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How Different Personalities Benefit From Gamification

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Several studies indicate the benefit of mapping gamification elements to personality. However, this mapping requires a strong understanding of the relationship between gamification elements and personality. The existing research that has tried to address this relationship is based on a self-report questionnaire that is obtained from only those learners who complete the entire study. Unfortunately, a bias may result from first forcing learners to complete an entire study and then ignoring learners who drop out in the middle of a study. To overcome this bias, we use a more objective approach to understand the relationship between personality and gamification. In our study, we use the dropout rate as a proxy for learner motivation. We hypothesize that learners who are more motivated by gamification elements will use the gamified website longer. Furthermore, because we use a different method than previous studies used, we analyse our data differently. Our solution is to use survival analysis to analyse our data, which confirms the benefit of using gamification to enhance learner motivation. Our results point to the relationship between the response of different personalities and gamification elements. In further studies, we recommend to use this same approach but with more gamification elements.

RESEARCH HIGHLIGHTS

- Gamification plays an important role in enhancing learners' motivation and engagement.
- Different personalities respond differently to gamification elements.
- The dropout rate can be used to measure learners' motivation.
- Enhancing the motivation of learners does not necessarily improve their learning.

Keywords: empirical studies in HCI; user studies; web-based interaction; HCI theory; concepts and models; user characteristics

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1. INTRODUCTION

Over the past few years, the popularity of online learning systems has increased, and much research has been devoted to the improvement of these systems. Recent research has explored the adaptation of learning systems to make them more suitable and enjoyable for learners. *Adaptation* refers to the process of tailoring something to meet users' needs (Brusilovsky, 2012). Accordingly, there have been several attempts to design learning systems based on the learners' characteristics, for instance, their individual skills, knowledge, affective states and personalities (Alshammari *et al.*, 2016; Beyer and Davis, 2012). In one example, Filippidis and Tsoukalas (2009) adapted the instructional design of a learning system based on learners' learning styles. The researchers concluded that the performance and satisfaction of the learners improved as a result of using this adaptive system. However, Dichev *et al.* (2014) argued that motivation is a crucial factor that must be considered to ensure successful learning outcomes. Moreover, Carini *et al.* (2006) stated that, if learners' motivation and engagement levels increase, it may serve as a positive predictor of their achievement.

Motivating and engaging learners in an online learning system can be a significant challenge. Some researchers have suggested the incorporation of gamification elements into

instructional design by using points, badges, and the like to enhance learners' motivation and engagement levels. Many studies have confirmed the positive effects of such gamification elements (Blohm and Leimeister, 2013; Stannett *et al.*, 2016). Nevertheless, the problem with these elements is that some learners find them tedious and annoying (particularly in long-term courses) (Fitz-Walter *et al.*, 2011), and other learners may focus on collecting points and badges instead of concentrating on the educational content (Faiella and Ricciardi, 2015). Theoretical work predicts that gamification will have different impacts on individuals with different personalities (Tondello *et al.*, 2016). Some learners will benefit from the gamification of the course, whereas others will be negatively affected.

Therefore, it has been recommended that a learner model be built and used to adapt the gamification elements based on the different personalities of the learners (Tondello *et al.*, 2016). To do so, it is important to understand the relationship between personalities and gamification. Previous research has attempted to investigate this relationship (Codish and Ravid, 2014b; Jia *et al.*, 2016). Most of these studies showed that individuals favoured different game elements depending on their personalities. For example, extroverts preferred leader boards, while introverts preferred physical rewards, such as gifts and key rings. In all these studies, the learners were required to complete the entire experiment, after which they were required to respond to self-report questionnaires that asked them to specify their preferred gamification elements. In some studies, the learners were asked to take a test to measure the extent of the knowledge gained throughout the course. However, the results obtained through the above studies may be unreliable and may not provide a good measure of motivation. This is because these studies forced learners to complete the course. Moreover, these studies did not consider the data on learners who dropped out part way through the experiments. It may be crucial to factor in these dropouts and to determine whether their dropping out was affected by the gamification elements. Therefore, in this study, we aim to understand the relationship between gamification elements and personalities by using different approach. We used the dropout rate as a proxy for motivation and engagement.

Based on the findings of previous research (Codish and Ravid, 2014a, 2014b; Jia *et al.*, 2016), we hypothesized that (H1), overall, learners would benefit from the existence of gamification elements; learners would like and be more motivated by the gamified version than the non-gamified version. However, we also hypothesized that the results would vary from personality to personality. For example, according to Laidra *et al.* (2007), highly conscientious learners always do well academically. These learners have their own triggers that will motivate them to complete the course. Therefore, we hypothesized that (H2) these learners would not gain any benefit from the gamification elements, that learners with this personality would display the same behaviour in the gamified and the non-gamified versions and that most of the learners with this personality would complete the course. Brooks (1984) showed that highly extroverted learners are more likely to enjoy competing with other friends on the leader board by collecting points and badges. Therefore, we hypothesized that (H3) these learners would be strongly motivated by gamification and would busily collect points and badges. In contrast, highly neurotic learners have been described as depressed and having low interest (Laidra *et al.*, 2007). These learners are easily made nervous and annoyed. The process of collecting points and competing with others on the leader board may demotivate these learners. They may feel nervous because of their positions on the leader board. Moreover, highly neurotic learners may feel depressed and sad if their positions on the leader board are not satisfying. These learners usually care about others' opinions of them (Costa and McCrae, 1980). Therefore, we hypothesis that (H4) the dropout rate of the highly neurotic learners in the gamified version to be higher than the dropout rate in the non-gamified version.

In this study, we built a learning website in two identical versions: one with gamification elements and the other without. Then we divided the 197 learners between the two versions, each with approximately the same number of learners and balanced with age, gender, levels of knowledge and personality types. We asked the learners to use the website at any time they liked and told them they were free to dropout at any time. During this experiment, we observed the dropout rate of the learners in both versions.

The results from our experiment confirm the overall benefits of using gamification in enhancing motivation and engagement. However, the results did not reveal a negative effect for any personality dimension. The learners were found to interact differently with the gamification elements depending on their personalities. Some types of learners were observed to be highly motivated by these elements, whereas others were not affected at all. This result could be explained by the fact that a limited number of gamification elements were used (namely, points, badges and leader boards), and these may not have had as obvious a cost on the learners as would the incorporation of, for instance, social elements. In addition, only a few learners had extreme scores on any of the specific personality dimensions. Therefore, future experiments should be conducted with long-term courses and with more learners to ensure that different personality dimensions are better represented.

It is important to understand the relationship between gamification elements and personalities. Different empirical studies have tried to assess this relationship. However, the common method researchers have used is based on a self-report questionnaire from only those learners who completed the whole study. Unreliable data may result from obliging learners to complete the whole study and then ignoring dropout learners (DoLs). To overcome this unreliability, our work contributes

in two different ways. First, by using the dropout rate as a proxy for motivation, we use a more ecologically realistic method to measure the effect of gamification. Second, we apply survival analysis to analyse our data in a new approach. These techniques we use in our research could be usefully applied to other areas.

