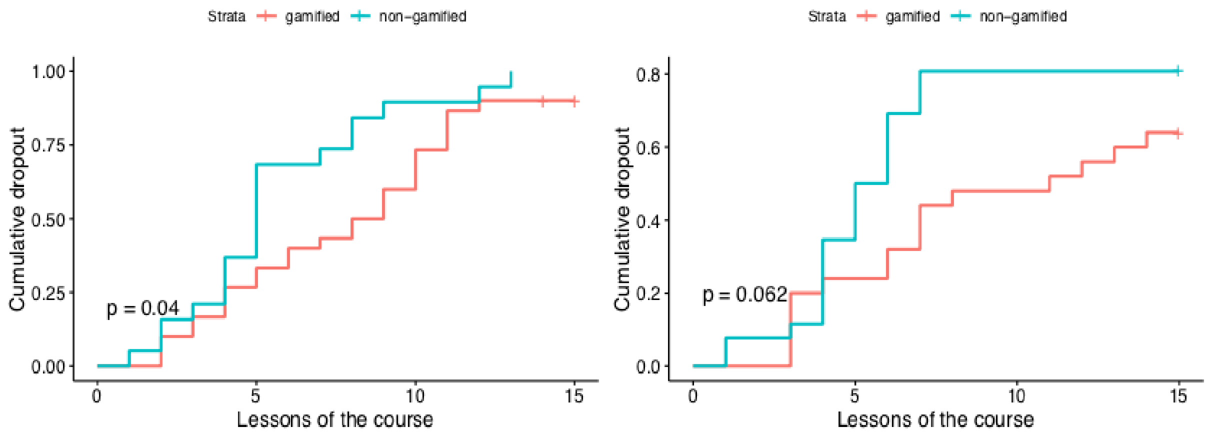


Figure 7.4: KM for the conscientiousness personality (experiment2): On the left, the KM graph for low conscientious learners, and on the right for the high conscientious learners.

After about two months, ensuring that all learners had either stopped using the learning

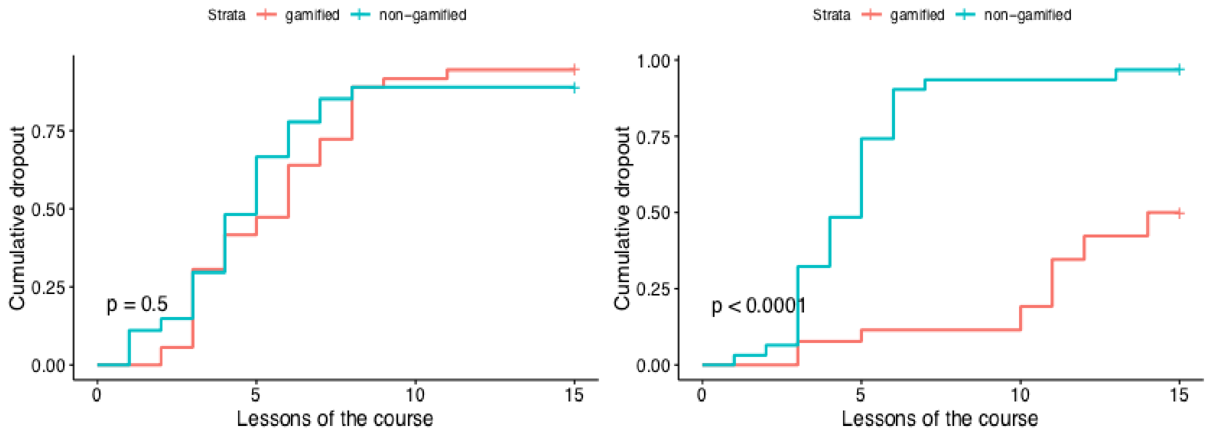


Figure 7.5: KM for the extroversion personality (experiment2): On the left, the KM graph for low extrovert learners, and on the right for the high extrovert learners.

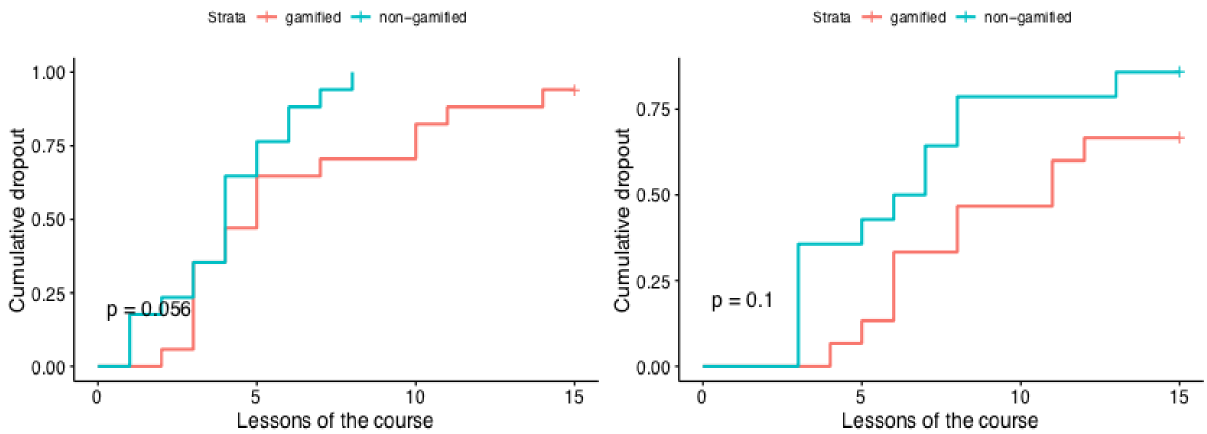


Figure 7.6: KM for the agreeableness personality (experiment2): On the left, the KM graph for low agreeable learners, and on the right for the high agreeable learners.

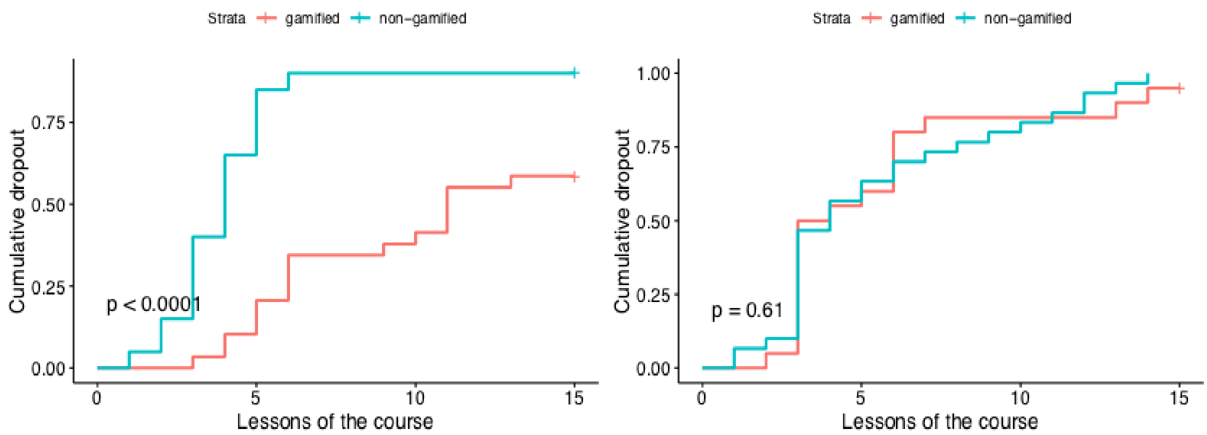


Figure 7.7: KM for the neuroticism personality (experiment2): On the left, the KM graph for low neurotic learners, and on the right for the high neurotic learners.

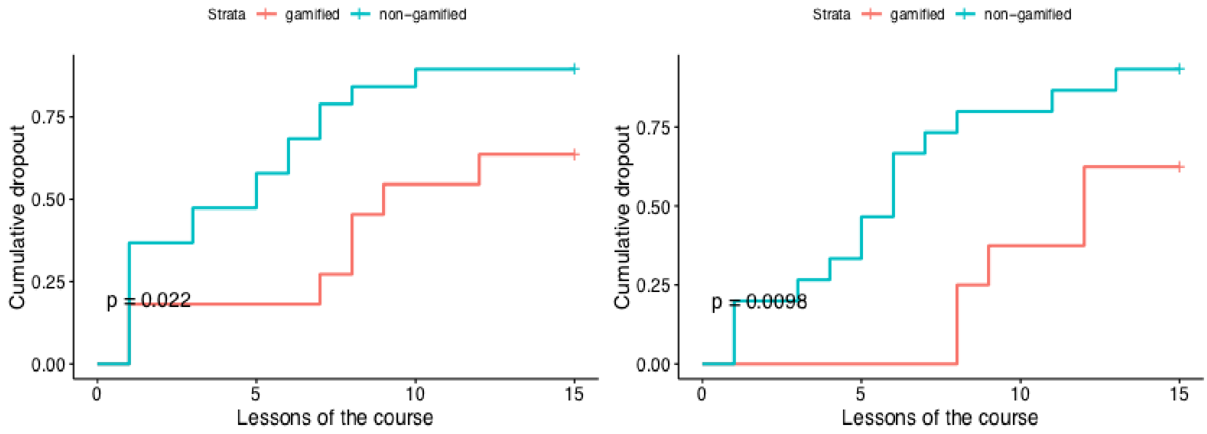


Figure 7.8: KM for the openness to experience personality (experiment2): On the left, the KM graph for low openness learners, and on the right for the high openness learners.

website because they had finished the course or had dropped out, we asked learners to complete a post-test similar to the pre-test they completed before the experiment. To determine whether gamification elements had any effect on the learners' outcomes, the results from the pre- and post-test were used to calculate the knowledge gain of each learner. Table 7.3 shows the average knowledge gain of all learners on each personality dimension.

In addition, the learners were asked to complete an ELS to measure their satisfaction with their version (i.e. gamified or non-gamified). Table 7.4 shows the average satisfaction scores of the learners on each personality dimension in both versions.

Given the conflict in the findings (learners were motivated and satisfied but did not gain knowledge), a further analysis was conducted to determine whether the chat had any effect on the learners' behaviour.

The number of messages from learners of different personality dimensions was examined. We hypothesised that high and low conscientiousness will send the same number of messages. While, highly extrovert learners will send an extreme number of messages compared to the low extrovert. In the same manner, we hypothesise that highly agreeable learners will send more messages than low agreeableness. In contrast, the highly neurotic learners will exchange the least number of messages. While, the high and low openness will send more messages than low openness. Table 7.5 shows the number of messages received from each personality dimension. In the table, we calculated the number of chats opened and the messages received from each personality dimension. In addition, after ensuring the normality by using shapiro Wilk test, we calculated the independent sample t-test to examine if there is any statistically significant difference between the number of messages received between the high and low extremes of each personality dimension.

Table 7.2: Summary of the results of Cox hazard model (experiment 2).

Personality	Number of learners	Coef	Exp(coef)=HR	p-value
High conscientious	37	0.247	1.84	0.06
Low conscientious	33	0.611	1.90	0.04
High extraversion	47	1.949	7.032	<0.0001
Low extraversion	40	0.1561	1.1689	0.5
High agreeableness	54	0.8998	2.45	0.1
Low agreeableness	50	0.4368	1.54	0.05
High neuroticism	48	0.1078	1.11	0.61
Low neuroticism	40	1.447	4.25	<0.0001
High openness	40	0.666	1.9475	0.0098
Low openness	37	1.4471	4.2508	0.022

7.2.3 Discussion

The experiment aimed to determine the effects of gamification elements on learners with different personality dimensions. To achieve this, a chat, which is considered a social gamification element, was added. This element could attract learners who are more talkative and who enjoy interactions with others. However, it could also distract learners, causing them to procrastinate.

The findings support the results of the first experiment and the related research, showing that the gamification elements improved the motivation and engagement of learners overall, thus supporting H1 (Cheong et al., 2013; Dichev et al., 2014). As a high number of participants were more satisfied with the gamified version, the result likewise supported H3. This finding corroborates the argument of Chen and Chih (2011) by showing a positive correlation between motivation and satisfaction.

However, in the study, learners who were assigned the gamified version exhibited less knowledge gain than did the learners using the non-gamified version. This result conflicts with H2 and was unexpected. It does not support the hypothesis that motivation can be considered a good predictor of learning outcomes. Several previous studies showed the benefits of social elements in improving knowledge gain (Swan and Shih, 2005).

After determining the effects of the gamified and non-gamified versions on learners, we examined the effects of gamification on different personality dimensions. As in experiment 1,

Table 7.3: Summary of the average knowledge gained in the gamified and non-gamified versions of the website (experiment 2).

Personality	Total number of learners	Knowledge gain in the gamified version			Knowledge gain in the non-gamified			Benefit from gamification
		N	μ	sd	N	μ	sd	
Overall learners	194	97	1.39	2.14	97	1.97	1.91	-0.58
High conscientious	37	23	2.12	1.5	14	2.6	1.7	-0.48
Low conscientious	33	18	2.51	0.45	15	2.16	1.86	0.35
High extrovert	47	23	1	2.1	24	2.04	1.45	-1.04
Low extroversion	40	24	2.04	1.9	16	1.73	1.65	0.31
High agreeableness	54	26	1.81	2.1	28	2.4	1.61	-0.59
Low agreeableness	50	28	2.01	2.39	22	2.23	1.14	-0.22
High neuroticism	48	26	1.42	1.8	22	1.78	2.01	-0.36
Low neuroticism	40	26	1.61	1.9	14	2.5	1.28	-0.89
High openness	40	21	1	2.4	19	2.37	1.5	-1.37
Low openness	37	23	1.27	1.53	14	1.64	10.94	-0.37

there were variations in the effects of gamification on learners with different personalities.

Motivation

Jia et al. (2016) found that highly conscientious learners are usually affected negatively by social elements. However, the results of the current experiment did not show any negative effects of the integrated gamification elements on the learners. Instead, the learners in the gamified and non-gamified versions had the same level of motivation, which supports H4. Previous studies showed a positive correlation between social elements and the extroversion personality dimension (Tondello et al., 2017b; Denden et al., 2018; Hallifax et al., 2019). Extroverted learners prefer to interact with others, which may explain why they perceived a significant benefit from gamification elements. In experiment 1, when the gamification elements were only points, badges and the leaderboard, the HR was 2.7. However, in the second experiment, the HR rose to 7.03, indicating that in the presence of the social element, the dropout rate of learners in the gamified version was seven times lower than that in the non-gamified version. Thus, highly extroverted learners were more motivated in the gamified version, which supports H7. By contrast, the learners with low extroversion (i.e. highly introverted) did not receive any significant benefit from the social gamification element when compared with highly extroverted learners. Introverted learners are usually quiet and focused on the task. Hence, they rarely used the chat, and they concentrated on the content of the online learning website. This finding was evident when the number of messages received

Table 7.4: Summary of the results of learners' satisfaction with the gamified and non-gamified versions (experiment 2).

Personality	Total number of learners	Satisfaction in the gamified version			Satisfaction in the non-gamified			Benefit from gamification
		N	μ	sd	N	μ	sd	
Overall learners	194	97	6.62	0.311	97	6.17	0.3	0.45
High conscientious	37	23	6.6	0.8	14	6.4	0.78	0.2
Low conscientious	33	18	6.4	0.78	15	6.07	0.73	0.33
High extrovert	47	23	6.64	0.58	24	6.1	0.49	0.54
Low extroversion	40	24	6.54	0.58	16	6.1	0.76	0.44
High agreeableness	54	26	6.64	1.3	28	6.4	1.1	0.24
Low agreeableness	50	28	6.32	0.8	22	6.28	0.87	0.04
High neuroticism	48	26	5.7	0.83	22	6.3	0.87	-0.6
Low neuroticism	40	26	6.3	0.78	14	6.3	0.75	0
High openness	40	21	6.5	0.78	19	6.3	0.83	0.2
Low openness	37	23	6.27	0.88	14	6.3	0.8	-0.03

from each personality dimension was calculated (Table 7.5). The lowest number of messages was received from the learners with low extroversion.

Highly agreeable learners like to communicate with and help others. However, no significant benefit for this personality was observed from the social gamification elements. The dropout rate of both learners with high and low agreeableness was almost the same in the gamified and non-gamified versions. Accordingly, we cannot support or reject H10.

Highly neurotic learners are usually negatively correlated with social elements (Hotard et al., 1989). These learners usually care about others' opinions, but they usually dislike interacting and communicating with others. In addition, Hotard et al. (1989) showed a correlation between neuroticism and introversion. However, no significant negative effect of the social gamification element on the motivation and engagement of these learners was observed. Hence, we do not have enough to support or reject H13.

Finally, the results showed that learners with high and low openness had the potential to benefit from a gamified website, where the gamification elements improved their motivation. The dropout rate of these learners in the gamified version was lower than that in the non-gamified version.

Table 7.5: The number of messages exchanged with the learners.

	Number of learners in the gamified version	Number of messages	Number of chats opened	Average (messages/chat)	P-value
High conscientious	23	1238	53	23.3	0.131
Low conscientious	18	1330	58	22.9	
High extrovert	23	3320	111	29.9	<0.0001
Low extroversion	24	343	26	13.1	
High agreeableness	26	1310	47	27.8	0.49
Low agreeableness	28	1305	36	36.2	
High neuroticism	26	980	47	20.8	0.001
Low neuroticism	26	2602	98	26.5	
High openness	21	1749	70	24.9	0.64
Low openness	23	1640	51	32.15	
Total	238	15817	597	26.49	

Knowledge gain

Based on the literature, motivation can be considered a good predictor of learning outcomes. Therefore, if the learners in the present study were more motivated in the gamified version, then their knowledge gain would be better. However, gamification had different effects on learners' motivation and knowledge gain. For example, both the high and low conscientiousness personality dimensions were motivated by gamification, but their responses to knowledge gain differed. Learners with low conscientiousness had greater gains in knowledge in the gamified version than did learners with high conscientiousness.

Ciorbea and Pasarica (2013) pointed out that highly extroverted learners differ in their knowledge gain in online learning courses. For example, the high energy and activity of these learners may cause them to be more engaged in learning activities, which may improve their knowledge gain. However, highly extroverted learners may also be so busy with their social life and social interactions that they could be distracted from learning. Results support the latter opinion. The highly extroverted learners did not learn much in the gamified version despite being highly motivated, which conflicts with H8. This result may be explained by the large number of messages received from the highly extroverted learners. By contrast, the learners with low extroversion learned more in the gamified version.

Neither the learners with high agreeableness nor those with low agreeableness received any significant benefit from gamification in terms of knowledge gain. These learners were busy with the social elements, which may have had negative effects.

The highly neurotic learners did not benefit from gamification regarding knowledge gain. This result was expected for several reasons. Ciorbea and Pasarica (2013) showed that there is a negative correlation between neuroticism and academic achievement. Highly neurotic learners usually have lower knowledge gain. Similarly, results showed that the neurotic learners were negatively affected by gamification. This finding was expected because of the correlation between the low neuroticism personality dimension and the high extroversion personality dimension.

The results showed that learners with high and low openness were also distracted by gamification, which negatively affected their knowledge gain.

Satisfaction

Motivation can be considered a predictor of learners' satisfaction (Chen and Chih, 2011). Most learners who used the system for longer were more satisfied. Hence, most of the learners who were highly motivated in the gamified version were also highly satisfied. Table 7.4 summarises the average results of the satisfaction of different learner personalities with the gamified and non-gamified versions.

The results varied among the different personality dimensions. For example, a negative effect of gamification on highly conscientious and highly neurotic learners was expected. However, the learners with these two personality dimensions were shown to have the same levels of motivation in both versions. This result may be explained by the optional nature of the social elements used in this study, which could be the reason for the similarities between the findings of experiments 1 and 2. Some learners chose not to use the social elements to contact others. There was no significant difference in the number of messages between learners with high and low conscientiousness. Further, the results of Pearson's correlation show that the correlation between the score of the conscientiousness personality and the number of messages was weak ($r=0.04$)

In contrast, highly extroverted learners chose to use the chat, which might be the reason for their increased motivation and satisfaction. However, the knowledge gain among these learners was worse in the gamified version, which conflicted with the findings in related studies (Cobb, 2009; Swan and Shih, 2005). This could be explained by the number of messages (3,000 messages) received from highly extroverted learners (see Table 7.5), implying frequent interactions could have hindered learning. We noticed that there was a statistically significant difference between the number of messages received from the learners with high and low extroversion (p-value<0.0001).

We also conducted Pearson's correlation test to determine whether there was a relationship between the score of the extroversion personality and the number of messages. The results found a strong association between the two (*r=0.71*).

However, the large number of received messages may not be the reason for the low level of knowledge gain, especially if the learners were discussing the course contents. Hence, it was essential to look to the texts and determine the topics these learners discussed.