2. BACKGROUND

The demand for online learning has dramatically increased because of new technologies. Online learning is defined as any class that offers the curricula and materials in online delivery mode (Richardson and Swan, 2003). While the online courses are described by Ally (2004) as the ability to access materials via the Internet for the purpose of interacting with instructors, lessons and other learners. The aim of this interaction is for learners to gain knowledge and to enhance their experiences.

Many studies emphasize the benefits of using an online learning system. Means *et al.* (2009) argue that the main benefit from an online course is the flexibility. Learners have the ability to access their study materials at any given time, from any location, and without extra costs related to accommodation or travel. However, learners in an online learning system may be demotivated because they may feel isolated from other learners and the instructors. Learners may miss the physical interaction and the body language. In addition, there is a delay in the responses that they receive from their instructors and other learners. All these issues may demotivate learners within online courses. Moreover, the online learning system considers all learners as, essentially, the same. Their differences in terms of preference, personality and learning style are not usually taken into account (Allen *et al.*, 2004).

2.1. Motivation and engagement

Motivation is an important area to researchers in psychology, computer science and business. It is defined by Sailer *et al.* (2013) as a psychological process that initiates and directs goal-oriented behaviours. According to Dichev *et al.* (2014), motivation is a crucial factor that needs to be enhanced to ensure learners' success. With the emergence of online learning systems, the focus of earlier research was on learners' achievement and how to enhance their performance upon completion of the online course. Lately, however, more studies have concentrated on the importance of learners' motivation and their engagement when interacting with the online learning system (Cheong *et al.*, 2013; De Oliveira *et al.*, 2010). Carini *et al.* (2006) stated that if learners' motivation and engagement are increased, these may serve as positive predictors of learners' achievement and performance. If learners engage more with the system, they will use it for a longer time, which in turn can enhance their performance.

Self-determination theory is one of the most popular theories used to explain motivation, particularly in the field of education (Dichev *et al.*, 2014). This theory was first proposed by (Ryan and Deci, 2000). They stated that humans continually and actively gain experience and expertise when they seek challenges. This theory categorizes motivation into two main types: intrinsic and extrinsic. For Stannett *et al.* (2016), intrinsic motivation is more important than extrinsic motivation. However, many other researchers have argued that for an application to be effective, both extrinsic and intrinsic types of motivation must be considered (Ryan and Deci, 2000).

Intrinsic motivation

Intrinsic motivation occurs when an activity matches a user's goals. Therefore, users are satisfied when they engage in an activity. Three factors must be considered to motivate users intrinsically: autonomy, competence and relatedness (Stannett *et al.*, 2016).

Autonomy can be achieved by aligning tasks with users' values. Users should be able to say, 'I am in control. I am doing things that follow my values.'

Competence can be achieved when users feel that they are working towards their own goals and objectives. Users should be able to say, 'Yes, I am doing it. I am getting better.'

Relatedness can be achieved when users feel that they are part of a group that has the same goals and interests.

Extrinsic motivation

In this type of motivation, users are motivated when they are provided with an external element. Isaksen and Ramberg (2005) defined extrinsic motivation as the external factors that will motivate learners to do an activity. For example, learners can be given physical rewards for completing a specific task (Ryan and Deci, 2000). Extrinsic motivation can be divided into the following categories:

External regulation when the learner performs an activity to receive a reward or to avoid any penalty.

Introjection regulation when the learner performs an activity for someone else, i.e. to meet others' expectation.

Identified regulation when the learners do an activity because the result of this activity has a personal value to the learner.

Integrated regulation when the learners perform the activity to satisfy and meet their psychological needs (Isaksen and Ramberg, 2005).

From another point of view, intrinsic and extrinsic motivation are complementary. Users can be motivated intrinsically and extrinsically on different scales. However, in the case of extrinsic motivation, learners will complete the task only if they are offered external rewards. Thus, learners may lose their ability to change their behaviour on their own.

2.2. Gamification

The concept of gamification has been increasingly used in marketing and business to attract customers. Lately,

gamification has been widely used in learning and education. Robson *et al.* (2015) believe that gamification will be extensively used in numerous applications. Gamification is defined in different ways according to the area involved. In education, it is described by Caponetto *et al.* (2014) as the process of using game thinking and game mechanics to solve problems. Lee and Hammer (2011) provided a similar definition of gamification in education. It is the use of game mechanics, game dynamics and a game framework to promote a desired behaviour. Most of these definitions have different phrasings but are similar in meaning. In these definitions, the focus is on changing learners' behaviours by motivating them with the use of gamification elements to enable better engagement. Most researchers focus on one aspect of the definitions, the use of game elements such as points and rewards in a non-game context (e.g. the learning environment) to enhance the motivation and engagement of learners.

Robson *et al.* (2015) showed that gamification is not a complete game. It includes specific elements, such as badges, rewards, levels, avatars, time constraints and leader boards (Blohm and Leimeister, 2013; De-Marcos *et al.*, 2014). In gamification, users achieve their goals in a game environment. For example, users who are concerned with their fitness and with sports can use a gamified application to motivate themselves. They can earn rewards and badges when they complete a specific exercise, or they can compete with their friends by publishing their levels or scores on social media, as seen in the Nike+ application (Cheong *et al.*, 2013). This application awards users with points and badges as they walk more steps. Users can also use their points to compete with others in the leader board or they can publish their results on social media, such as Twitter (Cheong *et al.*, 2013; Stott and Neustaedter, 2013).

In the same way, gamification is used in online courses to increase learners' engagement. According to Stott and Neustaedter (2013), using gamification in learning can increase students' achievements. Students imagine that they are in a game, and thus they are less likely to fail or fear failure. In addition, by using levels and progress in gamified learning applications, students can start from one point until they stop or fail. An important feature that can be provided by gamification is rapid feedback. In addition, gamification supports and improves learners' social skills. This benefit is possible because of the interaction between learners, which can be either cooperative or competitive (Dichev *et al.*, 2014). Recently, many studies have attempted to examine the effect of gamification on learners. For example, Cheong *et al.* (2013) asked 76 students to use QuickQuiz, an application designed to motivate learners. After 4 weeks, the participants were asked to complete a self-report questionnaire about their engagement. Of the learners, 77% confirmed that they were more motivated because of gamification elements and that they enjoyed using gamification elements. Barata *et al.* (2011) asked 52 learners to complete a questionnaire about their engagement after using two versions of a learning application, one with gamification elements and the other without. The results indicate that most of the learners enjoyed the gamification elements. Although positive effects of gamification were shown by some studies, other researchers claim that there is not any significant difference in satisfaction between learners assigned to a gamified online learning system and those using a non-gamified system. It is claimed by Merry *et al.* (2012) that the level of learners' knowledge and their motivation in a gamified learning system does not show any improvement compared to those in traditional learning systems. Moreover, other studies argue that gamification elements can be a boring or annoying technique for some learners. In addition, others have agreed that the effects of gamification might only apply in the short-term (Fitz-Walter *et al.*, 2011). To address these issues, Tondello *et al.* (2016) suggested designing and adapting gamification elements on the basis of learners' attributes, such as learners' affective states and personalities.

2.3. Personality

Previous research has confirmed that personality has a major influence on individuals' behaviour, such as their academic performance and choice of job (Costa and MacCrae, 1992). Personality can be defined as a set of characteristics and psychological factors that are used to describe how individuals feel, think and interact with others. These characteristics can be identified as personality traits. Personality traits provide a deep understanding of personality and comprise all aspects of individuals and how they interact with the outside world (Hofstee, 1994). There are different models of personality that are widely used. For example, Eysenck's theory of personality, the Myers–Briggs Type Indicator, and the Big Five personality traits (Eysenck and Eysenck, 1975), (Lawrence, 1993). In this article, the focus is on the Big Five personality model as it is one of the most popular and has been widely used in similar research.

2.3.1. The big five personality model

A common way to analyse users' personalities is through the five-factor model of personality known as the Big Five model (Goldberg, 1981). This model divides users' traits into five categories: extraversion, neuroticism, agreeableness, conscientiousness and openness to experience. The first dimension of the Big Five personality model that has universal agreement is extraversion. Individuals who are extraverted are usually active, talkative, social, and assertive. The second dimension is neuroticism or emotional instability. The common traits associated with this personality are being anxious, depressed, angry, embarrassed, emotional, worried and insecure. The third dimension is agreeableness, which some researchers refer to as likeability or friendliness. The common

traits of this dimension are being flexible, trusting, cooperative, forgiving and soft-hearted. The fourth dimension is called conscientiousness or conscience. It is also labelled by other researchers as conformity or dependability. The traits associated with this personality are being careful, responsible, organized and prepared. Furthermore, others state that this dimension of personality is associated with the traits of being hardworking, achievement-oriented and persevering. This can explain the amount of research that has been done to examine the correlation between conscientiousness and academic achievement and job performance. The fifth personality trait is openness to experience, which has been expressed by other researchers as being intellectual. The traits associated with this personality dimensions are being imaginative, cultured, curious and broad-minded (Barrick and Mount, 1991; Rothmann and Coetzer, 2003; Hogan and Hogan, 1989). The summary of the traits associated with each dimension are shown in Table 1.

2.3.2. *Big five instruments*

Many instruments have been created for the purpose of assessing the Big Five personality traits. The most popular instruments that are cited in the research are the NEO Five Factor Inventory (NEO-FFI) and the Big Five Inventory (BFI). There are many versions of each of these instruments. For the version of the NEO-FFI that was developed by Costa and MacCrae (1992), there is a version called the NEO-PI that contains 181 self-report questions and another version with 240 questions. However, the lengths of these two versions make it difficult to use them in research. Most learners will select random answers to finish all of the questions. Thus, the 60-question NEO-FFI version was developed. This instrument has since been modified into several shorter instruments, each containing 10 questions (Aluja *et al.*, 2005; Costa and MacCrae, 1992). However, most of these short instruments suffer from reliability problems. Moreover, because the NEO-FFI is not free, many researchers have focused instead on a free version of the BFI that was developed by John *et al.* (1991). This tool has fewer questions (numbering 46). In addition, this tool has a higher reliability score than the NEO-FFI. There are several versions of the BFI, in many languages, that are suitable for a variety of ages. For example, there are versions that target adults and others that are appropriate for children or parents (John *et al.*, 1991).

TABLE 1. The big five personality traits.

Personality types	Characteristics
Extraversion	Social, active and high energy
Neuroticism	Depressed, worried, anxious and nervous
Agreeableness	Helpful, trusting, friendly and kind
Conscientiousness	Hard-working, prepare and organized
Openness to experience	Curious, open-minded and imaginative

2.4. Adaptation

Recent research has shown that learners' performance is much better when they are taught individually than when they are in a classroom with other learners (Desmarais and Baker, 2012; Franzoni *et al.*, 2008). This is because the instructor can better understand the most effective way to deliver the information to the student and to ensure that he or she engages with the learning content. However, this becomes more difficult in an online learning system in which the instructor and learners are physically separated. However, it is claimed by many researchers that the 'one-size-fits-all' approach is difficult to apply in online learning systems. Consequently, many researchers have shifted to adapt learning technologies and contexts to meet users' needs (Alshammari *et al.*, 2016).

Adaptation is a procedure for tailoring something to satisfy users' needs and wants (Brusilovsky, 2012). In terms of learning, Magoulas *et al.* (2003) explained adaptation as the process of organizing the learning environment to accommodate differences among learners. One method of adaptation was illustrated in (Shen *et al.*, 2009), where it is argued that the design of the learning contents based on the mood and the emotion of leaners can help to improve the learners' performance. This can be accomplished by designing the learning system based on the affective states and moods of learners (Shen *et al.*, 2009). Adaptation based on emotional measures enhances the performance of the learners. However, measuring and recognizing the emotions of learners requires advanced tools that may be expensive and difficult to use (Shen *et al.*,2009). Thus, researchers have shifted to adapting educational content based on learners' knowledge and learning styles (Alshammari *et al.*, 2016). For example, Beyer and Davis (2012) point out the importance of analysing the educational content to make it suitable for each learner. Again, the consideration of the knowledge level and experience of learners is a crucial and useful technique for enhancing learners' performance (Alshammari *et al.*, 2016), but it is difficult to design specific material for each individual learner. Adapting educational content and instructional design based on learners' learning styles can enhance the learners' performance and satisfaction, as shown by Franzoni *et al.* (2008) and confirmed by Alshammari *et al.* (2016). Researchers argued that adaptation can enhance learners' performance and satisfaction and the perceived usability of online learning systems. However, some studies highlight the instability of individual learning styles, since they can change according to the affective state of the learners and their knowledge levels (Alshammari *et al.*, 2015).

Shoda and Mischel (1998) argued that learners' personalities are considered a stable characteristic. Therefore, it may be better to focus on adapting educational content and determining whether personality has any effect on learners' performance and achievement. For instance, conscientious learners are considered to be dependable and responsible, and thus they may have good class attendance and high academic averages (Busato *et al.*, 2000). Bidjerano and Dai (2007) showed that personality might be responsible for persistence and consistency in processing information. Users who are more open to experience usually prefer to have a deep understanding of information and are capable of elaborate processing. However, learners who are more agreeable and extraverted are likely to prefer peer learning and collaborative work. Extraverted learners often encounter difficulties when using problem-solving strategies. They sometimes cannot solve or overcome problems easily because of a lack of concentration.

Gamification has been used to enhance learners' motivation recently (Cheong *et al.*, 2013). However, some research show that it is more effective if the design is based on the learners themselves (Tondello *et al.*, 2016). For example, the elements of gamification can be personalized on the basis of learners' moods or affective states. However, these states are not stable and learners will be in different moods on different days (Shen et al, 2009). In addition, assessing the moods and the affective states of learners is difficult (Shen *et al.*, 2009). To address this, adapting gamification elements to learners' personalities has been suggested (Tondello *et al.*, 2016). For example, research has argued that extraverted learners prefer social elements (such as chats and leader boards) as a way to motivate them, whereas introvert learners are demotivated by these elements.