For this, a brief content analysis was conducted. To do so, the messages were classified based on the topic discussed, as follows (Table 7.6): (1) on-topic messages related to the course content; (2) off-topic messages unrelated to the course, such as fashion or travel; (3) greetings or messages related to manners, such as expressing gratitude; and (4) gamification or messages related to the gamification elements, such as asking about the number of points and badges collected by another learner.

The number of messages received from the learners according to each code was determined. Table 7.7 shows the results.

Table 7.6: The codebook used to define the messages.

Code	Definition	Example
T (Topic)	Messages relevant to the topic (Microsoft Excel)	Which operation has priority in the following formula in Excel: $3 * 2 + 1/4$
O (Off-topic)	Messages related to any topic other than Microsoft Excel (e.g, fashion, travel, weather)	Who was the winner of the last football game between Al-Hilal and Al-Naser?
G (Greeting)	Messages representing greetings or welcoming messages.	How are you? Where are you from?
GM (Gamification)	Messages related to gamification, such as points and badges.	How many points and badges did you collect?

Table 7.7 reveals that a high number of off-topic messages were received from highly extroverted learners. Most of the messages received from these learners were about topics other than the course contents, such as fashion, sports and travel. Figure 7.10 shows the number of messages received by each personality dimension.

The results did not show any significant difference in the number of messages received from the learners with high and low agreeableness. Further, the correlation between agreeableness and the number of messages was weak (*r=-0.02*). Figure 7.9 shows an example of a conversation pattern of a highly extroverted learner compared with that of other personality dimensions, such as high conscientiousness and high agreeableness. The number of messages from the learners with high and low agreeableness could be the reason they stayed in the course and were more satisfied with the gamified version. However, it may also be the reason

Table 7.7: The total number of messages (on-topic, off-topic, greeting and gamification)

Personality		In-topic	Off-topic	Greeting	Game-fiction	Total
High conscientious	N	300	574	321	43	1238
	%	24.2	46.3	25.9	3.6	100
Low conscientious	N	148	507	639	36	1330
	%	11.1	38.1	48.1	2.7	100
High extraversion	N	571	1615	864	270	3320
	%	17.2	48.5	26.02	8.1	100
Low extraversion	N	54	152	123	14	343
	%	15.7	44.32	35.8	4.08	100
High agreeableness	N	286	551	400	73	1310
	%	21.8	42.06	30.9	5.6	100
Low agreeableness	N	164	599	443	99	1305
	%	12.5	45.9	33.9	7.7	100
High neuroticism	N	98	416	433	33	980
	%	10	42.4	44.3	3.3	100
Low neuroticism	N	476	1206	748	172	2602
	%	18.29	46.3	28.7	6.6	100
High openness	N	265	759	638	87	1749
	%	15.5	43.3	36.4	4.8	100
Low openness	N	258	765	480	151	1654
	%	15.5	46.2	29.2	9.1	100

for their low knowledge gain.

Following the highly extroverted learners, the learners with low neuroticism sent more than 2,000 messages, 44% of which were off topic. This high number of off-topic messages sent by the highly extroverted learners and the learners with low neuroticism may explain their improvement in motivation and engagement and the simultaneous negative effect on their knowledge gain. There was a statistically significant difference between the number of messages between the high and low neuroticism personalities (p-value = 0.002). Further, the results of Pearson's correlation showed a negative relationship between the neuroticism personality and the number of messages (*r=-0.34*)

In addition, both the learners with high and low openness used the chat frequently. However, there was no statistically significant difference in the number of messages between the high and low extremes in this personality dimension (p-value = 0.65). Further, the result of Pearson's correlation was 0.05.

The learners with low extroversion and high neuroticism exchanged the fewest messages. This finding can be explained by the traits associated with these personalities, such as the preference of not communicating with others. Furthermore, use of the chat function was optional.

In addition, as found in the first experiment, the correlation between personality dimensions affected the results. For example, it was not expected that the highly conscientious learners

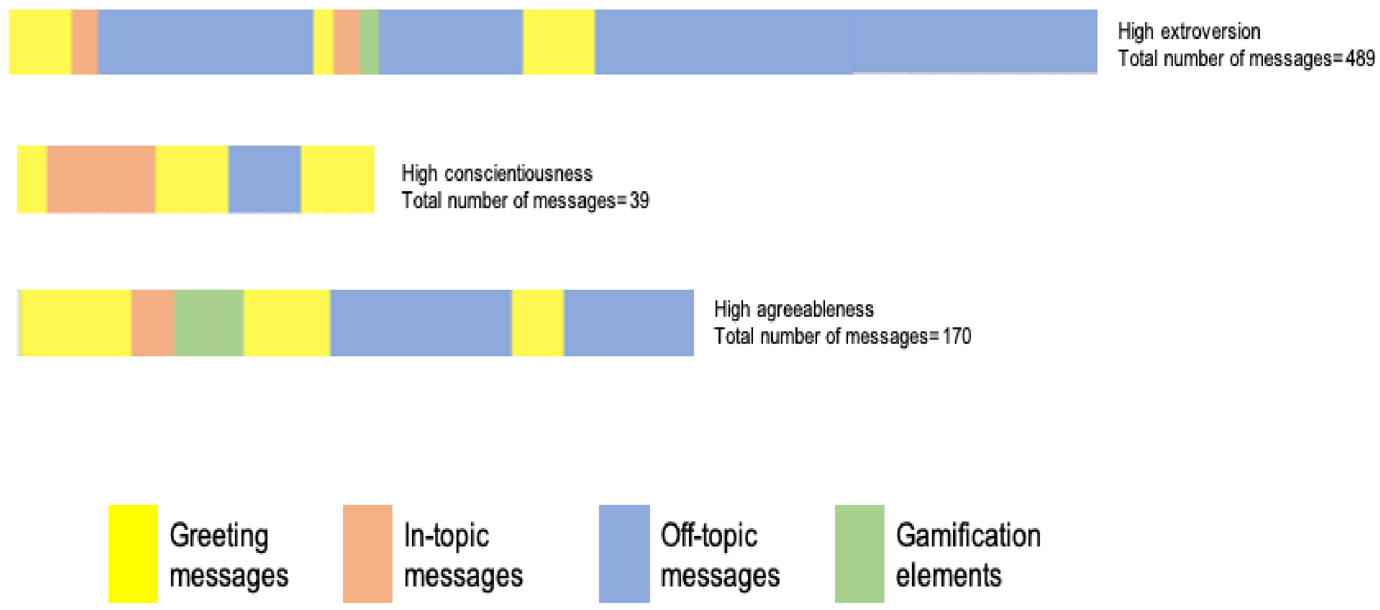
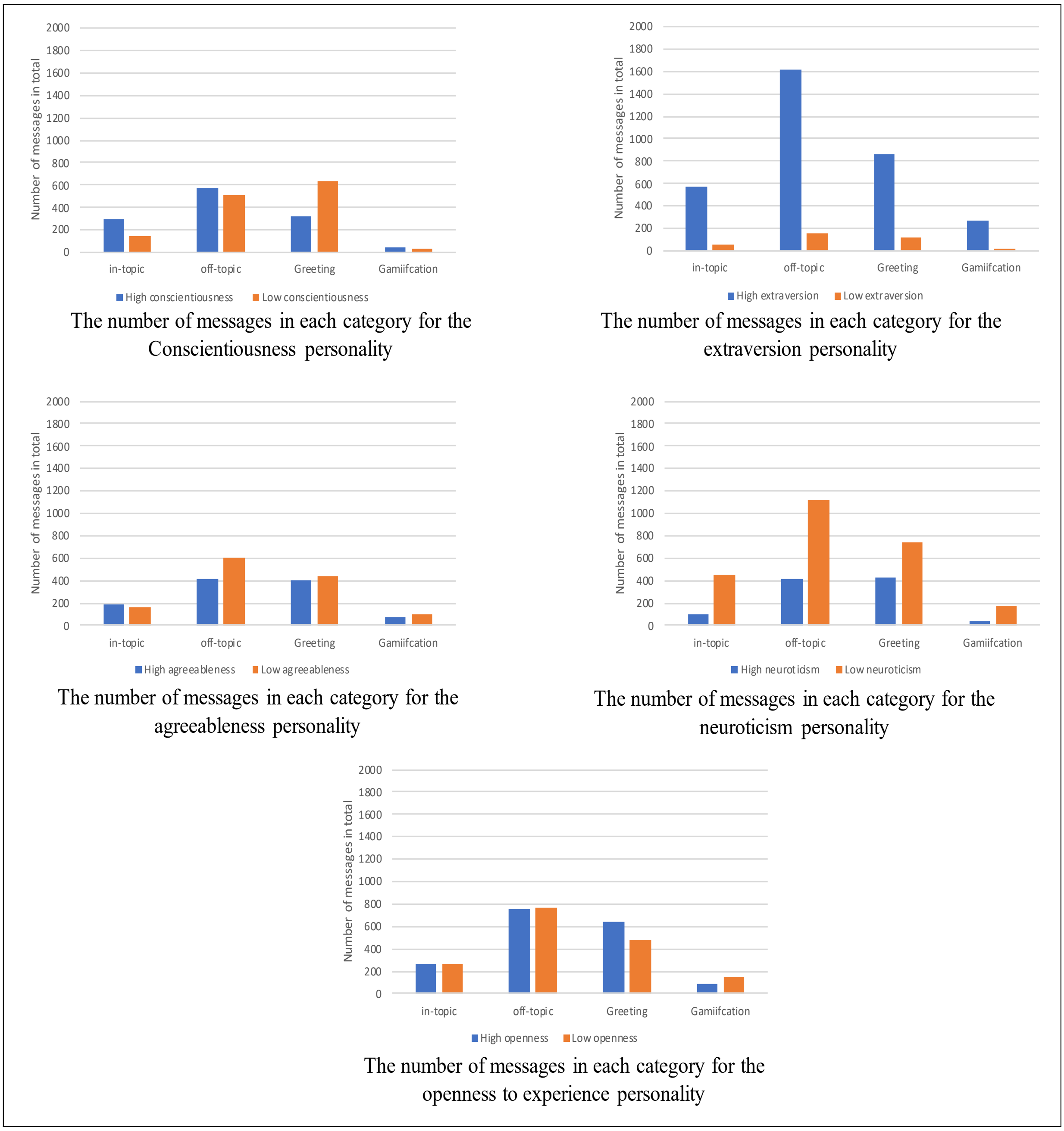


Figure 7.9: An example of the pattern of messages among learners with different personality dimensions.

would use the chat as frequently as they did and that almost 46% of their messages would be off topic. This result might be explained by the positive correlation between the conscientious and agreeable personality dimensions. In addition, the few messages sent by the highly neurotic learners were from those who were both highly neurotic and highly extroverted.

This study conducted several analyses to obtain a greater understanding of the relationship between gamification and personality. We found that most learners enjoyed the gamification elements, and they were motivated by the gamified version. However, the same elements had a negative effect on some personality dimensions, such as high extroversion. The social element distracted these learners, who spent their time chatting about topics unrelated to the course.

Therefore, social gamification elements are important and useful for some learners, such as those with the high extroversion and low neuroticism personality dimensions. The social elements helped them persevere in the course. However, these may need to be controlled. For example, the conversation could be redirected every time the learners discuss topics unrelated to the course. For example, a teacher could say, 'That's enough. Let's talk about the course now'. Another way to control the social elements could be to use them as rewards. For example, the social elements can only be unlocked when the learner achieved a specific number of points.



The number of messages in each category for the Conscientiousness personality

The number of messages in each category for the extraversion personality

The number of messages in each category for the agreeableness personality

The number of messages in each category for the neuroticism personality

The number of messages in each category for the openness to experience personality

Figure 7.10: The number of messages exchanged by each personality dimension, in each code.

7.3 Conclusion

This chapter explained in detail the second experiment, which attempted to understand the relationship between gamification and personality. In this experiment, we tried to examine the effect of the points, badges, leaderboard and social elements on the motivation, knowledge gain and satisfaction of learners.

The results show variations in the learner's response behaviour in using the social elements. Some learners use these elements probably and effectively, which reflects positively on these learners' behaviour. However, there are other groups of learners who may get distracted by integrating the social elements. These learners send so many messages that it negatively affects their knowledge gain. Furthermore, there are learners, such as the highly extrovert ones, who are highly motivated and satisfied with the social elements but their progress is negatively affected. Thus, we can conclude that gamification elements have varied effects on learners with different personality dimensions. In addition, learners with the same personality dimension have different effects on different measurements under the same gamification elements.

The results from this experiment show interesting findings that can be used in further research. For example, it was noticeable that some learners sent a message in each chat opened while other groups of learners would keep on sending messages until they receive a reply. In addition, other personality dimensions know how to control their chats and manage their learning and interaction with others while others may get distracted by the same gamification elements.

Chapter 8

Experiment Three

8.1 Introduction

This chapter is an extension of the previous three chapters aimed to understand the relationship between gamification and personality.

8.2 Experiment 3

In this experiment, a better understanding of how learners with various personality dimensions interact with gamification elements was sought.

8.2.1 Method

This experiment was conducted in the same way as the previous two. However, in the gamified version, different gamification elements, such as points, badges, leaderboards, avatars and motivational phrases were used.

In the gamified version, the presentation of the points, badges and leaderboard was the same as in the first and second experiments. The avatar was presented to the learners as shown in Figure 8.1. In the choosing of the avatar, we aimed to make it generally acceptance by all learners in the same way. We tried to avoid any colours that could be linked to either boys or girls. In addition, in the choosing the avatar, we decided to be presented as a cartoon animal that is common in the country that will hold the experiment. The avatar was presenting at intervals (usually every two minutes) accompanied by a phrase, such as 'You can do it! Don't give up!'. Hence, if the learner spent more than 5 minutes on the same page, then the avatar could be presented to the learners twice.

After obtaining ethical approval from the head teachers, parents and learners, 142 students aged 16-18 years old (64 boys and 78 girls) at four different schools in Saudi Arabia participated in the study. They completed the required registration forms on the website at school and then used the website anytime and anywhere. The participants were made aware that they were free to drop out at any time.

After two months, and after ensuring that no active learners were still using the website, the learners completed a post-test and ELS questionnaire. However, because of several issues, such as school holidays, it was not possible to conduct the second post-tests.

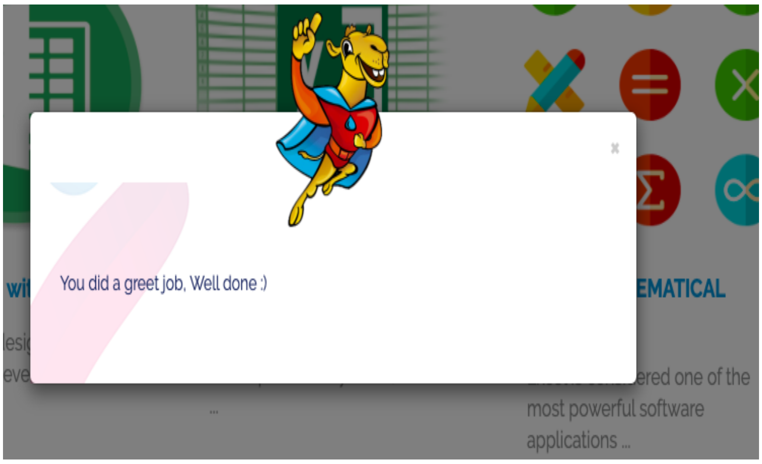


Figure 8.1: Screenshot of the avatar integrated with the gamified version of the website.

8.2.2 Results

As in the first and second experiments, the KM of all learners was plotted (Figure 8.2). It showed that the dropout rate in the non-gamified version was lower than the dropout rate in the gamified version. Next, the Cox hazard was applied to determine whether the difference in the dropout rate was significant (Table 8.1).

The results showed a negative value of the *coef*, indicating that the learners' dropout rate in the non-gamified version was almost 0.87 lower than in the gamified version. However, the difference between the dropout rate in the two versions was not significantly different at a p-value of 0.4.

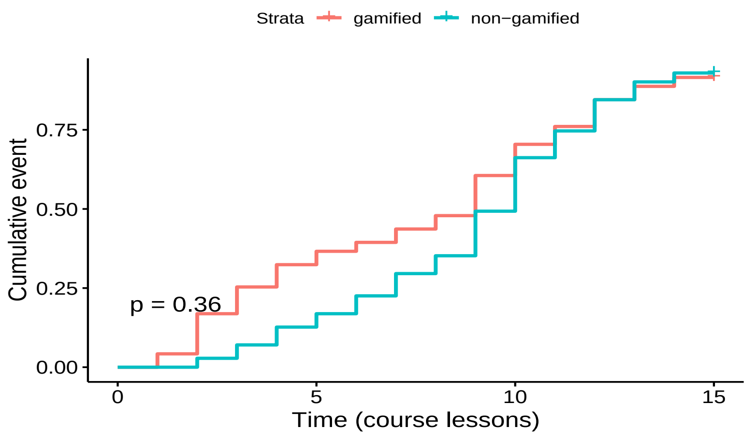


Figure 8.2: KM of the overall learners in the gamified and non-gamified versions in the third experiment.

Table 8.1: The result from Cox regression when it is applied on the overall learners (experiment 3).

	Coef	Exp(coef)=HR	Se(coef)	z	Pr(>|z|)
Version	-0.139	0.87	0.175	-0.795	0.427
Likelihood ratio test= 16.29 on 1 df,				p= 0.36	
Wald test = 16.33 on 1 df,				p= 0.37	
Score (Logrank) test= 18.82 on 1 df				p= 0.4	

In the next step, the KM for the high and low extremes in each personality dimension was plotted (Figures 8.3, 7.5, 8.5, 8.6 and 8.7). Then, the Cox hazard analysis applied (Table 8.2).

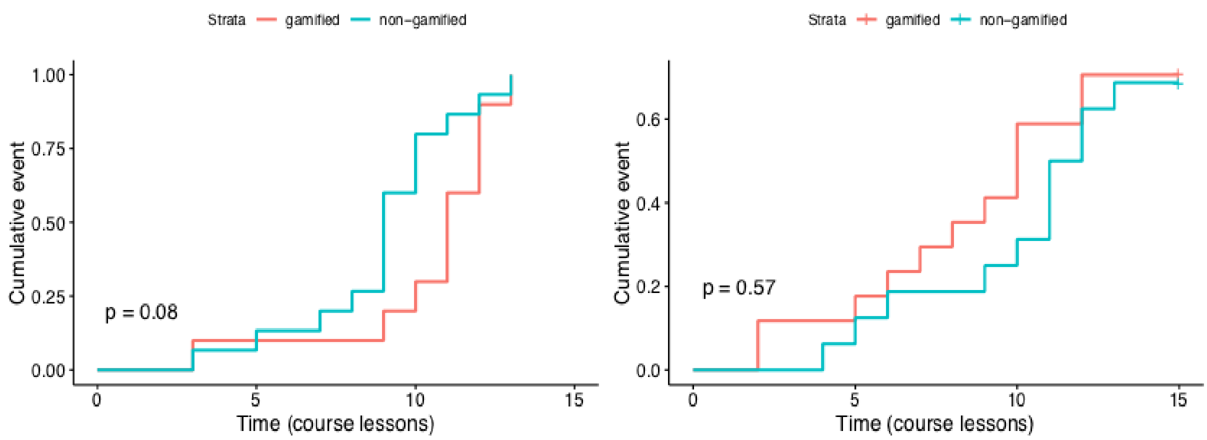


Figure 8.3: KM for the conscientiousness personality (experiment 3): On the left, the KM graph for low conscientious learners, and on the right for high conscientious learners.

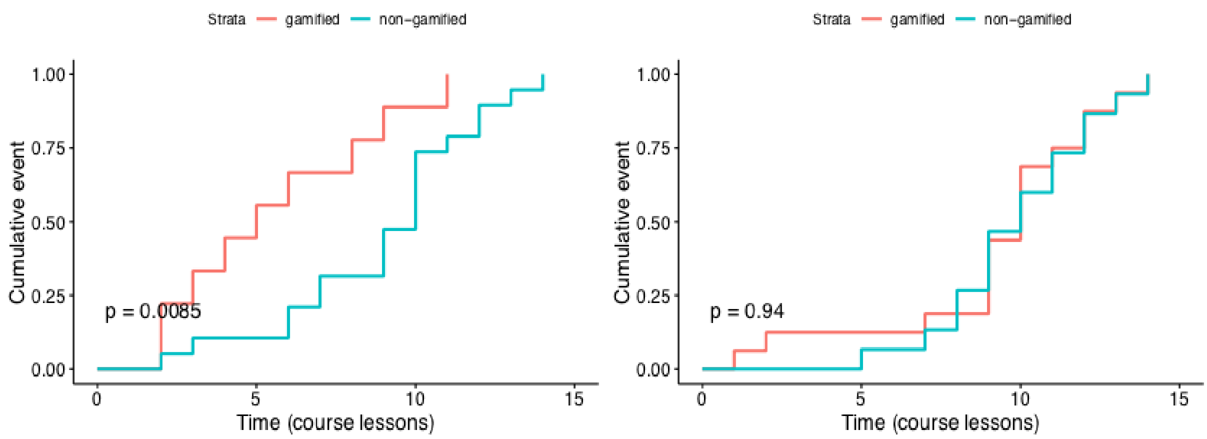


Figure 8.4: KM for the extroversion personality (experiment 3): On the left, the KM graph for low extrovert learners, and on the right for high extrovert learners.