A few recent studies have attempted to investigate the relationship between gamification and learners' personalities (Codish and Ravid, 2014a, 2014b). One of these studies was that of Jia *et al.* (2016), who examined learners' preferred elements. They asked users to complete a personality test and a test to report their favourite element and whether they found this element enjoyable and helpful. This experiment was based on a self-report questionnaire where users filled the personality test and then indicated their preferred gamification elements. Another experiment was conducted by Codish and Ravid (2014a), who focused on only one dimension of personality, that of extraversion. In their experiment, they assessed users' personalities by administering the FFI questionnaire. A total of 133 undergraduate students participated and took a gamified course. At the end of the term, the learners were asked about the gamification elements they preferred. After that, Codish and Ravid (2014b) used a paper prototype to define the relationship between gamification elements and all personalities. The results of all of these experiments confirmed that the extravert learners preferred points, badges and leader boards, whereas the introvert and neurotic learners were more motivated by rewards. The experiments showed that highly conscientious users were motivated by level and progress elements.

Most of the studies relevant for gamification have addressed the relationship between gamification and personality by using a self-report questionnaire that was filled in by learners who had completed an entire gamification experiment. Such an approach may provide unreliable results. This is because these studies forced participants to complete the entire experiment and then to fill in a questionnaire about what they liked and enjoyed it. However, this approach conflicts with the main aim of gamification, to increase learners' motivation. Furthermore, these works excluded DoLs from the analysis. This could significantly bias the results, since these learners might be the ones in which we are most interested. It is essential to understand the reason behind their dropping out: is it because of the gamification elements or not?

In this study, we followed a different approach to measure learners' motivation and engagement. Motivation is a psychological construct that is difficult to measure directly. However, there are some theoretical and practical works that provide guidelines on how to measure motivation. One of these methods is using 'completion' and 'in-completion' of a task as a measurement of motivation. According to Park and Choi (2009), in the online courses, learners who were more motivated (more satisfied and more interested in the course) were less likely to leave or to drop out from the course.

In addition, Touré-Tillery and Fishbach (2014) pointed out that prior knowledge and level of motivation were the two essential factors that determined whether the course was eventually completed. In view of these points, in this study, we used the dropout a proxy for motivation and engagement. Thus, after balancing the prior knowledge of learners, we hypothesized that learners who are more motivated will complete more lessons.

3. METHOD

This study aims to build a deep understanding of the effects of gamification on learners who have different personalities. Most of the relevant studies addressed this relationship by asking learners who had completed an entire experiment about the most enjoyable and reliable elements. This may provide unreliable results. Following this logic, we measured the effect of gamification on personality by observing the dropout and the completion rates for a course. Thus, we used these rates as a proxy for measuring learners' motivation and engagement. We hypothesized that learners who are more motivated by gamification elements would use the gamified online course for longer. Which may turn to improve learners' performance as suggested by Carini *et al.* (2006).

3.1. Participants

Before beginning the experiment, ethical approval was granted by the schools. In addition, a consent form was sent to the students' parents to obtain their approval, to explain the purpose of the experiment and to confirm that all data collected will be anonymous and secure. The students and their parents were informed that they have the option to drop out of the experiment at any time.

We asked 197 learners from different high schools in Saudi Arabia to participate in the experiment. The participants consisted of 107 females and 90 males and were between 16 and 18 years old.

3.2. Setup

We built two identical versions of a learning website. One version included gamification elements (points, badges and leader board) and the other lacked these elements.

The objective of the website was to teach the learners how to use Microsoft Excel. The course was divided into 15 lessons and began with an introductory topic, such as creating tables and presenting graphs, and progressed to advanced topics, such as mathematical and logical functions.

After each lesson, there was a quiz consisting of a few questions on the lesson. In the gamified version, correctly answered questions yielded 1 point. After collecting 5 points, the learner received a badge that changed the learner's position on the leader board. Figure 1 shows a screenshot of the online learning website in the two versions: (i) the gamified version and (ii) the non-gamified version.

At school, the learners were asked to complete three registration forms:

- A form containing questions to solicit demographic information.
- A pre-test on the taught topic in order to determine the learners' knowledge level. This served to balance the prior knowledge of learners between the two groups.
- A BFI personality test to identify each learner's personality type.

After obtaining the results from the BFI personality test, we divided each personality type into three categories: low, average and high.

We did the classification by plotting the score for each personality type on the x-axis and the frequency of learners with each personality type on the y-axis. Then, we labelled the scores for personality that lay in the bottom 25% of the data as the low quartile and the data lay in the top of 25% of the data as the high quartile. Finally, the data lying between the 25 and 75% cut-off boundaries were labelled average. This classification is based on arbitrary cut-off points.

In this study, we analysed data only for the high and low personality types because we believed that the effects would be strongest for learners at the high and low extremes of each personality type.

Figure 2 shows an example of the classification of one personality type (the conscientious personality). Learners with a conscientiousness score of 1 or less were considered to have low conscientiousness; learners who had a score higher than 1 and lower than or equal to 3.8 were considered average; and learners who had a conscientiousness score higher than 3.8 were considered to have high conscientiousness.

3.3. Procedure

After using the registration forms to obtain values and to classify personality type, we ran our experiment as a between-subjects study. We divided learners into two groups: one group used the gamified version and the other used the non-gamified version. Both groups contained approximately the same number of learners and were balanced by gender and age (obtained from the demographic test), knowledge level (obtained from the pre-test) and personality score (obtained from the BFI test). We balanced the groups to maximize the likelihood that the difference in the dropout rate between the two groups would occur only because of the gamification elements.

Following registration, learners were asked to use the website whenever and wherever they wished. The learners could also stop using the website whenever they wanted. We anticipated that, as the course progressed, some learners would drop out at various stages. We refer to these as DoLs in our study. After 6 weeks, most of the learners had either dropped out or completed the experiment.

Because we were using the dropout rate as a proxy for motivation, we needed a special type of analysis that considers the time spent on the system and the status of the learner as dependent variables. This type of analysis is called survival analysis, which is a common type of statistical analysis used in medicine, the biological sciences and engineering. Survival analysis can be defined as a set of methods used to analyse the participants' time spent in the experiment, from the time of entering the experiment until the event of interest occurs (Jager *et al.*, 2008). This event can be death, disease or dropping out. Survival analysis uses the information obtained from learners who completed the course and from learners who dropped out.

There are two main concepts in survival analysis: survival and hazard functions. The survival function provides the probability of the learner's survival at each time point, while the hazard function provides the probability that an event will occur (Clark *et al.*, 2003).

Survival analysis can be used to compare the survival between two groups. One of the most common methods is the Kaplan–Meier graph, which is used to plot the survival distribution for two groups. The issue with this test is that it is used to compare the cumulative survival distribution between two groups at arbitrary chosen points and does not present the

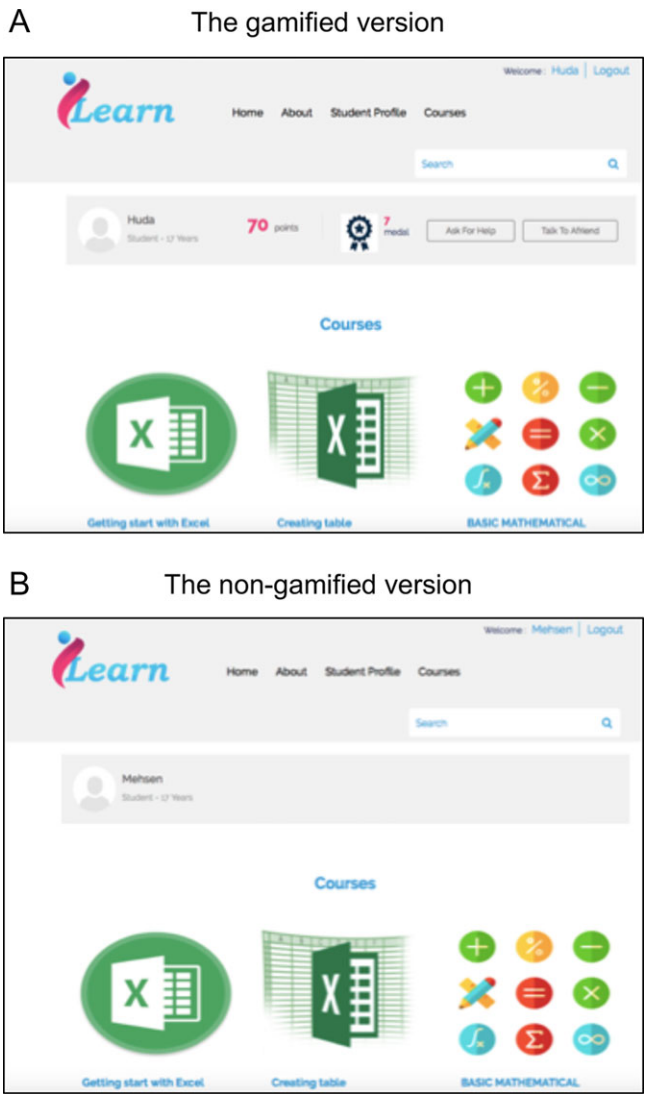

FIGURE 1. A screenshot of the online learning website in the two versions ((i) the gamified version, (ii) the non-gamified version)

differences between the groups at all times. For determining continual differences between two groups, researchers have used the log-rank test. This is based on the *P*-value obtained from chi-square tests. However, the problem with these two non-parametric methods is that both are used with categorical data, and they are less effective if applied with continuous data. Furthermore, these tests only show whether there is a difference between the two groups; they do not indicate how much of a difference there is. Therefore, most researchers use a specific type of regression that addresses these issues. This method is called the Cox proportional hazard model (Walters, 1999).

The Cox hazard model is used to evaluate the effect of specific factors on the rate of a particular event happening (death, dropout), which is called the hazard rate (HR). This model analyses the relationship between the hazard function and the

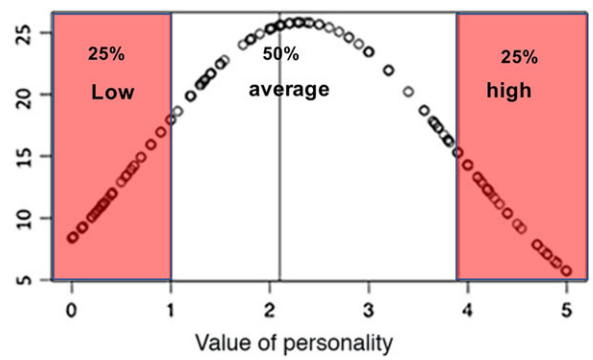

FIGURE 2. The classification of the conscientiousness personality.

predictors or the treatment. By assuming a nonlinear relationship between the hazard function and the predictors, the Cox hazard model allows for the isolation of the treatment's effect from other variables. The Cox hazard model can be expressed by a hazard function, which can be calculated using software such as R or SAS using the following formula (Singer and Willett, 1993), (Walters, 1999):

$$h(t) = h_{0(t)} \times \exp(b_1x_1 + b_2x_2 + \cdots + b_px_p)$$

where, $h(t)$ is the hazard function, $b_1, b_2, \ldots, b_p$ are the coefficients used to determine the effect size of covariates and $h_0(t)$ refers to the baseline hazard, which indicates the value of hazard at time 0.

The Cox hazard model can indicate whether there is any difference between groups, since this technique calculates the *P*-value using three different tests. In addition, the Cox hazard model shows whether the hazard is increased or decreased by examining the sign of the regression covariate. Defining the variation between the two groups can be done by examining the value of $\exp(b_i)$; this is called the hazard ratio (HR). The value of HR can be interpreted as follows (Singer and Willett, 1993; Walters, 1999):

HR = 0, there is no effect
HR < 1, the hazard is decreased
HR > 1, the hazard is increase

Hypotheses

Most of the current work found a positive effect of gamification, namely, increasing the learners' motivation in online courses. Due to that, we hypothesized that the learners assigned to the gamified version would be more motivated and would use the learning website for longer periods than the learners assigned to the non-gamified version (Cheong *et al.*, 2013; Codish and Ravid, 2014a).

H1: Overall, learners will use the gamified version for a longer period, indicating that they are more motivated by gamification elements.

TABLE 2. The number and the personalities of participants.

	Gamified			Non-gamified		
Personality	Male	Female	Total	Male	Female	Total
High conscientiousness	10	14	24	11	15	26
Low conscientiousness	12	12	24	7	23	30
High extraversion	10	9	19	8	9	17
Low extraversion	5	8	13	8	12	20
High agreeableness	7	13	20	7	11	18
Low agreeableness	7	8	15	9	9	18
High neuroticism	9	13	22	9	8	17
Low neuroticism	6	9	15	5	10	15
High openness	4	6	10	6	7	13
Low openness	7	6	13	9	11	20

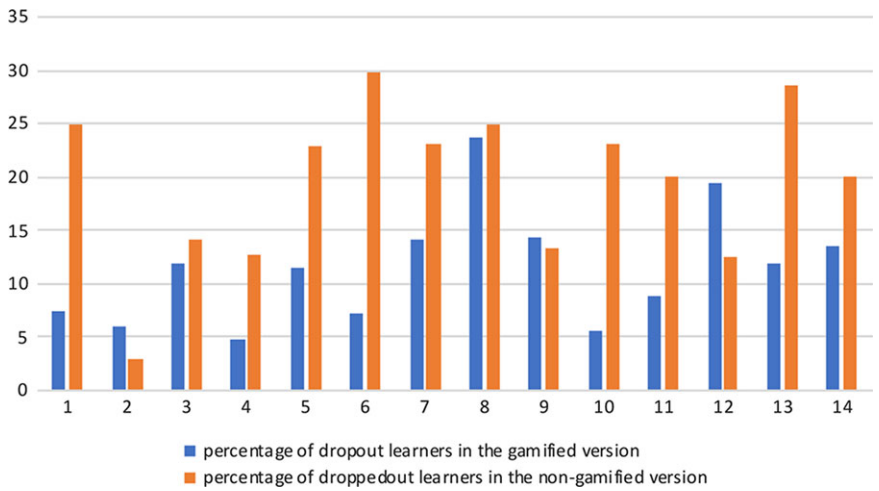

FIGURE 3. The percentage of the dropout learners at each lesson in the gamified and the non-gamified versions.

Regarding personality, we believed that, depending on their personality types, learners would respond differently to gamification elements. Highly conscientious learners have been described as hard-working and always display better performance (Laidra *et al.*, 2007). In addition, some of the previous research has found that this type of learner may prefer not to have gamification elements to motivate them, because they have their own trigger (Jia *et al.*, 2016). Therefore, we hypothesized that highly conscientious learners would display the same behaviour in the gamified and the non-gamified versions. These learners would not be impacted by gamification.

H2: Highly conscientious learners will display the same motivation in the gamified and the non-gamified versions.