As in the previous experiments, at the end of the experiment, knowledge gain and satisfaction were measured. Table 8.3 and Table 8.4 show summaries of the results regarding knowledge gain and satisfaction levels, respectively, among the different personalities.

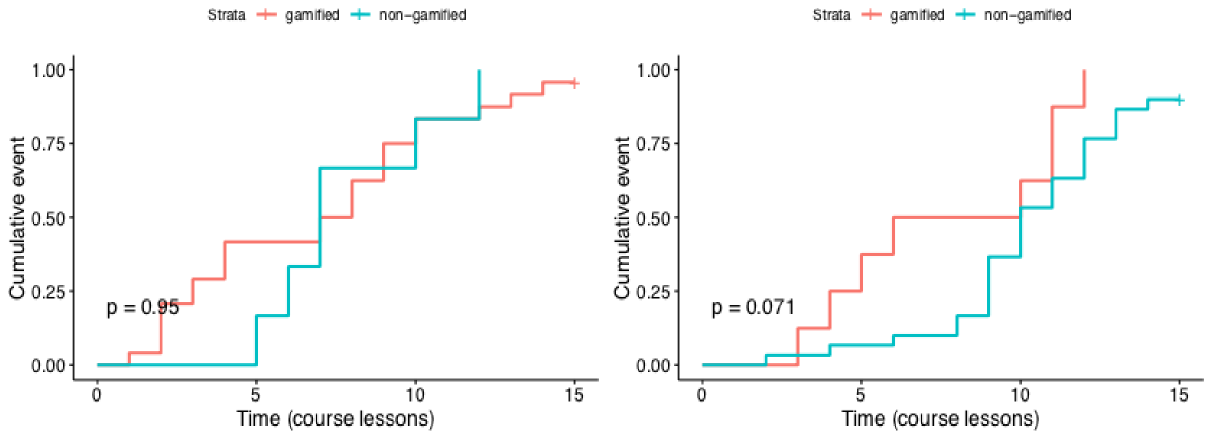


Figure 8.5: KM for the agreeableness personality (experiment 3): On the left, the KM graph for low agreeable learners, and on the right for high agreeable learners.

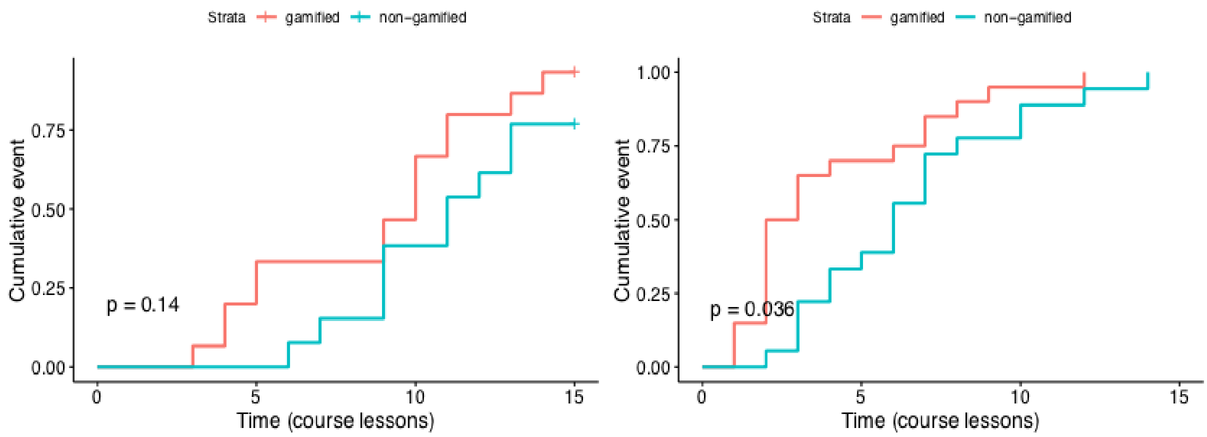


Figure 8.6: KM for the neuroticism personality (experiment 3): On the left, the KM graph for low neurotic learners, and on the right for high neurotic learners.

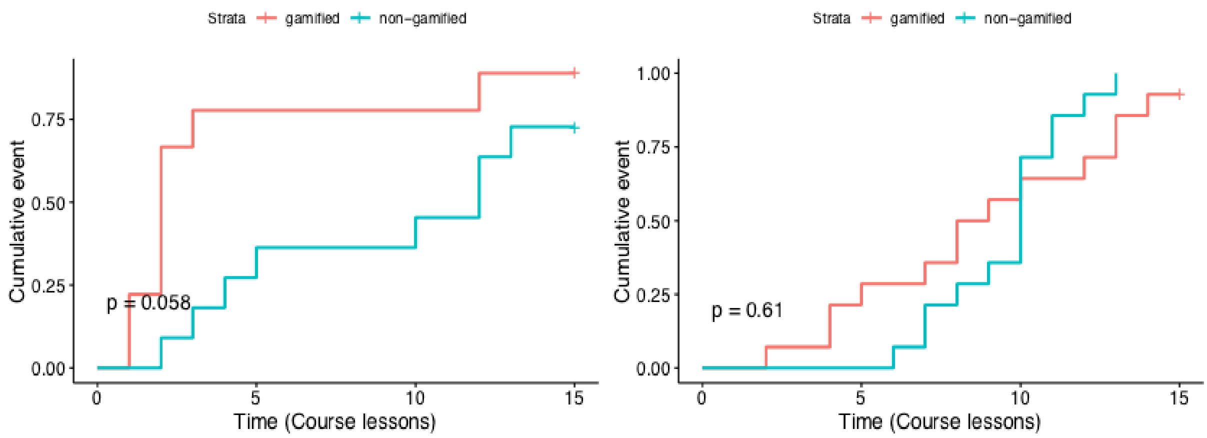


Figure 8.7: KM for the openness to experience personality (experiment 3): On the left, the KM graph for low openness learners, and on the right for high openness learners.

Table 8.2: Summary of the results of Cox hazard model (experiment 3)

Personality	Number of learners	Coef	Exp(coef)=HR	p-value
High conscientious	33	-0.23	0.79	0.6
Low conscientious	25	0.62	1.8	0.08
High extraversion	31	-0.03	0.96	0.9
Low extraversion	28	-1.04	0.35	0.008
High agreeableness	38	-0.73	0.48	0.07
Low agreeableness	30	0.03	0.96	0.9
High neuroticism	38	-0.67	0.5	0.036
Low neuroticism	28	-0.58	0.56	0.14
High openness	28	0.27	1.31	0.61
Low openness	20	-0.97	0.37	0.058

8.2.3 Discussion

Most previous related studies showed the benefits of presenting avatars and motivational phrases (Sheth, 2003); (Falloon, 2010); (Bergmann et al., 2017). Because avatars allowed learners to express themselves and their emotions, they positively affected knowledge gain (Sheth, 2003). Other studies showed improvements in motivation and engagement, especially among users of virtual world games (Falloon, 2010). However, in the present study, no positive effects on the learners' motivation were found with this type of gamification element. Furthermore, the results of the Cox hazard analyses showed that most learners preferred the version without gamification elements. Furthermore, the learners' knowledge gain in the gamified version was lower than that in the non-gamified version.

Most learners did not see a significant benefit of this type of gamification. The findings are summarised below.

Motivation

Most of the learners in our study, regardless of their personality, stayed longer on the non-gamified version. The dropout rate in the non-gamified version was lower than in the gamified version for most personality dimensions (Table 8.2). Learners with low conscientiousness, low agreeableness and high openness personality dimensions were more motivated by the gamified version, whereas learners with other personality dimensions were demotivated by the gamification elements. Highly neurotic learners were also those who disliked them the

Table 8.3: Summary of the average knowledge gained in the gamified and non-gamified versions of the website(experiment 3).

Personality	Total number of learners	Knowledge gain in the gamified version			Knowledge gain in the non-gamified			Benefit from gamification
		N	μ	sd	N	μ	sd	
Overall learners	142	71	0.94	1.64	71	1.33	1.77	-0.39
High conscientiousness	33	17	2.23	1.7	16	2.75	1.6	-0.52
Low conscientiousness	25	11	1.8	1.6	14	0.6	1.05	1.2
High extraversion	31	16	1.375	1.5	15	1.6	2.09	-0.225
Low extraversion	28	11	0.44	0.72	17	1.3	1.29	-0.86
High agreeableness	20	10	0.5	0.75	18	2	1.57	-1.5
Low agreeableness	30	20	0.7	1.6	10	1.3	1.5	-0.6
High neuroticism	38	20	0.05	1.6	18	0.61	1.8	-0.56
Low neuroticism	28	15	1.9	1.7	13	2.23	1.64	-0.33
High openness	28	14	0.57	1.28	14	1.21	1.25	-0.64
Low openness	20	9	0.44	1.5	11	2.09	2.11	-1.65

most and were the most demotivated by them. This finding may have been due to the nature of the design of the avatar in the experiment, which was presented to the learners every two minutes, annoying most of them. However, some learners may not have preferred the avatar used in the experiment.

Knowledge gain

Similar to the results for the learners' motivation, the results for knowledge gain were also negative. Most learners with different personality dimensions did not learn in the gamified version as much as they did in the non-gamified version, as shown in Table 8.3. This result may be explained by the rapid rate of dropouts.

Satisfaction

Learners' satisfaction in the gamified and non-gamified versions were similar, especially among the low conscientiousness learners (Table 8.4). However, some personality dimensions, such as the high and low extroversion learners, preferred the gamified version.

In this experiment, a positive correlation between the effects of gamification on motivation and satisfaction was found. Most of the learners who were not motivated in the gamified version were not satisfied.

Only a few previous studies have been conducted to determine the relationship between avatars and personality dimensions. Jia et al. (2016) found a negative relationship between avatars and high openness users. Where users with this personality described the avatar as an annoying. However, no significant negative effects on the high openness learners was

Table 8.4: Summary of the results of learners' satisfaction with the gamified and non-gamified versions (experiment 3)

Personality	Total number of learners	Satisfaction in the gamified version			Satisfaction in the non-gamified			Benefit from gamification
		N	μ	sd	N	μ	sd	
Overall learners	142	71	6.1	0.63	71	6.07	0.7	0.03
High conscientiousness	33	17	6.33	0.43	16	6.5	0.4	-0.17
Low conscientiousness	25	11	5.75	0.7	14	5.66	0.73	0.09
High extraversion	31	16	6.29	0.69	15	5.9	0.59	0.39
Low extraversion	28	11	6.03	0.67	17	5.8	0.87	0.23
High agreeableness	28	10	5.8	0.91	18	5.9	0.58	-0.1
Low agreeableness	30	20	6.05	0.65	10	6.3	0.54	-0.25
High neuroticism	38	20	6.05	0.46	18	6.15	0.58	-0.1
Low neuroticism	28	15	6.16	0.69	13	6.07	0.9	0.09
High openness	28	14	5.87	0.75	14	5.6	0.93	0.27
Low openness	20	9	6.16	0.35	11	6.38	0.7	-0.22

found. Furthermore, results showed a slight benefit from the gamified version, which may have been due to the different implementations of avatars in the study.

In addition, negative effects of the avatar could be explained by its design and integration into the gamified version. Most gamified online learning systems integrate avatars that can be customized by learners. For example, users can choose the gender and accessories to make it resemble themselves. In some studies, the avatar was presented as a means by which the learner could play a role in a virtual story. As suggested by Vasalou and Joinson (2009), learners usually prefer avatars that are part of their experience in the online learning system. In our study, the avatar in the gamified version was used to present motivational phrases. These phrases were the second factor in demotivating the learners. Some may find the phrases too aggressive and annoying. This supports findings from previous related studies that most users disliked Microsoft Office avatars, such as Clippit (Swartz, 2003). They described these elements as distracting, and they complained about the space they occupied on the screen. Other users disliked it that these characters appeared without permission (Swartz, 2003).

To validate this reasoning, some learners were asked informal questions about their reasons for dropping out (Figure 8.8). The results of this simple questionnaire were used to verify and validate whether the avatars and motivational phrases were the primary reason for the dropout rate.

Based on these findings, we concluded that the integration of the avatar and the motivational phrases had a negative effect on the learners in our sample. This can be explained by the poor design of the avatar in this experiment. For example, the avatar was presented to learners as a static graphic without proper integration into the course. In addition, the same graphic was presented to learners every two minutes. Thus, if the learners spent more than two minutes on the same task, then the graphic would be presented twice. This design can be considered an example of the bad design that implies that gamification may have a negative effect on learners, as shown in Chapter 2 section 2.5.3; 37. The avatar must be chosen and customised by the learner, and it must be a part of the learner's experience in the gamified system.

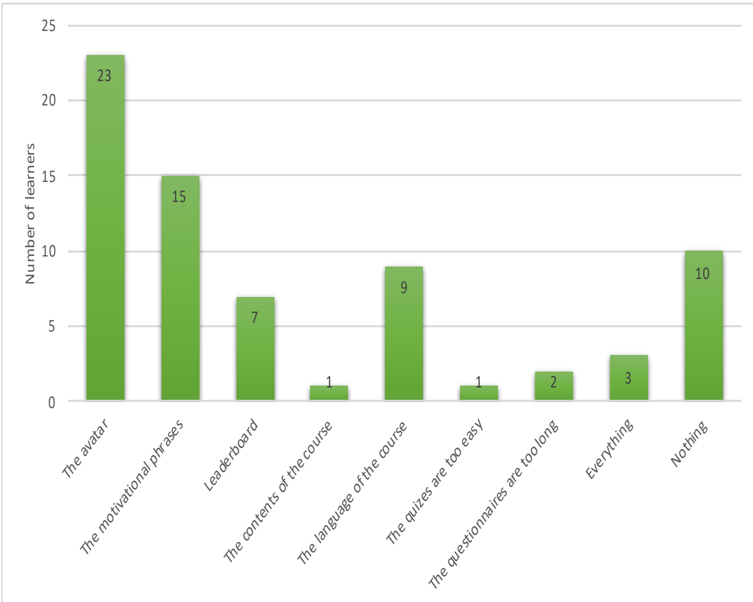


Figure 8.8: Histogram representing the reasons for dropout rates in the third experiment.

8.3 Conclusion

This chapter explained the third experiment that was conducted to understand the relationship between gamification elements and personality dimensions. The results of this study demonstrated that the negative effect of gamification could be clearly presented if the design of the gamification elements was not a part of the course. The avatar in this study was shown to learners in intervals without any relation to the learners' progress in the course.

In the previous three chapters, we ran three studies, each designed to be conducted with a combination of gamification elements. We were aware that this design was not perfect. However, we aimed to understand the effects of most gamification elements, and it was difficult to conduct a separate study of each gamification element. Using this design may affect the reliability of the results. It could not be determined whether positive effects were due to a single or a combination of elements.

We conducted the three studies as between-subject studies. First, the learners registered on the website by filling in three forms: demographic information, a BFI to measure learners' personality dimensions, and a pre-test to measure prior knowledge of the course. Learners were then equally divided into two groups, each of which was balanced in terms of age, gender, personality and prior knowledge level. One group used a version of the website that included gamification elements, and the second group used a version of the website that did not. After the registration, the learners were free to use the websites at any time and in any location, and were free to drop out whenever they wished. We used the dropout rate as a proxy for motivation. After ensuring that all learners had stopped using the website, a post-test to measure their knowledge gain was undertaken, which was calculated by subtracting the results of the pre-test from the results of the post-test. In addition, learners filled in an ELS to measure their satisfaction.

The overall results showed that most of the gamification elements improved the learners' motivation. However, the avatar and motivational phrases (experiment 3) negatively affected it. The results also showed variations in the effects of gamification according to learners' different personality dimensions.

The high and low extremes of each personality dimension were considered because most learners have neutral personality dimensions, and the effects of gamification would thus be the most evident in extreme personality types (Hurtz and Donovan, 2000). Thus, in the three studies, the differences in the effects of gamification on the high and low extremes of the personality dimensions were examined.

The results showed that highly conscientious learners received little benefit from the gamification elements in improving their motivation. However, the low conscientious learners received a significant benefit. The high-extroverted learners received the greatest benefit. These learners were motivated by points, badges and the leaderboard, and their motivation and satisfaction were increased. However, they were distracted by the social element. Although these learners enjoyed and engaged with the social element, it may have been the reason for the reduction in their knowledge gain. The highly agreeable learners were shown to benefit significantly from the gamification elements. These learners stayed longer in the course, and they enjoyed the gamified version. However, the social elements also distracted them.

In contrast, the highly neurotic learners benefited the least from gamification. These learners had almost the same levels of motivation and engagement in the gamified and non-gamified versions in the presence of points, badges, leaderboard and social elements. However, avatars and motivational phrases had a negative effect.

The findings from these experiments can be explained in different ways. The interaction among the personality dimensions plays an important role in changing the results. In these studies, each personality dimension was dealt with individually. However, in reality, the five personality dimensions are combined in individuals based on the FFM (Hofstee, 1994). In addition, these personality dimensions are correlated, which may have affected the reliability of the results. For example, in the first experiment, a positive effect of gamification on the highly neurotic learners was found unexpectedly. This finding was explained by the correlation between the neurotic and extroverted personalities in the sample of learners.

The three experiments were designed conservatively to avoid other variables creating bias in the results. For example, in choosing the avatars, all the learners were presented with the same avatar in the same way. However, regardless of their personality dimension, most learners disliked the avatars and motivational phrases. However, some previous studies suggested that if an avatar were chosen to suit users' characteristics, it might serve to motivate them (Sheth, 2003).

Another factor that must be considered in the analyses of the results is the participants. In the three studies, the learners were high-school students between 16 and 18 years old. These learners may not have had the freedom to use an online learning website at any time and any location. Moreover, these learners may have had other commitments, such as their regular schoolwork.

Furthermore, it is important to note that additional factors could have affected the results. For instance, a learner's context might have had a significant effect. For example, if the learner used the website while surrounded by family and friends, then he or she would be less likely to use the social element. Friendships must also be considered. For example, if the learner was highly conscientious, he or she would encourage friends to complete their studies, regardless of whether they were assigned to the gamified or non-gamified versions of the course.

In addition, several tests were conducted using different measurements, such as motivation, knowledge gain and satisfaction on the high and low extremes for each personality dimension, to understand how these dimensions interacted with different combinations of gamification elements. Different studies argued that the multiple tests may have reduced the accuracy and the validity of the p-value obtained from these tests. Therefore, studies suggest using correction tests, such as the Bonferroni test (Napierala, 2012). However, it may be difficult to apply these correction tests in this thesis for different reasons. One such reason is that, in this thesis, we aimed to build an understanding of which extreme personality benefits from gamification elements. However, if we consider the corrected the p-value, we may find no significant difference between learners' behaviour in the gamified and non-gamified versions. In addition, these tests assume that there is no correlation between the independent variables. However, in the studies, positive correlations were found between some personality dimensions. For example, a correlation between (e.g., the conscientiousness and agreeableness).

The issues discussed herein may have reduced the reliability of the obtained results. However, the variations in the responses of different personality dimensions to the gamification elements indicated that it is worth adapting elements based on the learners' characteristics. In addition, the results showed that personality profiles could be considered a good predictor of learners' behaviour when using gamified systems.

The results also provide us a better understanding for choosing the best gamification elements for each personality dimension. For example, it is not a matter of which version of the online learning website should be given to highly conscientious individuals, because these learners will always do their best. The highly extroverted learners, for instance, should be provided with the most gamification elements, such as the social elements with more control. For instance, a conversation could be started where the topics are unrelated to the course. In these cases, the system must dynamically change and redirect the topic of the conversation.

Chapter 9

Building and Evaluating the Model

9.1 Introduction

Chapter 4 discusses three steps that need to be considered when building a model to match the combination of different gamification elements to learners' personality dimensions: (1) understanding the relationship between them, (2) building the model to match dimensions to the most beneficial elements and (3) evaluating the effectiveness of the model.

Chapters 5, 6,7 and 8 describes three experimental studies that were conducted to understand the relationship between gamification and personality. The results, together with the theoretical findings and the results from the literature, were used to build a prediction model that can match gamification elements to learners' personalities. This chapter presents the steps required to build and evaluate the model.

9.2 Overview

The results obtained from the experiments were used to build an adaptive model (Chapter 6,7 and 8). These experiments were designed as between-subject, which is considered a reliable approach to avoid any learning effect. However, this design increases the random noise and therefore, required more subjects. The results were combined with the literature (Table 3.2) and theory to build an adaptive model. This model predicts the most suitable gamification elements for each learner's personality profile.