In contrast, highly extroverted learners have been shown to prefer seeing points and badges (Brooks, 1984). In addition, highly extroverted learners have been described as liking challenges and preferring to compete with others (Codish and Ravid, 2014a). Therefore, we hypothesized that these learners would prefer points, badges and a leader board and would be more motivated by the gamified version.

H3: Highly extroverted learners will use the gamified version for longer, indicating that they are more motivated by gamification elements.

The existence of the leader board and some other competitive elements may demotivate highly neurotic learners. These learners always care about the opinions of others and seeing their names in unsatisfactory positions on the leader board may make them nervous and depressed (Costa and McCrae, 1980).

H4: Highly neurotic learners will become demotivated by the gamification elements.

Other research has pointed out that agreeability and openness lead to a preference for gamification elements (Jia *et al.*, 2016). Therefore, we hypothesized that other personality types, such as those with high agreeability and openness to experience, would benefit from gamification and that their

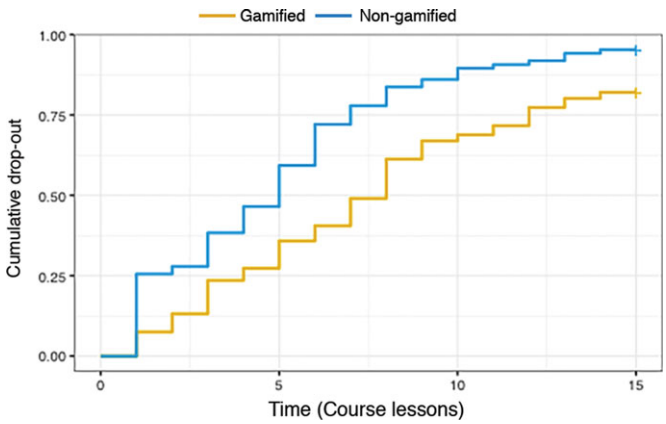

FIGURE 4. The Kaplan–Meier plots for overall learners in the gamified and the non-gamified versions.

motivation would be stronger with the gamified version (Codish and Ravid, 2014b).

H5: Highly agreeable learners will be more motivated by gamification elements.

H6: Highly open learners will be more motivated by gamification elements.

4. RESULTS

In this study, we asked 197 learners with different personalities (Table 2) to use one of two online learning systems. They were free to drop out at any time. Figure 3 shows the percentage of DoLs at each lesson in the gamified and the non-gamified versions.

We plotted the cumulative survival function for the overall learners in the gamified and non-gamified versions using a Kaplan–Meier graph to analyse the data. In this analysis, the digital time refers to the lesson number, and the event of interest is the cumulative number of dropouts. Figure 4 shows the plots of the learners' cumulative dropout rates in the gamified and the non-gamified versions.

Then we used the Cox hazard model to determine whether there were any significant differences and the size of the differences. Table 3 shows the result from the Cox hazard model after applying a built-in function in R that calculates this. The *P*-value from each of the three tests was <0.05, which indicated that there was a statistically significant difference in the number of DoLs between the gamified and the non-gamified versions. The value of coef refers to the regression covariate. If table coef value is positive, then the dropout rate is higher in the second group, and if the coef value is negative, then the dropout rate is low. The result of our analysis was 0.6636, which showed that the second group (which received the non-gamified version) had a higher dropout rate than the first group. The result of exp(coef) refers to the HR, which shows

TABLE 3. The result from Cox regression when it is applied on the overall learners.

	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 = 2.687e-0.5
Wald test = 18.02 on 1 df,					P = 2.185e-0.5
Score(Logrank) test = 18.64 on 1 df,					P = 1.58e-0.5

TABLE 4. The results of the logistic regression.

Term	Coefficient	Std-Err	z-Value	P-value
Conscientious	1.48	0.40	3.67	0.017
Extraversion	1.33	0.50	2.66	0.007
Agreeableness	0.40	0.38	1.03	0.30
Neuroticism	−0.883	0.35	−2.511	0.012
Openness	−0.21	0.43	−0.50	0.61

how much the two groups differ. In our analysis, the result for the HR was 1.94, which meant that the dropout rate in the second group was almost twice as high as in the first group. The Cox hazard result showed that gamification had a positive effect and increased learners' motivation, in general.

However, we need to thoroughly understand which personality types were motivated by the gamification elements and which were not. Therefore, we applied a logistic regression to our data. We used the five personality traits as the independent variables. The dependent variable was a binary value that was 0 if the learner was a dropout or 1 if the learner completed the course. Table 4 shows the results of the logistic regression. In the table, the *P*-value obtained for the z statistic showed that there was a statistically significant difference in course completion that depended on personality traits (conscientiousness, extraversion and neuroticism). The coefficients in the table show the relationship between the predictors (personality traits) and the probability of the completion of the course. A positive value for the coefficient indicates that the probability of completing the course increased when the score for the personality type increased. 'Std-err' in the table shows the standard error of the coefficient estimate, that is, the accuracy of the coefficient. However, we could not use the logistic regression to determine which version was the best for each personality type because of the different times (different lessons) at which learners dropped out.

To determine the effects of gamification on each personality, we compared the survival distribution for the highly conscientious learners in the gamified and non-gamified versions and for the low conscientiousness learners in both versions. Figure 5 shows the Kaplan–Meier graph for the high conscientiousness learners in the gamified and the non-gamified versions. Next, we applied the Cox hazard model to find the

difference between the dropout rate of the high conscientiousness learners in both versions. Table 5 shows the results from the Cox hazard model. The *P*-value from the likelihood test was 0.14, which shows that there was not a statistically significant difference between the dropout rate of the highly conscientious learners in the gamified and the non-gamified versions. However, the positive value of the covariate shows that the dropout rate of the highly conscientious in the non-gamified version was higher than their dropout rate in the gamified version.

Figure 6 shows the Kaplan–Meier graph for the low conscientiousness learners in the gamified and the non-gamified versions. The results show the dropout rate in the non-gamified version was higher than the dropout rate in the gamified version. Table 6 shows the results from the Cox hazard model. The *P*-value from the likelihood test was 0.0027, which indicates that there was a significant difference between the dropout rates in the two versions. The positive value of the coef indicates that the dropout rate was higher in the non-gamified versions. The value of HR was 2.5, which indicates that the dropout rate was more than twice as high in the non-gamified version as in the gamified version.

The Cox proportional hazard is applied to measure the difference between the highly extraverted learners in the gamified and the non-gamified versions. We found there was a significant difference between the two versions for these types of learners. The dropout rate for the highly extraverted learners was almost a third higher in the non-gamified version while the low extraverted learners showed no significant benefit from gamification.

The highly neurotic learners are shown to have a significant benefit from gamification, which conflicted with our expectation. There is a significant difference between the dropout rates in the gamified and the non-gamified versions. This result may be explained because of the positive correlation between extroverted and neurotic personality traits in our sample (Table 7).

Figures 7–10 show the rest of the Kaplan–Meier graph for other personalities and Table 8 shows a summary of the results obtained from applying the Cox hazard model.