After obtaining predictions about the most suitable gamification for each learner, we validate the model with the existing data obtained from the studies in Chapter 5.

The prediction model is then evaluated to examine its effectiveness by using new data obtained from a further study.

9.3 Building the model

Before building the model, we must first gain more understanding of the influence of different combinations of gamification elements on the behaviour of learners with different personality profiles. For this, data from the three experiments were combined. The three studies were conducted using the same approach and by learners with similar profiles, with no change to the contents of the course besides the integration of different gamification elements. The data were then analysed to predict the most suitable gamification elements for each learner's personality dimensions. However, this process was not trivial, and several issues were encountered. One challenge was the correlation between personality dimensions. In the previous studies, we dealt with each dimension individually. However, there are some issues with this. Based on the FFM, each individual's personality profile consists of a combination of the five dimensions (Hofstee, 1994). This occurred in the data, as there were correlations between personality dimensions, which are shown in Table 9.1. In building the model, we accepted this issue and considered to deal with each dimension individually.

Table 9.1: The correlation between personality dimensions.

	Conc.	Extr.	Agree.	Neuro.	Openness
Conc.	1	0.093	0.45	0.028	0.048
Extr.	0.093	1	0.05	-0.24	-0.004
Agree.	0.45	0.05	1	-0.11	-0.012
Neuro.	0.028	-0.24	-0.11	1	-0.1
Openness	0.048	-0.004	-0.012	-0.1	1

In addition, there was another challenge: multiple measurements. In Chapter 6,7 and 8, the effect of gamification on learners using different scales and measurements, such as motivation, knowledge gain and satisfaction, was analysed. In addition, various responses from learners towards these measurements under the same gamification elements were examined. However, it is difficult to build the adaptive model considering these three measurements. We decided to focus on one primary objective (motivation) and make the other two measurements (knowledge gain and satisfaction) secondary objectives. We made this decision because motivation was the primary measurement in the studies. Further, values for knowledge gain and satisfaction were not available in some studies.

We next sought a regular pattern in learners' behaviours when interacting with various combinations of gamification elements. To do this, one of the machine learning algorithms could be used, but these techniques require a large amount of data, which was not available.

To build the model, the data were manually scanned to validate the decision in the previous step and an algorithm for choosing the best version for each combination of personalities was proposed. Course progress was the primary measurement for making this decision. However, if a specific learners with the same personality profile responded the same way under different gamification elements, another measurement, such as knowledge gain or satisfaction, was considered. Algorithm 1 shows the procedure that was followed in the process of choosing the matched gamification elements for each weighted personality:

Algorithm 1: How to choose the best gamification elements.

Result: The best combination of multiple gamification elements
Set *best_version* = *NULL*;
if *there is an entry* **then**
  choose the best version for improving motivation;
  if *the motivation is equal under different gamification elements* **then**
    choose the best version for improving knowledge gain;
  else
    choose the best version for improving satisfaction;
  end

A reliable prediction for matching gamification to learners' personality profiles based on the data was achieved. The model-building design was also supported by theoretical evidence and studies in the literature (Table 3.2). All the results together provide insight into how to assign the most suitable gamification elements to learners based on their personality profiles. Learners who are highly neurotic gained little benefit from gamification; thus, they may require a learning website with no gamification elements. While, learners who are highly extrovert gained a significant benefit from most of the gamification elements.

After building this prediction model to match gamification elements to learners' personalities, predictions needed to be validated. One way to achieve this was by using the data obtained from the studies described in Chapter 5. It may not be scientifically valid to validate the predictions based on the data used to obtain the same model. However, no other data was available for validation. Thus, we used learners' personality dimension scores to build a prediction about learners' behaviour (motivation) in the assigned version. Then the predicted behaviour was compared to the actual behaviour. The agreement between the prediction and the real behaviour was measured using the confusion matrix ((Visa et al., 2011); Table 9.2).

Table 9.2: The confusion matrix

	T	F
P	TP	FP
N	TN	FN

In the table:

TP: true positive; observation is positive (learner is motivated) and predicted as positive.

TN: true negative; observation is negative (learner lacked motivation) and predicted as negative.

FP: false positive; observation is negative and predicted as positive.

FN: false negative; observation is positive and predicted as negative.

We applied the confusion matrix to our data. Table 9.3 shows the results.

Table 9.3: The confusion matrix applied in our data

	T	F	Total
P	211	82	293
N	151	89	240
Total	362	171	533

The accuracy and the overall success rate based on the following formula were then measured: $Overallsuccessrate = \frac{TP+TN}{TP+TN+FN+FP} = 0.68$. The accuracy of the proposed model was good but not perfect as the behaviour of the learners under different gamified versions showed some similarities. Further, some special cases were not covered in the model. Uncommon cases of unexpected correlation between some personality dimensions emerged. For example, if a learner is both highly extroverted and highly neurotic, the model may not recommend the best gamification element for them.

9.4 Evaluating the model

For this purpose, we used a matched/mismatched approach (Ford and Chen, 2001). Learners in both the matched and mismatched groups were provided with the same learning materials. The integrated gamification elements were the only differences between the two groups. In the matched group, the learners were provided with a version that matched their personality profiles (this version could be either integrated with matched gamification elements or lack them). In the mismatched group, the version did not match learners' personality profiles (the learners were provided with mismatched gamification elements or without any). This method was chosen for several reasons (Alshammari, 2016):

- Only a limited number of subjects could be used to evaluate the model's effectiveness.
- This method made it easier to examine whether matching the gamification elements to a personality profile is effective by examining the variations between the matched and mismatched groups.

- By designing the experiment using this approach, the setup could be clearly understood and implemented. As such, the same design used in the previous experimental studies was applied.

- Learners in the matched and mismatched groups were provided with the same learning materials. This eliminates the effect of any possible learning factors.

By using this approach, the aim was to answer this research question:

Does matching a learner's personality profile to the predicted optimal combination of gamification elements improve their motivation, knowledge gain and satisfaction level?

9.4.1 Hypotheses

Three hypotheses were proposed:

H1: Matching a learner's personality profile with the most suitable combination of gamification elements will improve their motivation in comparison to the learners in the mismatched group.

H2: Matching a learner's personality profile with the most suitable combination of gamification elements will improve their knowledge gain in comparison to the learners in the mismatched group.

H3: Matching a learner's personality profile with the most suitable combination of gamification elements will improve their satisfaction in comparison to the learners in the mismatched group.

9.4.2 Method

Setup:

To conduct the study, five versions of an online learning website were designed (`http://i-learn1.study`). They were identical in content and overall presentation. The only difference was in the kinds of gamification elements presented. The course content contained the same lessons presented in Table 5.2. Figure 9.1 shows examples of screenshots from the different versions of the website. In assigning the learners, we realised that the design of the avatar in the third experiment was annoying. As a result, most of the learners were demotivated and dropped out of the course early. Despite this issue, we still want to investigate the effect of the avatar on learners with different personality dimensions. Therefore, we will include avatars in one of the website versions.

- Version 1: includes points and badges.

- Version 2: includes points, badges and a leaderboard.
- Version 3: includes points, badges, a leaderboard and social elements (a chat).
- Version 4: includes points, badges, a leaderboard and avatars.
- Version 5: no gamification elements.

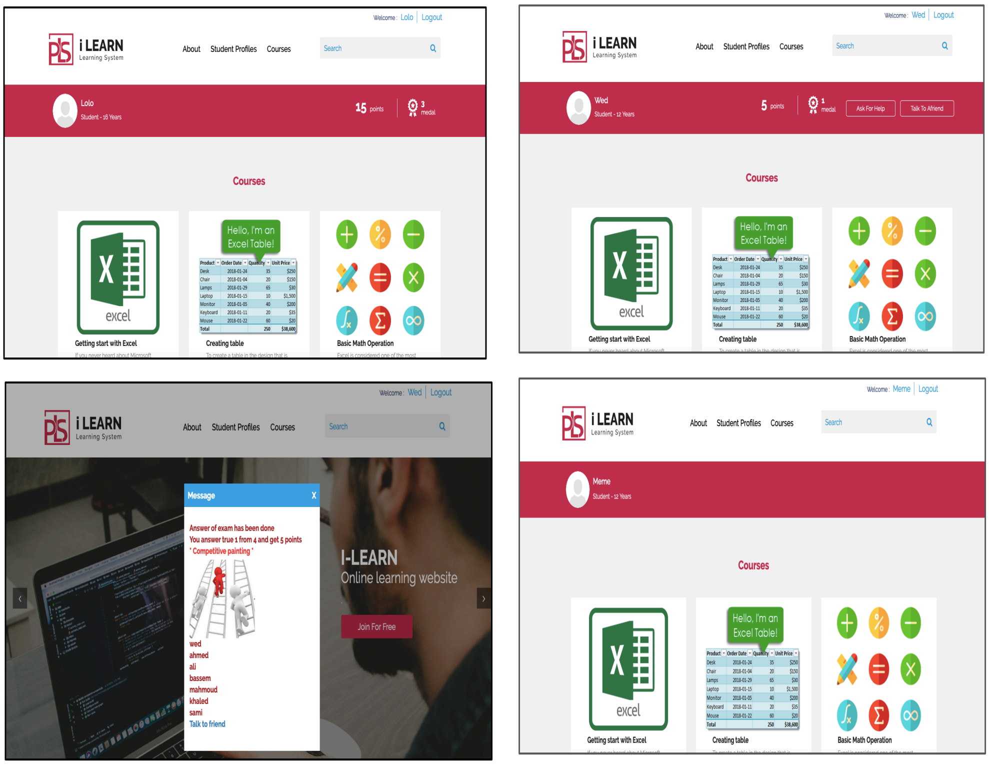


Figure 9.1: Examples of screenshots of integrating different gamification elements into the online learning website.

Participants

370 learners (169 boys and 201 girls) ranging in age from 16 to 18 from six different schools in Saudi Arabia agreed to participate in the study (see Chapter 5 for information about participant selection (Section 5.3.2; page 95)).

To register, the learners completed three forms that are explained in detail in section 5.3.3; page 98.

Measurements

In this study, the following were measured:

- The dropout rates in the matched and mismatched groups. These rates were used as proxies for learner motivation levels.
- Learners' short-term knowledge gain by subtracting the result of the pre-test from the result of the post-test.

- Another post-test to measure long-term knowledge gain, administered two months later.

- An ELS tool to measure satisfaction levels (Wang, 2003).

Procedure

The learners were divided into two equal groups, which were balanced in terms of age, gender, prior knowledge level and personality profile. One group was assigned to a version of the website that best matched their personality profile, as suggested by the model. The second group was assigned to a version of the website that did not match their personality profile. In this group, learners were assigned to the version opposite that which matched their personality profile. If a learner, for instance, had a personality which suggested using points, badges, leaderboards and social elements, then he/she was provided with these gamification elements, while a non-gamified version of the website was provided if the learner was assigned to the mismatched group. It was expected that the worst experiences would be from those who were assigned to the mismatched version.

After being assigned to one of the two groups (matched/mismatched), learners could use the website wherever and whenever they chose. They were free to drop out at any time. While the learners were using the online learning website, their usage was observed, and their dropout rate was recorded as a proxy for their motivation.

In the second version of the website, when the social elements were added, the chat was deliberately presented as optional for learners. This created the same effect as that of the version which lacked this element for the learners who did not use the chat. Thus, in cases where learners had not used the chat by the end of the third lesson, chat sessions were initiated with them. After a welcoming message, we followed learners with the topics they discussed, as in experiment 2 in section 7.2; page 117.

After ensuring that all the learners had either finished the course or dropped out, learners were asked to complete a post-test to measure their short-term knowledge gain. They also completed the ELS to measure their satisfaction level (Wang, 2003). We also aimed to measure learners' long-term knowledge gain since knowledge retention can shift with time. However, it was not possible to run both planned post-tests because the summer holiday was underway. Thus, only one post-test and the ELS were provided to learners after the summer holiday. Figure 9.2 shows the flow of the experiment.

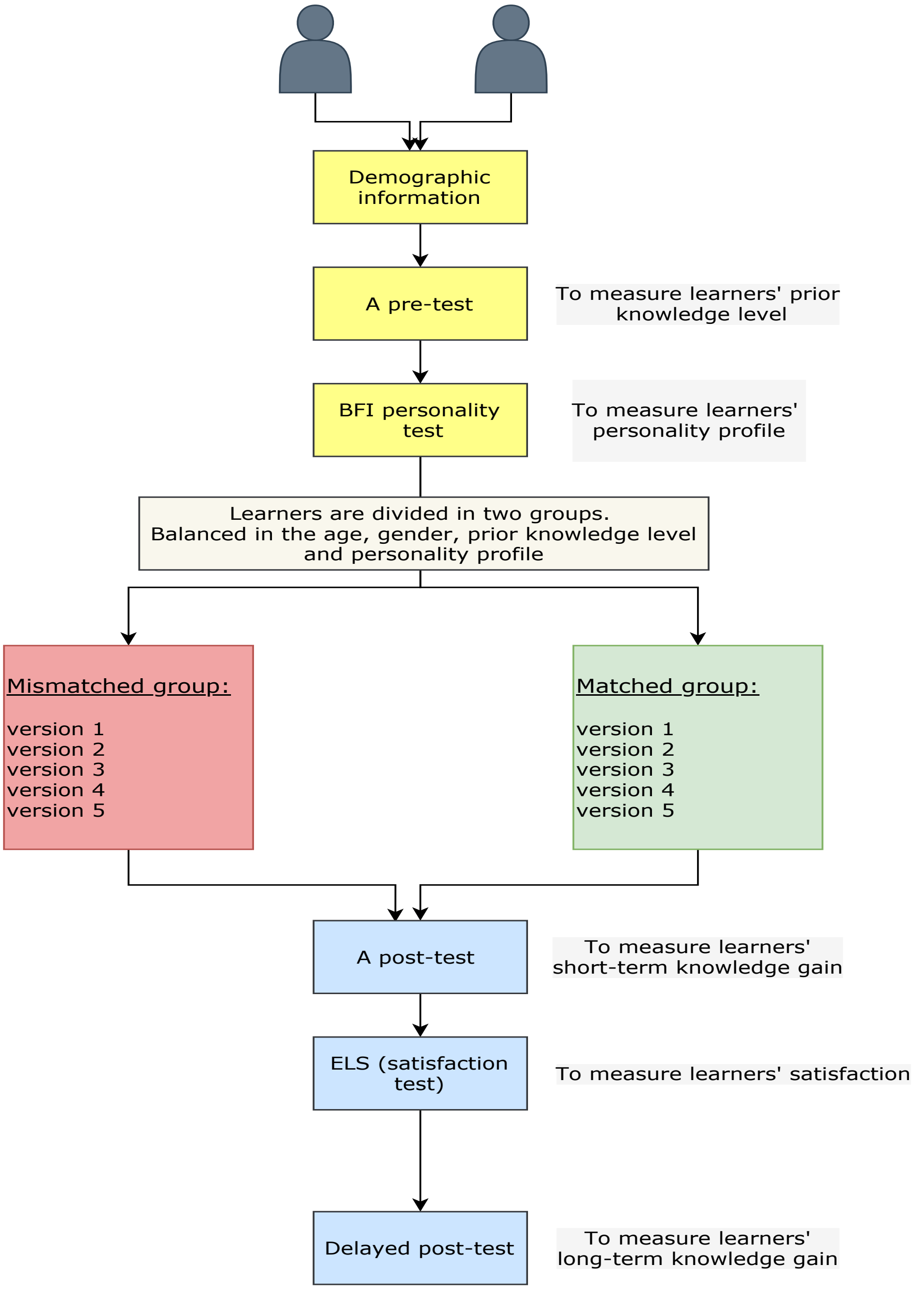


Figure 9.2: The flow of the experiment.

9.4.3 Results

To analyse the data, the cumulative dropout rate for both groups using KM was plotted. Figure 9.3 shows the KM of the dropout rate for learners in the two groups. As seen in the figure, the curve of the learners' dropout rate in the matched group was lower than the dropout curve of the learners in the mismatched group.

To obtain a deeper understanding of the dropout rates, the Cox proportional hazards model was used to examine whether there was a significant difference in the dropout rate between the learners who were assigned a version of the website that matched their personality profile and those who were not. The results of the p-value was <0.0001; indicating that there was a significant difference between learners' dropout in the matched and mismatched groups (Table 9.4).

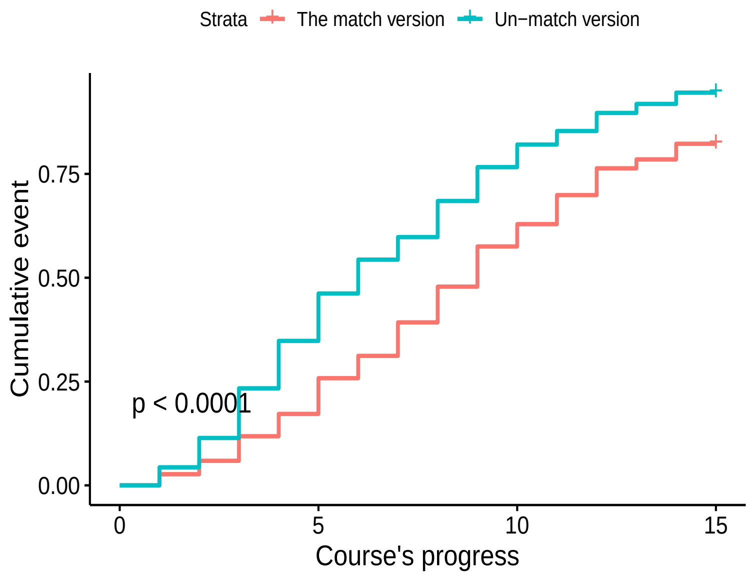


Figure 9.3: The Kaplan-Meier (KM) for the learners in the matched and mismatched groups.

Table 9.4: The result of the Cox hazard.

	Coef	Exp(coef)=HR	Se(coef)	z	Pr(>|z|)
Version	0.5502	1.7336	0.1118	4.921	8.6e-07
Likelihood ratio test= 55.45 on 1 df,				p= 9e-0.7	
Wald test = 55.96 on 1 df,				p= 9e-0.7	
Score (Logrank) test= 55.67 on 1 df				p= 9e-0.7	

We applied unpaired t-tests to examine whether there was a significant difference in the means of the knowledge gain in the matched and mismatched versions. The results from the t-tests provided a p-value = 0.011. This p-value shows the variation between the knowledge gain in the two groups (Table 9.5 and Figure 9.4).

After evaluating the knowledge gain, the same analysis was applied to study learners' satisfaction levels. The p-value from the t-test was 0.097. The results did not show that there was a significant difference between the satisfaction levels in the matched and mismatched groups. Furthermore, the averages of satisfaction in both groups were very similar, and the score was high for both groups. Table 9.6 and Figure 9.5 show the results.

Table 9.5: Summary of the results of the learners' knowledge gain in the two groups.

Knowledge gain in the matched version		Knowledge gain in the mismatched version		Benefit	P-value
μ	σ	μ	σ		
1.56	1.67	0.99	2.09	0.57	0.011

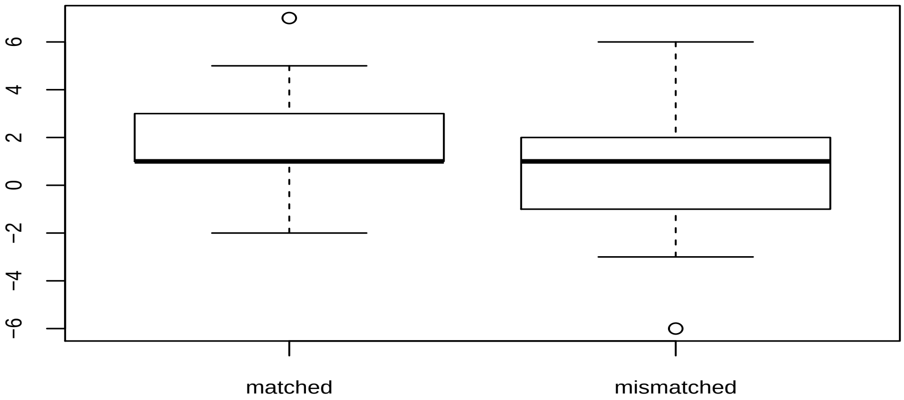


Figure 9.4: Boxplot for learners' knowledge gain.

Table 9.6: Summary of the results of the learners' satisfaction in the two groups.

Satisfaction in the matched version		Satisfaction in the mismatched version		Benefit	P-value
μ	σ	μ	σ		
6.19	0.45	6.10	0.49	0.09	0.097

9.4.4 Discussion

This study aimed to evaluate the effectiveness of the proposed predictive model, which matches a combination of gamification elements to personality profiles. Variations between the behaviours of learners who were assigned to the matched version and learners who were assigned to the mismatched version were compared.

The results supported hypothesis H1 as the proposed model improves learners' motivation. The dropout rate of the learners who were assigned to the matched versions of the website was 1.7 times lower than the dropout rate of the learners who were assigned to the mismatched versions. This indicates that learners' motivation in the matched version was better than it was in the mismatched version. This result was not surprising because the model was built based on the effect of gamification elements on learners' motivations as the primary objective. It is important to note that the positive effect of gamification was clearly presented in the early stages of the lesson. However, at the later stages, learners in both groups were dropping out. This supports what is suggested from literature in Chapter 2 (section 2.5.3) that the effect of gamification can be presented on the short-term and this benefit will be reduced on the long-term (Fernandes and Junior, 2016).

However, highly neurotic learners who were assigned to the version with social elements in

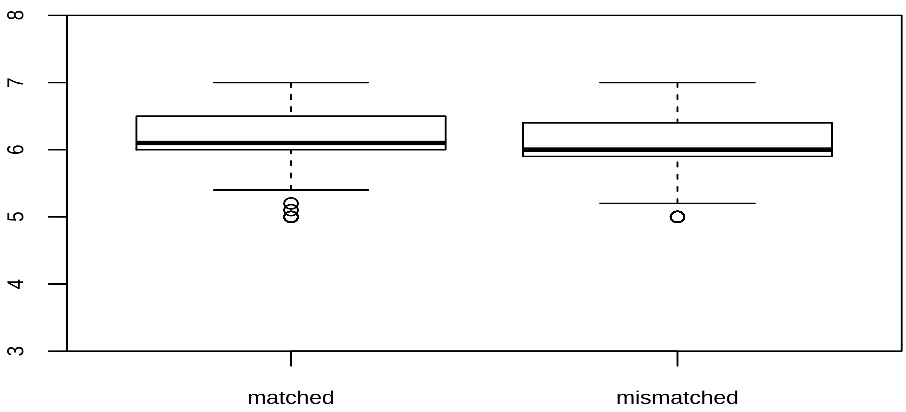


Figure 9.5: Boxplot for learners' satisfaction.

the mismatched version did not drop out as expected. This may have been because the chat was optional, and most of those who were assigned to the social version chose not to use it. This is the same finding that is presented in Chapter 5. In circumstances where the chat had not been used by the end of the third lesson, communication was initiated by the researcher. After exchanging general greetings, some learners (in the mismatched group) stopped using the website. Thus, social elements might be considered a demotivating factor for these learners.

By contrast, learners who were predicted to benefit from social elements (i.e. those who are highly extroverted learners) exhibited a significant benefit from the social version. As in the previous study, these learners sent several messages that were not related to the course.

The results show that learners who were assigned to the matched version of the website benefited by improving their knowledge gain as suggested by hypothesis H2. While the learners in the mismatched version had a higher dropout rate, learners who left the website early would not have learned as much as those who remained enrolled in the course. Thus, measuring the knowledge gain of learners who dropped out and the learners who completed the course may have biased the results. Therefore, it is suggested that the course should be divided into levels so that learners who stop at each level can then be compared with their peers.

In the previous experiments, some highly extroverted learners who were motivated in the course became distracted by the gamification elements, which negatively affected their knowledge gain. To evaluate this, the behaviour of those learners was examined using the correlation between knowledge gain and having an extroverted personality. At 0.06, the correlation was weak in the matched version. This confirmed earlier results, which showed that learners with this personality became more involved in the social elements than in concentrating on the course content. This indicates that providing a static adaptive website with social elements may not be ideal. The adaptation process must be done dynamically, especially when involving social elements, by either redirecting conversations or restricting access to those elements outright for certain learners.

In this study, it was not possible to conduct both post-tests to measure both the short- and long-term knowledge gain. We conducted only one post-test after the summer holiday. This delay can be considered another reason for the significant difference between the knowledge gain in the two groups. Learners in the mismatched group were less likely to be interested in the website; thus, they retained less of the presented material.

The last measurement considered was learners' satisfaction. From the previous experiments and the literature (Chen and Chih, 2011), a clear positive correlation exists between motivation and satisfaction. Our study corroborated this, with most participants who were highly motivated in the matched version also feeling satisfied. However, when the satisfaction levels of the learners in the matched and mismatched groups were compared, no significant difference was found between the learners' satisfaction in each group, as indicated by the p-value (0.097). In hypothesis H3, we proposed that learners' satisfaction in the matched group would be much higher than in the mismatched group. However, there is no enough evidence to support H3. Further, the results cannot be considered a poor result because the satisfaction level in both groups was high. In addition, after learners finished the course, a significant amount of time passed before the satisfaction test was offered (after they had returned from the summer holiday). This may explain the result; learners may have forgotten some of the details of their interaction experiences with the website.

Another limitation of this study is the limited number of gamification elements. We used only the elements that were evaluated in Chapter 6, 7 and 8. Further, we used a combination of gamification elements. The individual effect of these elements cannot be ascertained. Therefore, it is unclear whether a result was caused by a single element or a combination of two or more elements.

The process that is required to build a reliable model is necessarily quite complex; as such, this model is not perfect. Several factors must be considered, such as the correlation between personality dimensions.

9.5 Conclusion

The aim of this chapter was to discuss how to build and evaluate a model that can predict the best combination of gamification elements for a learner's personality profile. In the analysis of the previous experiments in Chapter 6, 7 and 8, learners with average personalities were ignored. Further, each personality dimension was analysed individually. For that, in this study, we used the full score of each personality dimension. After that, the effect of different combinations of gamification elements on the motivation of the learners was reviewed by using the real value of each personality dimension. The focus was motivation as the primary measurement to simplify the process and because some values of the other two measurements (knowledge gain and satisfaction) were not available. In addition, several studies have predicted that improving motivation can be a good tool for improving knowledge gain (Schunk, 2016). Other studies have also observed that there is a positive correlation between motivation and satisfaction level (Chen and Chih, 2011).

We then used the data that were obtained in Chapter 6, 7 and 8 to find a prediction model that was used to match gamification elements to a learner's personality profile. The obtained prediction is supported by the related research studies as well as what is suggested by the theory based on the facets that are associated with each personality dimension. The predictions were evaluated by the existing data, which were obtained from Chapter 5.

Next, it was essential to evaluate the effectiveness of the model. We did this by running a new experiment using the matched/mismatched approach. The results found significant benefit of the model in improving learners' motivation and knowledge gain, while learners reported comparable levels of satisfaction in both groups. This might be explained by the time that had elapsed before learners completed the satisfaction questionnaire (two months after completing the online course). Nevertheless, the learners' satisfaction in both groups was high.

In building this model, the real score of each personality dimension was used. This may be considered an effective approach. However, the correlation between personality dimensions must be considered.

Although the suggested model benefitted the learners, the model is not perfect, and several issues must be resolved. One such issue is the use of a few gamification elements to build the model.

The gamification elements that were used in the proposed model may not be as effective if they are used in areas other than learning or if they are used by other learners. For example, they may not be effective if used by younger children, who may prefer more sounds and animation. Conversely, adult learners may prefer elements that indicate progress, such as bars or levels. Thus, the benefit of this model may be restricted to the kinds of learners in this study. However, we may consider this model a starting point, and we may need to conduct several studies on other groups of learners with various age ranges. These studies were conducted in Saudi Arabia; however, the model may not be effective if used by other groups of learners with different cultures and in different countries.

In addition to learners' ages and cultures, several other factors must be considered in building the model, such as the locations in which learners interacted with the website or the friends who surrounded them at that time. Thus, we may need to consider other attributes that are related to learners and their context in building the final model, as explained in Chapter 4. Further, the model must be implemented dynamically because most of the benefit from the gamification elements affected learners over the short term (Fernandes and Junior, 2016). To avoid this issue, the model must track the learners' motivations and their behaviours towards the gamification elements. If a learner starts to become bored, the system must adapt by either eliminating the existing gamification elements or by providing new ones.

Chapter 10

Conclusions

10.1 Introduction

This chapter summarises the work done in this thesis and provides an answer to the main research questions. The main contributions of the thesis to the field will be discussed and its limitations will be considered. This chapter will also present potential resolutions to these issues for future studies.

10.2 Summary

Online learning is gaining in popularity because of the potential advantages it provides, especially flexibility in time and location (Knowles and Kerkman, 2007); (Anderson, 2008). However, one of the main shortcomings of online learning is the increased number of dropouts as a result of the lack of motivation and engagement felt by learners (Willging and Johnson, 2009). Motivation is a critical factor in the learning process and can be used as a predictor of success (Lee et al., 2013). Several suggestions were made in this thesis regarding techniques that could be used to improve learners' motivation, such as gamification (Filsecker and Hickey, 2014).

Gamification has different meanings depending on its application (Bunchball, 2010); (Huotari and Hamari, 2012). One of the general definitions of gamification, suggested by Domínguez et al. (2013), is the use of game elements in non-game contexts for a specific purpose, such as to change users' behaviour and increase their motivation. Many studies have shown the effectiveness of gamification in improving learners' motivation and engagement in online courses (Simões et al., 2013); (Dennis and O'Toole, 2014). Other studies, however, have identified negative effects, especially in the long term (Dichev et al., 2014); (Jia et al., 2016). For example, some learners found gamification elements to be boring, annoying, or a waste of time (Ferrara, 2013); (Jia et al., 2016).

Because of the varied effects of gamification on users, an adaptive model that can be tailored to an online learner's attributes was proposed. The suggested framework consists of the basic components of any other adaptive model, such as the domain model, the gamification model, the learner model and the context model, discussed in Section 4.3; page 84.

Because of the novelty of the idea of adaptation, considering every attributes of all online learners is difficult. One of the most stable attributes of how learners think and feel is personality (Hofstee, 1994). Section 4.4 showed that the process of adaptation requires several stages: first, the relationship between gamification and personality must be understood; second, the adaptive model must be built; and third, the proposed adaptive model must be evaluated.

Chapter 5 describes three experimental studies conducted to understand the relationship between gamification and personality. In each experiment, different combinations of gamification elements and their effects on learners with different personality dimensions were assessed by measuring the participants' motivation, knowledge gain, and satisfaction. These experiments revealed the variety of effects of gamification.

The results from these three studies were used along with those from related studies in the literature and the suggestions from the characteristics associated with each personality dimension to build the model. Predictions for matching the most suitable gamification elements to learners' personality profiles were considered by examining the data manually and using clustering. We then test the predictions based on the existing data.

To evaluate the effectiveness of the proposed model, we ran a new experiment using a match/mismatch approach. In the matched group, learners were provided with a version from the website that the model predicts matched their personality with a combination of gamification elements or a lack of such elements where certain users disliked them. In the mismatched group, learners were provided with another version from the website in which gamification, or its lack, did not match their personality profile. The results from this experiment showed that those learners in the matched group experienced benefits in terms of improvements in their motivation and knowledge gain.

10.3 Re-visited research questions

The work discussed in this thesis has tried to addressed the following main research question:

How can we adapt gamification elements based on learners' personality profile?

To answer this question, we first needed to answer several smaller research questions. One of these was:

Q1: Do learners with different personality dimensions respond differently to different gamification elements?

To build the model, it was necessary to determine which gamification elements would be beneficial to specific personality dimensions and which would not. To do this, three experiments were conducted using different gamification elements. For each, an online learning website with two versions was built; one version included gamification elements, and the other lacked them. In the first study, the most common gamification elements; points, badges, and a leaderboard, were used. In the second, social elements were added, such as chat. In the third study, avatars and motivational phrases were also used.

In each study, nearly 200 learners registered on the website, filling in their demographic information, BFI and a pre-test to determine their prior knowledge level. The learners were then divided equally into two groups that were balanced with respect to their ages, gender, personality profile and prior knowledge levels. After completing these steps, the learners were free to use the website at any time and in any place. Furthermore, they were free to drop out at any time. During their use of the learning website, the dropout rates were monitored and used as a proxy for motivation and engagement. It was hypothesised that learners who are more motivated by gamification elements would use the gamified version longer. After ensuring that all learners had either finished the course or dropped out, they completed a post-test in order to measure their knowledge gain and then to complete an ELS satisfaction tool to measure their satisfaction level.

The results from these studies showed the varied effects of gamification on the behaviour of learners with different personality dimensions. For example, highly conscientious learners were shown to not receive any significant benefits from any of the gamification elements. The highly neurotic learners also did not benefit from gamification. These learners also sometimes suffered negative effects from some of the gamification elements, such as the avatar. By contrast, highly extroverted learners were shown to benefit the most from gamification. Gamification elements helped these learners stay with the course for longer. However, if not controlled, these elements had the potential to become a distraction for these learners. This was clearly demonstrated in one study in which the extroverted learners who used the website longer were shown to be spending extra time using the social tools to chat rather than concentrating on the learning content. This led to reduced knowledge gain.

The results from the three experiments were also used to answer the following research questions:

Q2: How should an adaptive gamification model be built and evaluated?

Q3: Is matching learners with different personality dimensions to a suitable gamification element beneficial?

After building a significant understanding, we were able to build predictions of the gamification elements most suitable for the different personality dimensions.

One of the challenges in building the model was the interaction between personality dimensions. In previous studies, only the high and low extremes of each personality dimension were analysed, ignoring learners who had an average score. For this reason, we applied a new technique combining the scores from each personality dimension without ignoring any data. We assigned a weight to each personality dimension based on the influence of each personality on the results (course progress). Then, the WSM was used to reduce the score of the five dimensions of personality into a single value.

Next, we aimed to obtain more insight into the interaction between the gamification elements and the learners' personality. One way to do this was by using clustering to determine which gamification elements were most beneficial for each range of weighted personality using the results from the experiments explained in Chapter 5. We also looked through the data manually to find the predictions. These predictions were supported using the results from related research studies in the literature.

The predictions used to build the adaptive model were tested using the existing data from Chapter 5.

Then, we evaluate the model to validate its effectiveness and determine whether it would be beneficial.

A new experiment using the matched/mismatched approach was conducted, as discussed in section 9.4; page 146.

After obtaining ethical agreements from schools, 370 learners participated in the study. They were divided into two groups: the participants in one were assigned the version that matched their personality profile (this version may contain different combinations of gamification elements or none), and the participants in the other group were assigned a version that did not match their personality profile. The groups were evenly balanced in terms of the number of learners and their ages, gender, weighted personality, and prior knowledge levels. The learners were then free to use the website whenever and wherever they liked, and they were free to drop out of the study at any time. The dropout rate was used as a proxy for motivation. Finally, the motivation level, knowledge gain, and satisfaction between the two groups were compared.

The results show that learners who were in the matched group were more motivated and had better knowledge gain than those who were assigned to the mismatched group. In terms of satisfaction, there was no significant difference between the two groups; both groups were highly satisfied.

The proposed model is not perfect, and it requires further updates. This model did not consider special cases of uncommon personality profiles. For example, if a learner is highly extroverted, the model will suggest most of the gamification elements, and if a learner is highly neurotic, the model will remove the elements. The problem emerges if the learner is highly extroverted and highly neurotic at the same time. The model will not be able to determine whether it should or should not provide the gamification elements. An additional problem is that the model was evaluated with learners in a specific age range. In Chapter 4, we suggest that all possible attributes related to the learners and their context in the model be included. This would lead to an answer for the last research question:

Q4: What other attributes should be used in conjunction with personality to best adapt gamification elements?

From the literature and experiments presented in Chapters 5 and 6, several attributes can be integrated with personality and could be considered good predictors of learner behaviour in gamified systems. For example, one of the main influences was learners' level of knowledge about the topic to be taught. Learners could become bored when taking an easy course even if they are matched with suitable gamification elements. Furthermore, previous experience must be considered. For example, whether the learner had used a gamified system before and his/her experiences with it.

Learners' moods and their health are also considered to have a major influence on the results, especially with learners who scored high in more than one dimension of the personality. For example, an unwell extroverted learner might not enjoy the gamification elements as much as other extroverted learners. Learning disabilities or special cases, such as learners with autism and dyslexia, must also be considered. Friendships could also affect the results. For instance, experiencing a gamified learning system at school with one's friends is different from experiencing the same gamified system alone on a train. Besides all elements related to the learner, the context and the physical environment of the learner must also be taken into consideration.

This thesis attempted to build the foundation for an adaptive model that can be used to match gamification elements to learners' personality.

10.4 Summary of contributions

Section 1.5; page 6 discussed the main contributions of this thesis to the literature and whether the results can be widely generalised. The contributions of this study can be divided into two main sections: how different personality dimensions interact with gamification elements and how the adaptive model can be built and evaluated.

10.4.1 Understanding the relationship between gamification and personality dimensions

The main aim of this study was to find rules for making predictions regarding how different personality dimensions interact with different gamification elements. This step was considered essential for building an adaptation model that uses personality.

A few studies have tried to understand the relationship between gamification and personality dimensions (Codish and Ravid, 2014a); (Codish and Ravid, 2014b); (Jia et al., 2016); (Tondello et al., 2017b). However, the methods and tools used in these studies suffered from reliability issues, discussed in detail in section 5.2; page 91. This thesis contributes to the field by offering a more objective approach that can be used to understand how different personalities interact with different combinations of gamification elements.

Because the methodology used here was different, a new kind of analysis to review data and reach a conclusion was needed. One of the statistical tests used to measure the difference in the motivation of the learners in the gamified and non-gamified versions was survival analysis. Two functions of survival analysis were used: the KM estimator and the Cox hazard model. Finally, the difference between knowledge gain and satisfaction in the two groups was measured.

In addition to the novel method used, the results presented in this thesis may serve as a basis for further research in the field.

A number of papers regarding this understanding of the relationship between gamification and personalities have been accepted and/or published, as presented in Section 1.6; page 7.

10.4.2 Building and evaluating the model

Chapter 4 discussed the general adaptive model framework that can be used as a basis for building further adaptive models. This framework requires that the adaptive model be implemented dynamically. This means that the adaptive system must adjust to any changes in the learner's behaviour. For example, if the learner starts to get bored, the system must provide a new gamification element. If the learner becomes distracted, the system should control the gamification element or block it.

However, at the current stage, not all learner and context attributes could be included in building the adaptation model. This is because of the limited number of studies available at the start of this research that examined the influence of gamification on learners. For this reason, we chose to adapt the gamification elements to personality. The results presented in Chapter 5 were then used in combination with those from other related studies to build the adaptive model. The suggestions from theories based on the characteristics associated with each personality dimension were considered.

After building the adaptive model, we examined the effectiveness of this model for improving learner experience. The results showed the positive effects of the adaptive model in improving learners' motivation and knowledge gain. Thus, another contribution of this thesis is that it determined that gamification elements are worth adapting, as this model can be beneficial for learners.

10.5 Limitations of the research

This research has some limitations that should be addressed and avoided in future research. In the experiments presented in Chapters 5 and 6, the contents of the domain model were fixed, as the domain model was not the focus. The experiments presented a particular course related to Microsoft Excel, and the course was presented to all learners in the same way and in the same order. However, learners have different preferences in receiving the contents of the course and have individual knowledge levels. Studies show that personalising the contents of the course based on learners' knowledge level and learning style can improve the learning outcome (Brown, 2007); (Alshammari, 2016).

The system in this research is delivered to users via any web browser. However, the mobility of the courses, such as whether learners can access the lessons at any time, from anywhere and using any connected device, should be considered. Thus, we suggest including mobile learning in designing similar studies. It is also important to mention that the course must be adjustable for presentation on any mobile or tablet screen.

At the beginning of the research, three experimental studies were conducted to understand the relationship between gamification and personality. Each of the studies had some limitations, which were discussed in Chapter 5. For example, a limited number of gamification elements were used, and the design of these elements was conservative. Furthermore, in each of these studies, a combination of gamification elements was integrated into the course. This may not be the ideal way to design a study on the subject because it makes it difficult to determine the gamification elements that motivated the learners; that is, were they motivated by individual gamification elements or by a combination of elements?

In the second experiment, the ability to chat was added. However, this feature was optional and required the learner to take the initiative. Learners unknowingly talking to the researchers. The researchers followed any topic introduced by the learner, which may be boring for some learners.

In the third experiment, the use of an avatar and motivational phrases were integrated. However, presenting the same avatar might annoy some learners, as argued by Sheth (2003). An avatar might be considered useless, particularly if the avatar is not representative of the learner and is not a part of their experience.

In the studies presented in Chapter 5, the scores for each personality dimension were classified into high, average, or low. We then applied statistical analyses only to the high and low extremes, ignoring learners who were in the middle. However, this may not have been ideal because participants who scored as average in each personality dimension were not included in the analysis (Altman and Royston, 2006); (Royston et al., 2006). Another limitation of the studies is the correlation between personalities, which was not considered. The concern is that this correlation may have an effect on learners' behaviour toward gamification elements.