5. DISCUSSION

The results from our study confirmed hypothesis H1 and the findings of previous research in the literature that gamification increases learners' motivation and engagement. However, the results also showed variations in the responses of different personality types to gamification. Some personality types benefit a lot from gamification, while other personalities do not. For example, our results supported hypothesis H2, which stated that conscientious learners would have the same level of motivation in the gamified and the non-gamified versions.

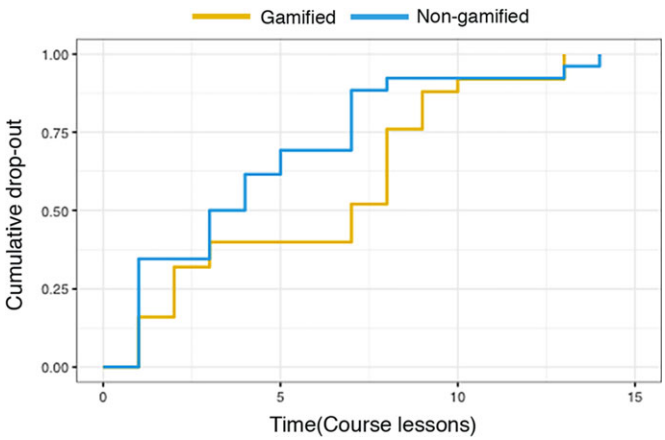

FIGURE 5. The Kaplan–Meier plots for highly conscientious learners in the gamified and the non-gamified versions.

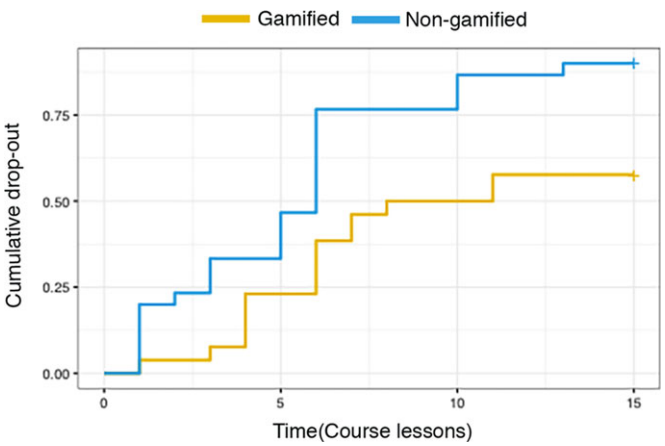

FIGURE 6. The Kaplan–Meier plots for the low conscientious learners in the gamified and the non-gamified versions.

TABLE 5. The result from the Cox regression on the highly conscientious learners in the gamified and the non-gamified versions.

	Coef	Exp(Coef) = HR	Se(Coef)	z	Pr(> |z|)
Version	0.42	1.532	0.29	1.46	0.143
Likelihood ratio test = 2.12 on 1 df,				$P = 0.1442$.	
Wald test = 2.14 on 1 df,				$P = 0.1432$.	
Score(Logrank) test = 2.17 on 1 df,				$P = 0.1406$.	

TABLE 6. The result from the Cox regression when it is applied to the low conscientious learners.

	Coef	Exp(Coef) = HR	Se(Coef)	z	Pr(> |z|)
Version	0.95	2.5	0.32	2.9	0.003

Likelihood ratio test = 8.94 on 1 df, $P = 0.0027$
Wald test = 8.47 on 1 df, $P = 0.0036$
Score(Logrank) test = 9.07 on 1 df, $P = 0.0026$

TABLE 7. The correlation between personalities.

	Conscientiousness	Extraversion	Agreeableness	Neuroticism	Openness
Conscientiousness	1	0.14	0.08	−0.09	−0.04
Extraversion	0.14	1	0.26	0.28	−0.04
Agreeableness	0.08	0.26	1	−0.27	0.02
Neuroticism	−0.09	0.28	−0.27	1	−0.03
Openness	−0.04	−0.04	0.02	−0.03	1

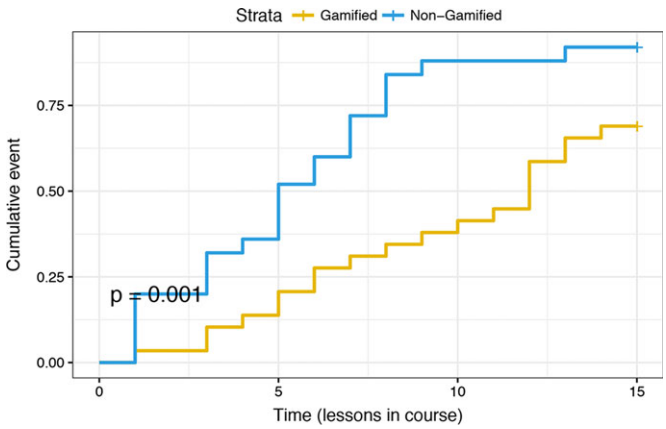

FIGURE 7. The result from the Kaplan–Meier when it is applied on the high extraversion learners.

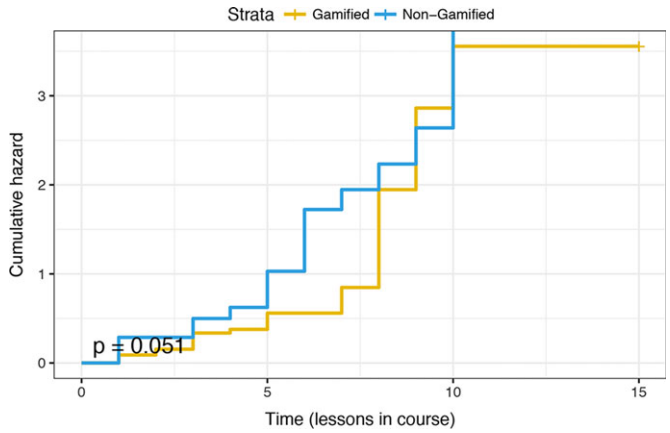

FIGURE 8. The result from the Kaplan–Meier when it is applied on the low extraversion learners.

These learners showed almost the same dropout rate on both website versions. These results confirm what was concluded by Jia *et al.* (2016): highly conscientious learners prefer not to have gamification elements to motivate them. However, they like being able to see their progress and how much they need to do to complete a course.

Additionally, highly extroverted learners are motivated by gamification elements, which supports hypothesis H3. Their dropout rate in the gamified version was lower than their dropout rate in the non-gamified version. This also confirms the conclusions of other studies. Codish and Ravid (2014a) noted that points and badges have a significant effect on highly extroverted learners, who enjoy collecting points, badges and rewards.

Some related studies, such as Jia *et al.* (2016), show that highly neurotic learners are affected negatively by gamification elements. These learners described these elements as 'silly' and 'toy-like'. However, the results of our study contradicted both some of the previous results in the literature and hypothesis H4. In our experiment, the dropout rate of highly neurotic learners using the gamified version was lower than their dropout rate using the non-gamified version. This phenomenon may be explained by several factors, such as the small number of learners with extreme personality types in our study. In addition, combinations of personality types have an effect; we found a positive correlation between neuroticism and extraverted personalities in our sample.

For the other learner personality types, such as the agreeable type and the openness to experience, we did not discover any effect. This can be explained by the small number of learners with extreme personality types and the correlation with other personality types. For that reason, we were unable to test hypotheses H5 and H6.