One of the measurements used to examine the relationship between gamification and personality was the difference in knowledge gain between learners in the gamified and non-gamified versions. However, this may be considered a problem because of the variation in the number of learners who dropped out in each condition. Some learners did well on the pre-test but dropped out in the earlier stages of the course. This gives these learners less space to grow in the post-test.

To build the model, the results of all the experiments were combined. However, these studies were conducted with different learners in different time periods, which increased the noise. We also included the results from related research, despite lacking detailed explanations of the procedures those studies used for obtaining and classifying the personality types.

The proposed model is not perfect and has several issues. It does not consider learners who may be special cases, such as learners who are both highly extroverted and highly neurotic.

In addition, there were some personality dimensions that were not significantly affected by the gamification elements employed. For example, there was insufficient data to build a prediction for the personality dimensions of agreeableness and openness. The model also did not consider other learner characteristics, such as the learner's mood or disability. These learners may need to have gamification elements that are designed in a special way that are neither annoying nor harmful to them.

A further concern is that the effectiveness of the model may be restricted to learners within a specific age range. This model might not be effective if it is used by younger or older learners. The effectiveness of the model might also be affected by other learner characteristics, such as culture, gender and emotion (Klock et al., 2015), as discussed in section 3.3.1; page 71. The proposed model was evaluated for the short-term only, leaving the possibility that the benefits of gamification may be reduced in the long-term (Fernandes and Junior, 2016).

10.6 Future Works

Thus, the current study has several limitations, and addressing these limitations in future research is essential. It is important to mention that the personalisation of gamification elements is challenging. There are different gamification elements that were not considered in this study. Thus, we suggest further studies be done with more gamification elements, such as levels, a progress bar, and rewards. Furthermore, a new classification for integrating gamification elements based on the cost of these elements on learners' time, for example, could be introduced; in designing the present study, points, badges, and leaderboards do not cost learners anything, and no action from learners is needed to engage with these elements. Thus, these elements and similar ones, such as progress bars, may be classified as basic, whereas social elements, including the ability to chat or discussion boards, can be costlier to learners and classified as 'social'. Another classification is based on customisation, which includes elements that require learners' imaginations and the interpretation of their preferences, such as choosing avatars or building a story. Thus, when users start using the system, they will be provided with the basic elements; after each improvement, the cost of the gamification can be increased. During usage, the system needs constant evaluation for any reduction in the learner's achievement, at which point the integrated gamification elements should be removed.

In the second experiment (section 7.2), the chat had been added. The design of the chat can be improved by establishing a script that contains rules on how to reply to learners. The introduction of scripts that are beneficial for different personality dimensions can be considered another area of research requiring further investigation. This could involve several studies on how different personality dimensions respond to different topics. The understanding gained could be used later to build an adaptive social interaction system based on personality. Such adaptation could be quite effective in any automated chat systems to reply to users by selecting replies to users in a way that will be more suitable and attractive to them.

The adaptive chat must be built dynamically. The system must observe the learner's behaviour within the system by monitoring their achievement and scores on the small quizzes throughout the course and by monitoring the time spent on the chat function. In these cases, if the learner is struggling with the course or a part of it, the system can either block social features or introduce topics that can enhance the learner's outcomes. If the user shows satisfactory progress, then the social features can be provided as a reward

The chat can also be designed to be a live chat that allows the learner to interact with his or her peers in real time. Learners may also be allowed to establish a group chat with groups of more than two learners. The role of the teacher or administrator would be to observe the conversation and control it to mitigate any risk (e.g. learners having off-topic discussions that may affect their achievement). This approach can give learners the feeling of being in a physical classroom in which a real teacher allows students to talk and collaborate and only interferes if students are struggling or have become distracted.

In the third experiment (section 8.2), avatars and motivational phrases were used. The design of the avatar can be improved by giving learners the freedom to customise their avatar, such as by choosing its gender and accessories. The avatar can be set up at the time of registration and can follow the learner through all stages of learning, becoming an integral part of the experience. It could, for example, celebrate or perform specific actions when the learner gains a point or earns a badge. Additionally, learners could collect badges to purchase customisations or accessories for their avatars. This can lead to enhanced motivation for some learners who enjoy this feature.

The motivational phrases can also be personalised to include the ideal phrases to motivate learners with specific personality dimensions. For example, some learners prefer to have words or expressions, such as 'Carry on! You are doing great', whereas other learners intensely dislike these phrases and consider them to be 'too pushy and annoying'. Others may prefer to have phrases that remind them of their actual progress, such as 'You've finished three lessons, and now you need to finish only five more!' These expressions need more investigation and can be considered a new area of research. The motivational phrases themselves must also be adapted to different personality dimensions. This can be done by understanding the preferred motivational phrases for each personality dimension.

In building the model, several objectives should be considered, such as improving learner motivation, knowledge gain, and satisfaction. Measuring these makes the process of decision-making more critical. In this thesis, the focus was on one primary objective: improving learners' motivation. It was expected that the model would improve learners' motivation. However, this model may not necessarily improve the learners' knowledge gain and satisfaction. Accordingly, if we had focused on improving knowledge gain or satisfaction, the model may not necessarily improve learners' motivation. Thus, it may be better to include all measurements and consider multiple-criteria decision analyses in building future models. Advanced techniques can be used to consider the three objectives, such as value-focused thinking. Value-focused thinking can be used to choose the best alternative or version for each personality in order to accomplish a specific objective [see (Keeney, 1996a); (Keeney, 1996b); (Kajanus et al., 2004); (Sheng et al., 2005)]

Building a static adaptive model is not ideal. The proposed model may be effective strictly in the learning domain and for learners of a specific age and of a specific culture, for example. For this reason, we may need to re-evaluate the model and examine how different contexts can influence its effectiveness and the user's experience. It may be necessary to use another group of users to evaluate the model with different applications.

Additionally, other attributes of learners must be considered. In this research, we chose to use personality as it is more stable. However, even if a user has a stable personality profile, their preferences may change over time. For example, if the learning system provides a long course with similar users, these users can communicate and discuss ideas. This may improve the motivation of some users, who may have disliked the social elements at the beginning. Another example is the highly introverted learner, who may dislike social elements; when they feel more confident, they may engage more with the social elements and grow to like them.

Further, evaluation of the model can be done by using other measurements, such as the number of clicks on the points or the badge icon or by using the time spent in the chat window compared with the time spent in the course, which is important to examine whether the learner spent their time chatting or studying. In particular, social elements can have a different long-term effect on learners. Learners may still be motivated by social elements if they discuss various topics. The leaderboard can also play a role in motivating users, such as in health-tracking systems where the user can choose different communities and can compete within them by, for example, walking a certain number of steps or performing a certain number of minutes of exercise.

We anticipated that learners would drop out under both conditions. One possible means to support this conclusion is by using qualitative analysis, such as through interviewing learners who dropped out and asking them about their reason for doing so. Using a mixed-method (quantitative and qualitative) approach in analysing the data will make it more reliable.

Few studies have attempted to address the long-term effects of gamification and adaptive gamification systems. Given the previous issues, it could be argued that we should build an adaptive model that is semi- or fully adaptable in the long-term by the users themselves. In this scenario, if the learner feels bored, they will have the ability to go into the system settings and change the gamification elements. Thus, the system is only responsible for matching the initial elements. Another possible way is to give the user full control in choosing the elements and their presentation from the beginning. The role of the model in this design is to provide suggestions to users. For example, some messages can be presented, such as 'You can now talk to your friend. Click on this button to try'.

This research and other similar ones can be used together to build an intelligent recommender system that can use the collaborative-filtering approach. By using this approach, a group of similar learners can be provided with gamification elements that are beneficial to them.

Gamification has been shown to have diverse effects on users. Adapting gamification elements may improve the user's experience in the short- and long-term. However, there is still a risk that users will be demotivated and no longer engaged after removing gamification elements, as argued by Wilson et al. (2015). They point out that some users stop doing exercises after gamification elements are removed. Furthermore, the adaptive gamification model must ensure that users are intrinsically motivated, so users will continue using the learning system even when there are no integrated gamification elements. One way to do this is by frequently adding and blocking the user's access to the gamification elements and consistently evaluating the system to measure the motivation and ability of users to complete the activities without gamification elements.

10.7 Conclusion

Motivation was considered an important factor in success in the online learning environment. Gamification was introduced in the online learning courses to increase learners' motivation. However, users are different, and their responses to gamification are also different. Some learners enjoy these elements, and others do not. From this viewpoint, this thesis aimed to build a model that can be used to adapt gamification elements to learners' personalities. Several experiments to examine the relationship between different gamification elements and different learners' personality dimensions were conducted. The results were added to the results from similar research to build a model that matches personality dimensions to the best gamification elements. The proposed model was shown to be beneficial for improving learner motivation and knowledge gain with the online learning environment in the short-term.

The idea of adapting gamification elements is still new and has been recently considered by different studies. This thesis has shown the effectiveness of adapting gamification elements to online learners' personality. The results from this thesis can be generalised in fields other than learning. Furthermore, this research can be considered as a starting point for further investigation that includes other attributes related to learner and their context for building a dynamic adaptive gamification model that can ensure users have the best possible experience with any gamified system.

Appendix A

Big Five Inventory (BFI)

Here are some statements that may or may not describe what you are like. Please choose the number that shows how much you agree or disagree that it describes you. For example, do you agree that you are someone who is bossy? Write a 5 if you agree strongly, a 4 if you agree a little, a 3 if you neither agree nor disagree, a 2 if you disagree a little, or a 1 if you disagree strongly. Ask if you don't know what a word means!

Statements	**The level of agreement**				
I am someone who ……………………	**Strongly disagree**	**Disagree a little**	**Neither agree or disagree**	**Agree a little**	**Strongly agree**
	1	**2**	**3**	**4**	**5**
1. Is talkative					
2. Tends to find fault with others					
3. Does things carefully and completely					
4. Is depressed, blue					
5. Is original, comes up with new ideas					
6. Reserved; keeps thoughts and feelings to self					
7. Is helpful and unselfish with others					
8. Can be somewhat careless					
9. Is relaxed, handles stress well.					
10. Is curious about many different things					
11. Is full of energy					
12. Starts quarrels with others					
13. Is a reliable worker					
14. Can be tense					
15. Is clever, thinks a lot					
16. Generates a lot of enthusiasm					
17. Has a forgiving nature					
18. Tends to be disorganized					
19. Worries a lot					
20. Has an active imagination					
21. Tends to be quiet					
22. Is generally trusting					
23. Tends to be lazy					
24. Doesn't get easily upset, emotionally table					
25. Is creative and inventive					
26. Takes charge, has an assertive personality					

27. Can be cold and distant with others					
28. Keeps working until things are done					
29. Can be moody					
30. Likes artistic and creative experiences					
31. Is sometimes shy, inhibited					
32. Is considerate and kind to almost everyone					
33. Does things efficiently (quickly and correctly)					
34. Stays calm in tense situations					
35. Likes work that is the same every time (routine)					
36. Is outgoing, sociable					
37. Is sometimes rude to others					
38. Makes plans and sticks to them					
39. Gets nervous easily					
40. Likes to think and play with ideas					
41. Doesn't like artistic things (plays, music)					
42. Likes to cooperate; goes along with others					
43. Is easily distracted; has trouble paying attention					
44. Knows a lot about art, music, or books					
45. Is the kind of person almost everyone likes					
46. People really enjoy spending time with me					

Appendix B

A typical example of pre- and post- test

Please answer the following questions:

Question	Available answer
▪ Microsoft Excel is ………….	• A graphical word processing program that user can type with. • An electronic spreadsheet that is used for sorting, organising, and manipulating data. • A presentation software used to create and show slides. • I don't know
▪ In Microsoft Excel, an active cell means…………..	• Any cell in the sheet. • B2. • A selected cell with a thick border. • I don't know.
▪ The name of the cell placed in the fifth row and column D is ……………	• D5 • 5D • D.5 • I don't know
▪ Which of the following functions is not entered correctly……..	• =10+14. • =B7+10. • 10+12. • I don't know.
▪ Which of the functions below calculates the result of adding all number in a row:	• TOTAL. • SUM. • ADD. • I don't know.
▪ If A is TRUE and B is TRUE, then the result of A XOR B is ..	• TRUE . • FALSE . • #ERROR . • I don't know.
▪ What is the result of 1+2*3-2	• 3 • 7 • 5 • I don't know
▪ Setting a password in your workbook means ..	• You can view the worksheet to print and read only. • You can open the workbook but you cannot edit the worksheet, except if you have the password. • You cannot open the workbook except if you have the password. • I don't know.

Appendix C

E-learner satisfaction tool (ELS):

	Statement	The level of satisfaction						
		Extremely Dissatisfied 1	2	3	4	5	6	Extremely Satisfied 7
System Interface	• The e-learning system is easy to use.							
	• The e-learning system is user-friendly.							
	• The content provided by the e-learning system is easy to understand.							
	• The operation of the e-learning system is stable.							
	• The e-learning system makes it easy for you to find the content you need.							
Learning contents	• The e-learning system provides up-to-date content.							
	• The e-learning system provides content that exactly fits your needs.							
	• The e-learning system provides sufficient content.							
	• The e-learning system provides useful content.							
Personalisation	• The e-learning system enables you to learn the content you need.							
	• The e-learning system enables you to choose what you want to learn.							
	• The e-learning system enables you to control your learning progress.							
	• The e-learning system records your learning progress and performance.							

Bibliography

Adams, M. and Makramalla, M. (2015). Cybersecurity skills training: An attacker-centric gamified approach. *Technology Innovation Management Review*, 5:5–14.

Alexander, P. A., Schallert, D. L., and Reynolds, R. E. (2009). What is learning anyway? a topographical perspective considered. *Educational Psychologist*, 44(3):176–192.

Allen, I. and Seaman, J. (2008). Staying the course online education in United States. United States of America: Sloan Consortium. Retrieved November 16.

Allgulander, C. and Fisher, L. (1986). Survival analysis (or time to an event analysis), and the cox regression model-methods for longitudinal psychiatric research. *Acta Psychiatrica Scandinavica*, 74(6):529–535.

Ally, M. (2004). Foundations of educational theory for online learning. *Theory and Practice of Online Learning*, 2:15–44.

Alshammari, M. (2016). *Adaptation based on learning style and knowledge level in e-learning systems*. PhD thesis, University of Birmingham.

Alshammari, M., Anane, R., and Hendley, R. J. (2014). Adaptivity in e-learning systems. In *Eighth International Conference on Complex, Intelligent and Software Intensive Systems*, pages 79–86. IEEE.

Altman, D. G. and Royston, P. (2006). The cost of dichotomising continuous variables. *BMJ*, 332(7549):1080.

Aluja, A., Garcıa, O., Rossier, J., and Garcıa, L. F. (2005). Comparison of the NEO-FFI, the NEO-FFI-R and an alternative short version of the NEO-PI-R (NEO-60) in Swiss and Spanish samples. *Personality and Individual Differences*, 38(3):591–604.

Alvarez, J. and Djaouti, D. (2011). An introduction to serious game definitions and concepts. *Serious Games & Simulation for Risks Management*, 11:11–15.

Anderson, J. R. (2010). *Learning and memory: An integrated approach*. Wiley, New York.

Anderson, T. (2004). Towards a theory of online learning. *Theory and Practice of Online Learning*, 2:109–119.

Anderson, T. (2008). *Theory and practice of online learning*. Athabasca University Press, Edmonton.

Andrade, F. R., Mizoguchi, R., and Isotani, S. (2016). The bright and dark sides of gamification. In *International conference on intelligent tutoring systems*, pages 176–186. Springer.

Appleton, J. J., Christenson, S. L., Kim, D., and Reschly, A. L. (2006). Measuring cognitive and psychological engagement: Validation of the student engagement instrument. *Journal of School Psychology*, 44(5):427–445.

Aroyo, L., Dolog, P., Houben, G.-J., Kravcik, M., Naeve, A., Nilsson, M., and Wild, F. (2006). Interoperability in personalized adaptive learning. *Journal of Educational Technology & Society*, 9(2):4–18.

Bailey, J. E. and Pearson, S. W. (1983). Development of a tool for measuring and analyzing computer user satisfaction. *Management Science*, 29(5):530–545.

Bakic, J., De Raedt, R., Jepma, M., and Pourtois, G. (2015). What is in the feedback? effect of induced happiness vs. sadness on probabilistic learning with vs. without exploration. *Frontiers in human neuroscience*, 9:584.

Barab, S., Sadler, T., Heiselt, C., Hickey, D., and Zuiker, S. (2007). Relating narrative, inquiry, and inscriptions: A framework for socio-scientific inquiry. *Journal of Science Education and Technology*, 16(1):59–82.

Barata, G., Gama, S., Jorge, J., and Gonçalves, D. (2013). So fun it hurts–gamifying an engineering course. In *International Conference on Augmented Cognition*, pages 639–648. Springer.

Bargh, J. A. and Chartrand, T. L. (1999). The unbearable automaticity of being. *American Psychologist*, 54(7):462.

Barrett, P. T., Petrides, K. V., Eysenck, S. B., and Eysenck, H. J. (1998). The eysenck personality questionnaire: An examination of the factorial similarity of p, e, n, and l across 34 countries. *Personality and Individual Differences*, 25(5):805–819.

Baylari, A. and Montazer, G. A. (2009). Design a personalized e-learning system based on item response theory and artificial neural network approach. *Expert Systems with Applications*, 36(4):8013–8021.

Beale, R. and Creed, C. (2009). Affective interaction: How emotional agents affect users. *International journal of human-computer studies*, 67(9):755–776.

Bechtel, W., Graham, G., and Balota, D. A. (1998). *A companion to cognitive science*. Blackwell, Massachusetts.

Beck, J. E. (2004). Using response times to model student disengagement. In *Proceedings of the ITS2004 Workshop on Social and Emotional Intelligence in Learning Environments*, volume 20.

Bellotti, F., Berta, R., De Gloria, A., D'ursi, A., and Fiore, V. (2013). A serious game model for cultural heritage. *Journal on Computing and Cultural Heritage (JOCCH)*, 5(4).

Bennet, N. L. and Fox, R. D. (1984). Learning styles in continuing medical education. *Journal of Continuing Education in the Health Professions*, 4(4):89–92.

Bergmann, N., Schacht, S., Gnewuch, U., and Maedche, A. (2017). Understanding the influence of personality traits on gamification: The role of avatars in energy saving tasks. In *Proceedings of the 38th International Conference on Information Systems (ICIS), Seoul, ROK, December 10-13, 2017. Research-in-Progress Papers.* AISeL, Seoul, ROK.

Berkling, K. and Thomas, C. (2013). Gamification of a software engineering course and a detailed analysis of the factors that lead to it's failure. In *2013 International Conference on Interactive Collaborative Learning (ICL)*, pages 525–530. IEEE.

Bista, S. K., Nepal, S., Colineau, N., and Paris, C. (2012). Using gamification in an online community. In *8th International Conference on Collaborative Computing: Networking, Applications and Worksharing (CollaborateCom)*, pages 611–618. IEEE.

Blom, J. and Monk, A. (2007). Theory of personalization of appearance: why people personalize their mobile phones and PCs. *Human–Computer Interaction. Behavior & Information Technology*, 26(3):237–246.

Böckle, M., Novak, J., and Bick, M. (2017). Towards adaptive gamification: a synthesis of current developments. In *Proceedings of the 25th European Conference on Information Systems (ECIS)*, pages 158–174.

Breuer, J. and Bente, G. (2010). Why so serious? on the relation of serious games and learning. *Journal for Computer Game Culture*, 4:7–24.

Brown, E. (2007). *The use of learning styles in adaptive hypermedia*. PhD thesis, University of Nottingham.

Bruner, J. S. (1966). *Toward a theory of instruction*, volume 59. Harvard University Press.

Brusilovsky, P. (1996). Methods and techniques of adaptive hypermedia. *User Modeling and User-adapted Interaction*, 6(2-3):87–129.

Brusilovsky, P. (1998). Methods and techniques of adaptive hypermedia. In *Adaptive hypertext and hypermedia*, pages 1–43. Springer.

Brusilovsky, P., Karagiannidis, C., and Sampson, D. (2004). Layered evaluation of adaptive learning systems. *International Journal of Continuing Engineering Education and Life Long Learning*, 14(4-5):402–421.

Brusilovsky, P. and Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. In *The Adaptive Web*, pages 3–53. Springer.

Bunchball, I. (2010). Gamification 101: An introduction to the use of game dynamics to influence behavior. Bunchball.

Burke, R. (2007). Hybrid web recommender systems. In *The Adaptive Web*, pages 377–408. Springer.

Busato, V. V., Prins, F. J., Elshout, J. J., and Hamaker, C. (1998). The relation between learning styles, the big five personality traits and achievement motivation in higher education. *Personality and Individual Differences*, 26(1):129–140.

Canamero, L. (2001). Emotions and adaptation in autonomous agents: A design perspective. *Cybernetics & Systems*, 32(5):507–529.

Candillier, L., Meyer, F., and Boullé, M. (2007). Comparing state-of-the-art collaborative filtering systems. In *International Workshop on Machine Learning and Data Mining in Pattern Recognition*, pages 548–562. Springer.

Cantillon, P., Wood, D. F., and Yardley, S. (2017). *ABC of Learning and Teaching in Medicine*. John Wiley & Sons.

Caponetto, I., Earp, J., and Ott, M. (2014). Gamification and education: A literature review. In *European Conference on Games Based Learning*, volume 1, pages 50–57. Academic Conferences International Limited.

Carliner, S. (2004). *An overview of online learning*. Human Resource Development(HRD) Press, Amherst, MA, 2 edition.

Carlyn, M. (1977). An assessment of the myers-briggs type indicator. *Journal of personality assessment*, 41(5):461–473.

Caspi, A. and Roberts, B. W. (2001). Personality development across the life course: The argument for change and continuity. *Psychological Inquiry*, 12(2):49–66.

Cassidy, S. (2004). Learning styles: An overview of theories, models, and measures. *Educational psychology*, 24(4):419–444.

Cercone, K. (2008). Characteristics of adult learners with implications for online learning design. *AACE journal*, 16(2):137–159.

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., and Thüs, H. (2013). A reference model for learning analytics. *International Journal of Technology Enhanced Learning*, 4(5-6):318–331.

Chen, K.-C. and Jang, S.-J. (2010). Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behavior*, 26(4):741–752.

Chen, P.-S. and Chih, J.-T. (2011). The relations between learner motivation and satisfaction with management training: An empirical study in Taiwan. *International Journal of Management*, 28(1):77–90.

Cheong, C., Cheong, F., and Filippou, J. (2013). Quick quiz: A gamified approach for enhancing learning. In *PACIS*, pages 206–219.

Chyung, Y., Winiecki, D. J., and Fenner, J. A. (1998). A case study: Increase enrollment by reducing dropout rates in adult distance education.

Ciorbea, I. and Pasarica, F. (2013). The study of the relationship between personality and academic performance. *Procedia-Social and Behavioral Sciences*, 78:400–404.

Cobb, S. C. (2009). Social presence and online learning: A current view from a research perspective. *Journal of Interactive Online Learning*, 8(3):241–254.

Cobb-Clark, D. A. and Schurer, S. (2012). The stability of big-five personality traits. *Economics Letters*, 115(1):11–15.

Cocea, M. and Weibelzahl, S. (2007). Cross-system validation of engagement prediction from log files. In *European Conference on Technology Enhanced Learning*, pages 14–25. Springer.

Codish, D. and Ravid, G. (2014a). Personality based gamification-educational gamification for extroverts and introverts. In *Proceedings of the 9th CHAIS Conference for the Study of Innovation and Learning Technologies: Learning in the Technological Era*, volume 1, pages 36–44.

Codish, D. and Ravid, G. (2014b). Personality based gamification: How different personalities perceive gamification. In *the 22nd European Conference on Information Systems*.

Colbert, A. E., Judge, T. A., Choi, D., and Wang, G. (2012). Assessing the trait theory of leadership using self and observer ratings of personality: The mediating role of contributions to group success. *The Leadership Quarterly*, 23(4):670–685.

Cole, J. and Foster, H. (2007). *Using Moodle: Teaching with the popular open source course management system*. O'Reilly Media, Inc.

Conard, M. A. (2006). Aptitude is not enough: How personality and behavior predict academic performance. *Journal of Research in Personality*, 40(3):339–346.

Costa, P. T. and McCrae, R. R. (1980). Influence of extraversion and neuroticism on subjective well-being: happy and unhappy people. *Journal of Personality and Social Psychology*, 38(4):668–678.

Cox, D. R. (2018). *Analysis of survival data.* Chapman and Hall/CRC.

Crowley, J. (1974). A note on some recent likelihoods leading to the log rank test. *Biometrika*, 61(3):533–538.

Curry, L. (1983). *An organization of learning styles theory and constructs.* PhD thesis, Dalhousie University.

Da Rocha Seixas, L., Gomes, A. S., and de Melo Filho, I. J. (2016). Effectiveness of gamification in the engagement of students. *Computers in Human Behavior*, 58:48–63.

Darejeh, A. and Salim, S. S. (2016). Gamification solutions to enhance software user engagement: a systematic review. *International Journal of Human-Computer Interaction*, 32(8):613–642.

Dascalu, M.-I., Bodea, C.-N., Mihailescu, M. N., Tanase, E. A., and Ordoñez de Pablos, P. (2016). Educational recommender systems and their application in lifelong learning. *Behaviour & Information Technology*, 35(4):290–297.

De Bra, P. (2008). Adaptive hypermedia. In *Handbook on information technologies for education and training*, pages 29–46. Springer.

De Bra, P., Brusilovsky, P., and Houben, G.-J. (1999). Adaptive hypermedia: from systems to framework. *ACM Computing Surveys (CSUR)*, 31:12.

De Bra, P. and Ruiter, J.-P. (2001). Aha! adaptive hypermedia for all. In *WebNet*, pages 262–268.

De Lemos, J., Sadeghnia, G. R., Ólafsdóttir, Í., and Jensen, O. (2008). Measuring emotions using eye tracking. In *Proceedings of measuring behavior*, volume 226, pages 225–226.

De Oliveira, R., Cherubini, M., and Oliver, N. (2010). Movipill: improving medication compliance for elders using a mobile persuasive social game. In *Proceedings of the 12th ACM international conference on Ubiquitous computing*, pages 251–260. ACM.

De Vicente, A. and Pain, H. (2002). Informing the detection of the students' motivational state: an empirical study. In *International Conference on Intelligent Tutoring Systems*, pages 933–943. Springer.

DeBoer, J., Ho, A. D., Stump, G. S., and Breslow, L. (2014). Changing course reconceptualizing educational variables for massive open online courses. *Educational researcher*, 43(2):74–84.

Deci, E. L., Koestner, R., and Ryan, R. M. (2001). Extrinsic rewards and intrinsic motivation in education: Reconsidered once again. *Review of Educational Research*, 71(1):1–27.

Denden, M., Tlili, A., Essalmi, F., and Jemni, M. (2018). Does personality affect students' perceived preferences for game elements in gamified learning environments? In *2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT)*, pages 111–115. IEEE.

Dennis, T. A. and O'Toole, L. J. (2014). Mental health on the go: Effects of a gamified attention-bias modification mobile application in trait-anxious adults. *Clinical Psychological Science*, 2(5):576–590.

Dichev, C., Dicheva, D., Angelova, G., and Agre, G. (2014). From gamification to gameful design and gameful experience in learning. *Cybernetics and Information Technologies*, 14(4):80–100.

Dicheva, D., Dichev, C., Agre, G., Angelova, G., et al. (2015). Gamification in education: A systematic mapping study. *Educational Technology & Society*, 18(3):75–88.

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology*, 41(1):417–440.

Domínguez, A., Saenz-de navarrete, J., De-Marcos, L., Fernández-Sanz, L., Pagés, C., and Martínez-HerráIz, J.-J. (2013). Gamifying learning experiences: Practical implications and outcomes. *Computers & Education*, 63:380–392.

Downes, S. (2008). Places to go: Connectivism & connective knowledge. *Innovate: Journal of Online Education*, 5(1):668–674.

Drira, R., Tirellil, I., Laroussi, M., Derycke, A., and Benghezala, H. (2006). What can we adapt in a mobile learning systems? In *Conference IMCL2006, Amman-Jordan*, pages 19–21.

Driscoll, M. (2002). Blended learning: Let's get beyond the hype. *E-learning*, 1(4):1–4.

Duncan, S. C. (2011). Minecraft, beyond construction and survival. *Well Played: a Journal on Video Games, Value and Meaning*, 1(1):1–22.

Efron, B. (1988). Logistic regression, survival analysis, and the kaplan-meier curve. *Journal of the American Statistical Association*, 83(402):414–425.

Egenfeldt-Nielsen, S. (2010). *Beyond edutainment: exploring the educational potential of computer games*. IT University of Copenhagen, Department of Innovation, Copenhagen.

Ertmer, P. A. and Newby, T. J. (2013). Behaviorism, cognitivism, constructivism: Comparing critical features from an instructional design perspective. *Performance Improvement quarterly*, 26(2):43–71.

Fabri, M., Elzouki, S. Y. A., and Moore, D. (2007). Emotionally expressive avatars for chatting, learning and therapeutic intervention. In *International conference on human-computer interaction*, pages 275–285. Springer.

Falloon, G. (2010). Using avatars and virtual environments in learning: What do they have to offer? *British Journal of Educational Technology*, 41(1):108–122.

Fernandes, F. T. and Junior, P. T. A. (2016). Gamification aspects in the context of electronic government and education: A case study. In *International Conference on HCI in Business, Government, and Organizations*, pages 140–150. Springer.

Ferrara, J. (2013). Games for persuasion: Argumentation, procedurality, and the lie of gamification. *Games and Culture*, 8(4):289–304.

Filsecker, M. and Hickey, D. T. (2014). A multilevel analysis of the effects of external rewards on elementary students' motivation, engagement and learning in an educational game. *Computers & Education*, 75:136–148.

Fitz-Walter, Z., Tjondronegoro, D., and Wyeth, P. (2011). Orientation passport: using gamification to engage university students. In *Proceedings of the 23rd Australian Computer-Human Interaction Conference*, pages 122–125. ACM.

Fitz-Walter, Z. J. (2015). *Achievement unlocked: Investigating the design of effective gamification experiences for mobile applications and devices.* PhD thesis, Queensland University of Technology.

Ford, N. and Chen, S. Y. (2001). Matching/mismatching revisited: An empirical study of learning and teaching styles. *British Journal of Educational Technology*, 32(1):5–22.

Frith, J. (2013). Turning life into a game: Foursquare, gamification, and personal mobility. *Mobile Media & Communication*, 1(2):248–262.

Furnham, A. (1992). Personality and learning style: A study of three instruments. *Personality and individual differences*, 13(4):429–438.

Garzotto, F. and Cristea, A. (2004). Adapt major design dimensions for educational adaptive hypermedia. In *EdMedia+ Innovate Learning*, pages 1334–1339. Association for the Advancement of Computing in Education (AACE).

Gatian, A. W. (1994). Is user satisfaction a valid measure of system effectiveness? *Information & Management*, 26(3):119–131.

Gershuny, B. S. and Sher, K. J. (1998). The relation between personality and anxiety: findings from a 3-year prospective study. *Journal of Abnormal Psychology*, 107(2):252.

Ghaban, W. and Hendley, R. (2018). Investigating the interaction between personalities and the benefit of gamification. In *Proceedings of the 32nd International BCS Human Computer Interaction Conference*, page 41. BCS Learning & Development Ltd.

Ghaban, W. and Hendley, R. (2019). How Different Personalities Benefit From Gamification. *Interacting with Computers*, 31(2):138–153.

Ghaban., W. and Hendley., R. (2019). Understanding the effect of gamification on learners with different personalities. In *Proceedings of the 11th International Conference on Computer Supported Education - Volume 2: CSEDU,*, pages 392–400. INSTICC, SciTePress.

Ghaban., W., Hendley., R., and Fleck., R. (2019). Investigating how social elements affect learners with different personalities. In *Proceedings of the 11th International Conference on Computer Supported Education - Volume 2: CSEDU,*, pages 416–423. INSTICC, SciTePress.

Gibbs, R. and Poskitt, J. (2010). Student engagement in the middle years of schooling (years 7-10): A literature review report to the ministry of education.

Glover, I. (2013). Play as you learn: gamification as a technique for motivating learners. In *EdMedia+ Innovate Learning*, pages 1999–2008. Association for the Advancement of Computing in Education (AACE).

Göker, A. and Myrhaug, H. I. (2002). User context and personalisation. In *Workshop proceedings for the 6th European Conference on Case Based Reasoning*, pages 1–7.

Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Cloninger, C. R., and Gough, H. G. (2006). The international personality item pool and the future of public-domain personality measures. *Journal of Research in personality*, 40(1):84–96.

Goldie, J. G. S. (2016). Connectivism: A knowledge learning theory for the digital age. *Medical Teacher*, 38(10):1064–1069.

González, C., Mora, A., and Toledo, P. (2014). Gamification in intelligent tutoring systems. In *Proceedings of the Second International Conference on Technological Ecosystems for Enhancing Multiculturality*, pages 221–225. ACM.

González, C. S., Toledo, P., Muñoz, V., et al. (2016). Enhancing the engagement of intelligent tutorial systems through personalization of gamification. *International Journal of Engineering Education*, 32(1):532–541.

Gooch, D., Vasalou, A., Benton, L., and Khaled, R. (2016). Using gamification to motivate students with dyslexia. In *Proceedings of the 2016 CHI Conference on human factors in computing systems*, pages 969–980. ACM.

Graf, S. et al. (2009). Advanced adaptivity in learning management systems by considering learning styles. In *Proceedings of the 2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology-Volume 03*, pages 235–238. IEEE Computer Society.

Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. *American Journal of Physics*, 66(1):64–74.

Hall, M., Caton, S., and Weinhardt, C. (2013). Well-being's predictive value. In *International Conference on Online Communities and Social Computing*, pages 13–22. Springer.

Hallifax, S., Serna, A., Marty, J.-C., Lavoué, G., and Lavoué, E. (2019). Factors to consider for tailored gamification. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, pages 559–572.

Hamzah, W. A. F. W., Ali, N. H., Saman, M. Y. M., Yusoff, M. H., and Yacob, A. (2014). Enhancement of the arcs model for gamification of learning. In *2014 3rd International Conference on User Science and Engineering (i-USEr)*, pages 287–291. IEEE.

Harasim, L. (2012). *Learning theory and online technologies.* Routledge, New York.

Hartnett, M., George, A. S., and Dron, J. (2011). Examining motivation in online distance learning environments: Complex, multifaceted and situation-dependent. *The International Review of Research in Open and Distributed Learning*, 12(6):20–38.

Hauger, D. and Köck, M. (2007). State of the art of adaptivity in e-learning platforms. In *LWA*, pages 355–360.

Hershkovitz, A. and Nachmias, R. (2009). Learning about online learning processes and students' motivation through web usage mining. *Interdisciplinary Journal of E-Learning and Learning Objects*, 5(1):197–214.

Hoekstra, A., Prendinger, H., Bee, N., Heylen, D., and Ishizuka, M. (2007). Presentation agents that adapt to users' visual interest and follow their preferences. In *International Conference on Computer Vision Systems: Proceedings*, pages 1–10, England.

Hofstee, W. K. (1994). Who should own the definition of personality? *European Journal of Personality*, 8(3):149–162.

Hotard, S. R., McFatter, R. M., McWhirter, R. M., and Stegall, M. E. (1989). Interactive effects of extraversion, neuroticism, and social relationships on subjective well-being. *Journal of Personality and Social Psychology*, 57(2):321.

Hothi, J. and Hall, W. (1998). An evaluation of adapted hypermedia techniques using static user modelling. In *Proceedings of the second workshop on adaptive hypertext and hypermedia*, pages 45–50.

Huang, E. Y., Lin, S. W., and Huang, T. K. (2012). What type of learning style leads to online participation in the mixed-mode e-learning environment? a study of software usage instruction. *Computers & Education*, 58(1):338–349.

Huang, H.-M. (2002). Toward constructivism for adult learners in online learning environments. *British Journal of Educational Technology*, 33(1):27–37.

Huotari, K. and Hamari, J. (2012). Defining gamification: a service marketing perspective. In *Proceeding of the 16th international academic MindTrek conference*, pages 17–22. ACM.

Hurtz, G. M. and Donovan, J. J. (2000). Personality and job performance: The big five revisited. *Journal of Applied Psychology*, 85(6):869.

Irani, T., Telg, R., Scherler, C., and Harrington, M. (2003). Personality type and its relationship to distance education students? course perceptions and performance. *Quarterly Review of Distance Education*, 4(4):445–453.

Isaksen, S. G., Lauer, K. J., and Wilson, G. V. (2003). An examination of the relationship between personality type and cognitive style. *Creativity Research Journal*, 15(4):343–354.

Jackson, C. and Lawty-Jones, M. (1996). Explaining the overlap between personality and learning style. *Personality and Individual Differences*, 20(3):293–300.

Jacobson, R. R. (2001). Differences between traditional and nontraditional students on the motivated strategies for learning questionnaire. *Dissertation Abstracts International*, 61(3-A):879.

Jia, Y., Liu, Y., Yu, X., and Voida, S. (2017). Designing leaderboards for gamification: Perceived differences based on user ranking, application domain, and personality traits. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 1949–1960. ACM.

Jia, Y., Xu, B., Karanam, Y., and Voida, S. (2016). Personality-targeted gamification: a survey study on personality traits and motivational affordances. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 2001–2013. ACM.

John, O. P. and Srivastava, S. (1999). The big five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: Theory and Research*, 2(1999):102–138.

Jonassen, D. H. (1991). Objectivism versus constructivism: Do we need a new philosophical paradigm? *Educational Technology Research and Development*, 39(3):5–14.

Jonassen, D. H. and Grabowski, B. L. (2012). *Handbook of individual differences, learning, and instruction*. Routledge, New York.

Jones, A. and Castellano, G. (2018). Adaptive robotic tutors that support self-regulated learning: A longer-term investigation with primary school children. *International Journal of Social Robotics*, 10(3):357–370.

Judge, T. A., Higgins, C. A., Thoresen, C. J., and Barrick, M. R. (1999). The big five personality traits, general mental ability, and career success across the life span. *Personnel Psychology*, 52(3):621–652.

Jung, H.-J. (2014). Ubiquitous learning: determinants impacting learnersâFIXME™ satisfaction and performance with smartphones. *Language Learning & Technology*, 18(3):97–119.

Kajanus, M., Kangas, J., and Kurttila, M. (2004). The use of value focused thinking and the a'wot hybrid method in tourism management. *Tourism Management*, 25(4):499–506.

Kamarulzaman, W. (2012). Critical review on affect of personality on learning styles. In *he 2nd International Conference on Arts, Social Science & Technology*, pages I2087-1–I2087-7. ERIC.

Kassambara, A. (2016 (accessed September 8, 2019)a). *Cox Proportional-Hazards Model*. `http://www.sthda.com/english/wiki/cox-proportional-hazards-model`.

Kassambara, A. (2016 (accessed September 8, 2019)b). *Survival Analysis Basics*. http://www.sthda.com/english/wiki/survival-analysis-basics.

Kaufhold, M.-A., Bayer, M., and Reuter, C. (2020). Rapid relevance classification of social media posts in disasters and emergencies: A system and evaluation featuring active, incremental and online learning. *Information Processing & Management*, 57(1):102132.

Kebritchi, M., Hirumi, A., and Bai, H. (2010). The effects of modern mathematics computer games on mathematics achievement and class motivation. *Computers & education*, 55(2):427–443.

Keeney, R. L. (1996a). *Value-focused thinking*. Harvard University Press.

Keeney, R. L. (1996b). Value-focused thinking: Identifying decision opportunities and creating alternatives. *European Journal of Operational Research*, 92(3):537–549.

Keller, J. and Suzuki, K. (2004). Learner motivation and e-learning design: A multinationally validated process. *Journal of Educational Media*, 29(3):229–239.

Keller, J. M. (2008). First principles of motivation to learn and e3-learning. *Distance Education*, 29(2):175–185.

Khaleel, F. L., Sahari, N., Wook, T. S. M. T., Ismail, A., et al. (2016). Gamification elements for learning applications. *International Journal on Advanced Science, Engineering and Information Technology*, 6(6):868–874.

Khan, F. A., Graf, S., Weippl, E. R., and Tjoa, A. M. (2010). Identifying and incorporating affective states and learning styles in web-based learning management systems. *IxD&A*, 9:85–103.

Kim, B. (2015). Designing gamification in the right way. *Library Technology Reports*, 51(2):29–35.

Kim, K.-J. and Frick, T. W. (2011). Changes in student motivation during online learning. *Journal of Educational Computing Research*, 44(1):1–23.

Kinoshita, T. J., Knight, D. B., and Gibbes, B. (2017). The positive influence of active learning in a lecture hall: an analysis of normalised gain scores in introductory environmental engineering. *Innovations in Education and Teaching International*, 54(3):275–284.

Klašnja-Milićević, A., Ivanović, M., and Nanopoulos, A. (2015). Recommender systems in e-learning environments: a survey of the state-of-the-art and possible extensions. *Artificial Intelligence Review*, 44(4):571–604.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., and Budimac, Z. (2011). Integration of recommendations and adaptive hypermedia into java tutoring system. *Computer Science and Information Systems*, 8(1):211–224.