One limitation of our work is using only a limited number of gamification elements (namely, points, badges and a leader board). The presence of these elements may not cost learners any time or be annoying for them. In addition, in this study we focused only on the effect of these elements for the length

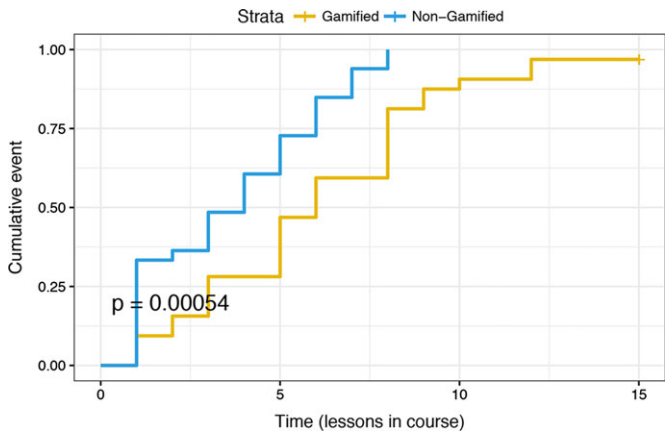

FIGURE 9. The result from the Kaplan–Meier when it is applied on the high neuroticism learners.

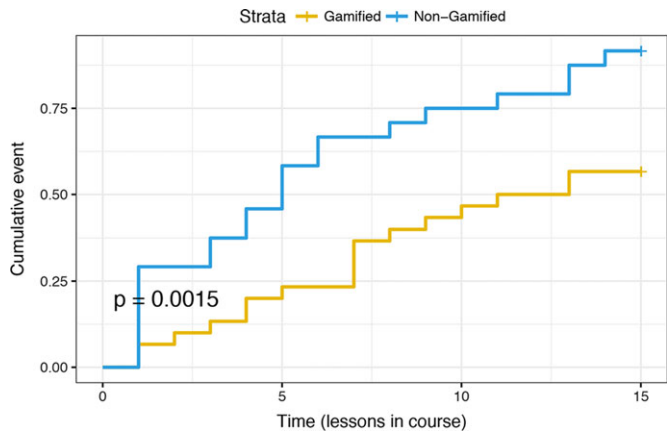

FIGURE 10. The result from the Kaplan–Meier when it is applied on the low neuroticism learners.

TABLE 8. A summary of the results obtained from the cox hazard model.

Independent variables in gamified vs. non-gamified versions	*P*-value	Coef	Exp (coef) = HR
Overall learners	2.68e-05	0.6636	1.9417
High conscientious	0.1442	0.4270	1.5326
Low conscientious	0.0027	0.9514	2.5894
High extrovert	0.0014	1.0098	2.7450
Low extrovert	0.0506	0.4436	1.5583
High neuroticism	0.0006	0.9426	2.5664
Low neuroticism	0.0012	1.004	2.729

of time the learner spent in the system and their completion of the course. Future studies should consider the knowledge gain of learners and how it is affected by gamification. Further, the low number of learners with extreme personality types, and the interaction between personality types, may also have had an effect on our results.

Thus, in order to achieve our aim of understanding the relationship between gamification and personality type, we need to run another experiment. In the new study, we should include more gamification elements that may have a significant effect on learners, such as social elements, motivational phrases and avatars.

6. CONCLUSION

Several researchers have recommended gamification as a technique to increase learners' motivation and engagement when they use online learning systems (Blohm and Leimeister, 2013; Stannett *et al.*, 2016). However, it has been suggested that the use of gamification elements, such as points, badges and social elements may have a negative effect on some learners, who might find these aspects annoying and tedious (Fitz-Walter *et al.*, 2011). Others may become so preoccupied with the gamification elements that they may lose focus on the course content (Faiella and Ricciardi, 2015). In order to overcome these negative effects, previous research has recommended that gamification elements be customized based on learners' attributes. One suggested attribute is personality type, as it is stable (Tondello *et al.*, 2016). Therefore, it is important to examine the relationship between gamification and learners' personality types. Theoretical models point to various effects of gamification on learners with different personality types (Tondello *et al.*, 2016). A few works examined this relationship. However, most previous works required participants to use a gamified learning system, after which those who finished the experiment were required to complete a questionnaire to determine the game element, they found most motivating (Codish and Ravid, 2014a; 2014b; Jia *et al.*, 2016). However, failing to consider learners who drop out from the experiment (or else forcing learners to complete an experiment) could have biased the results. It is important to identify the reasons why they withdrew, which may relate to gamification elements. In addition, using a self-report questionnaire may yield unreliable results.

Therefore, to overcome the issues of the previous studies, our research investigated a new approach to measuring learners' motivation. We used the number of learners who dropped out of the experiment as a proxy for motivation and engagement. We hypothesized that learners who are highly motivated by gamification elements would use the gamified online learning system for longer. The focus of this research was to measure the motivation and engagement of learners. Therefore, the knowledge gained, and the learners' performance were not measured.

For our experiment, we built a learning website to teach Microsoft Excel in two identical versions, one with gamification elements and the other without. Then we divided 197 learners among the two versions (balancing the number of

learners, gender, personality and knowledge). The learners were free to use the website whenever they wanted and drop out from the experiment at any time. During the experiment, we observed the dropout rates of the learners in the two versions. To analyse our data, we needed survival analysis, a special type of analysis that included learners who stayed in and those who dropped out of the experiment. As we had continuous data, we used the Cox proportional-hazard model.

Our results confirmed the results from the literature. The results showed that gamification increased the motivation of the learners in general. However, the results also showed that the motivational benefit of gamification varied across personality type. For example, there were some personality types whose motivation benefited significantly from gamification, such as the highly extrovert type. In contrast, other personality types, benefited less from gamification, such as the highly conscientious type.

In our results, we did not anticipate any negative effect of gamification on learners. This may imply that one should provide gamification elements to all personality types and that it would be worthless to adapt the gamification elements at this stage. However, we believe that some personality types would be demotivated by the gamification elements. This negative effect might appear more clearly in a long-term study. This is what we noticed in our study. The number of the dropout learners in the gamified version increases over time. In addition, in our study, we used only a limited number of gamification elements. Presenting points and badges to the learners may not be time consuming or annoying. Further, we did not measure whether the gamification elements had any effect on the learners' knowledge gain. We need to test our hypothesis that learners will display better performance if they use the learning website for longer durations.

Thus, because of all the previous limitations, we need to plan further studies with more gamification elements. For example, we can incorporate social elements, avatars and motivational phrases. These kinds of elements are expected to be annoying for some personalities and distracting for others. In fact, we did a pilot study with social elements, which will not be reported here. We found that some of the highly extrovert learners were really motivated by these elements. They use the gamified version for longer. However, their knowledge gain in the gamified version was worse than their knowledge gain in the non-gamified version. Thus, we may need to control the way that we provide these gamification elements to these kinds of learners.

Research on gamification is important to ensure the effectiveness of intelligent online learning systems. These new systems must observe learners and provide them with gamification elements that match their stable characteristics. The gamification elements provided must be updated based on the behaviour of learners in the gamified course and on other short-term factors, such as mood and the physical context. In reality, this is what a good teacher would do—observe how learners interact with the system, then control and manage gamification elements and the system in a way that provides an effective learning platform.

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