Klock, A. C., Gasparini, I., Pimenta, M. S., and de Oliveira, J. P. M. (2015). Everybody is playing the game but nobody's rules are the same?: Towards adaptation of gamification based on users' characteristics. *Bulletin of the IEEE Technical Committee on Learning Technology*, 17(4):22–25.

Knowles, E. and Kerkman, D. (2007). An investigation of students attitude and motivation toward online learning. *InSight: A Collection of Faculty Scholarship*, 2:70–80.

Kobsa, A., Koenemann, J., and Pohl, W. (2001). Personalised hypermedia presentation techniques for improving online customer relationships. *The Knowledge Engineering Review*, 16(2):111–155.

Kobsa, A., Müller, D., and Nill, A. (1998). Kn-ahs: An adaptive hypertext client of the user modeling system bgp-ms. *Readings in Intelligent User Interfaces*, pages 372–380.

Koch, N. and Wirsing, M. (2002). The munich reference model for adaptive hypermedia applications. In *International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems*, pages 213–222. Springer.

Kop, R. and Hill, A. (2008). Connectivism: Learning theory of the future or vestige of the past? *The International Review of Research in Open and Distributed Learning*, 9(3).

Kuo, I. (2015). Nike+: building community and competitive advantage with gamification. *Gamification*, 8.

Laidra, K., Pullmann, H., and Allik, J. (2007). Personality and intelligence as predictors of academic achievement: A cross-sectional study from elementary to secondary school. *Personality and Individual Differences*, 42(3):441–451.

Lee, Y., Choi, J., and Kim, T. (2013). Discriminating factors between completers of and dropouts from online learning courses. *British Journal of Educational Technology*, 44(2):328–337.

Lin, D. Y. and Wei, L.-J. (1989). The robust inference for the cox proportional hazards model. *Journal of the American Statistical Association*, 84(408):1074–1078.

Lin, F., Graf, S., and McGreal, R. (2004). Adaptive and intelligent web-based educational systems. Guest Editorial Preface.

Linn, M. C. (1996). Cognition and distance learning. *Journal of the American Society for Information Science*, 47(11):826–842.

Magoulas, G. D., Papanikolaou, Y., and Grigoriadou, M. (2003). Adaptive web-based learning: accommodating individual differences through system's adaptation. *British Journal of Educational Technology*, 34(4):511–527.

Mahdavi, I., Fazlollahtabar, H., Heidarzade, A., Mahdavi-Amiri, N., and Rooshan, Y. (2008). A heuristic methodology for multi-criteria evaluation of web-based e-learning systems based on user satisfaction. *Journal of Applied Sciences*, 8(24):4603–4609.

Manouselis, N., Drachsler, H., Vuorikari, R., Hummel, H., and Koper, R. (2011). Recommender systems in technology enhanced learning. In *Recommender systems handbook*, pages 387–415. Springer.

Maravanyika, M., Dlodlo, N., and Jere, N. (2017). An adaptive recommender-system based framework for personalised teaching and learning on e-learning platforms. In *2017 IST-Africa Week Conference (IST-Africa)*, pages 1–9. IEEE.

Marczewski, A. (2018). *Even Ninja Monkeys Like to Play: gamification, game thinking and motivational design.* Independently published.

Martens, R., Gulikers, J., and Bastiaens, T. (2004). The impact of intrinsic motivation on e-learning in authentic computer tasks. *Journal of Computer Assisted Learning*, 20(5):368–376.

Martí-Parreño, J., Seguí-Mas, D., and Seguí-Mas, E. (2016). Teachers? attitude towards and actual use of gamification. *Procedia-Social and Behavioral Sciences*, 228:682–688.

Mattheiss, E., Hochleitner, C., Busch, M., Orji, R., and Tscheligi, M. (2017). Deconstructing pokémon go–an empirical study on player personality characteristics. In *International Conference on Persuasive Technology*, pages 83–94. Springer.

Mayer, R. E. (2002). Multimedia learning. In *Psychology of Learning and Motivation*, volume 41, pages 85–139. Elsevier.

McCrae, R. and Costa, P. (2008). The five-factor theory of personality. *0. P. John, RW Robins, LA Pervin (Eds), Handbook of personality: Theory and Research*, pages 159–181.

McCrae, R. R. and Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, 52(1):81–90.

McKimm, J., Jolie, C., and Cantillon, P. (2006). Abc of learning and teaching web based learning. BMJ. v326. p870-873.

Michael, D. and Chrysanthou, Y. (2003). Automatic high level avatar guidance based on affordance of movement. In *Eurographics (Short Papers)*.

Mills, M. (2010). *Introducing survival and event history analysis*. Sage, Los Angeles, CA.

Monterrat, B., Lavoué, E., and George, S. (2014). Toward an adaptive gamification system for learning environments. In *International Conference on Computer Supported Education*, pages 115–129. Springer.

Mora, A., Riera, D., González, C., and Arnedo-Moreno, J. (2017). Gamification: a systematic review of design frameworks. *Journal of Computing in Higher Education*, 29(3):516–548.

Morales, R., Van Labeke, N., Brna, P., and Chan, M. E. (2009). Open learner modelling as the keystone of the next generation of adaptive learning environments. In *Intelligent User Interfaces: Adaptation and Personalization Systems and Technologies*, pages 288–312. IGI Global.

Morford, Z. H., Witts, B. N., Killingsworth, K. J., and Alavosius, M. P. (2014). Gamification: the intersection between behavior analysis and game design technologies. *The Behavior Analyst*, 37(1):25–40.

Motti, V. G. and Vanderdonckt, J. (2013). A computational framework for context-aware adaptation of user interfaces. In *IEEE 7th International Conference on Research Challenges in Information Science (RCIS)*, pages 1–12. IEEE.

Mukhopadhyay, M., Pal, S., Nayyar, A., Pramanik, P. K. D., Dasgupta, N., and Choudhury, P. (2020). Facial emotion detection to assess learner's state of mind in an online learning system. In *Proceedings of the 2020 5th International Conference on Intelligent Information Technology*, pages 107–115.

Mustafa, Y. E. A. and Sharif, S. M. (2011). An approach to adaptive e-learning hypermedia system based on learning styles (aehs-ls): Implementation and evaluation. *International Journal of Library and Information Science*, 3(1):15–28.

Napierala, M. A. (2012). What is the bonferroni correction. *AAOS Now*, 6(4):40.

Nash, S. (2005). Learning objects, learning object repositories, and learning theory: Preliminary best practices for online courses. *Interdisciplinary Journal of E-Learning and Learning Objects*, 1(1):217–228.

Nayir, F. (2017). The relationship between student motivation and class engagement levels. *Eurasian Journal of Educational Research*, 71:59–77.

Neyer, F. J., Mund, M., Zimmermann, J., and Wrzus, C. (2014). Personality-relationship transactions revisited. *Journal of personality*, 82(6):539–550.

Nguyen, L. and Do, P. (2008). Learner model in adaptive learning. *World Academy of Science, Engineering and Technology*, 45(70):395–400.

Nijim, S. and Grist, P. (2020). Growing organizational capacities for increased online learning, working, and health. *The Business of Pandemics: The COVID-19 Story*, page 97.

Noftle, E. E. and Robins, R. W. (2007). Personality predictors of academic outcomes: big five correlates of gpa and sat scores. *Journal of Personality and Social Psychology*, 93(1):116.

Oblinger, D., Oblinger, J. L., and Lippincott, J. K. (2005). *Educating the net generation*. EDUCAUSE, Boulder, CO.

O'Brien, H. L. and Toms, E. G. (2008). What is user engagement? a conceptual framework for defining user engagement with technology. *Journal of the American society for Information Science and Technology*, 59(6):938–955.

Onah, D. F., Sinclair, J., and Boyatt, R. (2014). Dropout rates of massive open online courses: behavioural patterns. *EDULEARN14 proceedings*, 1:5825–5834.

Orji, R., Nacke, L. E., and Di Marco, C. (2017). Towards personality-driven persuasive health games and gamified systems. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 1015–1027. ACM.

Ormrod, J. E. and Davis, K. M. (2004). *Human learning*. Merrill London.

Oulasvirta, A. and Blom, J. (2008). Motivations in personalisation behaviour. *Interacting with Computers*, 20(1):1–16.

Papastergiou, M. (2009). Digital game-based learning in high school computer science education: Impact on educational effectiveness and student motivation. *Computers & education*, 52(1):1–12.

Paramythis, A. and Loidl-Reisinger, S. (2003). Adaptive learning environments and e-learning standards. In *Second European Conference on E-learning*, volume 1, pages 369–379.

Park, D. H., Kim, H. K., Choi, I. Y., and Kim, J. K. (2012). A literature review and classification of recommender systems research. *Expert systems with applications*, 39(11):10059–10072.

Park, S.-T. and Chu, W. (2009). Pairwise preference regression for cold-start recommendation. In *Proceedings of the third ACM conference on Recommender systems*, pages 21–28. ACM.

Pintrich, P. R. and Schunk, D. H. (2002). *Motivation in education: Theory, research, and applications*. Prentice Hall.

Polzin, T. S. and Waibel, A. (2000). Emotion-sensitive human-computer interfaces. In *ISCA tutorial and research workshop (ITRW) on speech and emotion*.

Popescu, E. (2010). Adaptation provisioning with respect to learning styles in a web-based educational system: an experimental study. *Journal of Computer Assisted Learning*, 26(4):243–257.

Popescul, A., Pennock, D. M., and Lawrence, S. (2001). Probabilistic models for unified collaborative and content-based recommendation in sparse-data environments. In *Proceedings of the Seventeenth conference on Uncertainty in artificial intelligence*, pages 437–444. Morgan Kaufmann Publishers Inc.

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, 135(2):322.

Qu, L. and Johnson, W. L. (2005). Detecting the learner's motivational states in an interactive learning environment. In *Proceedings of the 2005 conference on Artificial Intelligence in Education: Supporting Learning through Intelligent and Socially Informed Technology*, pages 547–554. IOS Press.

Richardson, J. and Swan, K. (2003). Examing social presence in online courses in relation to students' perceived learning and satisfaction.

Riding, R. J. and Wigley, S. (1997). The relationship between cognitive style and personality in further education students. *Personality and individual differences*, 23(3):379–389.

Rothmann, S. and Coetzer, E. P. (2003). The big five personality dimensions and job performance. *SA Journal of Industrial Psychology*, 29(1):68–74.

Royston, P., Altman, D. G., and Sauerbrei, W. (2006). Dichotomizing continuous predictors in multiple regression: a bad idea. *Statistics in Medicine*, 25(1):127–141.

Ryan, R. M. and Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1):68.

Sadler-Smith, E. (2001). The relationship between learning style and cognitive style. *Personality and Individual Differences*, 30(4):609–616.

Sailer, M., Hense, J., Mandl, J., and Klevers, M. (2014). Psychological perspectives on motivation through gamification. *Interaction Design and Architecture Journal*, (19):28–37.

Schunk, D. (2016). *Learning theories: an educational perspective.* Pearson, Carolina del Norte.

Seaborn, K. and Fels, D. I. (2015). Gamification in theory and action: A survey. *International Journal of human-computer studies*, 74:14–31.

Sheng, H., Nah, F. F.-H., and Siau, K. (2005). Strategic implications of mobile technology: A case study using value-focused thinking. *The Journal of Strategic Information Systems*, 14(3):269–290.

Sheth, R. (2003). Avatar technology: giving a face to the e-learning interface. *The e-Learning Developers' Journal*, pages 1–10.

Shifroni, E. and Shanon, B. (1992). Interactive user modeling: An integrative explicit-implicit approach. *User Modeling and User-Adapted Interaction*, 2(4):331–365.

Simões, J., Redondo, R. D., and Vilas, A. F. (2013). A social gamification framework for a k-6 learning platform. *Computers in Human Behavior*, 29(2):345–353.

Sinclair, J., Boyatt, R., Rocks, C., and Joy, M. (2015). Massive open online courses: a review of usage and evaluation. *International Journal of Learning Technology*, 10(1):71–93.

Siritongthaworn, S. and Krairit, D. (2006). Satisfaction in e-learning: the context of supplementary instruction. *Campus-Wide Information Systems*, 23(2):76–91.

Škuta, P. and Kostolányová, K. (2016). The inclusion of gamification elements in the educational process. *DIVAI 2016*, pages 421–429.

Song, Y., Dixon, S., and Pearce, M. (2012). A survey of music recommendation systems and future perspectives. In *9th International Symposium on Computer Music Modeling and Retrieval*, volume 4.

Sosnovsky, S. and Dicheva, D. (2010). Ontological technologies for user modelling. *International Journal of Metadata, Semantics and Ontologies*, 5(1):32–71.

Standage, M., Duda, J. L., and Ntoumanis, N. (2005). A test of self-determination theory in school physical education. *British Journal of Educational Psychology*, 75(3):411–433.

Stannett, M., Sedeeq, A., and Romano, D. M. (2016). Generic and adaptive gamification: A panoramic review.

Stott, A. and Neustaedter, C. (2013). Analysis of gamification in education. Technical Report 2013-0422-01, Simon Fraser University, Surrey, BC, Canada.

Su, C.-H. and Cheng, C.-H. (2015). A mobile gamification learning system for improving the learning motivation and achievements. *Journal of Computer Assisted Learning*, 31(3):268–286.

Sung, S. Y. and Choi, J. N. (2009). Do big five personality factors affect individual creativity? The moderating role of extrinsic motivation. *Social Behavior and Personality: an International Journal*, 37(7):941–956.

Suzuki, K., Camurri, A., Ferrentino, P., and Hashimoto, S. (1998). Intelligent agent system for human-robot interaction through artificial emotion. In *SMC'98 Conference Proceedings. 1998 IEEE International Conference on Systems, Man, and Cybernetics (Cat. No. 98CH36218)*, volume 2, pages 1055–1060. IEEE.

Swan, K. and Shih, L. F. (2005). On the nature and development of social presence in online course discussions. *Journal of Asynchronous Learning Networks*, 9(3):115–136.

Swartz, L. (2003). *Why people hate the paperclip: Labels, appearance, behavior, and social responses to user interface agents*. PhD thesis, Stanford University Palo Alto, CA.

Tang, T. Y. and McCalla, G. (2003). Smart recommendation for an evolving e-learning system. In *Workshop on Technologies for Electronic Documents for Supporting Learning, International Conference on Artificial Intelligence in Education*, pages 699–710.

Thalmayer, A. G., Saucier, G., and Eigenhuis, A. (2011). Comparative validity of brief to medium-length big five and big six personality questionnaires. *Psychological Assessment*, 23(4):995–1009.

Tondello, G. F., Mora, A., and Nacke, L. E. (2017a). Elements of gameful design emerging from user preferences. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, pages 129–142. ACM.

Tondello, G. F., Orji, R., and Nacke, L. E. (2017b). Recommender systems for personalized gamification. In *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, pages 425–430. ACM.

Tondello, G. F., Wehbe, R. R., Diamond, L., Busch, M., Marczewski, A., and Nacke, L. E. (2016). The gamification user types hexad scale. In *Proceedings of the 2016 annual symposium on computer-human interaction in play*, pages 229–243. ACM.

Topping, G. D. and O'Gorman, J. (1997). Effects of faking set on validity of the neo-ffi. *Personality and Individual Differences*, 23(1):117–124.

Triantafillou, E., Pomportsis, A., and Georgiadou, E. (2002). Aes-cs: adaptive educational system based on cognitive styles. In *Second International Conference on Adaptive Hypermedia and Adaptive Web-based Systems, Malaga, Spain*.

Tschofen, C. and Mackness, J. (2012). Connectivism and dimensions of individual experience. *The International Review of Research in Open and Distributed Learning*, 13(1):124–143.

Tseng, J. C., Chu, H.-C., Hwang, G.-J., and Tsai, C.-C. (2008). Development of an adaptive learning system with two sources of personalization information. *Computers & Education*, 51(2):776–786.

Udvari, S. J. and Schneider, B. H. (2000). Competition and the adjustment of gifted children: A matter of motivation. *Roeper Review*, 22(4):212–216.

Vallerand, R. J., Gauvin, L. I., and Halliwell, W. R. (1986). Negative effects of competition on children's intrinsic motivation. *The Journal of Social Psychology*, 126(5):649–656.

Vasalou, A. and Joinson, A. N. (2009). Me, myself and I: The role of interactional context on self-presentation through avatars. *Computers in Human Behavior*, 25(2):510–520.

Vasilyeva, E., Puuronen, S., Pechenizkiy, M., and Rasanen, P. (2007). Feedback adaptation in web-based learning systems. *International Journal of Continuing Engineering Education and Life Long Learning*, 17(4/5):337–357.

Viriyapong, R., Yosyingyong, P., Nakrang, J., and Harfield, A. (2014). A case study in applying gamification techniques on mobile technology for mathematics high school students to learn polynomial functions.

Visa, S., Ramsay, B., Ralescu, A. L., and Van Der Knaap, E. (2011). Confusion matrix-based feature selection. *Midwestt Artificial Intelligence and Cognitive Science (MAICS)*, 710:120–127.

Waldrop, M. M. (2013). Massive open online courses are transforming higher education-and providing fodder for scientific research. *Nature*, 495(440):160–163.

Walter, F. E., Battiston, S., Yildirim, M., and Schweitzer, F. (2012). Moving recommender systems from on-line commerce to retail stores. *Information Systems and E-business Management*, 10(3):367–393.

Walters, S. J. (1999). *What is a Cox model?* Hayward Medical Communications, England.

Wang, C.-H., Shannon, D. M., and Ross, M. E. (2013). Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education*, 34(3):302–323.

Wang, M.-T. and Eccles, J. S. (2013). School context, achievement motivation, and academic engagement: A longitudinal study of school engagement using a multidimensional perspective. *Learning and Instruction*, 28:12–23.

Wang, Y.-S. (2003). Assessment of learner satisfaction with asynchronous electronic learning systems. *Information & Management*, 41(1):75–86.

West, C. K., Farmer, J. A., and Wolff, P. M. (1992). *Instructional design: Implications from cognitive science*. Allyn and Bacon, Boston.

Wilkes, C. W. and Burnham, B. R. (1991). Adult learner motivations and electronic distance education. *American Journal of Distance Education*, 5(1):43–50.

Willging, P. A. and Johnson, S. D. (2009). Factors that influence students' decision to dropout of online courses. *Journal of Asynchronous Learning Networks*, 13(3):115–127.

Williams, G. C., McGregor, H. A., Sharp, D., Levesque, C., Kouides, R. W., Ryan, R. M., and Deci, E. L. (2006). Testing a self-determination theory intervention for motivating tobacco cessation: supporting autonomy and competence in a clinical trial. *Health Psychology*, 25(1):91–101.

Wilson, D., Calongne, C., and Henderson, B. (2015). Gamification challenges and a case study in online learning. *Internet Learning Journal*, 4(2):84–102.

Wilson, G. D., Barrett, P. T., and Gray, J. A. (1989). Human reactions to reward and punishment: A questionnaire examination of gray's personality theory. *British Journal of Psychology*, 80(4):509–515.

Winn, W. (1990). Some implications of cognitive theory for instructional design. *Instructional Science*, 19(1):53–69.

Wolfe, R. N. and Johnson, S. D. (1995). Personality as a predictor of college performance. *Educational and Psychological Measurement*, 55(2):177–185.

Wongso, O., Rosmansyah, Y., and Bandung, Y. (2014). Gamification framework model, based on social engagement in e-learning 2.0. In *2014 2nd International Conference on Technology, Informatics, Management, Engineering & Environment*, pages 10–14. IEEE.

Wu, H., De Bra, P., Aerts, A., and Houben, G.-J. (2000). Adaptation control in adaptive hypermedia systems. In *International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems*, pages 250–259. Springer.

Wu, H., De Kort, E., and De Bra, P. (2001). Design issues for general-purpose adaptive hypermedia systems. In *Proceedings of the 12th ACM Conference on Hypertext and Hypermedia*, pages 141–150. ACM.

Xu, Y. (2012). Literature review on web application gamification and analytics. Technical Report 1-05, University of Hawai'i, Honolulu, HI.

Yahaya, A., Yahaya, N., Ismail, J., Sharif, Z., Saud, M. S., Kosinin, A. M., Abbas, F., et al. (2011). Effects of personality trait, motivation factors on performance of customer service personnel (csp): A case of mph bookstores. *African Journal of Business Management*, 5(11):4519–4530.

Yarandi, M., Jahankhani, H., Dastbaz, M., and Tawil, A.-R. (2011). Personalised mobile learning system based on item response theory. In *6th Annual Conference on Advanced Computing and Technology*, pages 208–115. Citeseer.

Zemliansky, P. (2010). *Design and Implementation of Educational Games: Theoretical and Practical Perspectives: Theoretical and Practical Perspectives.* IGI Global, New York.

Zigoris, P. and Zhang, Y. (2006). Bayesian adaptive user profiling with explicit & implicit feedback. In *Proceedings of the 15th ACM international conference on Information and knowledge management*, pages 397–404. ACM.